AN INTEGRATED FRAMEWORK FOR GAS TURBINE BASED POWER PLANT OPERATIONAL MODELING AND OPTIMIZATION

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AN INTEGRATED FRAMEWORK FOR GAS TURBINE BASED POWER PLANT OPERATIONAL MODELING AND OPTIMIZATION

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b	=	Shape parameter of Weibull distribution
c	=	Random variable
d	=	Rate of performance degradation
e	=	Age reduction factor; conversion factor for the number of start/stop cycle to operating hours
y	=	Capital charge factor
h	=	Scale parameter of Weibull distribution; average plant efficiency
t	=	Age
t_m^-	=	Age of the system immediately before it enters the m^{th} preventive maintenance
t_m^+	=	Age of the system immediately after it undertakes the m^{th} preventive maintenance
Δ	=	Percentage of performance loss
a, b, c	=	Coefficients of performance degradation function
c_{om}	=	Cost rate of operations and maintenance
C_{cm}	=	Cost of corrective maintenance
$C_{failure}$	=	Cost of failure
C_{fuel}	=	Cost of fuel
C_h	=	Operation and maintenance cost per factored fired hours
C_{lr}	=	Loss of revenue due to plant unavailability
C_{om}	=	Cost of operations and maintenance excluding fuel cost
COE	=	Cost of electricity
d	=	Day index for each year

D = Number of days

$DCOE$ = Daily cost of electricity

DGR = Daily gross revenue

DNR = Daily net revenue

DSS = Daily cumulative spark spread

DSS^{*} = Optimal daily cumulative spark spread

E^{D} = Demand of electric energy

f = Probability density function

f_{s} = Starting frequency

F = Distribution of failure of an item

Fc = Price of fuel

g = Failure rate reduction factor or performance degradation reduction factor

GR = Gross revenue

h = Hazards rate function

H = Cumulative hazard function

H_{a} = Actual fired hours

H_{f} = Factored fired hours

Hm = Remaining factored fired hours before next scheduled preventive maintenance

HR = Heat rate

k = Index for type of day; technology impact factor

K = Technology impact vector

L = Life of an item

L_{ISH} = Age of an item using the independent starts and hours method

L_{EOH} = Age of an item using the equivalent operating hours method

m = Maintenance factor

m_{h} = Maintenance factor on operating hours

m_s	=	Maintenance factor on starts
Mp	=	Price of electricity
n	=	Number of days in a year for each type of day
nr	=	Net revenue rate
P	=	Power output rate; probability
Q	=	Depreciation
R	=	Reliability
RSE	=	Response surface equation
SS	=	Spark spread
S_a	=	Actual starts
S_f	=	Factored starts
Sm	=	Remaining factored starts before next scheduled preventive maintenance
t	=	Calendar time; time index for each day; technology upgrade status
t_m^-	=	The calendar time immediately before the system enters the m^{th} preventive maintenance
t_m^+	=	The calendar time immediately after it undertakes the m^{th} preventive maintenance
T	=	A period of time; technology vector
Ta	=	Ambient conditions
TCR	=	Total capital requirement
T_{eq}	=	Equivalent annual utilization at rated power output hours/annum
T_{firing}	=	Firing temperature
u_{var}	=	Variable cost of operation, maintenance and repair
U_{fix}	=	Fixed cost of operation, maintenance and administration
v_m^-	=	Virtual age of the system immediately before it enters the m^{th} preventive maintenance

v_m^+ = Virtual age of the system immediately after it undertakes the m^{th} preventive maintenance

V = Virtual age

W_m = The work scope of the maintenance or upgrade

X = Time interval between two consecutive maintenances

YSS = Yearly cumulative spark spread

YSS^* = Optimized yearly cumulative spark spread

SUMMARY

The deregulation of the electric power market introduced a strong element of competition. Power plant operators strive to develop advanced operational strategies to maximize the profitability in the dynamic electric power market. New methodologies for gas turbine power plant operational modeling and optimization are needed for power plant operation to enhance operational decision making, and therefore to maximize power plant profitability by reducing operations and maintenance cost and increasing revenue.

In this study, a profit based, lifecycle oriented, and unit specific methodology for gas turbine based power plant operational modeling was developed, with the power plant performance, reliability, maintenance, and market dynamics considered simultaneously. The generic methodology is applicable for a variety of optimization problems, and several applications were implemented using this method.

A multiple time-scale method was developed for gas turbine power plants long term generation scheduling. This multiple time-scale approach allows combining the detailed granularity of the day-to-day operations with global (seasonal) trends, while keeping the resulting optimization model relatively compact. Using the multiple time–scale optimization method, a profit based outage planning method was developed, and the key factors for this profit based approach include power plant aging, performance degradation, reliability degradation, and, importantly, the energy market dynamics. Also a novel approach for gas turbine based power plant sequential preventive maintenance

scheduling was introduced, and a profit based sequential preventive maintenance scheduling was developed for more effective maintenance scheduling.

Methods to evaluate the impact of upgrade packages on gas turbine power plant performance, reliability, and economics were developed, and TIES methodology was applied for effective evaluation and selection of gas turbine power plant upgrade packages.

CHAPTER 1

MOTIVATION

1.1 The Deregulation of Electric Power Market

The electric power system is one of the most complex systems of today's civilization [1]. Although there are no two electric power systems alike, some common fundamental characteristics of a generic electric power system include generation, transmission, and distribution [2]. Electric power is generated using synchronous machines that are driven by mechanical power such as gas turbines, and/or steam turbines. A second major source of power is from hydroelectric dams with power produced from water turbines. And a third source of power is from nuclear power plants. Though not extensively used in the United States, nuclear power is a major source of power in some foreign countries, such as France. The generated power is then transmitted on high voltage lines from the generating sites over long distances to load centers, from which it is distributed to the end customers.

There is an ongoing major change in the global electricity power market, the change from a regulated power to a deregulated power. The US electric power market is undergoing a tremendous transformation in following this trend. Deregulation of other industries other than the electricity industry has led to substantial cost savings on the part of industry participants, lower prices to consumers, and the emergence of new products.

It is found that, in airline[*], telephone, and gas industries, the vertically integrated monopolies could not provide services as efficiently as competitive firms [3]. Analogous to the resulting competition inside these industries, the electric power industry plans to improve its efficiency by introducing competition. It is planned that the reduction of electricity cost will be achieved by driving prices through market forces and more competition. It is hoped that this will be accomplished by creating an open environment, which will allow users to choose their electric power supplier.

The primary goal of electric power market deregulation is to introduce more competition and therefore to reduce the cost of electricity. The electric power industry reform has been motivated by several factors other than high electricity prices and a shift away from a monopoly. Technology development, particularly the improvement in the efficiency of the gas turbine power plant, has also been a booster [4].

In the vertically integrated electric power industry before deregulation, each utility controlled and owned all or most of generation, transmission and distribution facilities and thus exercised a monopoly on selling electric power to customers within its geographical region. One of its most important characteristics of this mode of ownership and operation is that the utility is obliged to sell and meet the electric power needs of its customers. Rates are set by state regulatory commissions [3], and the utility realizes a fixed profit that is established by the commission. Electric power is sold on a cost-plus

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[*] *The airlines as a group are in terrible shape. However, they are in a much different situation with airlines historically competing with one another for the same customers in most cases. Their problem is that in many cases the older airlines cannot cut costs effectively – pilots union problems, etc. They, like the GENCOs have the major expense of fuel.*

basis, and costs are transferred to the end-use consumers. As a result, the decision support system for power plant operation is centralized, and there is no incentive to reduce costs.

Under the deregulated electric power market, generation, transmission and distribution are owned by different entities, and the independent system operator (ISO) serves as a neutral operator responsible for maintaining instantaneous balance of the electric power system [3]. An ISO is independent of any participants with commercial interests in the system operation. A generation company (GENCO) is a regulated or non-regulated entity that operates and maintains existing generating plants. Transmission systems (TRANSCOs) are composed of an integrated network shared by all participants, and they transfer electricity from GENCOs to distribution companies (DISCOs). TRANSCOs are regulated to provide non-discriminatory connections and comparable services for cost recovery. A distribution company (DISCO) is an entity that distributes electricity to its customers in a certain geographical region. These three entities and their relationships in the vertically integrated utility and the deregulated power system are shown in Figure 1.1.

In a deregulated power market environment, the *GENCOs* find themselves in a strong competitive environment, and the overall cost of producing power is the key to their survival. This means high efficiency, both in the power plant and in operations and maintenance, is at a premium, and to increase profits the power generators have to supply electric power at the lowest possible cost. Consequently, the decision support system for power system operation is decentralized. The generation companies have to make their own operational decisions based on electric power market signals, power plant performance, and reliability considerations.

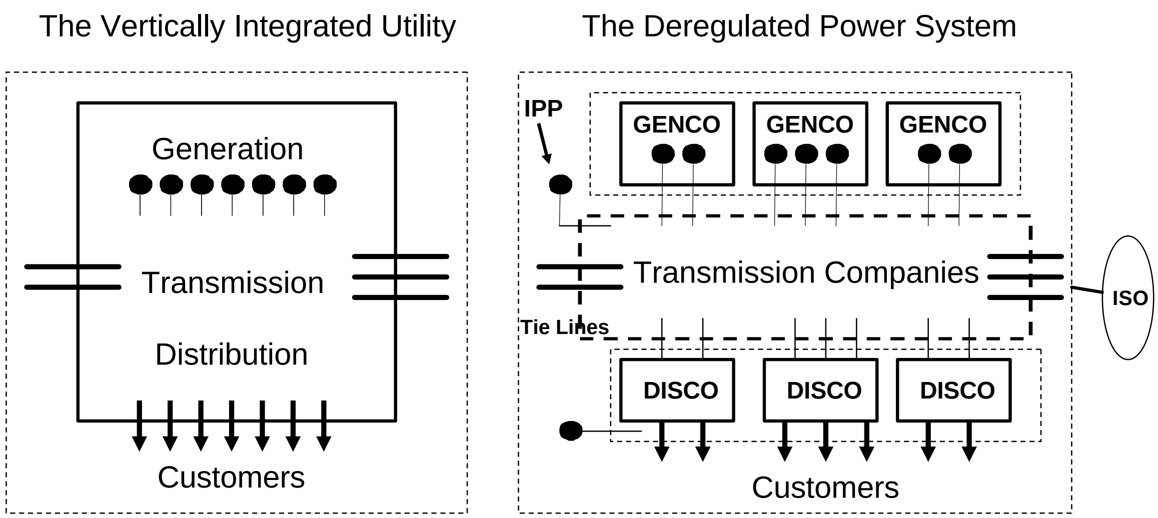

Figure 1.1 The Deregulation of Electric Power System

The deregulated market based electric power industry has changed the economics of power generation, the relative effectiveness of different types of fuel and power plants, the source and availability of finance, and the willingness of power generators to accept risk. Under the new electric market, the capital cost and payback time of a new power plant is critical, because electric energy production becomes riskier. Risk and its mitigation play a more important role in the decision making process. In this regard, constructing new plants with long lead times and high capital cost is inherently riskier than plants with short lead times, low investment capital cost ones.

Power generating plants are opened, operated and closed on the basis of demand and market prices, and, in turn, the market prices will be determined primarily by the decentralized decisions of competing power generators instead of through regulation [5]. This introduces more dynamics in terms of long term and short term power demand and supply, and electricity prices. The rapid change in the power demand and market prices favors those power plants that are capable of operating efficiently at a wide range of power output levels.

The emphasis of this research is on efficient power generation using industrial gas turbine power plants. Transmission and distribution will be treated as constraints if necessary.

1.2 Gas Turbine Based Power Plants

Gas turbine based power plants have been favored in recent time as a result of the changes described in the previous section. Compared to large power stations such as coal-fired stations and nuclear stations, the capital investment of gas turbine driven power plants is lower and the construction lead times are shorter [6]. In addition, the gas turbine based power plants provide sufficient operational flexibility to adjust the power generation schedule based on the fast changing power demand and market electric price. In particular, the combined cycle power plants have been favored for their high efficiency and low level of emissions. For these reasons, the demand for gas turbines increased substantially during the 1990's, when the deregulation of electric power industry initially took place.

A primary reason for the rapid growth in the use of gas turbine power plants for electric power generation is the combined cycle plant, which couples the gas turbine and the steam turbine. A gas turbine engine run by itself is called a "simple cycle" gas turbine, and with a thermal efficiency of nominally 35 – 40%, it is used almost exclusively as peaking plant to provide power during periods of high demand. The exhaust gas temperature from a gas turbine engine is high – between 850 -- 1100ºF, and for the combined cycle power plant this energy in the exhaust is partially recovered in a heat recovery steam generator (HRSG), a series of heat exchangers, to produce super-heated steam. The steam then expands in a steam turbine to increase the output power by nominally one third. This combination of gas turbine, HRSG and steam turbine is called a combined cycle power plant, and thermal efficiencies as high as 60% may be attainable with such a plant in the near future.

A combined cycle power plant derives its name from the fact that a gas turbine engine, which operates on the Brayton cycle, is combined with a heat recovery and steam turbine system, which operates on the Rankine cycle. The exhaust gas from the gas turbine is nominally at 1000ºF, and it is the source of energy to the heat recovery steam generator (HRSG) to produce superheated steam. In the process, the exhaust gas is reduced to approximately 300ºF. The steam expands through the steam turbine increasing shaft power to the generator, and, as a result, the thermal efficiency of the system is increased significantly – from approximately 33-38% to 50-55%.

A HRSG is a series of heat exchangers – economizers to heat water close to saturation, evaporators to produce saturated steam and superheaters to produce superheated steam. A relatively simple HRSG design will operate at a single water/steam pressure through the Rankine cycle circuit, but in an effort to extract the maximum amount of energy from the gas turbine exhaust gas there may be one or two higher pressure circuits added to the system. Each added pressure level increases power output from the steam turbine, but the complexity and cost of the HRSG system and the steam turbine are also increased.

As a result of high efficiency, relatively low investment cost and reduced time for bringing a new plant on line, the orders for gas turbines in 1999, almost exclusively used in the combined cycle plant design, totaled 67 gigawatts (GW), which accounted 58% of the total demand of that year. The total orders for steam turbines for combined cycle application were 17 GW [4]. Before the late 1980s, the gas turbine based power plants were primarily simple cycle plants, and, as mentioned above, they were generally used as backups to provide electric power during peak demand periods [4]. Today, the combined cycle plant with heat recovery and steam turbines coupled with the gas turbine engines are commonplace, and it is almost certain that the demand for combined cycle power plants will be sustained in the near future.

One of the by-products of the deregulation of the electric power industry is that it led to a reduction in the number of power plant suppliers. Deregulation exposes small companies to a situation where they are not able to develop the capabilities and resources to compete in such a highly competitive environment [4]. Today the biggest three gas turbine suppliers are General Electric (GE), Siemens, and Alstom. These three companies accounted for 80% of new power plant orders worldwide rated by power output, and GE is the largest supplier [4]. In 1997 Siemens purchased the energy operations of Westinghouse of the United States. General Electric Company of the United Kingdom and Alcatel Alstom of France formed Alstom. In 1999, Alstom merged with ABB the power engineering business, which was formed by the ASEA of Sweden and Brown Boveri of Switzerland.

1.3 Operations and Maintenance Services

The life cycle costs of power plants can be decomposed into three major elements: project investment cost, fuel cost, and plant operations and maintenance cost. Project capital investment costs have been reduced by nearly 50 percent compared to those of 10 years ago. With the improvement of gas turbine technology, power plant efficiency has improved significantly, and this leads to the reduction of fuel expenditures. However, operation and maintenance expenditures have increased due to the relatively higher operation and maintenance cost of advanced technology combustion turbines, and it therefore has become a more important cost element. Today the operation and maintenance cost can comprise up to 15% to 20% of the total life cycle costs [7].

One of the influences of deregulation is on the provision of services associated with power plants. The service market is growing rapidly, and one of the reasons for this is the increase in outsourcing by electricity generators. The market for services is becoming increasingly attractive for power plant suppliers due to its high profitability. About 10 years ago, GE started its service business, and today one-third of its engineers are in services. In 2001, GE contractual services agreements totaled 15 billion dollars, and it is expected that the contractual services agreements will deliver revenues of 33 billion dollars in 2005 [7].

As addressed earlier, the risk associated with operating a power plant is a major concern for today's power generators, especially in the gas turbine environment, where plant performance degradation, reliability and availability are important factors. New gas turbine technologies bring with it the expectation of better performance and long parts life. However, this is based on the assumption that the plant is operated and maintained effectively; otherwise the expected benefits will be eliminated [7].

Risk management varies from the situation where the plant owner owns all the risk with no insurance and partners to a situation where all of the risk is assigned to a third party, the service contractor. The traditional approach for managing power plant operations risks has been transactional. The owner buys parts, repairs and services in the case of outage, and the overall objective is to reduce the cost associated with maintenance. With this approach, options for providing increased value to the owner are subordinated. In contrast, the contractual services approach, which focuses on maximizing value instead of minimizing price, aligns the business goals of both services supplier and plant owner. In this situation, the fixed price maintenance and performance guarantees are provided for the plant owner, and the services provider takes part of the plant risks. The plant owner's risks are therefore reduced for future price uncertainty, technology changes, and component parts life [7].

Today a large number of gas turbine based power plant owners have transferred the risks associated with equipment availability and performance to the power plant suppliers through long-term service agreements (LTSA), operation and maintenance agreements (O&M), and contractual performance agreements [7]. These services agreements are usually structured to meet needs of the plant owner, and the operational decisions to maximize the profit for the plant owner are aligned with the pricing of the services agreements. As a result, the services provider behaves like a power generator. The objective of these agreements is to align operational goals of the plant owner and the service provider so as to maximize power plant productivity. Furthermore, the service provider through the contractual performance agreement is responsible for daily operation of the power plant, in which performance and reliability/availability are the key elements for consideration. This involves the making of operational decisions in the strong competitive environment to maximize plant profitability. The power plant productivity is performed through operational optimization such as generation scheduling, maintenance scheduling, outage planning, and advanced technology upgrades. To do this effectively, the issues of power plant operation in this dynamic environment have to be fully understood. The development of an advanced operational optimization environment and decision support system has become a major task for the power plant supplier providing the maintenance and operational services outlined above.

1.4 The Needs for Change

The deregulation of the electric power market introduces a market based operational environment for power plant operators, and the independent power producers. As a result, the electric power market is a decentralized system. This essentially drives the power plants to operate for profit. A different operational philosophy, which is profit based, lifecycle oriented and unit specific instead of the traditional cost based and fleet wide approach, is needed in this decentralized electric power market. This requires the development of a systematic approach for gas turbine based power plants operational modeling and optimization.

Although power systems optimization has been extensively studied in the literature, there are relatively few publications on realistic gas turbine based power plant modeling and operational optimization. Thus, the gas turbine based power plant operational optimization problem has not been well established. One reason is that the industries are not interested in publications. The other reason is that relatively little research effort has been focused on the practical aspects of the problem, especially for sophisticated systems such as the gas turbine based power plant.

1.4.1 Integrated Power Plant Operational Modeling and Optimization

Power plant operational decision-making is a complex problem, and operational decisions are based on power plant internal characteristics and the external business environment. On the one hand, the power plant is operating in a dynamic electric power market, and external factors such as the power demand and supply, price of electricity, and fuel cost are stochastic in nature. On the other hand, the gas turbine based power plant itself presents a very complex mechanical system. It is a multiple-component repairable aging system, and as the power plant accumulates operating hours, it experiences performance and reliability degradation, i.e., the heat rate increases, the output rate decreases, and it is subject to increasing risk of failure.

Similar to the external factors, the reliability degradation exhibits a stochastic behavior as well. Operational flexibility is one of the most important characteristics of the gas turbine based power plant, which is important for power plant operating in a dynamic environment. The output rate of the power plant can be adjusted to ensure the optimal response to the dynamic market by manipulating its operating conditions, i.e., the load mode, fuel type, and power augmentation, etc. However, this flexibility also makes the modeling of the power plant performance and reliability more complicated. Timely maintenance activities are required to stop further degradation, and/or to restore the performance and reliability of the power plant. The infusion of power plant upgrades also improves the performance and/or reliability. Simultaneous consideration of performance, reliability and the electric power market are essential when these operational decisions are made.

The operational optimization in the vertically integrated electric power market aimed to minimize total operations cost, since electricity price was dedicated by the regulatory organizations, and cost minimization was the only option to maximize profit. In the deregulated electric power market, however, this philosophy has changed. Electricity price in the deregulated market is determined by market competition. This changes the optimization problem considerably. Traditionally the generation scheduling and outage planning optimization were performed separately, which meant the short term and long term productivity were not coordinated, and the impact of generation scheduling on power plant entire service life was not addressed. However, from the total system perspective, short term, local level optimization does not necessarily mean a long term, system level optimum, not to mention that generation scheduling and outage planning are actually highly correlated. Furthermore, most existing methodologies available in the literature make simplified assumptions on plant performance, reliability, and maintenance effectiveness, while the complexity of gas turbine driven power plant operation and maintenance has not been well addressed. However, operational flexibility, performance and reliability degradation and restoration, and maintenance effectiveness are important characteristics of multiple component sophisticated gas turbine driven power plant systems.

1.4.2 Profit Based Operational Optimization

The ultimate goal of the power plant operation is to maximize its profitability. In the vertically integrated electric power market, power plant generation scheduling and maintenance scheduling have been targeted to minimize operations cost. This is because, in the regulated electric power market, maximizing profit can be only achieved by minimizing cost, since the energy price and load projection are given for power plant generators. In the deregulated market, profit can be maximized by increasing revenue and reducing *operations* cost simultaneously.

<u>Profit Based Generation Scheduling</u>

In the regulated electric power market, generation scheduling problems, such as unit commitment, aim to minimize costs while meeting all demand. The unit commitment problem is defined as scheduling generating units to be in service in order to minimize total production cost while meeting constraints such as power demand, spinning reserve, minimum up and down time [8]. In the deregulated environment, the price of electricity plays a more important role for decision making on generation scheduling, and the objective of generation scheduling is not to minimize production cost, but to maximize the profit of the power plant operators. Unlike the utilities that have an obligation to meet the customer demand in the regulated power market, the utilities in the deregulated market can choose operating strategies to partially meet the projected demand and reserve, and therefore maximize the profit. Therefore, traditional generation scheduling methods need to be modified or replaced due to this changing electric market.

Because of the need to maximize profit, traditional generation scheduling methods need to be modified or replaced due to this changing electric market. A review on generation scheduling is performed by Yamin [9], in which profit based unit commitment problems are introduced.

In the deregulated power market, the decisions on generation scheduling can be based on the difference between the incremental cost and incremental revenue. If the incremental cost is lower than the incremental revenue, the plant operator may decide to generate more energy to attain more profit, otherwise it will reduce the amount of energy to be generated, or even stop running the generators. Energy price is no longer given. As a result, it is influenced by the biding strategies of the utility players, and all market information is reflected in the market price. A profit-based generation scheduling problem introduces more factors that influence the decision-making, which makes the problem more complicated.

Profit Based Outage Planning and Maintenance Scheduling

Traditionally, for complicated systems such as a gas turbine power plant, maintenance cost and on-line availability are two of the most important concerns to the equipment owner. However, in the deregulated electric power market, cost and reliability are not the only concerns. The goal is to maximize plant profitability, and this requires the evaluation of many different factors, which involve system performance, the aging and reliability of equipment, maintenance practices and market dynamics including the price and availability of fuel and the generation of revenues in competing markets.

As pointed out by Wang, most optimal maintenance models in the literature use the optimization criterion: minimizing system maintenance cost rate but ignoring reliability performance [10]. However, maintenance aims to improve system reliability. For multiple component systems, minimizing system maintenance cost does not necessarily mean maximizing the system reliability measures. To achieve the best operating performance, both the maintenance cost and reliability measures should be considered simultaneously. Wang argues that maintenance optimization should aim to provide optimum system reliability/availability and safety performance at lowest possible maintenance cost, which can be achieved either by minimizing maintenance cost rate while maintaining system's reliability/availability requirement, or by maximizing system reliability while meeting system maintenance cost requirement [10].

However, in the deregulated electric power market cost and reliability are not the only concerns of maintenance practice. The optimal goal of maintenance optimization is to maximize plant profitability, not maximizing availability. For a complicated system such as gas turbine driven power plant, performance degradation is also an important issue for power plant maintenance as well as reliability deterioration. Maintenance activities have a strong influence on the performance such as output rate and heat rate, as well as reliability. Therefore, performance restoration is another important consideration for gas turbine driven power plant.

Furthermore, in the market-based environment, the electricity market shows strong dynamics, and an optimized maintenance cost and maximized plant availability does not necessarily mean optimized profitability, since other factors, such as fuel cost, electricity price, and power demand and supply also play a big role. This suggests that in a market-based environment, the maintenance practices should be optimized to achieve the maximized profit, and to achieve this goal the maintenance optimization has to be incorporated with generation scheduling and energy market signals.

An example for this is the outage schedule problem. Typically unit outage is scheduled when the power demand or price of power is low. In case an outage is supposed to be performed during peak demand period, the plant operator may consider shifting the outage to a period when power demand is not high, so as to achieve the highest possible profit during the peak demand period. To make such a decision, the expected payback and risk should be balanced.

Therefore maintenance practices should be targeted to maximize plant profit. Performance and reliability restoration, maintenance cost, together with energy market signals, are key factors for maintenance schedule decisions.

Although the profit based maintenance scheduling approach is intuitive, it is a surprise to see that research effort on this approach is rare in the literature. With profit based generation scheduling, more factors are involved in the profit based maintenance approach. Maintenance cost is no longer the only concern, and price signals are again an important factor. Power plant performance and reliability has to be considered jointly in this profit-based approach.

1.4.3 Lifecycle Oriented Operational Optimization

The lifecycle concept has many different connotations, and is used to describe a lifecycle assessment methodology, which often implies a quantitative “cradle-to-grave” assessment of a system's environmental impact loadings [11]. Lifecycle for a system is defined as the entire life of a system, which includes design, development, installation, operation, maintenance, and disposal. Lifecycle cost can be defined as the total cost of acquisition and ownership of a system over its useful life. The power plant lifecycle modeling here includes modeling of power plant design and configuration, reconfiguration, and operation and maintenance. In this study, it is assumed that the design and manufacturing of the power plant has been completed, and the power plant has been put into operation. Therefore, in this situation, the lifecycle actually refers to the entire service life of the power plant.

Power Plant Lifecycle Considerations

The lifecycle considerations for a power plant includes the lifecycle productivity and lifecycle cost. The traditional generation and maintenance planning usually did not consider the lifecycle cost/benefit trade off, and the time scale was usually for a relative short time period. To achieve optimum lifecycle profitability, the impact on *long-term* plant profitability should be addressed when short-term generation and maintenance scheduling is performed. In a traditional regulated power plant, generation and maintenance scheduling is performed separately, and the coupling between generation and maintenance scheduling is not well established. This means that "optimal" operational decisions based only on short-term considerations may actually have a negative impact on the plant lifecycle profitability over a longer period.

Maintenance cost constitutes a significant proportion of operating cost. Traditionally to reduce preventive maintenance cost is one of the major objectives while satisfying reliability requirements. Short term maintenance scheduling tends to focus on optimal timing of maintenance activities, and it is not able to address the influence of the maintenance activity on a longer-term basis. In the deregulated environment, a short-term objective to cut down maintenance cost may take precedence over a longer-term life cycle perspective. Long-term models tend to determine the optimal lifespan of the plant, but they are not able to model the operational aspects or accurately reflect the effectiveness of maintenance [12]. Chattopadhyay introduces the idea of life cycle maintenance, which is able to consider both short-term issues and those of optimal retirement of plant equipment. Optimization is performed over a longer term timeframe typically over the entire life of the generating assets spanning over several years or decades, and technical considerations such as heat rate, forced outage rate and capacity degradation as well as economic drivers such as long term spot price forward curve and contract portfolio must be considered [12]. However, the life cycle maintenance concept introduced by Chattopadhyay does not consider a shorter timeframe, which is the dependence between generation scheduling and maintenance scheduling.

Coupling of Generation and Maintenance

Gas turbine units accumulate degradation and damage as they accumulate operating hours, and their performance and reliability deteriorates as they age. Preventive maintenance such as combustion inspection, hot gas path inspection, and major inspection are scheduled at prescribed maintenance intervals for each gas turbine unit. For example, the maintenance interval for a MS7F gas turbine engine is 24000 factored fired hours and 900 factored starts, respectively, whichever happens first [13]. This means that a hot gas path inspection will be performed when the factored fired hours reaches 24000 hours or the factored starts reaches 900 hours.

These maintenance intervals are based on assumed standard operating conditions. In reality, the operating conditions for each gas turbine may vary from site to site, and unit to unit. This suggests that each unit should be treated individually. A comprehensive preventive maintenance management system must take into account unit operating history. The unit age or operating status depends on the unit usage history, and therefore unit usage will be the major factor for maintenance scheduling. The unit degradation rate depends on the operating conditions. The operating condition where gas turbine components are working depends on gas turbine design, its operating mode, and the external environment such as ambient conditions, fuel type and air quality. There are several primary factors that affect the power systems equipment life, and therefore maintenance scheduling. These factors include starting cycle, power setting, type of fuel, and level of steam or water injection. A set of these operating parameters is usually referred to as an operating profile. In an approach employed by industry for gas turbine maintenance scheduling, the baseline operating profile (under which a maximum maintenance interval is set using gas fuel) is defined as base load power setting with no steam or water injection. Maintenance factors are introduced to establish the maintenance required when the power plant operates under conditions that differ from the baseline [13]. These maintenance factors depend on the operating profile under which a gas turbine is operating.

The operating profile of a gas turbine unit is directly the result of the generation scheduling. Unit commitment establishes unit scheduling and determines when and which unit is in operation, and therefore it determines the startup and shutdown cycle. Economic dispatch determines the output rate for each unit so that the most economical generation arrangement is scheduled. This, again, determines the operating profile of the unit.

The setting of operating profiles has a direct impact on power plant productivity and unit degradation rate, on which the maintenance cost rate depends. A gas turbine firing at peak load will have a higher power output and therefore has a higher short term spark spread* to the plant operator than at base load or part load, given a high demand of electric power. However, the life consumption of equipment of a gas turbine firing at peak load will be more significant than at base load or part load, since the firing temperature is higher. This results in a higher life cycle cost, because the maintenance factor is higher, and therefore a shorter maintenance interval and a high maintenance cost per unit operating time will result. This also applies to power augmentation with steam or water injection, which also results in increased power output but also in increased maintenance factors.

The situation becomes more complicated if the dynamics of value of power and price of fuel are taken into consideration. The following example can illustrate the issues involved: In the summer the demand for power is so high that the plant operator may want to run the plant with peak load and power augmentation to increase plant output for high short term high spark spread, even though the life consumption of the plant accelerates and the risk of forced outage increases substantially. In addition, the plant maintenance schedule may be strongly impacted. The plant operator is trying to schedule the outage in such a manner that the plant revenue is optimized and the maintenance cost minimized, thus optimizing the overall long-term payback. During a peak demand, the plant operator may consider postponing a scheduled preventive maintenance so as to achieve the short-term profit due to the wide spark spread, but this decision has to be validated with consideration of the increased risk and performance degradation due to the postponed maintenance. In order to achieve this objective, the dynamic nature of value of power, price of fuel, plant performance degradation, and system reliability need to be fully understood.

The generation schedule has a direct impact on maintenance schedule, and therefore, the preventive maintenance schedule problem involves generation scheduling. On the other hand, the preventive maintenance scheduling also has an impact on generation scheduling. The preventive maintenance scheduling determines the available unit usage (for example, the available factored fired hours and factored starts for a given time planning horizon) for each unit. With the given factored fired hours and starts, the generation scheduling problem assigns daily factored fired hours and starts to each day of the given time period. This suggests that the generation scheduling and preventive maintenance scheduling cannot be solved separately.

Therefore maintenance and generation scheduling are actually highly correlated. Maintenance considerations should be taken into account when generation scheduling is performed, and vice versa. A joint consideration for generation and maintenance is

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[*] A definition for spark spread is the difference between the spot market value of natural gas and electricity at a given time, based on the conversion efficiency of a given gas-fired plant.

therefore needed. Also, energy market dynamics and power plant performance and reliability deterioration should be considered jointly to achieve a joint generation and maintenance scheduling approach. Separate generation and maintenance scheduling will not result in a real long-term optimal solution.

In summary, the traditional operation and maintenance scheduling approach does not really lead to optimal solutions. In actuality, the impact of operations scheduling on maintenance has to be considered. To achieve the life cycle optimal solution, joint operation and maintenance scheduling and multiple time line scheduling need to be considered. Therefore, there is a need to develop a life cycle generation and maintenance framework, which aims to optimal generation and maintenance scheduling. This objective is achieved only with the consideration of economics and the technical aspects of operational optimization over the service life of a generating unit. The goal is to maximize the profit of the unit.

Long Term Generation Scheduling

Preventive maintenance is usually planned much earlier than it will occur, since preventive maintenance involves in inventory planning, human labor planning, and it has to satisfy the power system constraints. For gas turbine driven power plants, the preventive maintenance, which includes combustion inspection, hot gas path inspection, and major inspection, is usually scheduled at least one or two years before it actually happens.

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For preventive maintenance scheduling, a projection of the unit usage, which depends on future electric power market and weather conditions in a relatively long term future time horizon, is required, and therefore system deterioration can be estimated based on this projected unit usage over this time horizon. This suggests that a generation schedule that involves a relatively long time horizon is a necessity for preventive maintenance scheduling. Only when the future operating profile is estimated could the exact time to perform maintenance can be determined. A joint generation and maintenance scheduling approach therefore requires a long-term generation schedule.

In current preventive maintenance planning procedures, it is usually assumed that the operating profile over the time horizon of interest is uniform. In actuality, however, in the market based operating environment, the operating profile shows strong variation due to market dynamics. An incorrect uniform operating profile assumption leads to an incorrect system deterioration estimation, and therefore incorrect preventive maintenance scheduling. This situation validates the value of an accurate long-term unit operating profile, and therefore the value of long-term generation scheduling.

Accurate future operating profile forecasting is the key to accurate preventive maintenance planning. An investigation of the electric power market dynamics and other factors that affect generation scheduling should be performed, and a methodology which is capable of capturing the variation of a future operating profile on a long-term basis is therefore necessary for accurate preventive maintenance planning.

1.4.4 Unit Specific Operational Modeling and Optimization

Historically gas turbine maintenance has been based on a fixed time interval according to recommendations from the power plant supplier. However, in reality the operating conditions for each gas turbine may vary from site to site, and from unit to unit. Maintenance performed with regard to the condition of the equipment may result in wasted resources for equipment that is aging less rapidly than expected, or equipment may experience high risk of failure if the equipment ages more rapidly than expected. This suggests that each unit should be treated individually. A unit-specific maintenance approach is therefore needed for effective gas turbine maintenance scheduling. For such an approach to be successful, accurate predictions of reliability and performance degradation for each gas turbine are necessary.

As addressed above, a unit specific maintenance philosophy is needed for effective gas turbine maintenance scheduling. For the unit specific maintenance approach, accurate reliability distribution for each gas turbine is necessary, which requires realistic reliability modeling based on unit operating conditions and maintenance history.

1.5 Summary

In summary, the deregulation of the electric power market has introduced a strong element of competition. Power plant operators strive to develop advanced operational strategies to maximize the profitability in the dynamic electric power market. Although there has been intensive research on power system optimization in general, the gas turbine based power plant operational optimization problem has not been well established. The operational optimization in the vertically integrated electric power market aims to minimize total operations cost, since electricity price was dictated by the regulatory organizations, and cost minimization is the only option to maximize profit. In the deregulated electric power market, however, this philosophy has changed. Electricity price in the deregulated market is determined by market competition.

Traditionally the generation scheduling and outage planning optimization has been performed separately, which means the short term and long term productivity are not coordinated, and the impact of generation scheduling on power plant entire service life is not addressed. However, from the total system perspective, short term, local level optimization does not necessarily mean a long term, system level optimum, not to mention that generation scheduling and outage planning are actually highly correlated. Furthermore, most existing methodologies in the literature make simplified assumptions on plant performance, reliability, and maintenance effectiveness, while the complexity of gas turbine based power plant operation and maintenance is not well addressed. However, operational flexibility, the tradeoffs related to performance and reliability degradation and restoration, and the maintenance effectiveness are important characteristics of multiple component sophisticated gas turbine based power plant systems.

A profit based, life cycle oriented, unit specific power plant operational modeling and optimization methodology is therefore needed for power plant operation to enhance operational decision making, and therefore to maximize power plant profitability by reducing operations and maintenance cost and increasing revenue.

The objective of this research is to create an integrated operational modeling and optimization environment for gas turbine based power plants. This environment is intended to maximize life cycle profitability through intelligent outage planning, maintenance scheduling, generation scheduling, and technology infusion. This approach matches the evolving electric power market and is capable of performing operational optimization under sophisticated situations.

CHAPTER 2

BACKGROUND

2.1 Introduction

Gas turbine units have been widely used for land electric power generation and marine surface ship power plant. Gas turbine based power plant operational decision-making is a complex problem, and operational decisions are based on power plant internal characteristics and the external environment. On the one hand, the power plant is operating in a dynamic electric power market, and the power demand and supply, price of electricity, and fuel cost are stochastic in nature. On the other hand, the gas turbine based power plant itself presents a very complex system. The gas turbine based power plant is a multiple-component repairable aging system. As the power plant accumulates operating hours, it experiences performance and reliability degradation, i.e., the heat rate increases, the output rate decreases, and it is subject to increasing risk of failure. Similarly to the external factors, the reliability degradation exhibits stochastic behavior as well.

Operational flexibility is one of the most important characteristics of the gas turbine based power plant, which is important for power plant operating in a dynamic environment. The output rate of the power plant can be adjusted to ensure the optimal response to the dynamic market by manipulating its operating conditions, i.e., the load mode, fuel type, and power augmentation, etc. However, this flexibility also makes the modeling of the power plant performance and reliability more complicated. Timely maintenance activities are required to stop further degradation, and/or to restore the performance and reliability of the power plant. The infusion of power plant upgrades also improves the performance and/or reliability. Simultaneous consideration of performance, reliability and the electric power market are essential when these operational decisions are made.

A profit based operational optimization essentially needs to consider all the factors that are involved in power plant revenue and associated cost. Therefore, market signals, namely, spot and contractual revenue, and technical drivers, which include power plant output rate and efficiency, performance degradation and restoration, and reliability degradation and restoration, are to be considered simultaneously for generation scheduling, maintenance scheduling, and outage planning. Unit specific modeling with consideration of operating conditions and maintenance activities provides accurate information to treat a power plant unit individually. Realistic models to analyze quantitatively the relationships between unit aging rate and operating conditions, and unit restoration and maintenance activities, are developed. Lifecycle oriented operational modeling and optimization is employed to balance short-term and long-term economic considerations. Methodologies for joint generation scheduling and maintenance scheduling with consideration of technology infusion are developed, which allow multiple time line operational optimization to achieve lifecycle optimal operation. The multiple unit operational optimization problems are also considered in this research. It is assumed that such an integrated approach is helpful for power plant operators to maximize lifecycle profitability through intelligent outage planning, maintenance scheduling, generation scheduling, and technology infusion.

In summary, an integrated operational modeling and optimization approach suggests that:

- A profit based lifecycle oriented operational optimization essentially needs to consider all the factors that are involved in producing power plant revenue and associated cost. There are two main issues, and they are to be addressed simultaneously: 1) the generation of revenue from both fixed contracts and the spot market; 2) technical drivers such as power plant output rate and efficiency, performance degradation and restoration, and reliability

- Unit specific performance and reliability modeling with consideration given to changing operating conditions and maintenance activities provides accurate information to treat plants or units individually. This requires the development of models to quantitatively analyze the relationships between unit aging rate and operating conditions.

- Lifecycle oriented operational modeling and optimization balances short-term and long-term economic considerations. Power plant upgrades evaluation and selection with consideration of coordinated power generation scheduling and outage planning is to be developed to allow operational optimization along multiple time lines.

2.2 Key Elements of the Integrated Framework

Three key tasks to accomplish this framework have been identified, and they are

1. To identify the key elements pertinent to the integrated operational modeling and optimization approach,

2. To develop a generic lifecycle environment for gas turbine power plant operational modeling,

3. To formulate and solve specific operational optimization problems.

The very first question for developing such an integrated approach is: what are the key factors that drive gas turbine power plants operational decision making?

In this integrated operational optimization approach, more factors are involved. A profit based operational optimization essentially needs to consider all the factors, which are involved in power plant revenue and associated cost. Therefore, the generation of revenue from both fixed contracts and the spot market and technical drivers such as power plant output rate and efficiency, performance degradation and restoration, and reliability are to be considered simultaneously. The economic and technical factors pertinent to operational modeling are shown in Figure 2.1.

In a unit specific approach, each unit is treated individually, which requires accurate and realistic performance and reliability modeling along with unit operating time line. Accurate models to analyze quantitatively the relationship between performance and reliability degradation and restoration and unit usage history and maintenance history are necessary technical enables.

The decision variables for power plant operational optimization include operating modes of power plant, outage timing, maintenance time and work scope, degree of maintenance, and technology options. Operating modes includes start/stop cycle, load setting, fuel type and quality, steam/water injection, etc. They have strong influences on the degradation and damage accumulation of gas turbine components, and therefore on performance degradation and reliability degradation. The decisions based on these models are to be made based on long term or lifecycle productivity of the power plant in a dynamic energy market. For such a decision making process, the influence of each decision variable on power plant economics in a stated period of time has to be established. In another words, the quantitative relationship between power plant operational activities, which include power plant usage, maintenance history, and technology infusion, and power plant economics, which includes power plant cost and revenue profiles, has to be established. These metrics essentially depend on market signals and contracts, and power plant performance and reliability, which depend on operational activities.

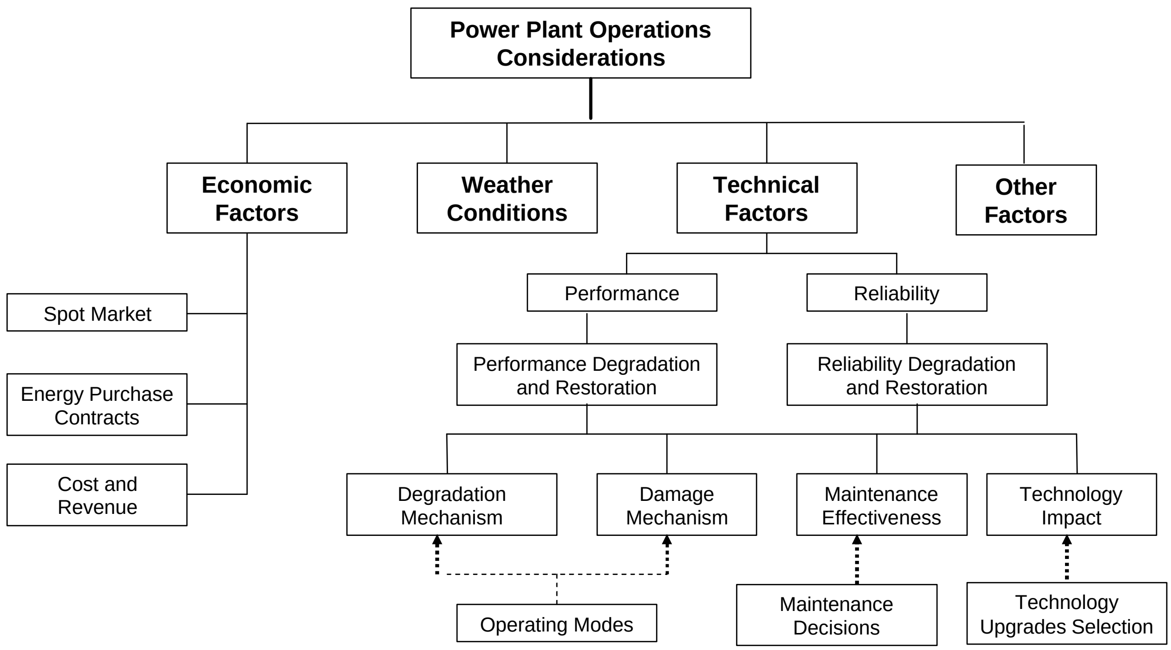

Figure 2.1 The Key Factors of Gas Turbine Power Plant Operational Modeling

Given that these quantitative relationships have been established, the financial profiles for a power plant as it accumulates operating hours can be constructed. Power plant operations risk can be evaluated based on its reliability distributions and system configuration. For any given operational history of a power plant, its performance, reliability, operations risk, fuel cost, operations and maintenance cost, and revenue can be constructed along the operating time line. This forms an integrated modeling environment for power plant economic analysis.

To develop an integrated framework that includes all the key elements pertinent to the proposed operational optimization approach, the problem is decomposed such that all key elements are identified. These include power generation economics, energy market forecasting, power plant performance, power plant reliability and risk assessment, maintenance considerations and policy, maintenance effectiveness, generation scheduling, maintenance scheduling, and technology infusion. Optimization techniques are also an integral element to identify the optimal solution for operational optimization. The integrated framework is shown schematically in Figure 2.2.

The following modules for the integrated modeling approach therefore include:

- Gas turbine power plant performance module—performance models for gas turbine engines and generators. For a combined cycle plant, there are additional models for steam turbines, and heat recovery steam generators.

- Gas turbine power plant reliability and risk assessment module

- Gas turbine power plant maintenance effectiveness module

- Gas turbine power plant upgrade impact module

- Energy market dynamics module, which includes electric power demand and supply forecasting, price of fuel and electricity forecasting, and bilateral contracts and spot market modeling

- Gas turbine power plant economics module, which evaluate the economics performance of gas turbine power plants

Please note that the performance and reliability modeling and validation depend heavily on the collection and validation of historic operational data, and therefore monitoring and diagnosis of plant performance data is also an integral part of the integrated framework.

For the gas turbine power plant operational optimization, the following modules are identified:

- Generation scheduling module, which includes unit commitment and economic dispatch
- Outage planning module
- Maintenance scheduling module
- Upgrade packages evaluation and selection (technology infusion) module

A further expansion of power plant optimization would include:

- Gas turbine power plants system design optimization module
- Power system generation planning module

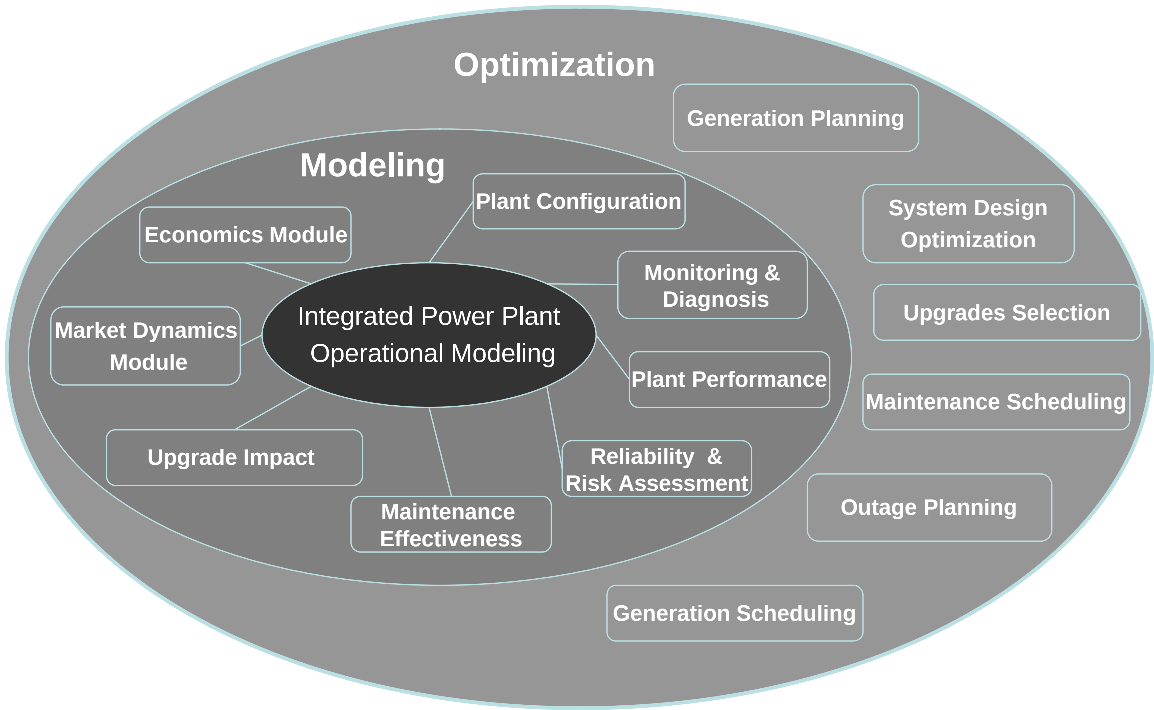

Figure 2.2 Power Plant Operational Modeling, Integration, and Optimization

2.3 The Integrated Operational Modeling

An integrated lifecycle operational modeling approach for gas turbine power plants is shown in Figure 2.3. The lifecycle operation and maintenance activities of a unit are modeled along an operating time line of a gas turbine power plant.

The entire operational lifespan of a power plant, which includes all of the operational activities during its service lifespan, is defined as a “system.” A decomposition of the operational activities along unit service life is shown in Figure 2.3. An activity that takes a period of time to accomplish is defined as a “component” of the system, and, by definition, the operation and maintenance problem is highly hierarchical. An outage is defined as a period of time, scheduled or unexpected, during which a particular power-producing facility ceases to provide generation. For power generation, outage can therefore be defined as a period of time, scheduled or unscheduled, during which a generating unit or other plant item is out of service for maintenance. A period between two consecutive outages is defined as an “operation period”.

In the highest level, shown in Figure 2.3, a system (a service life of a unit) is decomposed into a set of continuous operation periods and outage periods. Each operation period can be further decomposed into a set of sub-periods for unit commitment problem, and the time frame of each is about one week. In a shorter time horizon, each unit commitment problem can be further decomposed into a set of economic dispatch problems. For each outage period, various maintenance activities can occur, such as water wash, combustion inspection, hot gas inspection, major inspection, or technology infusion. Please note that online water wash can also apply during an operation period.

A power plant deteriorates as it accumulates operating hours. Damage is accumulated as the unit accumulates operating hours. Residual life for each components of plant can be determined using their service life limits. The probability of forced outage of each part can be estimated, and associated operational risk can therefore be estimated.

Along the operating timeline, energy market signals are forecast. The forward time-based curves include electric power demand and supply, price of fuel and price of electricity, and these market signals are stochastic in nature. In an imperfect competitive market, the reactions of each market players need to be considered, and an agent based analysis model would be helpful for analyzing the behaviors of several key players in the electric power market, and for constructing the electricity price forward curves. These curves usually show strong long-term, seasonal, and daily trends.

The cumulative operations and maintenance cost can be calculated based on the operating and maintenance history, together with an associated cost database. Fuel cost and revenue curves can therefore be constructed using market signals and plant electricity output and efficiency.

Therefore, a procedure to model the operation of power plant along its operating timeline can be developed, and plant performance, reliability, risk, and system level economics can be evaluated as the power plant accumulates operating hours.

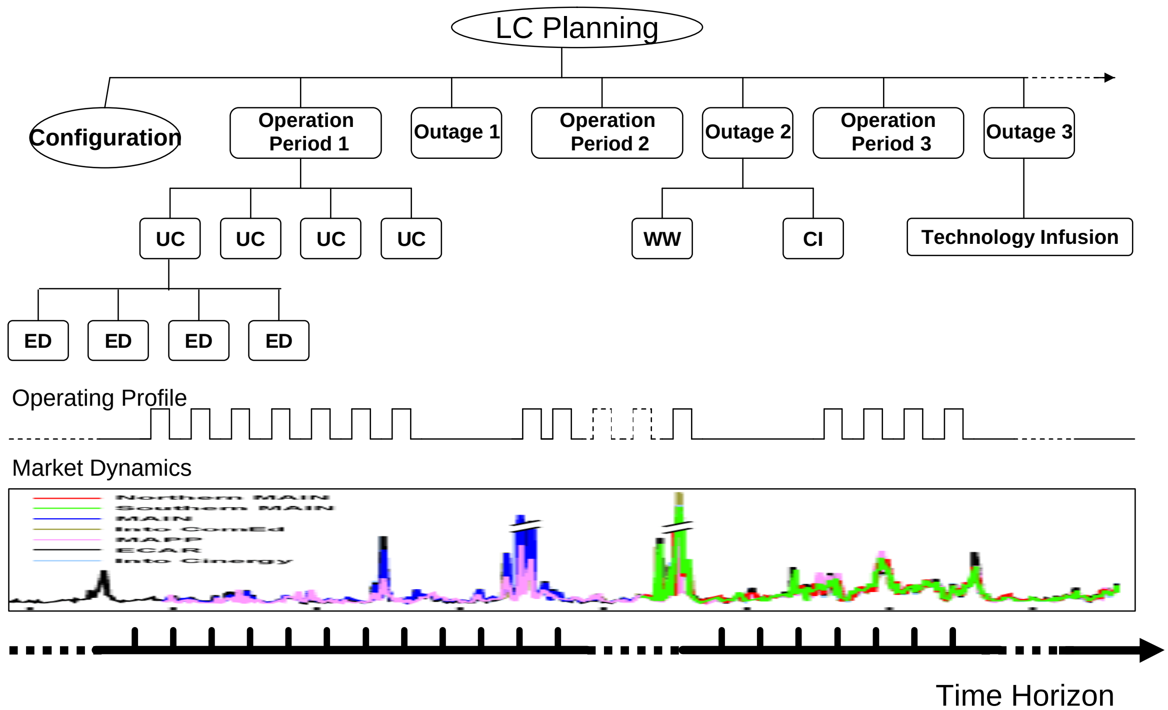

Figure 2.3 An Integrated Lifecycle Operational Modeling

In such a lifecycle modeling approach, using market signals as input, together with performance and reliability consideration, the operational decisions can be made, and their impact on power plants short term and long-term productivity can be evaluated instantly. This environment provides a platform for advanced lifecycle oriented optimization. A representation of an integrated lifecycle operational modeling environment with performance, reliability, and system level economics is shown in Figure 2.4.

2.4 Technical Enablers for Operational Modeling

To address the quantitative relationship between power plant operational activities and power plant system level economic metrics, such as fuel cost, operations and maintenance cost, accumulated spark spread, profit, several technical enablers are required.

The first enablers are forecasting techniques. Forecasting on electricity power market demand and supply, and price of fuel and price of electricity are essential for the profit-based approach. The importance of dynamics for the electric power market cannot be overly addressed. A lot of research work has been done on electricity power market forecasting. Weather forecasting is also an important input. The weather conditions here include ambient temperature, ambient pressure, and humidity. On the one hand, weather conditions have impact on the performance of gas turbine based power plant, and, on the other hand, weather conditions have a strong impact on electricity power demand.

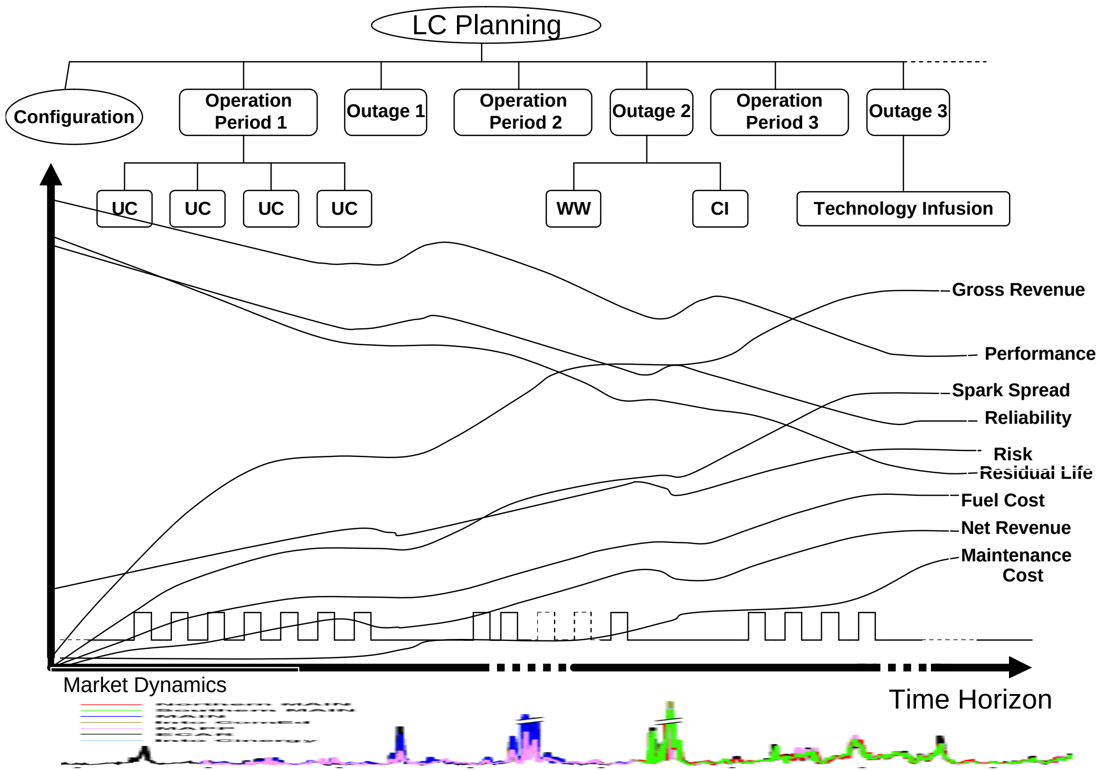

Figure 2.4 Power Plant Performance, Reliability, and Lifecycle Economics

A second enabler is a power plant performance modeling method. The performance model should be able to evaluate unit performance under a variety of operating conditions. Furthermore, it should be able to capture performance degradation as the unit accumulates operating hours, and be able to evaluate degradation rate based on unit operating modes. It should also be able to evaluate performance restoration due to maintenance and technology infusion.

A third enabler is the reliability modeling methods. These models should be able to address reliability degradation as the unit accumulates operating hours, and evaluate reliability degradation rate based on unit operating modes. It should also be capable of evaluating reliability restoration due to maintenance and technology infusion.

Power plant operational activities include power plant generation schedules, maintenance activities, and power plant upgrade (technology infusion). Power plant system level economic metrics depend on market signals and contracts, power plant performance, and power plant reliability. Performance and reliability of a gas turbine driven power plant is strongly influenced by the working load and the environmental conditions. Performance and reliability degradation due to unit usage and their restoration due to maintenance are important inputs to construct revenue and cost curves. Technology infusion also has an impact on power plant performance and reliability, and therefore affects power plant system level economic performance. The energy market signals, which include power demand forecasting, fuel and electricity price forward curves, are also important drivers for decision-making. This suggests that the following quantitative relationships are required:

- Forecasting of electric power demand and supply, price of fuel and price of electricity in a stated period of time
- Power plant performance, which include output rate and efficiency as functions of operating mode and external operating environment
- Power plant performance degradation rate as functions of operating conditions and accumulated performance degradation as functions of accumulated service life with consideration of usage history
- Power plant performance restoration as functions of maintenance activities
- Power plant reliability degradation as functions of unit usage history due to aging, with consideration of operating conditions
- Power plant reliability restoration as functions of maintenance activities
- Power plant performance and reliability improvement as functions of technology infusion

2.5 Operational Optimization

The ultimate objective of developing an integrated operational modeling environment is to provide a means to evaluate gas turbine power plant economics performance, and therefore provide an analytical means for power plant operational decision-making.

Operational optimization is twofold, one is to formulate the optimization problem, and the other is to develop optimization techniques to solve the problem. The problem formulation is highly coupled with the operational modeling methods, and the way to handle performance, reliability, and cost is most important for the problem formulation. For the profit based, lifecycle oriented operational optimization approach, the problem formulations will be more complicated than those used for traditional formulations, since more factors are involved and more detailed models are introduced. Also, other practical considerations should be taken into consideration. Optimization techniques for power plant operational optimization have been studied extensively, and numerous optimization techniques are available. Reference [2] introduces several optimization techniques, which are applicable for electric power systems optimization. Many of the elements can be borrowed from existing techniques, which are available in the literature, although some techniques, which meet the requirement of this integrated operational optimization problem, may still have to be developed.

As addressed before, the proposed approach is profit based and lifecycle oriented. This suggests that generation, outage planning, maintenance scheduling, and upgrades selection are performed in a coordinated approach. The optimization techniques should be able to address the complexity of the nonlinear, stochastic nature of the problem, and to balance long term and short term objectives.

Different levels operational optimization methods are to be developed, which include generation scheduling, maintenance scheduling, outage planning, and technology infusion. Market signals and power plant performance and reliability are the key drivers, and short term and long-term operational optimization are therefore coordinated using these market and technical factors.

For a power plant with a given configuration, operational optimization includes generation scheduling, outage planning, and maintenance scheduling. Inventory optimization is also an important task to facilitate maintenance activities, and reduce maintenance cost. The objective of the optimization is to maximize plant profitability by optimizing the operating profile, outage timing and duration, maintenance timing, work scope, and the extent of maintenance. However, when upgrade packages are introduced, the configuration of the power plant system may change, and this may change the power plant performance and reliability.

For operational optimization problems, the optimization approach may be different from that for system design problems. One reason for this is that there is less uncertainty with operational optimization problems than there is with system design problems, and therefore it is possible to develop physics based models or statistical models to forecast the dynamics of the operational environment. Another reason is that for operational optimization, the objective is usually associated with the scheduling of operational activities along the operational timeline, which requires the modeling of evolving operational parameters along the timeline. For this reason, assigning a distribution but without addressing its dynamics over a time horizon is not a feasible approach.

Numerous optimization techniques for electric generation scheduling have been proposed, which include deterministic techniques, meta-heuristic techniques, and stochastic techniques. The deterministic optimization techniques include exhausted enumeration, priority list method, integer/mixed integer programming method, dynamic and linear programming method, branch-and-bound method, and Lagrangian relaxation. The meta-heuristic approaches include expert systems, fuzzy logic, artificial neural networks, simulated annealing, and genetic algorithms, etc.

In the deregulated electric power market, the formulation of generation scheduling problems requires the model to include the electricity market, since the price is no longer set by the regulators, but by open competition. For example, the hourly spot prices have shown evidence of being highly volatile. This introduces more difficulties in the optimization problem. Stochastic models are introduced to account for the volatility of spot prices. A lot of research effort on the generation scheduling problem under deregulated electric power market is introduced in Ref. [14][15][16][17][18].

Power plant operational scheduling involves multiple sites, and each site involves multiple units. Thus, the modeling and optimization methodologies should be able to perform analysis and operational optimization for multi fleet/sites/units, and reach the level of system/units/components/parts level analysis. The methodologies should be generic and not be site/unit specific.

Although the formulation problem for preventive maintenance scheduling is very different from that of generation scheduling, the techniques to solve generator maintenance scheduling problems are similar to those to solve generation power scheduling problems.

The multiple unit system is more sophisticated than the single unit system, and the optimization techniques to solve the problems are different from those for single unit problems. The difference is that a multiple unit system introduces more operational flexibility than does a single unit system. The unit commitment and economic dispatch problems have been extensively investigated, and existing models can be borrowed and applied to this proposed approach.

2.6 Gas Turbine Power Plant Operational Optimization Problems

Basic power plant operations planning includes a maintenance schedule for generation equipment, a unit start up and shut down schedule, and a procedure to adjust generation output to meet predicted demand. The power plant operator may also consider the improvement in plant performance and reliability through advanced technology packages. Some of the questions that the power plant operators are trying to answer follow:

- What is the optimal/robust schedule to run the gas turbine units in the most efficient way, while meeting all kinds of constraints?
- When should the next outage occur?
- What should be the maintenance work scope for the scheduled outage?
- What if there is a departure of outage from the scheduled outage plan?
- What is the economic benefit (payback) if certain upgrade packages are infused to the system?

A schematic representation of power plant optimization as a function of time is shown in Figure 2.5. The power plant operational considerations include short term generation scheduling, maintenance scheduling, and long term generation planning. These optimization problems are associated with different time scales.

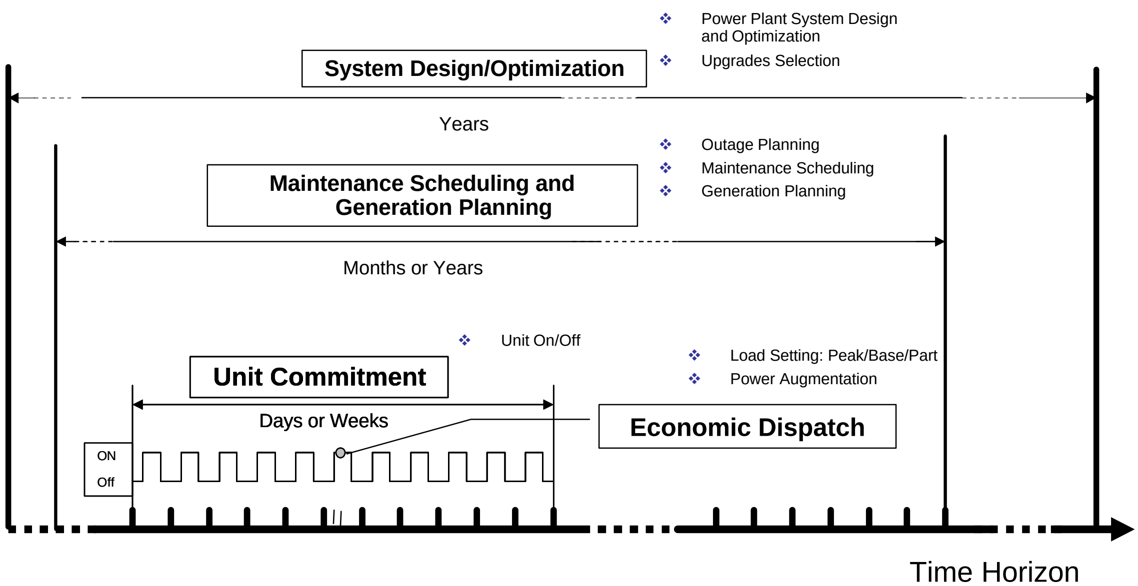

Figure 2.5 Power Plant Operational Optimization as a Function of Time

2.6.1 Generation Scheduling

Generation scheduling problems have been extensively studied, and they include unit commitment and economic dispatch. Electric utilities are required to commit enough generating units to meet the load demands in the electric power systems. However, the electric power market is dynamic in nature, and the customer load demands change with time. For example, load demand is typically higher during the daytime and early evenings when industrial loads are high, and lower during late evening and early mornings. Thus, to satisfy electric power demand while operating the power system economically, the commitment of generating units is also dynamic in nature. Unit commitment is therefore an important sub-problem of generation scheduling, which make decisions on the generating units to be in service (on/off) during each interval of the scheduling period. The goal is to meet the system demand and reserve requirement at the lowest possible cost for the total scheduling period, subject to a variety of equipment, system/operation and environmental constraints [19].

The basic idea of gas turbine power plant generation scheduling is to make a generation schedule based on market information/projection so as to minimize operations cost or maximize profit. This is done by manipulating operating profile, i.e., unit startup and shutdown, load mode, fuel type and steam injection to adjust power plant output rate. The unit commitment problem is to decide which units should be operated in the subsequent operation period so that the plant profit or cost can be optimized. For given units in operation, economic dispatch determines the power rate for each unit so that the power demand can be satisfied in such a way that the profit or cost is optimized. The time period that economic dispatch evolves is usually 5-30 minutes.

Unit commitment has been extensively studied in the literature, and review on the formulation and solving techniques on unit commitment can be found in Ref. [9] [20][21][22].

Unit commitment is also called pre-dispatch, and its function fits between economic dispatch and maintenance scheduling. It schedules the on and off times of the generating units, and calculates the hourly generation schedule while meeting a variety of constraints. Prior to a solution to the economic dispatch problem, the unit commitment problem should be solved.

Thus, unit commitment needs to be performed in advance. Most power generators cannot be turned on instantly and produce power. Although fast starts and emergency starts are possible for gas turbine based power plant, they will accelerate the degradation of the power generators, which induces high lifecycle cost. Therefore, they are not used extensively. To make sure the generation can meet the predicted power demand with adequate reserve margin, the decisions on which units are to be operated for each time period needs to be planned in advance. The units are chosen so as to optimize the expected total cost or profit over a long-term horizon, since the predicted power demand may not match the actual demand along the operating time line. To determine the start up and shut down schedules for power generation units, factors such as start up cost, minimum run time, and rate of response need to be considered.

Economic dispatch is the problem of finding the optimal combination of power generation, which minimizes the total fuel cost while satisfying the power balance equality constraint and several inequality constraints. Research efforts on solving the economic dispatch problems can be found in Ref. [23][24][25].

2.6.2 Outage Planning and Preventive Maintenance Scheduling

Maintenance planning has a strong impact on profitability of a gas turbine power plant. The decision of maintenance inspection problem is two-dimensional, one is to determine when the next inspection should occur, and the other is to determine what maintenance work scope to take, i.e., what maintenance action to take. In this study, the emphasis is on the determination of the optimal timing of the preventive maintenance.

When to perform the maintenance is an issue, and outage planning is the determination of the timing of power plant shut down to perform the next preventive maintenance. It is necessary to plan the outage in advance for utility, industrial and cogeneration plants, so as to minimize plant down time, and to save cost. Performing the preventive maintenance earlier than necessary is a waste of resource, yet if it is delayed too long, the resulting degradation in reliability will lead to high risk of failure, and the resulting loss of performance will cause a loss of revenue. Another issue is the seasonal variations. Ideally, preventive maintenance would be done in periods when the demand for electric power is low, typically in the spring and fall months.

Historically gas turbine maintenance is based on a fixed time interval according to recommendations from the power plant supplier. However, in reality the operating conditions for each gas turbine may vary from site to site, and from unit to unit. This suggests that each unit should be treated individually. A unit specific maintenance philosophy is therefore needed for effective gas turbine maintenance scheduling. For the unit specific maintenance approach, accurate reliability distribution and performance degradation for each gas turbine is necessary.

Numerous models on generation scheduling and maintenance scheduling have been published. There are plenty of maintenance optimization models in the academic literature, but not all of them have potential for successful application. It is important to identify the models that are applicable to practical problems. Also a lot of optimization techniques exist to solve the generation and maintenance scheduling problems. Unfortunately, not all of them are suitable for practical problems. A maintenance model is defined as mathematical model which aims to find the optimum balance between the costs and benefits of maintenance while taking all kinds of constraints into account [27]. Dekker performs a review on the maintenance optimization models, and points out that that there is a significant gap between maintenance theory and practice [26]. He also points out that the successful application of maintenance optimization is not obvious, and that many models have been developed for math purposes only. Mathematical analysis and techniques, rather than solutions to solve real problems, have been central in many papers on maintenance optimization models. Furthermore, Dekker points out that industries are not interested in publications [26]. To have academics study industrial problems, they have to be exposed to the real industrial problems and be rewarded if they solve them.

Scarf also performs a review on the development of mathematical models in maintenance [27], and he also points out that mathematical models in maintenance should consider the applicability in real industry, not just the academic interests. It should be as simple and transparent as possible for application and understandable for engineers and decision makers.

Generation scheduling and maintenance scheduling models, which address realistic performance, reliability, and maintenance effectiveness considerations, have rarely been seen in the literature. However, as addressed earlier, to develop optimization models, which produce sound results for generation and maintenance scheduling, realistic models, which consider the complexity of gas turbine driven power plant, must be developed.

2.6.3 Power Plant Upgrades Evaluation and Selection

Performance and reliability are the most important characteristic aspects of gas turbine technologies. Advanced technology improvements have been made and many advanced technologies are applied to new unit production. However, these advanced technologies can also be applied to field units, which have been put into operation for a certain time period to achieve increased performance, reliability, and useful life [28]. Additionally there are also technology developments, which are targeted to improve performance and reliability for field units. These advanced technology packages can improve efficiency, increase output, or extend maintenance intervals. A power plant operator may consider infusing these upgrade packages to enhance the performance of its generating units, based on the increasing demand, needs of improving efficiency, or maintenance considerations.

In reality, a pool of technology options for power plant upgrade is usually available. It is an important task to select technology options from amongst this pool such that the resulting overall economic benefit for the power plant operator and/or the power plant equipment providers is maximized. The complexity of the problem increases with the number of the available technology options.

The decision on the introduction of power plant upgrades is based on the long-term economic performance of each upgrade. For such a decision-making, the impact of upgrade on overall plant economics has to be evaluated. The economic benefit from upgrade packages results from the interaction of many complex economic and plant performance and reliability parameters [29]. A full evaluation of the economic benefit of power plant upgrades would require the consideration of the technical factors of the power plant, which include its configuration, performance, and reliability characteristics, and external market signals, such as price of fuel and price of electricity, future electric power demand and supply, electricity sales and fuel purchase contracts stipulations, etc.

Advanced methods are needed for accurate and efficient evaluation of each technology upgrade options. For such a method an approach, which analyzes and optimizes the financial payback from the standpoint of both the power plant manufacturer and power plant operator is required.

2.7 Gas Turbine Power Plants Operational Modeling

2.7.1 Power Plant Performance

The gas turbine power plant performance is a function of the power plant design and configuration, and the operating conditions where it works. The power plant operating conditions include the following:

- Ambient conditions and site elevation
- Inlet and exhaust loss
- Fuel
- Water or steam injection
- Performance enhancement

An introduction to these factors follows.

Design and Configuration

Gas turbines

A variety of gas turbine designs have been developed by industries. Heavy duty and aero-derivative gas turbines with a variety of performance have been used for power generation and industrial applications. The performance of generator drive heavy-duty gas turbines designed by General Electric Company is shown in Table 2.1 [28]. These performance data are for base load with ISO conditions.

Combined Cycle Power Plants

The combined cycle power plant is made up of three major systems, the gas turbine engine, the heat recovery steam generator and the steam turbine. Of the major systems the gas turbine engine is a fixed design offered by a manufacturer, and the steam turbine is also a fairly standard design available from a manufacturer, but it may be somewhat customized for the project. In contrast, the heat recovery steam generator (HRSG) offers many different design options, and its design is highly customized and integrated with the steam turbine.

A combined cycle power plant derives its name from the fact that a gas turbine engine, which operates on the Brayton cycle, is combined with a heat recovery and steam turbine system, which operates on the Rankine cycle. The exhaust gas from the gas turbine is nominally at 1000ºF, and it is the source of energy to the heat recovery steam generator (HRSG) to produce superheated steam. In the process, the exhaust gas is reduced to approximately 300ºF. The steam expands through the steam turbine increasing shaft power to the generator, and, as a result, the thermal efficiency of the system is increased significantly – from approximately 33-38% to 50-55%.

A HRSG is a series of heat exchangers – economizers to heat water close to saturation, evaporators to produce saturated steam and super heaters to produce superheated steam. A relatively simple HRSG design will operate at a single water/steam pressure through the Rankine cycle circuit, but in an effort to extract the maximum amount of energy from the gas turbine exhaust gas there may be one or two higher pressure circuits added to the system. Each added pressure level increases power output from the steam turbine, but the complexity and cost of the HRSG system and the steam turbine are also increased.

There are a variety of combine cycle power plants used for power generation. The performance of single shaft gas turbine combined cycle power plant provided by General Electric Company is shown in Table 2.2 [58].

Table 2.1 GE Generator Drive Gas Turbine Ratings ([28]GER-3567H)

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GE Generator Drive Product Line									
Model	Fuel	ISO Base Rating (kW)	Heat Rate (Btu/kWh)	Heat Rate (kJ/kWh)	Exhaust Flow (lb/hr) $x10^{-3}$	Exhaust Flow (kg/hr) $x10^{-3}$	Exhaust Temp (degrees F)	Exhaust Temp (degrees C)	Pressure Ratio
PG5371 (PA)	Gas	26,070.	12,060.	12,721	985.	446	905.	485	10.6
	Dist.	25,570.	12,180.	12,847	998.	448	906.	486	10.6
PG6581 (B)	Gas	42,100.	10,640.	11,223	1158.	525	1010.	543	12.2
	Dist.	41,160.	10,730.	11,318	1161.	526	1011.	544	12.1
PG6101 (FA)	Gas	69,430.	10,040.	10,526	1638.	742	1101.	594	14.6
	Dist.	74,090.	10,680.	10,527	1704.	772	1079.	582	15.0
PG7121 (EA)	Gas	84,360.	10,480.	11,054	2361.	1070	998.	536	12.7
	Dist.	87,220.	10,950.	11,550	2413.	1093	993.	537	12.9
PG7241 (FA)	Gas	171,700.	9,360.	9,873	3543.	1605	1119.	604	15.7
	Dist.	183,800.	9,965.	10,511	3691.	1672	1095.	591	16.2
PG7251 (FB)	Gas	184,400.	9,245.	9,752	3561.	1613	1154.	623	18.4
	Dist.	177,700.	9,975.	10,522	3703.	1677	1057.	569	18.7
PG9171 (E)	Gas	122,500.	10,140.	10,696	3275.	1484	1009.	543	12.6
	Dist.	127,300.	10,620.	11,202	3355.	1520	1003.	539	12.9
PG9231 (EC)	Gas	169,200.	9,770.	10,305	4131.	1871	1034.	557	14.4
	Dist.	179,800.	10,360.	10,928	4291.	1944	1017.	547	14.8
PG9351 (FA)	Gas	255,600.	9,250.	9,757	5118.	2318	1127.	608	15.3
	Dist.	268,000.	9,920.	10,464	5337.	2418	1106.	597	15.8

Table 2.2 GE Single-shaft Steam and Gas Ratings ([58]GER-3767C)

UNIT DESIGNATION	STEAM CYCLE	NET PLANT POWER	NET PLANT HEAT RATE (LHV) Btu/kWhr	KJkWhr	THERMAL EFFICIENCY
60Hz					
S106B	Non-Reheat, 3-Pressure	59.8	7005	7390	48.7
S106FA	Reheat, 3-Pressure	107.1	6440	6795	53.0
S107EA	Non-Reheat, 3-Pressure	130.2	6800	7175	50.2
S107FA	Reheat , 3-Pressure	258.8	6090	6425	56.1
S107G	Reheat, 3-Pressure	350.0	5885	6210	58.0
S107H	Reheat, 3-Pressure	400.0	5690	6000	60.0
50Hz					
S106B	Non-Reheat, 3-Pressure	59.8	7005	7390	48.7
S106FA	Reheat, 3-Pressure	107.4	6420	6775	53.2
S109E	Non-Reheat, 3-Pressure	189.2	6570	6935	52.0
S109EC	Reheat, 3-Pressure	259.3	6315	6660	54.0
S109FA	Reheat, 3-Pressure	376.2	6060	6395	56.3
S109H	Reheat, 3-Pressure	480.0	5690	6000	60.0

Notes: 1. Site Conditions-59 F, 14.7 psia, 60% RH (15 C, 1.013 bar, 60%)

Ambient Conditions and Site Elevation

The gas turbine performance is affected by anything that changes the density and or mass flow of the air intake to the compressor, since it is an air-breathing engine. The air density is a function of ambient temperature, and pressure, and humidity [30]. The air density increases as the ambient temperature decreases, and it reduces as the site elevation increases. Also, humid air is less dense than dry air. As a result, these factors have impact on the performance of gas turbine engines [30]. Since these conditions vary from day to day, and from location to location, it is convenient to define some standard conditions for comparative purpose. The International Standards Organization (ISO) established standard conditions, which are used by the gas turbine industry. The standard conditions are 59F/15C, 14.7psia/1.013bar, and 60% relative humidity [30].

Fuel

Modern heavy-duty gas turbines are designed to operate under different type of fuels. The fuels available are natural gas and liquid fuels -- distillate, crude, residual oil, etc. These fuels have various heating values, and thus this affects the gas turbine output and heat rate.

Performance enhancement

Operational flexibility is one of the most important characteristics of the gas turbine based power plant, which is important for power plant operating in a dynamic environment. The output rate of the power plant can be adjusted to ensure the optimal response to the dynamic market by manipulating its operating conditions, i.e., the load mode, fuel type, and power augmentation, etc. However, this flexibility also makes the modeling of the power plant performance and reliability more complicated.

The following options are available to enhance performance when additional output is needed.

Inlet Cooling

Lowering the compressor inlet temperature can increase the turbine output and heat rate, and this can be accomplished by installing an evaporative cooler or inlet chiller in the inlet ducting downstream of the inlet filters.

Water or Steam Injection

Steam or water can be used for NOx control or for power augmentation. Injecting steam or water into the head end of the combustor can reduce the NOx, and the gas turbine output rate increases due to the increase in the mass flow. For power augmentation purposes, the steam can be injected into the compressor discharge casing of the gas turbine as well as the combustor. The application of steam or water injection will have impact on the power plant inspection intervals [30].

Peak Rating

The rating table for gas turbines is based on base load under ISO conditions. Peak rating is the achieved by increasing the firing temperature to generate more power. As with the application of steam or water injection, this leads to a shorter maintenance interval.

2.7.2 Gas Turbine Based Power Plant Aging

Gas turbine engines accumulate degradation as they accumulate operating hours, and their power output rate and heat rate deteriorate, and the failure rates increase. Aging of the gas turbine power plant is one of the key issues for effective operational planning.

<u>Gas Turbine Operating Conditions</u>

The gas turbine is a complex system with numerous components. The heavy-duty gas turbines are designed to withstand severe duty. The hot parts of the engine are working under severe environmental conditions, namely, high flow rate, hot gases, and frequent temperature changes due to start-up and shut-down, and therefore they have a relatively short lifespan. The hot gas path parts include combustion liners, end caps, fuel nozzle assemblies, crossfire tubes, transition pieces, turbine nozzles, turbine stationary shrouds, and turbine buckets [13].

The unit operating modes and external operating environment, which includes ambient conditions and air quality, determines the working environment of the gas turbine parts. The gas turbine unit can operate in different operating modes, and a typical operating mode refers to the start/stop cycle, power load setting, type of fuel, and steam/water injection settings. The load setting can be base load, which is usually running for a long continuous time for combined cycle units, peak load, which is used to provide more power to meet peak demand, and part load. The start/stop cycle can be normal base load start/stop, part load start/stop, emergency start/stop, fast load start/stop, and trips. The fuel type can vary from natural gas fuel, distillate fuel, and residual fuel. Steam/water injection can be employed for emission control purpose or for power augmentation purpose [13].

Gas turbine units have been used widely for land electric power generation and marine surface ship power plant, and they show different operating modes due to different customer needs. Gas turbine units used to meet different customer needs show different start frequency, namely, the ratio between number of starts and number of operating hours. Some land-based gas turbines are utilized to provide electric power on a continuous basis, while others are used only to meet peak consumer demand for a short operation period during each day. If a unit is operating on a continuous basis, and experience very few start and stop thermal cycles, this unit is usually called base load unit. A unit used to meet daily peak loads will accumulate an increased number of starts and stop thermal cycles, and this unit is called a daily start and stop unit. Some gas turbine units may be operated on a weekly start and stop basis to meet some customer's need, and those units are referred as weekly start and stop units.

The operating conditions have very important impacts on the aging rate of power plant systems. A component submitted to adverse operating conditions has a large aging rate than that submitted to normal operating conditions. For example, the damage accumulation of the buckets of a gas turbine firing at peak load will be faster than those firing at base load or part load, and therefore more significant aging will result.

Major Factors that Affect Equipment Life

The gas turbine's life is affected by many factors, and the mechanism of how these factors affect equipment life has to be well understood to produce effective maintenance planning. The most important factors include starting cycle, power setting, type of fuel, and level of steam or water injection. These factors have a direct impact on the life of critical gas turbine parts, and therefore they influence the maintenance interval.

Fuel type and quality--- Different types of fuels can be used for gas turbines, and they range from natural gas to residual oils. The type of fuel used for gas turbine engines has an important impact on maintenance schedule. Natural gas fuel is considered as the optimum fuel with regard to turbine maintenance. As for residual fuels and crude oil fuels, they generally release higher amounts of radiant thermal energy, which results in a subsequent reduction in combustion hardware life, and they frequently contain corrosive elements such as sodium, potassium, vanadium and lead. These corrosive elements lead to accelerated hot corrosion of turbine nozzles and buckets. Distillate fuels do not generally contain high levels of these corrosive elements, but harmful contaminants can be present in these fuels, which lead to higher maintenance requirements than with natural gas fuel [13].

Load setting---Firing temperature is related with the load setting of the gas turbine unit. Gas turbine engines operating at peak load will result in a higher firing temperature than at base load. Under higher firing temperatures, the hot gas path parts are subject to higher temperature hot gas, and this leads to high metal temperature, which reduces hot gas path components lives. However, a reduction in load does not necessarily mean a reduction in firing temperature. For example, for combined cycle heat recovery application, firing temperature does not decrease until load is reduced below approximately 80% of rated output.

Steam/water injection---Steam or water injection can be used for emission control or for power augmentation. When steam or water are added to the gas flow, higher gas conductivity results, which increases the heat transfer to the buckets and nozzles and can lead to higher metal temperature and reduce parts life. The impact of steam or water injection on parts life depends on the way the gas turbine is controlled. For example, GE describes two types of control curves based on the way that firing temperature is controlled. These are dry control curve and wet control curve. Under the dry control curve, the firing temperature is reduced when steam or water injection is employed, under the wet control curve, the firing temperature is maintained constant, and steam or water injection leads to additional power output [13].

Another effect of steam or water injection is that it increases the aerodynamic loading on the turbine components that results from the injected water increasing the cycle pressure ratio. This increased aerodynamic load also leads to a reduction of parts life.

Cyclic effects---The cyclic effects introduced during startup, operation, and shutdown of the turbine unit can affect component life. Also, operating conditions other than the standard startup and shut down sequence can potentially reduce the life of the hot gas path parts, rotors, and combustion parts.

The Accumulated Damage Mechanism

Gas turbine wears in different ways for different service duties. The causes of wear of hot gas path components are categorized as two types, which are continuous duty application and cyclic duty application. The causes of wear due to continuous duty application include rupture, creep deflection, high cycle fatigue, corrosion, oxidation, erosion, rubs/wear, and foreign object damage. The causes of wear due to cyclic duty application include thermal mechanical fatigue, thigh-cycle fatigue, rubs/wear, and foreign object damage [13].

The crack length of the hot gas parts is used as an indication of the safety index, and it determines the maintenance schedule interval. A certain limit for the crack length is set for a particular type of part, and a hot gas part whose crack length is beyond this limit is scheduled a repair or replacement. For peaking gas turbine units, thermal mechanical fatigue is the dominant limiter of life. While for continuous duty machines, creep, oxidation, and corrosion are the dominant limiters of life. Intuitively one would imagine that the consideration of interaction between thermal mechanical fatigue, creep, oxidation, and corrosion is necessary for understanding the overall life consumption mechanism for gas turbines [13].

2.7.3 Performance Degradation

As addressed earlier, maintenance practices are targeted to minimize risk, improve reliability, and restore/upgrade system performance. As the system accumulates operating hours, the performance degradation increases, and the probability of forced outage increases. Timely preventive maintenance should be performed to prevent the system from further degradation, and to restore the system performance and reliability to some extent. The performance degradation of a gas turbine unit is due to the degradation of its components, which depends on the unit usage history. All turbomachinery experiences losses in performance with time [31]. Diakunchak points out that, even under normal engine operating conditions, with a good inlet filtration system and using a clean fuel, the engine flow path components will become fouled, eroded, corroded, covered with rust scale, damaged, etc, and that the result will be degradation in engine performance, which will get progressively worse with increasing operating time.

Thus, the gas turbine performance deteriorates as its operating hours accumulate, and the economic impact of engine performance degradation is significant. Diakunchak performed an approximate analysis on the economic impact of performance degradation. In the example, a simple cycle gas turbine engine with 46.5MW output, using natural gas fuel, operating 8000 hours per year, was studied, and an average yearly decrease in power of 3% and increase of heat rate of 1% was estimated. This amount of performance degradation will lead to a total cost of 1.5 million dollars per engine over three years of operation [31].

Both operating factors, which include starting cycle and power setting, and environmental factors, which include the air, water and fuel that enter the gas turbine, affect gas turbine degradation, have an influence on performance degradation. The majority of the power loss in a gas turbine is due to compressor degradation. Brooks points out that gas turbine performance degradation can be classified as recoverable and non-recoverable losses. Recoverable losses are usually associated with compressor fouling and can be partially rectified by water washing or mechanically cleaning the compressor blades and vanes with the compressor casing removed.

Please note that performance degradation is a function of the operating mode, not just the number of operating hours [31]. Therefore, unit operating modes as well as number of operating hours should be considered for performance degradation modeling. Diakunchak describes the most important factors affecting the industrial gas turbine engine performance degradation with service time. They include contaminants, fouling, types of filters, coatings, cleaning, corrosion, erosion, damage, engine operation and faulty maintenance practices.

The manner that the engine is operated will have an effect on the performance degradation rate. The starting cycle results in the most severe hot end thermal gradients experienced during normal engine operation. At ignition the combustor exit temperature exceeds that during normal operation for a short time until the control system regulates the fuel and air flows to lower it. Therefore, the oxidation and corrosion experienced by the hot gas path is most severe at this time and will add to the engine aging process. An engine subject to many starting and emergency trip cycles and/or is operated for considerable periods of time at peak rating will have more severe performance degradation than an engine operating at or below base load rating.

Detection of the extent of the performance degradation is necessary before appropriate actions, such as online water wash or off line water wash, be taken. Economic consideration is an important factor for determination of the optimal frequency of engine cleaning frequency, such as water wash frequency. Washing the compressor more frequently than necessary is a waste of resource, yet if it is delayed too long, the resulting loss of performance will cause a loss of revenue. Diakunchak recommends that the compressor should be water washed when the estimated mass flow decrease reaches the 2 to 3% level [31].

2.7.4 Reliability Degradation

The gas turbine unit is subject to increasing probability of failure as it accumulates operating hours, and preventive maintenances should be scheduled to prevent the unit from further degradation. The relationship between reliability, system age, and maintenance is shown in Figure 2.6.

Historically gas turbine maintenance is based on a fixed time interval according to recommendations from the power plant supplier. However, in actuality the operating conditions for each gas turbine may vary from site to site, and unit to unit. This suggests that each unit should be treated individually. Maintenance performed with regard to the condition of the equipment may result in wasted resources for equipment that is aging less rapidly than expected, or equipment may experience high risk of failure if the equipment ages more rapidly than expected. Industrial experience shows that the traditional fleet specific maintenance practice is overly conservative. A unit specific maintenance philosophy is therefore needed for effective gas turbine maintenance scheduling. For the unit specific maintenance approach, accurate reliability distribution for each gas turbine is necessary, which requires realistic reliability modeling based on unit operating conditions and maintenance history. Reliability based and condition based maintenance has been brought about for this need. In the past several decades, risk based preventive maintenance has gained many proponents.

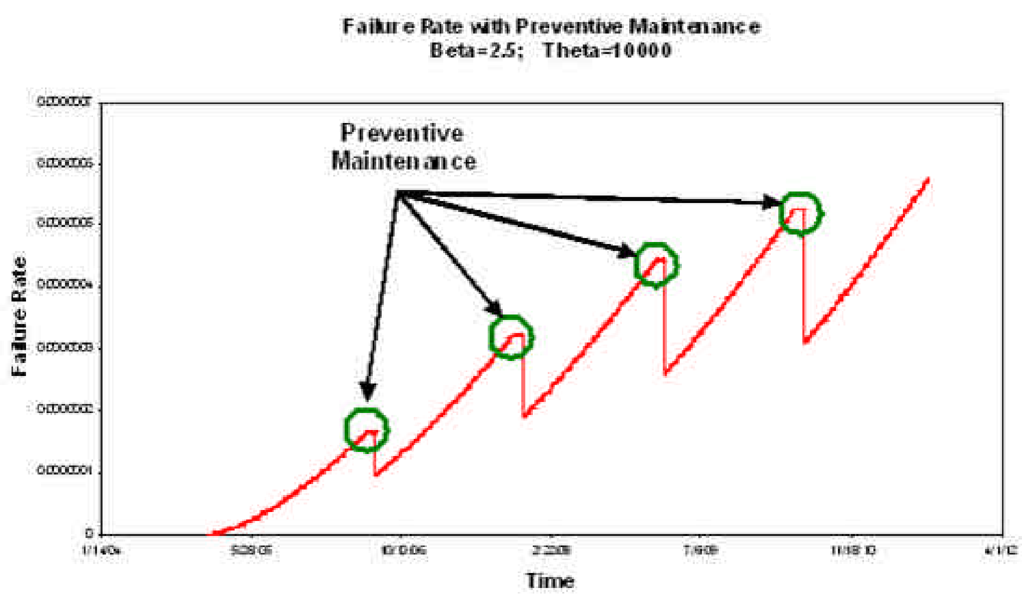

Figure 2.6 Failure Rate as a Function of Age and Maintenance

Operational risk is evaluated as the product of probability of system failure and the economic consequences of system failure. A gas turbine system is an aging system in that its components are subject to severe operating conditions, and it experiences degradation as it is put into operation. This suggests that the gas turbine reliability and performance are subject to degradation, and the degradation rate depends on how it is used, that is, the operating conditions of the gas turbine determines the aging process of its components, and therefore reliability and performance degradation. The gas turbine unit is subject to increasing operational risk as its operating time accumulates. Damage limit is the criterion for maintenance decisions. To reduce the risk, some of the parts need to be repaired or replaced when the accumulated damage reaches the limit.

Therefore, to assess the operational risk of a gas turbine unit and therefore schedule a reasonable maintenance interval, the damage accumulation mechanism needs to be fully appreciated. The damage accumulation process is highly dependent on the operating history (unit usage) of the system. Gas turbine components experience different amounts of damage accumulation when the gas turbine unit is run in different operating modes. The hot gas path parts will accumulate more damage when the engine runs in peak load rather than in base load. This is because of the higher firing temperature at the peak load setting. The gas turbine damage accumulation mechanisms include cyclic duty application and continuous duty application. They both contribute to unit degradation, and they are not independent. A good appreciation of the interdependency of the damage accumulation mechanisms due to cyclic duty application and continuous duty application is necessary for accurate accumulative damage modeling.

It has been addressed above that gas turbine reliability is greatly influenced by the operating conditions. A reliability model, which is able to address the influence of operating condition, is desirable for further maintenance analysis. Furthermore such a model would allow the plant operator to make reliability forecasting given a future operating profile. However, most of the reliability models consider the calendar time or service time as the only parameters that influence reliability characteristics during its operation. These types of models are perhaps useful for systems always working under normal operating conditions. However, if the working condition of a system deviates away from normal condition, for example the working condition is more severe than the normal condition, the system age evolves faster than the situation under normal condition. This is the case when a gas turbine operates in peak load mode instead of base load mode. Another example is when the gas turbine experiences a trip[*] rather than a normal base load shut down.

In summary, the gas turbine used for power generation is a multiple component repairable complex system. Gas turbine unit maintenance scheduling is targeted to improve system reliability, minimize system operation risk, and restore or upgrade system performance so as to optimize power plant lifecycle profitability. Optimal maintenance scheduling requires accurate assessment of power plant system reliability and operation risk, which depend on the aging (physical status) of the components of the system, i.e., the accumulated damage due to unit usage. This usage may include continuous duty application and cyclic duty application. The operating conditions vary with time due to the dynamics of the grid load demand. A methodology for reliability modeling, which is able to account changing operating conditions, is valuable for maintenance scheduling. The maintenance practices serve to restore the gas turbine

[*]Turbine trips (shutdown of the turbine) occur when the protective functions of the control system act as a result of detecting such events as over speed, over temperature, high rotor vibration, fire, loss of flame, or loss of lube oil pressure.

system reliability by repairing or replacing some of its parts which otherwise are subject to high operational risk if they are used continuously.

2.7.5 Maintenance Effectiveness

Early studies of maintenance models usually assumed that, after corrective or preventive maintenance, the system is one of the two extreme situations, either as good as new or as bad as old, and that maintenance time is negligible and thus discounted. These assumptions are obviously not true for a power plant, which is a sophisticated multiple component system. Realistic reliability modeling maintenance scheduling for a sophisticated system such as gas turbine driven power plant has rarely been seen in the literature. Much of the recent work in the maintenance field concentrates on models using a Non Homogeneous Poisson Process or a Markov Renewal Process [32]. Dascalu points out that these models are not realistic ones in that tacit assumptions were made. Barlow and Proschan (1965) attempted to remedy this by using stochastic processes for reliability modeling and still hold the assumption that the times to failure be statistically independent and identically distributed [33]. In the real world, this is not what happens. Assessing the reliability of repairable systems with consideration to maintenance is a difficult task due to the complexity of the models. Dascalu also states that almost all models in the maintenance field are using a Non Homogeneous Poisson Process (corresponding to minimal repair activities) and Renewal Processes (corresponding to replacement activities), and that using a single distribution function for the times to failure throughout the life of the system is a misconception. Dascalu argues that the distribution function would change due to corrective maintenance, and he proposes an approach for reliability modeling using a semi-Markov chain model with a Weibull distribution. Then a Monte Carlo simulation method is used to model the random effects of preventive maintenance [32]. The effect of the repair on the system is quantified using the concept of virtual age. The reliability distributions after a maintenance activity are usually different from those used before the maintenance activity. Thus, a different reliability distribution is assumed each time a corrective maintenance is performed.

The maintenance practice has a strong impact on engine performance restoration, and the degree of restoration depends on the extent of maintenance activity. Maintenance practices to performance restoration include online water wash, off line water wash, combustion inspection, hot gas path inspection, and major inspection. A list of the maintenance practices follows:

- Online water wash
- Off line water wash (with casing off)
- Steam cleaning
- Abrasive cleaning with hand scouring
- Replacement of hot gas path parts with refurbished or brand new parts

Application of new technology is also an option for performance and reliability restoration. Advanced technology components are usually designed to improve the performance and/or reliability of the engine. As an example, upgrade packages have been designed to improve control of sealing and leakage flows [28]. Development of models to evaluate the influence of upgrade packages on performance and reliability will be helpful for efficient selection.

2.8 Research Questions and Hypothesis

To implement such an integrated approach for power plant operational modeling and optimization, the following research questions are identified for developing such an integrated approach for gas turbine power plant operational modeling and optimization:

1. What are the limitations of the current adopted philosophies and methods for power plant operational optimization? What are the needs for changes for a power plant operational optimization in the deregulated electric power market?

2. Is it possible to develop a profit based, lifecycle oriented, and unit specific approach for gas turbine power plant operational modeling and optimization, which considers performance, reliability, and market signals simultaneously?

3. What are the key elements for the proposed operational modeling and optimization approach?

4. How are the quantitative relationships between power plant degradation (aging) rate and unit operating modes evaluated? How are the quantitative relationships between performance and reliability degradation and operating conditions evaluated? How to evaluate the quantitative relationships between performance and reliability restoration and maintenance activities?

5. How is the coupled long term generation and profit based outage-planning problem formulated and solved?

6. How is a profit-based, lifecycle oriented, and unit specific maintenance scheduling method different from the current adopted maintenance scheduling method? How is it formulated and solved?

7. How is an upgrade packages evaluation and selection problem formulated and solved with consideration of power plant operational decisions?

8. How is a combined cycle power plant design optimization problem formulated and solved?

CHAPTER 3

GAS TURBINE BASED POWER PLANT PERFORMANCE AND RELIABILITY MODELING

3.1 Introduction

The following tasks are identified to accomplish the proposed power plant operational modeling:

1. Develop and validate performance models using power plant system configuration and historic operational data for simple cycle and combined cycle power plants. Develop power plant performance meta-modeling and validation methods. The operational flexibility of a gas turbine driven power plant is an important issue. For optimization purposes, the capability to evaluate efficiently and accurately the performance of a power plant under a variety of operating modes is very important. Meta-models can also be created to perform short term and long-term economic analyses for each technology alternative. Using these models, probability analysis can be performed with consideration of uncertainty.

2. Develop power plant performance degradation modeling methods with consideration of operating conditions. Operating conditions have a strong influence on component aging rate, which includes performance degradation rate and reliability degradation rate, and the quantitative connections between

operating conditions and performance degradation are to be established. Statistical or empirical methods will be employed instead of physics based modeling methods, since the mechanisms for performance degradation have not been fully understood, and the physics based modeling methods/tools are not available. Furthermore, physics based performance modeling methods are extremely computationally expensive.

Two methods are proposed to evaluate quantitatively the influence of operating conditions on performance degradation. One use the idea of maintenance factor, for which the influence of various operating conditions is taken into account using different maintenance factors, and the accumulated degradation, is based on the accumulated maintenance factors. The other approach is the proportional degradation rate method. In this approach, a baseline degradation function is established, and the influence of operating conditions is modeled using covariates in the relative performance degradation function.

3. Develop a power plant performance restoration modeling method with consideration of maintenance effectiveness. One of the objectives of maintenance is to restore power plant performance. The quantitative relationship between performance restoration and maintenance activities needs to be established before maintenance interval is optimized. The virtual age method is employed to model the impact of maintenance on performance restoration by assigning a younger age to the item. This method is to be integrated with the performance degradation models to evaluate performance restoration.

4. Develop parts/components reliability degradation modeling methods with consideration of operating conditions. Operating conditions have a strong influence on the reliability degradation rate. Again, statistical or empirical methods will be employed. One approach is to use maintenance factors (service factors) to model the influence of operating conditions on reliability degradation. Other methods, which include proportional hazards method, proportional intensity method, and accelerated life test are also investigated. In these approaches, a baseline reliability function is first established, and then the influence of operating conditions on reliability are modeled as covariates in the relative reliability functions. The virtual age method will work with reliability degradation methods to model reliability with consideration of operating conditions and maintenance activities.

In the following sub sections specific performance and reliability models are introduced, and then a generic procedure to evaluate power plants economics performance is introduced.

3.2 Power Plant Performance Modeling and Validation

Power plant performance is a function of power plant design, technology upgrade, its operating mode, ambient conditions, and degradation. Power plants accumulate degradation as they accumulate operating hours. Let t be the calendar time, and t be the age of the system. It is assumed that the system ages only when it is in operation, and it ages as it accumulates its operating hours. Let $P(t)$ be the electricity power output rate of the power plant, and $HR(t)$ the heat rate. They are functions of system design, technology option, operating mode, ambient conditions, and performance degradation of the power plant. Power output rate and heat rate are given by Equation (3.1) and (3.2), respectively.

$$P(t) = P\begin{pmatrix} system\ design,\ techno\log y\ upgrade,\ operating\ \mathrm{mod}\, e(t), \\ ambient\ conditions(t),\ \deg radation(t) \end{pmatrix} \tag{3.1}$$

$$HR(t) = HR\begin{pmatrix} system\ design,\ techno\log y\ upgrade,\ operating\ \mathrm{mod}\, e(t), \\ ambient\ conditions(t),\ \deg radation(t) \end{pmatrix} \tag{3.2}$$

Performance degradation is a function of system design and unit usage history, which include unit operating history and maintenance activities. Therefore performance degradation can be given by

$$Degradtion(t) = Degradation(system\ design,\ unit\_usage\_history(t)) \tag{3.3}$$

The actual output rate and heat rate of the power plant with consideration of degradation can be evaluated as long as the degradation is estimated. Let P_0 and HR_0 be the output rate and heat rate of the power plant at the beginning of its service life, when no performance degradation has occurred. Let $\Delta^P(t)$ be the degradation of output rate at time t, and $\Delta^{HR}(t)$ be the degradation of heat rate at time t. The degraded output rate and heat rate can be calculated using the following equations:

$$P(t) = P_0 \cdot \left(1 - \Delta^p(t)\right) \tag{3.4}$$

$$HR(t) = HR_0 \cdot \left(1 - \Delta^{HR}(t)\right) \tag{3.5}$$

Maintenance activities and technology infusion have impacts on power plant performance. In the engineering practices, performance restoration parameters are estimated using an empirical database, and it is used to model the impacts of maintenance activities. For example, a certain percentage increase in output rate and decrease in heat rate may be applied to estimate power plant performance restoration when a major maintenance is performed. In this research, a virtual age concept is applied to the evaluation of performance restoration due to maintenance. This will be addressed further in the consecutive chapters.

3.2.1 Gas Turbine Power Plant Performance Modeling Tools

The combined cycle power plants are complicated multiple components systems, with gas and steam turbines, heat exchanger equipment, condensers, deaerators, pumps, and the like.

A gas turbine performance model is employed to perform the gas turbine performance analysis. The system level performance is generated based on the technology input metrics. For combined cycle power plant, these gas turbine performance data are fed into as input a combined cycle performance analysis code, and the performance data for the combined cycle power plant is therefore calculated.

The GateCycle™ Computer program is employed to evaluate the performance of combined cycle power plants.

The modeling tool for gas turbine performance is the Gas Turbine Performance (GTP hereafter), which is a gas turbine performance modeling software developed by GE Energy.

GateCycle™ is heat balance software used for evaluating the performance of existing and conceptual combined cycle power plant systems. It combines an intuitive, graphical user interface with detailed analytical models for the thermodynamic, heat-transfer, and fluid-mechanical processes within power plant, which allows users to run design and simulation studies of any complexity. From a build palette, equipment icons can be selected and arranged on a graphical drawing page, and the plant configuration can be finalized by connecting power plant components using steam, gas, and water lines [34].

There are various options to model gas turbines using GateCycle. The DATA GT Heat Rate Method is employed to model gas turbine in this study. The following parameters are required to define the gas turbine performance.

- Engine net power
- Engine heat rate
- Engine exhaust flow rate
- Engine exhaust flow temperature
- Engine exhaust flow pressure
- Engine exhaust flow entropy
- Fuel low heating value
- Generator efficiency
- Auxiliary losses

GateCycle provides CycleLink™ to allow user to run a model from within Excel™. CycleLink is a powerful utility based inside Microsoft Excel™ that allows you full access to data within GateCycle. In this study, CycleLink is used to read the gas turbine rating table from the output data of GTP, and feed them into GateCycle to define the gas turbine performance [34].

A representation of combined cycle power plant is shown in Figure 3.1. This combined cycle power plant is with a single gas turbine and a three-pressure steam turbine.

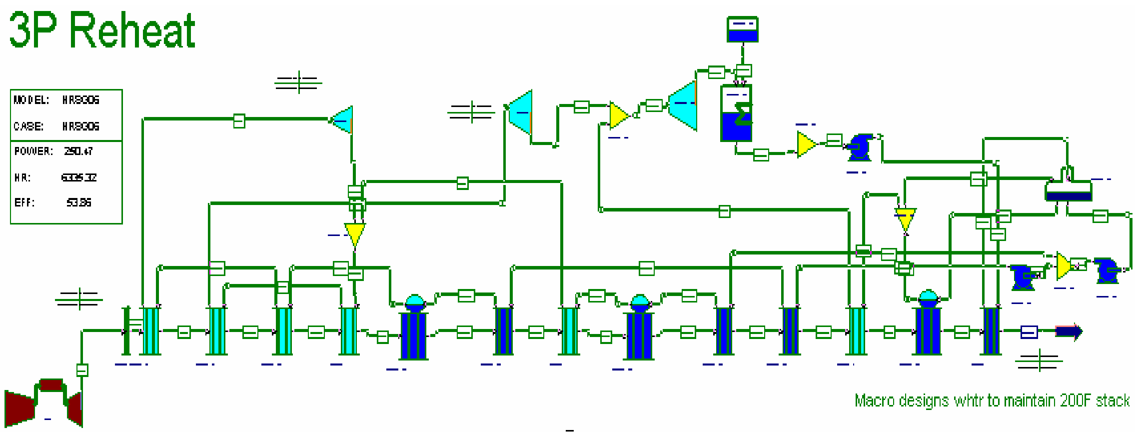

Figure 3.1 Combined Cycle Power Plant Model Using GateCycle

3.2.2 Performance Validation

The purpose of power plant performance calibration and validation is to ensure the accuracy of performance simulation. The parameters defining the performance models are tuned so that, for a given operating conditions, the simulated performance data matches the historical performance data.

Plant historical operational data is extracted and used to calibrate and validate plant performance models. For performance validation purpose, the following operational data is extracted from the historic database.

- Ambient conditions
- Power plant operating modes, such as fuel type, power augmentation, inlet guide vane angle, and control curve load type (part/base/peak), etc.
- Power plant component degradation factors, including the degradation coefficients for compressor, combustors, and turbine
- Power plant performance data, such as net output rate, heat rate, firing temperature, etc
- Power plant maintenance history, such as start up and shut down, trips

Performance Validation for Gas Turbine

Historic data to define the operating conditions of gas turbine is extracted, and they are feed into the gas turbine performance model as inputs. These include the ambient conditions and gas turbine operating modes. The gas turbine performance model is executed, and the simulated gas turbine performance output is obtained. If the simulated performance data and the historic performance data do not match well with regard to given acceptable tolerance, the parameters defining the gas turbine performance model is adjusted. This process is repeated until the simulated gas turbine performance agrees with the performance from historical database. The same procedure is applied to calibrate the combined cycle power plant performance model.

For combined cycle power plant, two separate procedures are performed for the validation of power plant performance, and they are the validation of gas turbine performance, and the validation of combined cycle power plant performance.

The following procedures are performed for gas turbine performance model calibration:

1. Extract gas turbine historic operational data on given time intervals, i.e., every 30 seconds or 5 minutes, for a given site/plant during a given time period, say, one week.

2. Use historic ambient conditions, degradation factors, and gas turbine operating modes as inputs for gas turbine performance model

3. Execute gas turbine performance model for each point of time chosen

4. Compare the simulated gas turbine performance data, i.e., output rate and heat rate, and the historic gas turbine performance data, and evaluate the error with regard to the simulation model

5. Tune the associated parameters in the gas turbine performance model based on the error

6. Iterate step 2-5 until the error is acceptable

<u>Performance Validation for Combined Cycle Power Plant</u>

Once the calibrated gas turbine performance model is obtained, the combined cycle power plant performance model can be calibrated by carrying out the following procedures:

1. Extract power plant historic operational data on given time intervals, i.e., every 30 seconds or 5 minutes, for a given site/plant during a given time period, say, one week.

2. Define the operating conditions and gas turbine output for the combined cycle power plant. These include ambient conditions, degradation factors, power plant (including steam turbine, HRSG, and the like) operating modes, and gas turbine performance output data, which includes output rate, heat rate, exhaust flow rate, exhaust flow temperature, etc.

3. Execute combined cycle power plant model for each point of time chose

4. Compare the simulated power plant performance data and the historic plant performance data, evaluate the error with regard to the simulation model

5. Tune the associated parameters in the power plant performance model based on the error

6. Iterate step 2-5 until the error is acceptable

The power plant calibration and validation procedures are illustrated in Figure 3.2.

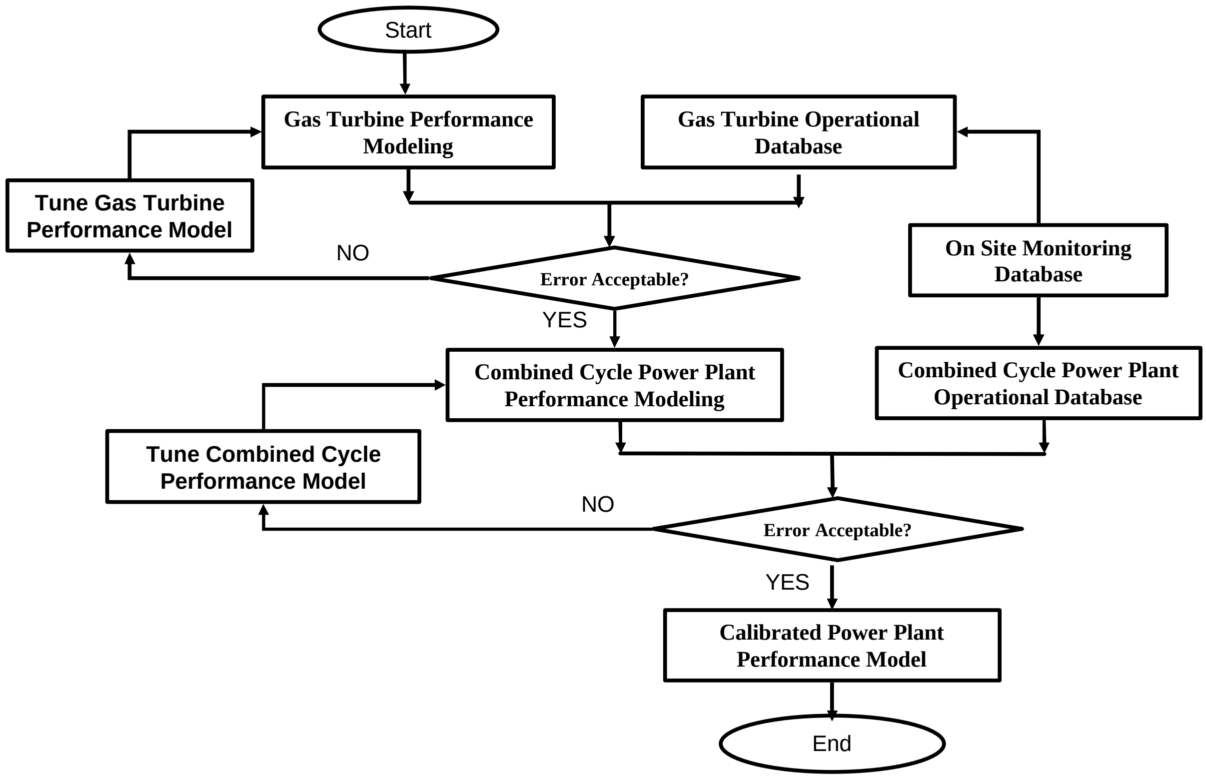

Figure 3.2 Power Plant Performance Calibration and Validation

The operational optimization requires efficient evaluation of power plant performance, since the optimization procedures require numerous case of evaluation of plant performance. However, performance evaluation using physics based models is extremely computationally expensive. Meta-models such as response surfaces equations are therefore very helpful for power plant operational optimization. The generation of response surface equations is introduced in Chapter VII.

3.3 Gas Turbine Power Plant Aging

In this study the aging and the failure rate function are defined only when the power plant is in operation.

Different methods for the determination of the age of a system exist. The most straightforward one is to determine the age of the system based on the calendar time the system experiences. However the age determined using this method does not take the actual usage of the system into account, since the system may not be put into operation all the time. Another method is to determine the age using the actual operating hours of the system. This method considers the usage of the system; however, it is not able to take the varying operating conditions into account. To develop a method for the determination of the age of a system that considers the actual usage of the system and the impact of varying operating conditions, appreciation of the accumulation of damage mechanisms is helpful.

The method for the evaluation of aging is highly correlated with the gas turbine maintenance philosophy. The major issue here is how to account for the accumulated damage. Traditionally a periodic maintenance interval based on unit age is employed for heavy-duty gas turbine maintenance, and the method to evaluate the age of the plant is based on a service factor (or maintenance factor) approach.

There are different philosophies of accounting for the interaction of cycles and hours in defining the maintenance interval. Currently there are two different approaches for maintenance interval planning. One is the so-called independent starts and hours approach, and the other the equivalent operating hours approach. A linear dependency of the start cycles and operating hours is usually assumed for the equivalent operating hours approach, and this is based on the assumption that creep and fatigue damage would be linear during the interval that would accelerate damage and reduce the capability of hot parts. A generalized starting frequency dependent approach, which makes maintenance interval schedules based on the starting frequency of the gas turbine unit, is proposed in this study.

3.3.1 The Independent Starts and Hours (ISH) Approach

In this approach, the interactions of life consumption mechanisms are assumed as second order effects, and therefore the maintenance planning is based on independent counts on starts and hours. Whichever criterion is first reached determines the maintenance interval [13].

Although the starts and hours are counted independently, the equivalencies within a wear mechanism are considered. This is based on the understanding that different operating modes can have significant different effects on the life consumption of gas turbine unit. For example, the working condition of the hot gas path parts is more severe when the gas turbine is running with distillate fuel than that with natural gas fuel. This leads to more significant life consumption. The factors considered for the equivalencies for hours based criteria include fuel type and quality, firing temperature setting, and the amount of water or steam injection [13].

To consider these effects, the idea of maintenance factor (service factor) is introduced. A baseline condition for operating hours is defined as a gas fuel unit operating continuous duty, with no water or steam injection, and the maintenance factor for this baseline is defined as 1. For an operation that differs from the baseline, maintenance factors are established that determine the increased level of maintenance that is required. In so doing, the influence such as fuel type and quality, firing temperature setting, and the amount of water of steam injection are considered with regard to hours based criteria. Similarly, baseline condition for starts can be defined, and maintenance factors can be defined based on the attributes of the actual starts. Start up rate and the numbers of trips are considered for starts based criteria [13].

Therefore the maintenance factor converts the effects of operating conditions deviating from the baseline to that of the baseline. For scenarios that the gas turbine unit is running in severe operating states other than the baseline condition, the corresponding maintenance factors will be greater than one, and hence the actual maintenance interval will be reduced.

The value of maintenance factors is obtained from engineering experience. Let $m_h(t)$ be the maintenance factor of operating hours at time t, and $m_s(i)$ the maintenance factor of start i. The equivalent life of a system can be defined using two types of matrices: one is the factored fired hours, and the other is factored starts. The factored fired hours h_f for operating period T is defined below:

$$h_f = \int_T m_h(t)dt \tag{3.6}$$

Factored fired hours will be used to determine system age. Operating parameters are employed as the decision variables here, and maintenance factors will be employed to define the aging rate.

Assume there are N startups during the operating time period T. Similarly the factored starts is defined as

$$S_f = \sum_{i=1}^{N} m_s(i) \tag{3.7}$$

To define the age of a gas turbine, the knowledge of both factored fired hours and factored starts are needed. In the independent starts and hours approach, the age of the gas turbine L_{ISH} is therefore given by

$$L_{ISH} = (h_f, S_f) \tag{3.8}$$

3.3.2 The Equivalent Operating Hours Approach

A different maintenance approach is referred to as equivalent operating hours [35]. In this approach, the interaction of the two different life consumption mechanisms due to continuous duty and cycle effects is assumed to be linearly dependent. The operating hours and starts are not counted independently, but rather a combined method considering both operating hours and starts is employed. The effects of cyclic duty (start-ups) is converted to those of continuous duty (operating hours) using a conversion factor, which is similar to the maintenance factor used in the hours and starts approach. Each starting cycle is converted to an equivalent number of operating hours [35]. The total equivalent operating hours is therefore determined. The maintenance intervals are based on the equivalent operating hours.

Similar to the operating hours and starts approach, the impact of factors other than actual operating hours on the lifespan are taken into account for the evaluation of the age of the gas turbine. These factors include the number of peak operating hours, the number of hours on alternative fuel, the number of hours on steam or water injection, and number of cycles, which include number of normal starts, number of emergency starts, number of trips, etc.[36]. A method to determine the age of the gas turbine L_{EOH} in equivalent operating hours is given in Reference [35], and is introduced below.

$$\begin{aligned} &L_{EOH} = actual\, operating\, hours + \\ &k_1 * (number\, of\ start - ups + number\, of\ trips * k_2) + \\ &peak\, operating\, hours * k_3 \end{aligned} \tag{3.9}$$

Where k_1 is the conversion factor for the number of start-ups, and k_2 is the conversion factor for the number of trips, and k_3 is the conversion factor for peak operating hours. k_1, k_2, k_3 is defined by

$$1\ start - up = k_1\ number\, of\ operating\, hours$$

$$1\ trip = k_2\ number\, of\ start - ups \tag{3.10}$$

$$1 \ peak \ operating \ hour = k_3 \ number \ of \ operating \ hours$$

3.3.3 Some Comments on the EOH and ISH Approaches

The accuracy of independent hours and starts approach may need further validation. The assumption that the interaction of failure mechanisms of continuous duty and cyclic duty as second order effect needs to be validated through theoretic and engineering practice validation.

The equivalent operating hours approach seems more reasonable since it considers directly the interaction of the failure mechanism of cyclic duty and continuous duty. The key for its success is the correct evaluation of dependency of the failure mechanism of continuous duty and cyclic duty, i.e., the accurate estimation of the conversion factors, which is not a trivial task. A fully appreciation of the interaction of the failure mechanism of cyclic duty and continuous duty is necessary for this approach.

A statistical study to analyze the interdependency between number of starts and number of running hours is performed by Ceschini and Carlevaro [37]. The study shows that interdependency between starts and hours does exist, and given the number of starts and the corresponding running hours this interdependency can be evaluated and the inspection intervals appropriately predicted. Furthermore, interdependency curves between number of hours and starts can be constructed for maintenance and inspection planning. Based on the analysis, the inspection and maintenance intervals for the transition piece and combustion liner are proposed for base load, mid range, and peaking units respectively. These intervals will increase as the start frequency decreases. The study provides a validation for the equivalent operating time approach.

Soechting and his co-workers performed another investigation of the damage accumulation rules applied to maintenance scheduling of industrial gas turbines [38]. The influence on part crack initiation resulting from creep-fatigue interaction mechanism and crack propagation to a repair limit was investigated. Gas turbines operating in three different modes, namely, base load, daily start-stop load, and weekly start-stop mode, are investigated. The objective of the research is to understand the physics and develop an improved life management procedure that accurately distinguishes the difference in maintenance intervals dependant on the usage of the engine. The investigation shows that the initiation of thermal fatigue cracks is dependent on the accumulation of start-stop cycles. The crack propagation of a crack to a repair limit depends on both cycle and time dependency (operating hours). Soechting and his co-workers also suggest that a linear damage rule is conservative in scheduling maintenance for high cyclic operators, and that the non-interaction assumption of start-stop cycles and operating hours is optimistic [38].

However, one may argue that the equivalent operating hours method may create the impression of longer maintenance intervals, while in reality more frequent maintenance inspections are required [13]. This argument still needs to be verified though. Furthermore, the equivalent operating method introduced by Moritsuka [35] considers only some of the factors which may reduce the life span of the gas turbine hot gas path parts, but it misses some other important factors, such as type of fuel and quality and the amount of steam or water injection.

3.3.4 The Generalized Equivalent Cumulative Age Approach

It is natural to believe that a combined index, which takes the effects of both the damage accumulated due to continuous operation and that due to start/stop cycles into consideration, will be valuable for industrial maintenance scheduling practice. However, a comprehensive representation of this combined index has not been seen in the literature. In this study, a definition for such an index is established, and, furthermore, a generalized approach for maintenance scheduling which combines the effects of continuous operation and start/stop cycle can be developed based on this approach.

To account for the interaction of different damage mechanisms, and establish a generic index for gas turbine aging evaluation, a generalized damage accumulation approach is developed.

Let L be the combined life consumption or accumulated damage of a gas turbine engine unit. Suppose there are N different continuous operating modes and M different start/stop cycles for a gas turbine engine unit. Let h_i be the number of operating hours for a specific continuous operating condition i, and $k_{h,i}$ the maintenance factor or service factor of operating condition i. Let s_j be the number of start-ups for a specific start/stop cycle j, and $k_{s,j}$ the maintenance factor or service factor for start/stop cycle j. Let e be the conversion factor for the number of start/stop cycle to operating hours. Let f_s be the starting frequency, which is the ratio between the number of starts and number of continuous operating hours.

The combined life consumption L or accumulated damage can be defined as:

$$L = (1-e)\sum_{i=1}^{N} k_{h,i} \cdot h_i + e\sum_{j=1}^{M} k_{s,j} \cdot s_j \tag{3.11}$$

Where

$0 \le e \le 1$ is a function of starting frequency f_s

$i = 1,2,\ldots N$

$j = 1,2,\ldots M$

An example of the definition of h_i and $k_{h,i}$, s_j and $k_{s,j}$ is shown in Tables 3.1 and 3.2, where $N = 18$, and $M = 7$ respectively. Please note that trips are categorized as a type of start/stop cycle. Similar definitions can be obtained if the operating options are different.

Please note that the definitions for operating modes, the start/stop cycle, and their coefficients for combustion inspection and hot gas inspection are different.

Let h_f be the total factored fired hours derived from actual fired hours and their corresponding maintenance factors. Let s_f be the factored starts derived from actual starts and trips and their corresponding maintenance factors. Namely

$$h_f \equiv \sum_{i=1}^{N} k_{h,i} \cdot h_i\ ,\ i = 1,2,\ldots N \tag{3.12}$$

$$s_f \equiv \sum_{j=1}^{M} k_{s,j} \cdot s_j\ ,\ j = 1,2,\ldots M \tag{3.13}$$

Table 3.1 The Definitions of Continuous Operating Modes for HGP Inspection

Power setting	Fuel type	Steam Injection	Water Injection	Operating Mode i
Base Load	Natural gas	On	Off	1
		Off	On	2
		Off	Off	3
	Distillate fuel	On	Off	4
		Off	On	5
		Off	Off	6
	Heavy fuel	On	Off	7
		Off	On	8
		Off	Off	9
Peak Load	Natural gas	On	Off	10
		Off	On	11
		Off	Off	12
	Distillate fuel	On	Off	13
		Off	On	14
		Off	Off	15
	Heavy fuel	On	Off	16
		Off	On	17
		Off	Off	18

Table 3.2 The Definitions of Start/Stop Cycle for HGP Inspection

Start/Stop Cycle Type		Start/Stop Cycle j
Start/stop Cycle	Part load start/stop cycle (<60%	1
	Normal base load start/stop cycle	2
	Peak load start/stop cycle	3
	Emergency starts	4
	Fast load starts	5
Trip	Part load trip	6
	Full load trip	7

Equation (3.11) is of the form:

$$L = (1-e)\cdot h_f + e \cdot s_f \tag{3.14}$$

It is obvious to see that the methodology here is a generalized one for the ISH and EOH approach. If e here is a constant and $0 < e < 1$, the generalized life consumption method becomes the equivalent operating hours method, which assumes a linear interdependency of number of continuous operating hours and number of starts. If $e = 0$ or $e = 1$, it becomes the independent hours and starts method.

Divide equation (3.14) by $(1-e)$

$$\frac{L}{(1-e)} = h_f + \frac{e}{(1-e)} s_f \tag{3.15}$$

Here $\frac{L}{(1-e)}$ is the normalized life limit in the form of operating hours, which we define is the equivalent operating hours life limit. Let L_h represent the equivalent life limit in the form of operating hours.

$$L_h \equiv \frac{L}{(1-e)} \tag{3.16}$$

The term $\frac{e}{(1-e)}$ defines the conversion factor between factors fired hours and factored starts.

Let

$$e' \equiv \frac{e}{(1-e)} \tag{3.17}$$

Then the operating hours based life equation is therefore

$$L_h \equiv h_f + e' s_f \tag{3.18}$$

3.4 Reliability Degradation and Restoration

3.4.1 Introduction to Reliability

Reliability can be defined as the probability that an item (component, equipment or system) will operate without failure for a stated period of time under specified conditions [39]. Reliability is the measure of the probability of successful performance of the system over a period of time.

Assume an item that fails at an unforeseen or unpredictable random age of $c > 0$. The random variable c has a distribution F. Let t be the age of an item. t can be calendar time, accumulated operating hours, or equivalent age with consideration of operating mode.

$F(t) \equiv P(c < t)$ is called the distribution function of t age to failure, where c is a random variable.

Let $R(t)$ be the survival function, and it is given by:

$$R(t) = 1 - F(t) \tag{3.19}$$

$R(t)$ is also called the reliability function.

Let f be the probability density function of F, and is given by

$$f(t) = F^{'}(t) \tag{3.20}$$

The hazards or failure rate function is defined by

$$h(t) = \frac{f(t)}{1 - F(t)} \tag{3.21}$$

The failure rate function $h(t)$ measures the proneness to failure at age t.

Let $H(t)$ be the cumulative hazard function, which is defined by:

$$H(t) \equiv \int_0^t h(u)du = -\ln(1 - F(t)) \tag{3.22}$$

The link between cumulative hazard function and the survival function is given by

$$P(c > t) = R(t) = \exp\left(-\int_0^t h(u)du\right) \qquad (3.23)$$

It is important to distinguish the difference between the system age and the calendar time. The age of the system is determined by its usage history, which is a function of calendar time t. Considerations need to be given to the operating conditions when evaluating the age of an item, and accumulated damage mechanisms of gas turbines. A representation of the relationship between the calendar time and the system age is shown in Figure 3.3. The relationship between the age and the calendar time can be given below:

$$t(t) = f(unit\_usage\_history(t)) \qquad (3.24)$$

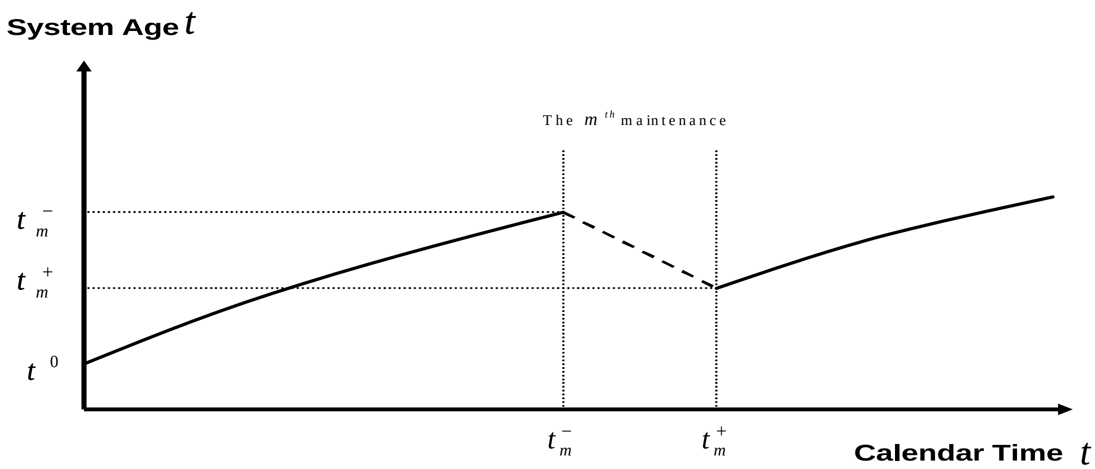

Figure 3.3 Calendar Time and System Age

3.4.2 Reliability Modeling Considering Operating Conditions

For performance and reliability degradation modeling, a physics based modeling will be more accurate than statistical or empirical methods. However, performance and reliability degradation mechanisms need to be well understood for physics based approach, which has not been accomplished today. Furthermore, physics based performance and reliability degradation modeling is extremely computationally expensive, which is not a good choice for efficient optimization purposes. Therefore statistical or engineering empirical models will be employed in this research.

It has been addressed above that gas turbine reliability is greatly influenced by the operating conditions. A reliability model that is able to address the influence of operating conditions is desirable for further maintenance analysis. Furthermore such a model would allow the plant operator to make reliability forecasting given a future operating profile. However, most of the reliability models consider the calendar time or service time as the only parameter that influences reliability characteristics. These types of models are perhaps useful for systems always working under normal operating conditions. However, if the working condition of a system deviates away from normal condition, for example the working condition is more severe than the normal condition, the system age evolves faster than the situation under a normal condition. This is the case when a gas turbine operates in peak load mode instead of base load mode, or the gas turbine experiences a trip rather than a normal base load shut down.

However, there have been a few efforts that are trying to include operating conditions into reliability modeling. There are two different categories of approach. One of them is the engineering approach that uses an equivalent age of the system instead of the actual service time or calendar time in the reliability function. A mechanism to convert the influence of operating conditions, which deviates from a nominal operating condition, is developed. This is done by computing service factors or maintenance factors to account the departure of operating condition from a baseline operating condition. The equivalent aging experienced by the unit is the production of the actual service time and the maintenance factors. This approach is generally employed by industry [13][35]. We will refer this approach as *the maintenance factor approach* later on.

The other approach, which has been seen in research literature, uses covariates to represent operating conditions in the reliability function. The operating conditions include the operating mode of the system and the external environment of the system, such as ambient temperature and air quality. Usually a baseline reliability function is employed to model the reliability behavior of the system under normal operating conditions. Another relative reliability function, which is a function of the covariates, is used to model the reliability behavior when its operating condition deviates from the normal condition. These methods include an accelerated life model, a proportional intensity model, and a proportional reliability model.

<u>The equivalent cumulative age approach</u>

In this approach, the effects of actual usage of the system and the varying operating conditions are converted to a combined index, which is the equivalent cumulative age of the system. A mechanism to convert the influence of operating conditions that deviate from a nominal operating condition is developed. This is done by establishing service factors or maintenance factors to account for the departure of operating condition from a baseline operating condition. The equivalent cumulative aging experienced by the unit is the integration of the age that the system experiences, which is the integration of the actual service time and the maintenance factors.

The method for the determination of the age of the gas turbine is introduced in section 4.2. In practice, the three approaches, which are the independent starts and hours approach, the equivalent operating hours approach, and the generalized equivalent cumulative age approach, may be employed in particular situations, depending on the availability of historic operational data.

In this research, the reliability distributions of heavy-duty gas turbines and their parts are assumed to be in the form of Weibull distributions. The Weibull distribution has been extensively used in industry. One reason for the popularity of this distribution is that it can be used to describe both increased failure rate and decreased failure rate as random variables. The other reason is that a logarithmic transformation of the Weibull random variable produces a random variable that belongs to the so-called “location-scale” which has several good features for statistical analysis [40].

Assume the reliability of the investigated item is a three-parameter Weibull distribution, which is frequently used for reliability modeling in the industries. For a specific system, we have

Probability density function: $$f(t) = \frac{b(t - t_0)^{(b-1)}}{h^b} e^{-\left(\frac{t-t_0}{h}\right)^b} \tag{3.25}$$

Failure rate function: $h(t) = \dfrac{b(t - t_0)^{(b-1)}}{h^b}$ (3.26)

Probability of failure: $F(t) = 1 - e^{-\left(\frac{t - t_0}{h}\right)^b}$ (3.27)

Probability of survive: $R(t) = e^{-\left(\frac{t - t_0}{h}\right)^b}$ (3.28)

Where $h > 0$ is the scale parameter, $b > 0$ is the shape parameter, and t_0 is the location parameter. If $t_0 = 0$, it becomes a 2 parameter Weibull distribution.

In a generic form, the equivalent cumulative age is given by

$$t = (1 - e)\sum_{i=1}^{N} k_{h,i} \cdot h_i + e\sum_{j=1}^{M} k_{s,j} \cdot s_j \tag{3.29}$$

Statistical regression analysis can therefore be performed once the equivalent cumulative age t is defined. Estimation of reliability distribution parameters can be achieved using techniques such as maximum likelihood method.

The general equivalent cumulative age approach evaluates the cumulative degradation of the system as it accumulates its operating hours, and therefore it is able to address the cumulative distribution functions of the system, such as the probability of forced outage of the system. In the cumulative approach, the impact of varying operating conditions on the failure rate and probability density function cannot be evaluated. Another approach that uses covariates to account for the varying operating conditions, establishes the link between the failure rate and the varying operating conditions.

Maintenance factor approach

A natural approach to consider the aging rate in the industry uses maintenance factors, which include factored fired hours and factored starts. For gas turbine maintenance scheduling (under which a maximum maintenance interval is set using gas fuel) the baseline operating profile is defined as a base load power setting with no steam or water injection. Maintenance factors are introduced to establish the maintenance required when the power plant operates under conditions that differ from the baseline. These maintenance factors depend on the operating profile under which a gas turbine is operated. Therefore, maintenance factors can be used to model the aging rate for gas turbine driven power plants. Both factored fired hours and factored starts or a combination of them can be used as the equivalent age of the system. The formulas to determine maintenance factors are given in Equation (3.6) and Equation (3.7).

Statistical regression analysis can therefore be performed once the factored fired hours and factored starts are defined. Estimation of reliability distribution parameters can be achieved using techniques such as the “maximum likely method”.

The proportional hazards method (PHM)

The reliability functions for the equivalent age reliability modeling method addressed above are based on the regression from a fleet wide data analysis. However, the unit history of a specific unit may differ substantially from the “normal” usage history. For example, the aging of a specific unit may differ from the “normal” condition in that it may suffer from poor quality fuel, wrong operation, and long time peak load operation. This kind of unit specific operation is not obtainable from the equivalent age based approach. These kinds of constraints can be overcome by employing the covariates based approach. Other proposed approaches for operating conditions modeling include the accelerated life mode (ALF) and the proportional hazards model. These models have been extensively used in the study of lifetime in medicine, reliability and economics. In these approaches, operating conditions are defined using covariates.

The proportional hazards model (PHM) is one of the most important statistical regression models, and it is widely used in the industry. It was first introduced by Cox [41], and has been extensively referred in the areas of biology, biomechanical engineering, and mechanical engineering. In recent years, a few publications have been seen in the literature that uses the proportional hazards method for reliability modeling of repairable systems with consideration of operating conditions.

Kumar performed a review on the application of proportional hazard model in Kumar performed a review on the application of the proportional hazard model in reliability analysis before 1995 [42]. This method has been applied to compare the hazard rates of various types of values operating under different conditions in a nuclear power plant. Jardine and his coworkers applied the proportional hazard method for precise reliability prediction using oil analysis for aircraft engine [43].

The hazards function, sometimes referred as the force of mortality (FOM), or failure rate function, $h(t)$, is defined as [44]:

$$h(t) = \mathop{Lim}_{d \to 0} \frac{\Pr(t < t \le t + d)}{d \Pr(t > t)} \tag{3.30}$$

Where t is the age to failure, and $t \geq 0$. The definition of t here is not clear, it may be defined as accumulated operating time, which is actual fired hours, or accumulated factored operating time, which is factored fired hours. Someone defines it as the calendar time. In the study it is more likely to be defined as system age, i.e. factored fired hours, or actual fired hours.

It is assumed that the hazard function of a system is the product of a baseline function $h_0(t)$, which is a time dependent function, and a positive function, $y\,(Z(t))$, which is dependent on the explanatory variables $z_{i,t}$, i =1, 2, 3,…, n. Therefore the hazard function is given by:

$$h[t, Z(t)] = y\ [Z(t)] * h_0(t) \qquad (3.31)$$

If $y\ > 1$, the failure rate is increased; if $y\ < 1$, the failure rate is reduced.

The cumulative hazard and reliability function can be obtained by:

$$h[t, Z(t)] = \int_0^{\infty} h[u; Z(t)]du \qquad (3.32)$$

If the covariates $Z(t)$ are independent of time, which means the power plant operates in a constant operating conditions, then we get:

$$H(t; Z) = \int_0^{\infty} h(u; Z)du = y\ (Z) * \int_0^{\infty} h_0(u)du = y\ (Z) * H_0(t) \qquad (3.33)$$

The relative function can be of various forms. Here the exponential form is selected due to its simplicity, where y is given by:

$$y\left[Z(t)\right] = e^{g^{T}Z(t)} \tag{3.34}$$

Where g is a $n \times 1$ vector, and g^{T} is the transpose of g .

Therefore, y can be given by:

$$y\left[Z(t)\right] = e^{g_1 z_1(t) + g_2 z_2(t) + \ldots + g_n z_n(t)} \tag{3.35}$$

The hazards function can be given by:

$$h\left[t, Z(t)\right] = h_0(t) e^{g_1 z_1(t) + g_2 z_2(t) + \ldots + g_n z_n(t)} \tag{3.36}$$

Assuming the base hazards function is Weibull type, and therefore we have:

$$h\left[t, Z(t)\right] = \frac{b}{h}\left(\frac{t}{h}\right)^{(b-1)} e^{g_1 z_1(t) + g_2 z_2(t) + \ldots + g_n z_n(t)} \tag{3.37}$$

Consider there are three operating parameters that have significant impacts on the unit aging process. Let $z_1(t)$ represent the load mode of the gas turbine, and $z_1(t)$ can be defined as

$$z_1(t) = \begin{cases} 1, & Power\ plant\ operates\ on\ peak\ load \\ 0, & Power\ platn\ operates\ on\ base\ load \end{cases}$$

Let $z_2(t)$ be the fuel type, and $z_2(t)$ can be defined as

$$z_2(t) = \begin{cases} 1, & Liquid\ fuel \\ 0, & Natural\ gas\ fuel \end{cases}$$

Let $z_3(t)$ be the power augmentation setting, and define

$$z_3(t) = \begin{cases} 1, & Steam\,injection\,on \\ 0, & Steam\,injection\,off \end{cases}$$

The failure rate function can therefore be expressed as

$$h[t, Z(t)] = \frac{b}{h}\left(\frac{t}{h}\right)^{(b-1)} e^{g_1 z_1(t) + g_2 z_2(t) + g_3 z_3(t)} \tag{3.38}$$

Where parameters b, h, g_1, g_2, and g_3 can be estimated using the maximum likelihood method.

The parameters of the baseline reliability distribution are estimated using historic operational data, and in this study, it is referred directly from the industrial database. The validation of the PHM model is beyond the scope of this research. It may be reasonable to assume that the parameter t here is the actual operating hours. However, the empirical model from industry may actually have equivalent age of the system as the age variable. In this case, the parameter t is assumed to be the actual operating hours. The covariates Z here are employed to model the impacts of operating conditions. This assumption is to be validated.

Unlike the equivalent cumulative age method, the proportional hazards method uses the relative reliability function to model the reliability when the operating conditions deviate from the baseline, and covariates to model the varying operating conditions. It is able to evaluate the influences of the varying operating conditions on the aging rate of the power plant, and therefore can provide a more detailed reliability modeling.

3.4.3 Reliability Restoration Under Imperfect Maintenance

<u>Modeling of imperfect maintenance</u>

One of the problems for realistic reliability modeling is the modeling of maintenance effectiveness. Maintenance can be classified into two major categories: preventive maintenance (PM) and corrective maintenance (CM). Corrective maintenance is any maintenance performed when the system is failed; while preventive maintenance is any maintenance performed while the system is operating [45]. Phan and Wang also classified the maintenance into 5 categories according to the degree to which the operating conditions of an item is restored. These are perfect, minimal, imperfect, worse, and worst maintenance, as address below [45].

Perfect repair or perfect maintenance: a maintenance action that restores the system to as good as new. The system has the same reliability distribution as a brand new one after perfect maintenance.

Minimal repair or minimal maintenance: a maintenance action that restores the system to the failure rate it had when it failed. The system operating state is often called as bad as old.

Imperfect repair or imperfect maintenance: a maintenance action which restores the system operating state to somewhere between as good as new and as bad as old.

Worse repair or worse maintenance: a maintenance action which makes the system's failure rate or actual age increase, but the system does not break down.

Worst repair or worst maintenance: a maintenance action that makes the system fail or break down.

Usually in the early studies of maintenance models it is usually assumed that, after corrective or preventive maintenance, the system is one of the two extreme situations, either as good as new or as bad as old, and that maintenance time is negligible. However, these assumptions are not true for a power plant.

Pham and Wang performed a literature research and discussed the treatment methods and optimal maintenance polices of single and multiple components systems. They classified the treatment methods into eight different categories, as address below.

Treatment method 1---(p,q) *rule*

Nakagawa [46] [46]treats the imperfect PM in this way: the component is returned to the as good as new state with probability p, and to as bad as old with probability q=1-p, after preventive maintenance.

Treatment method 2---(p (t), q (t)) rule

Block et al. introduces this method. After maintenance, a system becomes as good as new with probability of p(t), and as bas as old with probability q(t)=1-p(t), where t is the system age [47]. This method seems more realistic since it takes the age of the system into consideration.

Treatment method 3---improvement factor

Malik introduces the concept of the improvement factor in the maintenance scheduling problem [48]. In this treatment method the imperfect repair changes the system time of failure curve to some newer time but not all the way to zero. Chan and Shaw suggest that failure rate is reduced after each preventive maintenance action, and the degree of reduction of failure rate depends on the system age and the number of preventive maintenances [49]. Two types of failure rate reduction are proposed, the failure rate with fixed reduction, and the failure rate with proportional reduction.

Treatment method 4---virtual age method

Kijima et al. [50] propose a model by using the idea of virtual age of a repairable system. Suppose V_{n-1} is the virtual age of the system immediately after the $(n-1)^{th}$ repair, the virtual age after the nth repair is

$$V_n = V_{n-1} + aX_n$$

Where X_n is the time between the $(n-1)^{th}$ repair and the n^{th} repair, and a is the degree of the n^{th} repair.

As Martorell and his coworkers [51] pointed out, this virtual age model is later referred to as proportional age reduction (PAR). Another virtual age method is proposed, which is referred to as proportional age setback method (PAS). Different from the PAR method, in the PAS approach, each maintenance activity is assumed to shift the origin of the time from which the age of the component is evaluated. Martorell et al. considers that the maintenance reduces proportionally by a factor of e, the age of the component immediately before it enters maintenance [51]. Suppose V_{n-1} is the virtual age of the system immediately after the $(n-1)^{th}$ repair, the virtual age after the nth repair is

$$V_n = (1-e)*(V_{n-1} + X_n)$$

The Virtual Age method is well suited for the multiple component system, and will be employed for this study.

Doyen and Gaudoin [52] propose two new classes of imperfect repair models. The repair effect is characterized by the change induced on the failure intensity before and after failure.

Treatment method 5—shock model method

In this model, the failure of a unit is represented as a first passage of time to a damage threshold, and the damage accumulating process is a stochastic process that describes the levels of damage. The damage level of the unit is subject to shocks occurring randomly in time. Upon occurrence damage, the unit suffers non-negative random damage, and each occurrence of damage, adds to the current damage level of the unit. Between shocks, the damage level of the unit stays constant. Using this model, Kijima and Nakagawa establish a cumulative damage shock model with a sequential preventive maintenance policy. Upon each maintenance, the amount of damage of the unit becomes b*Y when it was Y before the preventive maintenance.

Treatment method 6---(a, b) rule

Wang and Pham treat the imperfect repair in such a way that after repair the lifetime of the system will be reduced to a fraction of α of the one immediately preceding it, where $0 < \alpha < 1$. They further assume that the repair time is non negligible, and upon each repair, the next repair time will be increased by a factor of β of the one immediately preceding it, where $\beta > 1$[53].

Treatment method 7---multiple(p,q) rule

Shaked and Shanthikumar consider a system whose components have dependent lifetimes and are subject to imperfect repair. For each component, the repair is imperfect according to the (p,q) rule [54]. They establish the joint distribution of time to the next failure of the functioning components and the joint density of the resulting lifetimes of the components and other probabilistic quantities of interest. From these the distribution of the lifetime of the system can be derived.

Other treatment methods

Nakagawa and Yasui modeled the imperfect maintenance in such a way that the failure rate is reduced as a function of some resource c_1 consumed in PM and a parameter [55]. After preventive maintenance the failure rate becomes:

$$\lambda(t) = g(c_1, \theta) \cdot \lambda(x+T)$$

Where the fraction reduction of failure rate $0 < g(c_1, \theta) < 1$, T is the time interval length of preventive maintenance, c_1 is the amount of resource consumed, and θ is a parameter. This method provides a link between maintenance effectiveness and resources consumed in preventive maintenance.

Lin and his co-workers propose a hybrid PM model which combines hazards rate model and age reduction model [56]. With the hybrid preventive maintenance model, the failure rate function after the first preventive maintenance can be given by

$$h(t_1 + x) = a_1 h(b_1 t_1 + x) \qquad \text{for } x > 0$$

Where a_1 is recovery factor for failure rate, and b_1 is the recovery factor for the unit age, and t_1 is the unit age right before the unit enters the first preventive maintenance.

In this hybrid model, it is assumed that the effects of each PM are modeled by two aspects: one for its immediate effect after the PM is completed and the other for the lasting effects when the unit is put into use again. Lin claims that this hybrid preventive maintenance model captures both effects, how much the effective age is reduced the instant PM is performed and how much faster the failure rate function will increase after the equipment is maintained [56].

<u>The general hybrid failure rate and virtual age method</u>

A general hybrid failure rate adjustment and virtual age method is employed here for the modeling of reliability restoration due to maintenance and upgrade. It is assumed that not only the failure rate of the system will be reduced the instant the maintenance or upgrade is performed, and shape and distribution parameters may change due to maintenance and upgrade. The instant impact of the maintenance activity and upgrade is modeled using the virtual age method, and the impact after the system is put back into operation is modeled using the failure rate adjustment method. The following assumptions are made:

- Each preventive maintenance action will change the actual age of components of a system and therefore the age of the system.
- The shape and distribution of the system and components reliability will not change, i.e., the shape and distribution parameters will not change due to maintenance.

To model the effects of maintenance on the unit reliability, the virtual age method is employed. As pointed out earlier there are two types of virtual aging models proposed by Martorell, namely, the proportional age setback (PAS) model and proportional age reduction (PAR) model [51]. The PAR model assumes that the maintenance can only reduce the relative damage accumulated since the last maintenance, while the PAS model assumes that the maintenance can reduce the damage of the unit accumulated in the whole lifetime since it entered service. Here the proportional age setback is employed to model the effectiveness of maintenance on the power plant reliability. In the PAS model, each maintenance activity is assumed to shift the origin of the time at which the age of the unit is evaluated. The maintenance reduces proportionally by a factor of e times the age the unit has immediately before it enters maintenance, where $0 \leq e \leq 1$. Obviously, if $e = 0$, the maintenance is minimal maintenance; if $e = 1$, the maintenance is perfect maintenance. Therefore, this model is a natural generalization of both as good as new (GAN) model and as bad as old (BAO) model. The virtual age concept is shown in Figure 3.4.

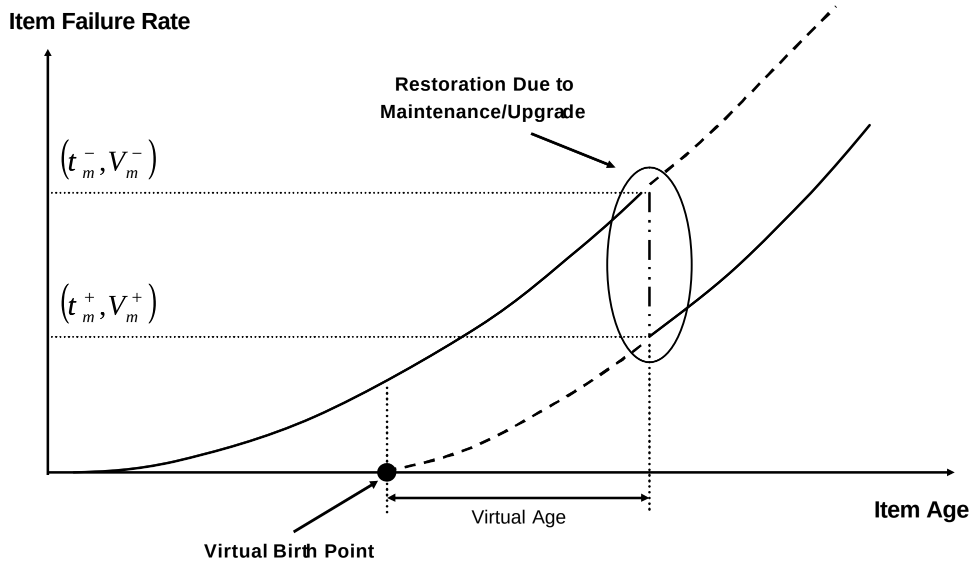

Figure 3.4 The Virtual Age Concept

Let t_m be the actual age of the item when it undertakes the m^{th} maintenance. Let e_m be the age reduction factor due to the m^{th} maintenance, V_m^- be the virtual age of the component immediately before it undertakes the m^{th} maintenance, and V_m^+ be the virtual age of the component immediately after it undertakes the m^{th} maintenance.

Assume the initial age of the component, which corresponds to the age when it is installed, is t_0.

The age of the item right after it undertakes the first maintenance is

$$V_1^+ = (1-e_1)\cdot V_1^- = (1-e_1)\cdot[(t_1 - t_0)+t_0] \tag{3.39}$$

After the second maintenance the virtual age of the component is

$$V_2^+ = (1-e_2)\cdot V_2^- = (1-e_2)\cdot(1-e_1)\cdot[t_0 + (t_1 - t_0)] + (1-e_2)\cdot(t_2 - t_1) \tag{3.40}$$

Generally the virtual age of the component immediately after its m^{th} maintenance is

$$V_m^+ = \left(\prod_{r=0}^{m}(1-e_{m-r})\right)\cdot t_0 + \sum_{k=0}^{m-1}\left(\left(\prod_{r=0}^{k}(1-e_{m-r})\right)\cdot(t_m - t_k)\right) \tag{3.41}$$

For a system with actual age t , where $t_{m-1} \le t \le t_m$, the virtual age of the system is

$$v = V_{m-1}^+ + t - t_{m-1} \tag{3.42}$$

Let the failure rate function of the item during the period between the $(m-1)^{th}$ and m^{th} maintenance is

$$h_{m-1}(t) = h[b_{m-1}, h_{m-1,} V(t)] \tag{3.43}$$

Where $V(t)$ is the virtual age of the item, and

$$t_{m-1} \le t \le t_m$$

$$V(t) = V_{m-1}^+ + t - t_{m-1} \tag{3.44}$$

The failure rate of the item immediately before it enters the m^{th} maintenance is

$$h_{m-1}(t_m) = h[b_{m-1}, h_{m-1,} V_m^-(t)] \tag{3.45}$$

The m^{th} maintenance reduces the failure rate of the item instantly to

$$h_m(t_m) = g(W_m, C_m)\, h_{m-1}(t_m) = g(W_m, C_m)\; h\left[b_{m-1}, h_{m-1,} V_m^-(t)\right] \tag{3.46}$$

Where $g(W_m, C_m)$ is the parameter to estimate the impact due to maintenance or upgrade on the failure rate of the system. It is determined by the work scope of the maintenance or upgrade W_m and the associated cost C_m as well, which is a function of the degree of the maintenance.

Assume the failure rate function of the item during the period between the m^{th} and $(m+1)^{th}$ maintenance is

$$h_m(t) = h\left[b_m, h_{m,} V(t)\right]$$

Where

$$t_m \le t \le t_{m+1}$$

$$V(t) = V_m^+ + t - t_{m+1}$$

The parameters b_m and h_m can be estimated using the historical data.

Therefore the failure rate of the item immediately after it undertakes the m^{th} function is

$$h_m(t_m) = h\left[b_m, h_{m,} V_m^+(t)\right]$$

Therefore

$$h\left[b_m, h_{m,} V_m^+(t)\right] = g(W_m, C_m)\; h\left[b_{m-1}, h_{m-1,} V_m^-(t)\right] \tag{3.47}$$

The virtual age of the item immediately after it undertakes the m^{th} maintenance can therefore be calculated using equation (3.47).

The age reduction factor e_m can therefore be determined using equation (3.48).

$$V_m^+ = (1 - e_m) \cdot V_m^- \tag{3.48}$$

<u>The induced reliability functions</u>

The induced reliability functions with consideration of maintenance can be derived from the base reliability function and the virtual age model.

The induced conditional failure rate function in the period $m+1$, after the m^{th} maintenance, is given by:

$$h_{m+1}(t) = h(V_m^+ + t - t_m^+) \tag{3.49}$$

Where t is the actual age of the system, and $u_m^+ \leq t \leq t_{m+1}^-$

$$V_m^+ = \left(\prod_{r=0}^{m} (1 - e_{m-r}) \right) \cdot t_0 + \sum_{k=0}^{m-1} \left(\left(\prod_{r=0}^{k} (1 - e_{m-r}) \right) \cdot (t_m - t_k) \right) \tag{3.50}$$

Since the virtual age of the component is a discontinuous function, obviously its failure rate function is not continuous. Similarly we can define:

$$h_m^- = h_m(V_m^-)$$

$$h_m^+ = h_m(V_m^+)$$

Where h_m^- is the failure rate of the component right before it enters the m^{th} maintenance, and h_m^+ is the failure rate of the component right after it undertakes the m^{th} maintenance.

The induced survivor function for the period $m+1$, after the m^{th} maintenance, is given by:

$$R_{m+1}(t) = R\left(V_m^+ + t - t_m^+\right) = \exp\left(-\int_0^v h(u)du\right) \tag{3.51}$$

Where $h(u)$ is a discontinuous function defined by Equation (3.26).

3.5 Performance Degradation and Restoration Modeling

3.5.1 Performance Degradation Modeling

The key elements of the power plant performance are the power output rate and heat rate. A prediction model of performance deteriorating with time is useful for the power plant operator to know the reasonable performance degradation after a specified number of services hours, because this helps to determine the cleaning/maintenance frequency. The exact degree of performance degradation occurring with service time is impossible due to the numerous factors addressed above, and due to the complexity of the engine configuration with numerous components. Kurz and Brun propose a methodology to simulate the effects of engine and driven equipment degradation [57]. With a relatively simple set of equations that describe the engine behavior, and a set of linear deviation factors derived from engine maps or test data, the equipment behavior for various degrees of degradation can be studied. However, that still does not provide an approach to predict engine performance degradation with service time.

Diakunchak points out that some ground rules or assumptions should be made if one attempts to make prediction of performance degradation [31]. Diakunchak introduces the assumed shape of the typical performance degradation versus service time curve, which is shown in Figure 3.5.

The following assumptions are made for the performance degradation model [31]:

- Types of fuel used. The types of fuel include natural gas, distillate oil, and heavy or crude oil
- Clean environment
- The engine will start its service life with brand new condition
- Continuous base load operation for three years before a major overhaul. The overhaul will restore the engine to almost as good as new condition
- Good filtration system used, clean operating environment, no major foreign object damage, coated compressor airfoils
- Proper operating and maintenance procedures
- Effective and regular cleaning/washing of the compressor over the operating period

The assumptions made above are not always correct. A more general model is proposed which allows that:

- The engine starts its service life with initial age T_0
- The major maintenance activities do not restore the status of the engine back to as good as new, but somewhere between as good as new and as bad as old
- The proposed performance degradation model should also be able to address the impact of variation of operating conditions, as well as the restoration effects of preventive maintenance

<u>The actual operating hours approach</u>

In this approach, the performance degradation of the power plant is a function of its actual operating hours. Let t be the actual operating hours of the power plant. Assume the engine is with age t_0 when it enters its service, and assume the equation that defines the curve is in the form given by

$$\Delta(t) = a \ln(b(t + t_0) + c) + \Delta_0 \tag{3.52}$$

Where Δ is the percentage of performance loss, which includes both power output and heat rate. a, b, c and Δ_0 are parameters which depend on the configuration and usage history of the engine. This form assumes that the performance of the engine degrades fast at the beginning of its entering the service, and then the degradation rate decreases as the service time of the engine increases.

For the power output rate and heat rate, different coefficients may apply to the above degradation equations.

The actual operating hours approach actually assumes that the only factor that influence performance degradation is the actual operating hours of the unit, however, a more accurate approach should be able to address the following factors:

- The impact of varying operating conditions, which include the gas turbine operating modes and external operating conditions, such as ambient conditions and air quality

- The impact of cyclic effects, which include startup and shutdown cycles

<u>The equivalent cumulative age approach</u>

To account for the influence of the varying operating conditions and the cyclic effects, an equivalent cumulative age approach is developed. Similar to the application of equivalent cumulative age concept for reliability modeling, this concept can also be applied to power plant performance degradation modeling. The definition of maintenance factors and equivalent cumulative age may be different due to the difference in degradation mechanisms between performance and reliability. However, a similar technical procedure to define equivalent cumulative age can be developed. Statistical regression analysis can then be performed to estimate the coefficients for the degradation functions.

In a generic form, the equivalent cumulative age is given by

$$t = (1-e)\sum_{i=1}^{N} k_{h,i} \cdot h_i + e\sum_{j=1}^{M} k_{s,j} \cdot s_j \tag{3.53}$$

Statistical regression analysis can therefore be performed once the equivalent cumulative age t is defined. Estimation of reliability distribution parameters can be achieved using techniques such as maximum likelihood method.

The general equivalent cumulative age approach evaluates the cumulative degradation of the system as it accumulates its operating hours, and therefore it is able to address the cumulative performance degradation of the system. In the cumulative approach, the impact of varying operating conditions on the degradation rate still cannot be evaluated. Another approach, which uses covariates to account for the varying operating conditions, establishes the link between the varying operating conditions.

<u>The proportional degradation rate approach</u>

The actual operating hours approach assumes specific operating conditions, and therefore the performance degradation is only a function of service life. This implies that the engine is running at a uniform operating profile and constant external environment. These assumptions are not true in that the external environment, such as the ambient conditions varies substantially with a strong seasonal and daily trend. Furthermore, the operating modes, which define the load setting, fuel type, and power augmentation, vary substantially due to the dynamic electric power market. The equivalent cumulative age approach does not establish a link between performance degradation rate and the varying operating modes.

As addressed earlier, the operating conditions significantly affect the engine degradation rate. To capture the effect of operating conditions on engine performance degradation, a model which does not only consider engine service life, but also its operating conditions, which include external operating environment and usage history, should be developed. The model should be able to link performance degradation rate and operating conditions. Obviously, such a model would be extremely useful for the determination of operating decisions when performance and economics are considered.

Let $d(t)$ be the degradation rate at time t, which is the incremental performance degradation per unit time. The degradation rate is defined as

$$d(t) = \Delta^{'}(t) = \frac{d\Delta(t)}{dt} \tag{3.54}$$

It is assumed that the degradation rate of a system is the product of a baseline function $d_0(t)$, which is a time dependent function, and a positive function, $f(Z(t))$, which is dependent on the explanatory variables $z_{i,t}$, i =1, 2, 3,…, n. Therefore the hazard function is given by:

$$d(t) = d_0(t) f[Z(t)] \tag{3.55}$$

Where $d_0(t)$ is the baseline degradation rate, which is a function of the time t. $f[Z(t)]$ is the relative degradation rate, which is a function of covariate $Z(t)$. $Z(t)$ is a vector with components of $Z_1(t)$, $Z_2(t)$ …, $Z_n(t)$, which define the operating conditions along the time line.

Equation (3.55) assumes that the gas turbine engine performance degradation rate is not only a function of its service life, but also a function of the usage history and external environment.

Let $f[Z(t)]$ be of the form

$$f[Z(t)] = \exp[l \bullet Z(t)] = \exp[l_1 z_1(t) + l_2 z_2(t) + \ldots + l_n z_n(t)] \qquad (3.56)$$

Where l is a vector with n components of l_1, l_2,..., l_n. The parameter l is to be determined using statistical analysis on historical performance data.

Assume the baseline degradation function of the form

$$d_0(t) = \frac{ab}{b(t+t_0)+c} \qquad (3.57)$$

Substitute $f(Z_t)$ with equation (3.56), and $d_0(t)$ with (3.57)

$$d(t) = \left(\frac{ab}{b(t+t_0)+c}\right)\exp[l_1 z_1(t) + l_2 z_2(t) + \ldots + l_n z_n(t)] \qquad (3.58)$$

Equation (3.58) shows that the degradation rate decreases as the service life increases, and it is asymptotic and it approaches zero as the service life approaches infinity.

Please note that the behavior of performance degradation might be different with regard to the effect of covariates because the mechanisms of degradation are different.

The accumulative degradation distribution can be achieved by integrating Equation (3.58) along the operating time line.

$$\Delta(t) = \int_0^t d(u)du + \Delta_0 = \int_0^t \left(\frac{ab}{b(u+t_0)+c} \right) \exp[l_1 z_1(u) + l_2 z_2(u) + ... + l_n z_n(u)] du + \Delta_0 \quad (3.59)$$

3.5.2 Performance Restoration Modeling

<u>The hybrid degradation rate and virtual age method</u>

As addressed earlier, maintenance practices, such as water wash or hot gas path parts replacement, will restore part of the performance, which improves the status of the engine. The degree of performance restoration depends on the extent of maintenance activity, which is mostly driven by economic considerations.

It is assumed not only the cumulative degradation of the system will be reduced the instant the maintenance or upgrade is performed, but also the degradation rate changes due to maintenance and upgrade.

A general hybrid method is developed which is able to address the instant impact of maintenance and/or upgrade, and the impact after the unit is put back into operation. The virtual age method is employed here to model the instant impact on performance restoration due to maintenance and upgrade. The impact after the system is put back into operation is modeled using the adjustment method on the degradation rate.

Here the proportional age setback (PAS) is employed to model the effectiveness of maintenance on the power plant reliability. In the PAS model, each maintenance activity is assumed to shift the origin of the time from which the age of the unit is evaluated. The maintenance reduces proportionally by a factor of e, which is the age the unit has immediately before it enters maintenance, where $0 \le e \le 1$. Obviously, if $e = 0$, the maintenance is minimal maintenance; if $e = 1$, the maintenance is perfect maintenance.

Let t_m be the actual age of the item when it undertakes the m^{th} maintenance. Let e_m be the age reduction factor due to the m^{th} maintenance, V_m^- be the virtual age of the component immediately before it undertakes the m^{th} maintenance, and V_m^+ be the virtual age of the component immediately after it undertakes the m^{th} maintenance.

Assume the initial age of the component, which corresponds to the age when it is installed, is t_0.

The age of the item right after it undertakes the first maintenance is

$$V_1^+ = (1-e_1)\cdot V_1^- = (1-e_1)\cdot[(t_1 - t_0) + t_0] \tag{3.60}$$

After the second maintenance the virtual age of the component is

$$V_2^+ = (1-e_2)\cdot V_2^- = (1-e_2)\cdot(1-e_1)\cdot[t_0 + (t_1 - t_0)] + (1-e_2)\cdot(t_2 - t_1) \tag{3.61}$$

Generally the virtual age of the component immediately after its m^{th} maintenance is

$$V_m^+ = \left(\prod_{r=0}^{m}(1-e_{m-r})\right)\cdot t_0 + \sum_{k=0}^{m-1}\left(\left(\prod_{r=0}^{k}(1-e_{m-r})\right)\cdot(t_m - t_k)\right) \tag{3.62}$$

For a system with actual age t, where $t_{m-1} \le t \le t_m$, the virtual age of the system is

$$v = V_{m-1}^+ + t - t_{m-1} \tag{3.63}$$

Let the cumulative degradation of the item during the period between the $(m-1)^{th}$ and m^{th} maintenance is

$$\Delta_{m-1}(t) = \Delta\left[a_{m-1}, b_{m-1,}\ c_{m-1},\ V(t)\right] \tag{3.64}$$

Where $V(t)$ is the virtual age of the item, and

$$t_{m-1} \le t \le t_m$$

$$V(t) = V_{m-1}^{+} + t - t_{m-1}$$

The cumulative degradation of the item immediately before it enters the m^{th} maintenance is

$$\Delta_{m-1}(t_m) = \Delta\left[a_{m-1}, b_{m-1,}\ c_{m-1}, V_m^{-}(t)\right] \tag{3.65}$$

The m^{th} maintenance reduces the cumulative degradation of the item instantly to

$$\Delta_m(t_m) = g(W_m, C_m)\Delta_{m-1}(t_m) = g(W_m, C_m)\ \Delta\left[a_{m-1}, b_{m-1,}\ c_{m-1}, V_m^{-}(t)\right] \tag{3.66}$$

Where $g(W_m, C_m)$ is the parameter to estimate the performance recovery due to maintenance or upgrade on the cumulative degradation of the system. It is determined by the work scope of the maintenance or upgrade W_m and the associated cost C_m as well, which is a function of the degree of the maintenance.

Assume the cumulative degradation of the item during the period between the m^{th} and $(m+1)^{th}$ maintenance is

$$\Delta_m(t) = \Delta[a_m, b_{m,}\ c_m, V(t)] \tag{3.67}$$

Where

$$t_m \le t \le t_{m+1}$$

$$V(t) = V_m^+ + t - t_{m+1}$$

Therefore the cumulative degradation of the item immediately after it undertakes the m^{th} function is

$$\Delta_m(t_m) = \Delta[a_m, b_{m,}\ c_m, V_m^+(t)] \tag{3.68}$$

Therefore

$$\Delta[a_m, b_{m,}\ c_m, V_m^+(t)] = g(W_m, C_m)\ \Delta[a_{m-1}, b_{m-1,}\ c_{m-1}, V_m^-(t)] \tag{3.69}$$

The virtual age of the item immediately after it undertakes the m^{th} maintenance can therefore be calculated using Equation (3.69).

The age reduction factor e_m can therefore be determined using Equation (3.70).

$$V_m^+ = (1 - e_m) \cdot V_m^- \tag{3.70}$$

<u>The induced performance degradation functions</u>

The induced performance degradation functions with consideration of maintenance can be derived from the performance degradation function and the virtual age model.

The induced degradation rate in the period $m+1$, after the m^{th} maintenance, is given by:

$$d_{m+1}(v) = d\left(V_m^+ + t - t_m\right) \tag{3.71}$$

Where t age of the system, and $t_m \le t \le t_{m+1}$.

$$V_m^+ = \left(\prod_{r=0}^{k}\left(1 - e_{m-r}\right)\right) \cdot t_0 + \sum_{k=0}^{m-1}\left(\left(\prod_{r=0}^{k}\left(1 - e_{m-r}\right)\right) \cdot t_{m-k}\right) \tag{3.72}$$

Since the virtual age of the engine is a discontinuous function, obviously its performance degradation rate function is not continuous. Similarly we can define:

$$d_m^- = d_m\left(V_m^-\right)$$

$$d_m^+ = d_m\left(V_m^+\right)$$

Where d_m^- is the degradation rate of the component right before it enters the m^{th} maintenance, and d_m^+ is the degradation rate of the component right after it undertakes the m^{th} maintenance.

The induced accumulative degradation function for the period $m+1$, after the m^{th} maintenance, is given by:

$$\Delta_{m+1}(t) = \int_0^t d(u)du + \Delta_m \tag{3.73}$$

3.6 Summary

This chapter addresses methods for gas turbine power plant performance modeling and validation, power plant aging, reliability degradation and restoration modeling, and performance degradation and restoration modeling. These models are used to evaluate gas turbine power plant performance and reliability under various operating conditions.

CHAPTER 4

GAS TURBINE BASED POWER PLANT ECONOMICS EVALUATION

4.1 Introduction

In this study, one of the major tasks is to develop a procedure to integrate power plant performance, reliability and risk, economics, and operational activities, so that the power plant system level economic metrics, such as cumulative revenue, fuel cost, risk, and operations and maintenance cost, can be evaluated along the operating time horizon. These system level economic metrics provide a basis to evaluate long term and short-term power plant profitability when performing operational optimization.

One approach for evaluating long-term system level economic metrics is to integrate the local economic metrics along the entire operating time horizon. For such an approach, the accuracy and efficiency needs to be balanced when long-term economics metric are to be evaluated. Numerous points of evaluation are required for this approach.

This chapter introduces a systematic approach to evaluate gas turbine power plants economics performance.

4.2 The Electric Power Market and Weather Conditions

There have been many research efforts on power demand and supply forecasting, electricity pricing, and price of fuel forecasting. Interested readers are referred to Ref.

[59][60][61][62][63][64][65]. Three major external factors are: price of electricity, price of fuel, and ambient conditions. Let t be the calendar time. The price of electricity, $Mp(t)$, Price of fuel $Fc(t)$, and ambient conditions, $Ta(t)$, are functions of calendar time.

In the deregulated power market, the price of electricity and price of fuel are stochastic in nature. Yet they still show daily, seasonal and long-term trends. For example, considering the time line in daily level, the price of electricity is usually lower between midnight and early morning than that during the day, because people use less electricity. It is also reasonable to assume that the price of electricity in the summer is higher than that in the spring and fall, because the demand of electricity is higher in the summer than in the spring and in the fall. In a market based operation environment, price of electricity and price of fuel are major driving factors for power plant operational planning. The weather conditions also show strong seasonal and daily trends, and they are stochastic processes. The weather conditions, i.e. the ambient temperature, ambient pressure, and relative humidity, are important factors that have impacts on gas turbine performance.

To investigate the behavior of price of electricity, price of fuel and ambient conditions is beyond the scope of this study. Yet a simple model, which is able to capture the variation of these variables, is necessary. For this purpose, a model is to be created to capture the dynamics of electric power market and ambient conditions. In this model price of electricity, price of fuel, and ambient temperature show daily variance, seasonal trends, and long-term trends.

A daily ambient temperature profile in a typical day in the summer is shown in Figure 4.1. It is assumed the ambient temperature is relatively low in the early morning, keeps increasing until noon, and then decreases and reaches the minimum at midnight. Random factors are used to model the stochastic nature of ambient temperature. A yearly ambient temperature profile, which shows a seasonal variation, is shown in Figure 4.2. The average ambient temperature is relatively low in the spring, keeps increasing in the summer, and then decreases in the fall and reaches the minimum in the winter.

Similarly, the daily variation of price of electricity is shown in Figure 4.3, and the seasonal variation in Figure 4.4. It is assumed that the price of electricity is lower between midnight and early morning than that during the day, and the price of electricity is higher in the summer than that in the spring, fall and winter, due to high power demand in the summer. Please note that these assumptions do not necessarily match actuality, and what is important here is the variation in a time line.

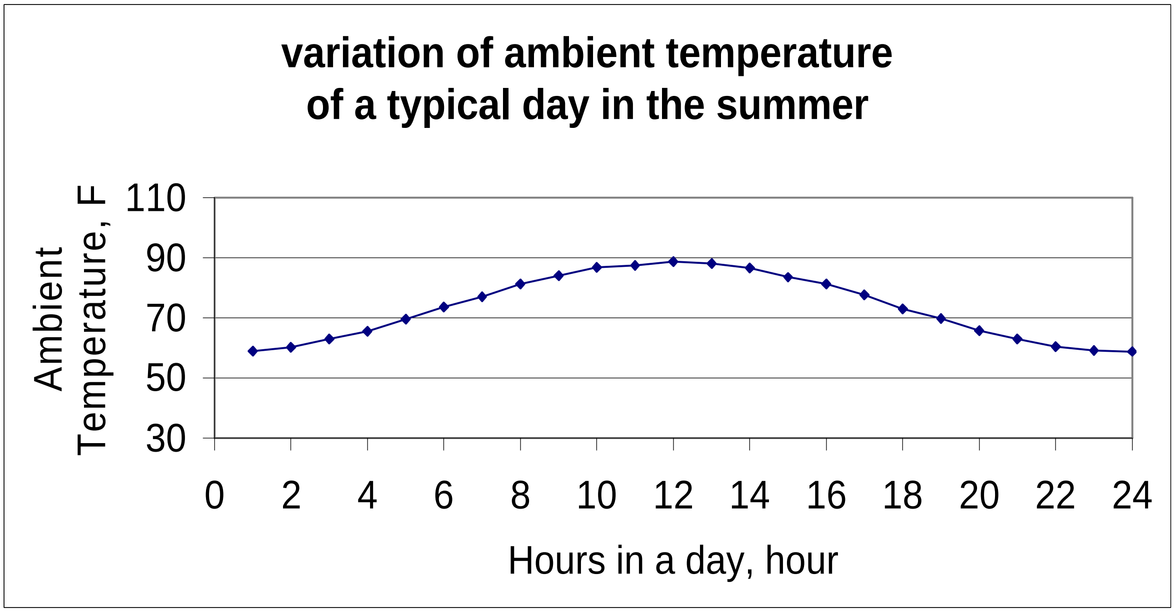

Figure 4.1 Daily Variation of Ambient Temperature

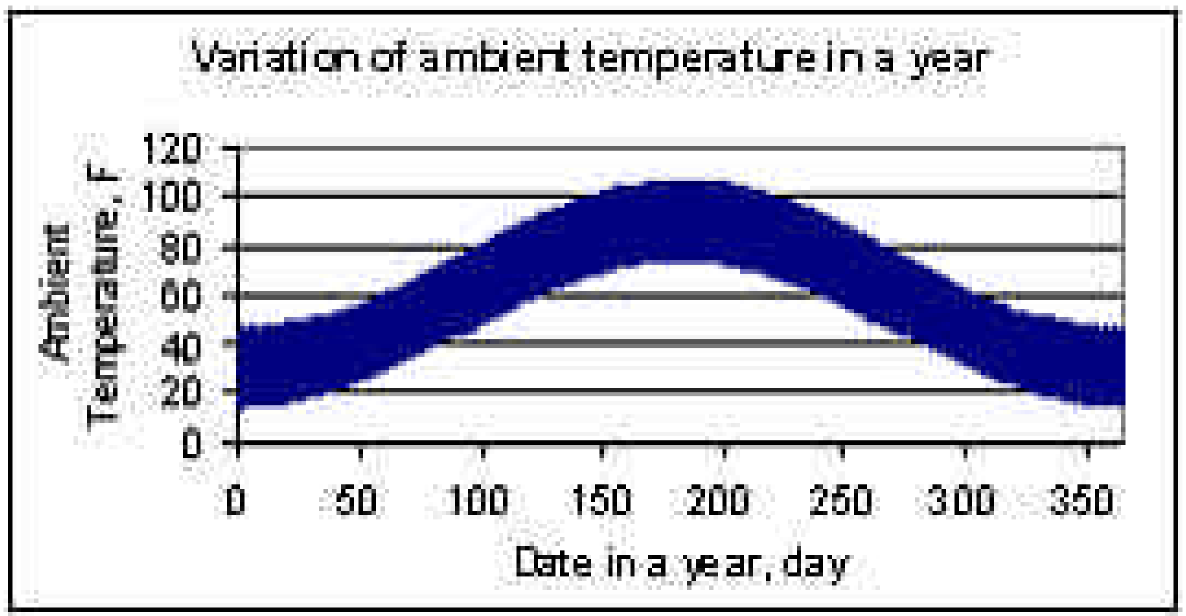

Figure 4.2 Yearly Variation of Ambient Temperature

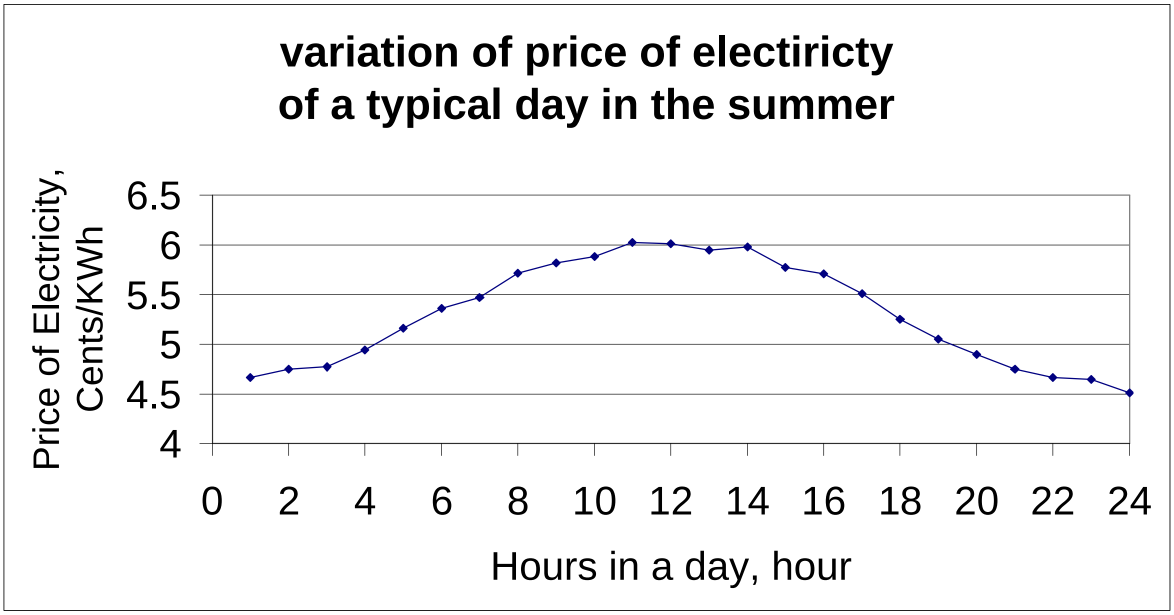

Figure 4.3 Daily Variation of Price of Electricity

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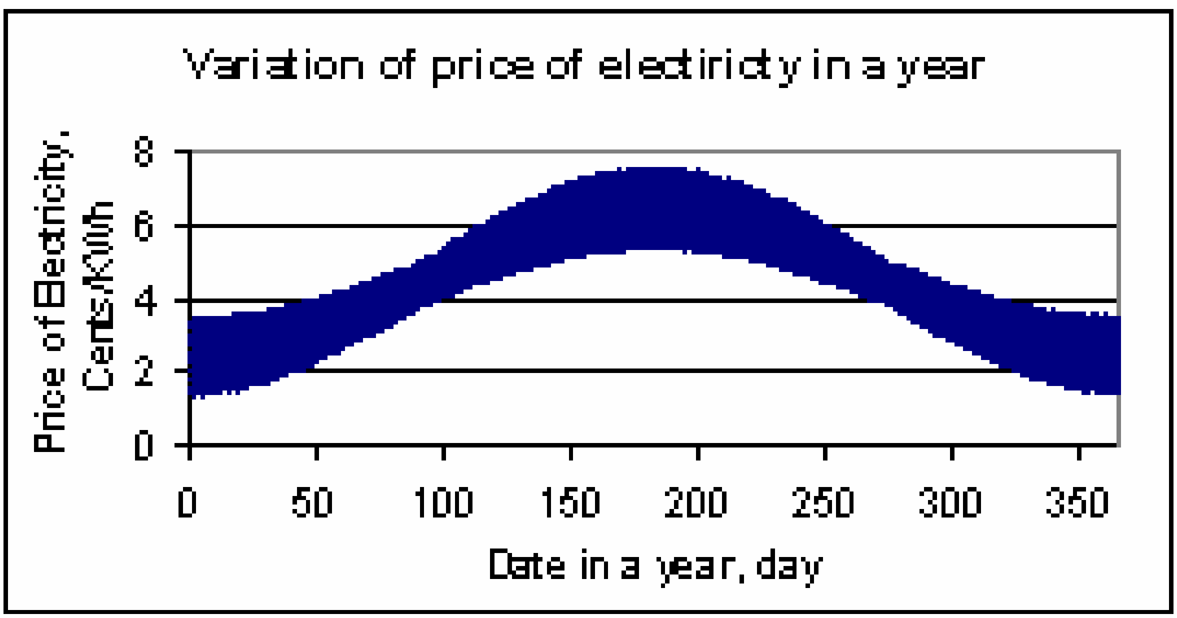

Figure 4.4 Yearly Variation of Price of Electricity

4.3 The Profit Equation

A generic procedure is developed to implement the integrated operational modeling environment. Models for economic factors and technical factors are developed, and procedures to model system level metrics, which include revenue, cost of fuel, spark spread, operations and maintenance cost, and risk, are developed. As a result, cumulative revenue, fuel cost, spark spread, and risk, are modeled based on power plant performance degradation, reliability degradation, price of electricity, cost of fuel, and operations and maintenance cost, as the power plant accumulates its operating hours.

Consider a power plant operating in the deregulated electric power market. To evaluate the economic performance of a power plant, an objective function, net revenue, or profit, is defined. The key elements that define the power plant profit is the value of power or gross revenue due to selling of electricity, cost of fuel, cost of operations and maintenance, and depreciation. The relationship is shown in Figure 4.5.

Figure 4.5 Elements of Power Plant Profit

For a given time period T, the net revenue NR or profit is defined below:

$$NR(T) = GR(T) - COE(T) \tag{4.1}$$

Here, GR stands for the total gross revenue of selling electricity, and COE for the total cost of electricity, which includes cost of fuel, cost of operations and maintenance, and cost due to depreciation.

Gross revenue of selling electricity during time period T is given by:

$$GR = \int_T Mp(t) * P(t) dt \tag{4.2}$$

Where $Mp(t)$ is the projected price of electricity at time t, and $P(t)$ is the electricity power output of the power plant at time t.

The cost of electricity during time period T is given by:

$$COE(T) = C_{fuel}(T) + C_{om}(T) + depreciation(T) \tag{4.3}$$

Where $C_{fuel}(T)$ is the cost of fuel during time period T, and $C_{om}(T)$ is the operations and maintenance cost. The depreciation parameter accounts for the investment cost of the power plant.

The cost of fuel is given by:

$$C_{fuel}(T) = \int_T F_c(t) * P(t) * HR(t) dt \tag{4.4}$$

Where $HR(t)$ is the heat rate of the power plant.

Therefore the power plant profit over a given period of time is given by

$$NR(T) = \int_T \left[P(t) * M_p(t) - F_c(t) * HR(t) * P(t)\right] dt - C_{om}(T) - Depreciation(T) \tag{4.5}$$

For accurate evaluation of power plant expected profit, the modeling of energy market, power plant performance and reliability are required. The key elements of the evaluation of power plant expected profit is shown in Figure 4.6. One emphasis of this research is on the development of unit specific models for performance and reliability degradation and restoration. The methods for modeling of these elements are further introduced in the following chapters.

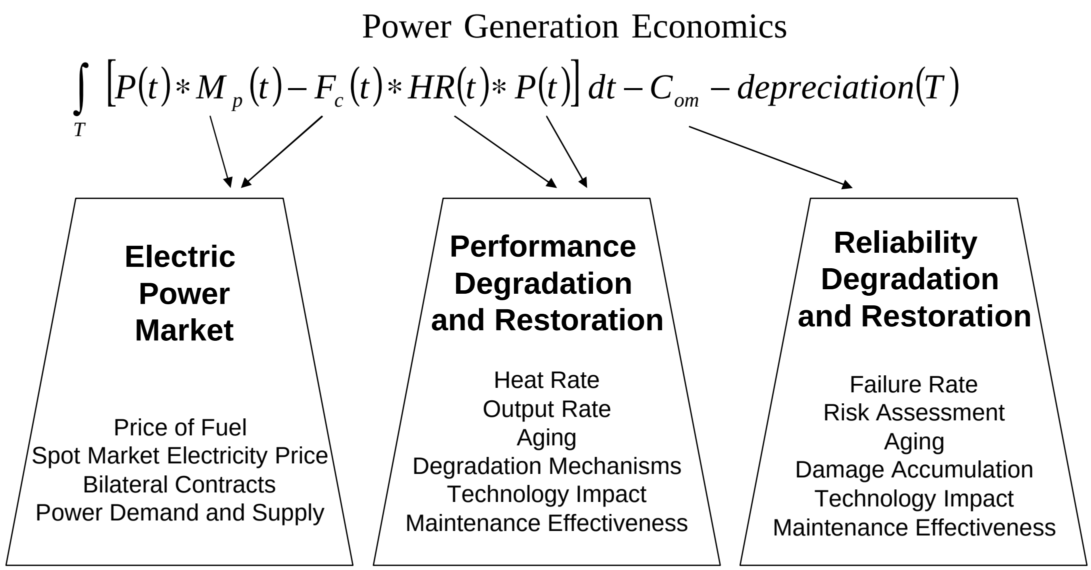

Figure 4.6 Power Generation Economics

Sometimes spark spread instead of net revenue is used as the objective function for operational optimization. As the conversion efficiency becomes greater, the spread between the market value of the gas and that of power derived by burning the gas becomes wider. The spread also becomes wider as the price of electricity gets higher. In this case spark spread is determined by price of electricity, price of fuel, and power plant heat rate. Spark spread (SS) is calculated using Equation (3.14):

$$SS(t) = 10 * Mp(t) - Fc(t) * HR(t) / 1000 \tag{4.6}$$

The units here for price of electricity, price of fuel, heat rate, and spark spread are cents/KWh, \$/MBTU, BTU/KWh, and \$/MWh, respectively.

A cumulative spark spread during time period T is calculated along the time line of operation. The cumulative spark spread is given by Equation (4.7), which is the difference between the gross revenue of selling electricity and cost of fuel during time period T.

$$\begin{aligned} SS(T) &= GR(T) - C_{fuel}(T) = \int_T SS(t)dt \\ &= \int_T \left(10 * Mp(d,t) - Fc(d) * HR(d,t) / 1000\right)dt \end{aligned} \tag{4.7}$$

In the calculation of cumulative spark spread, the depreciation and the operations and maintenance cost are not included. Note that depreciation accounts for the total investment cost, and it is determined by the design of the power plant. The operation and maintenance cost C_{om} are not included in the cumulative spark spread.

The time value of the money needs to be addressed by using an appropriate interest rate and inflation rate. In so doing, the net present value can be evaluated.

A detailed introduction to evaluate the cost of operations and maintenance is given in the section below.

4.4 Risk and Cost of Maintenance

4.4.1 Brand New Single Component System

Consider firstly a brand new single component system.

The assessment of risk and calculation of operations and maintenance cost depends on the nature of the contract signed by the power plant operator and the service provider, which defines the assignment of power plant operational risk. Two scenarios are considered here.

1. The power plant operator takes risk, and there is no out-sourcing of operations and maintenance services.

2. The operations and maintenance services are provided by out-sourcing, and the services provider takes all the operational risks.

<u>Scenario (1): Risk taken by the power plant operator</u>

Assume there is no out-sourcing for operations and maintenance services, and therefore the power plant operator takes all the operational risk. In this scenario, the elements of cost and revenue of power plant operator is shown in Figure 4.7.

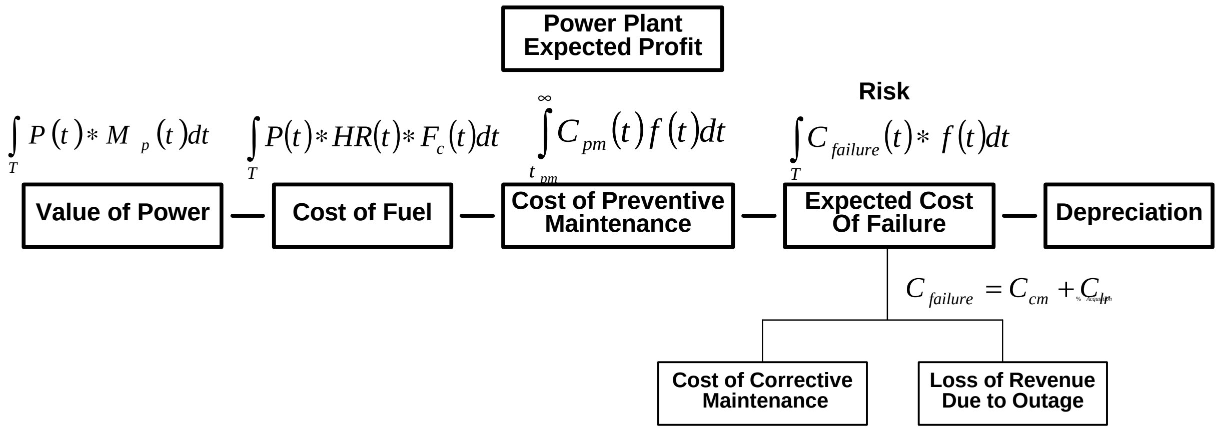

Figure 4.7 Power Plant Expected Profit When No Outsourcing O&M Services

The power plant is subject to forced outage or failure, with a failure rate that depends on unit configuration, unit usage history, and current operating mode. The failure of the power plant is stochastic in nature. The consequence of forced outage or failure of the power plant is defined here as operational risk. To account for this operational risk, an estimation of the probability of failure and the consequence of failure is required.

Operational risk is the combination of probability of the failure and the consequence of the failure. The risk of a component or system failure during a period of time T is quantified using the expected consequence of failure, and is defined below:

$$Risk(T) \equiv \int_T C_{failure}(t) \cdot f(t)dt \qquad (4.8)$$

Where $C_{failure}$ is the consequence of the failure, and $f(t)$ is the probability density function.

The consequence or cost of the failure here includes the direct cost to the system due to failure, which includes the cost due to the component itself and cost due to damage to other components in the system. Corrective maintenance is performed to restore the system to its normal operating status, and therefore this part of cost is referred to as cost of corrective maintenance. The cost of failure also includes the loss of revenue due to the system unavailability caused by the failure. The cost of failure can therefore be given as

$$C_{failure} = C_{cm} + C_{lr}$$

Where C_{cm} is the cost of corrective maintenance, and C_{lr} is the cost due to loss of revenue.

The cost of failure is evaluated on a set basis. A failure of a gas turbine blade will usually lead to serious damage to the entire stage, and its subsequent sets. For example, if a blade in first stage breaks, it will cause severe damage to the second stage nozzle, second stage blade, and other downstream components.

To evaluate the cost due to loss of revenue, an estimation of the expected duration of the outage caused by the failure is required. Once the expected duration of the outage is given, the expected system level economic metrics such as revenue, fuel cost, operations and maintenance cost, and net revenue during that outage period, can be evaluated, as if the failure does not occur. The expected net revenue during the outage period is then used as the cost due to loss of revenue.

Let T_{outage} be the duration of the outage due to failure. The cost due to loss of revenue is given by:

$$C_{lr}\left(T_{outage}\right) \equiv NR\left(T_{outage}\right)$$
$$= \int_{T_{outage}} Mp(t) * P(t)dt - \int_{T_{outage}} F_c(t) * P(t) * HR(t)dt - C_{om}\left(T_{outage}\right) - depreciation\left(T_{outage}\right) \quad (4.9)$$

Assume a preventive maintenance is performed with cost C_{pm} when the unit reaches a stated age t_{pm}, and corrective maintenance is performed whenever the system fails.

The operations and maintenance cost here include cost of preventive maintenance, and cost of forced outage, which include the cost of corrective maintenance, and loss of revenue due to unavailability of the plant. For a given time period T, the operations and maintenance cost is therefore given by

$$C_{om}(T) = C_{pm}(T) + C_{failure}(T) \quad (4.10)$$

The probability that the power plant will not fail and therefore a preventive maintenance will actually take place during period T is $\int_{t_{pm}}^{\infty} f(t)dt$.

The expected cost of preventive maintenance during time period T is

$$E\left[C_{pm}(T)\right] = C_{pm} \int_{t_{pm}}^{\infty} f(t)dt \quad (4.11)$$

The expected operations and maintenance cost can be given by:

$$E\left[C_{om}(T)\right] = E\left[C_{pm}(T) + C_{failure}(T)\right] = C_{pm} \int_{t_{pm}}^{\infty} f(t)dt + \int_{T} C_{failure}(t) \cdot f(t)dt \quad (4.12)$$

The expected net revenue or profit of a power plant over the stated period of time T is therefore given by:

$$E(NR^{pp}) = \int_T \begin{array}{l} \lfloor P(t)*M_p(t) - F_c(t)*HR(t)*P(t) \rfloor \, dt \\ -\left[C_{pm} \int_{t_{pm}}^{\infty} f(t)dt + \int_T C_{failure}(t) \cdot f(t)dt \right] \end{array} - depreciation(T) \qquad (4.13)$$

<u>Scenario (2): Risk transferred to the services provider</u>

In this scenario, the services provider provides the power plant operations and maintenance services. The power plant operator and the services provider sign a contract. The services provider receives a service fee by providing operations and maintenance services, and he is obliged to maintain the performance and reliability of the power plant, and therefore takes all the operational risk of running the plant.

The elements of power plant cost and revenue are shown in Figure 4.8.

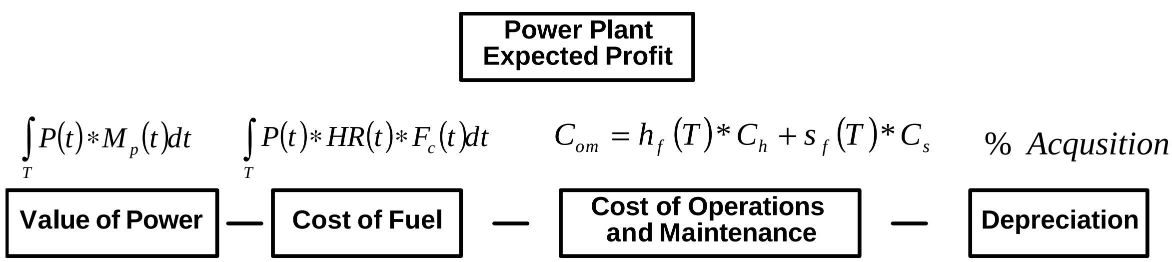

Figure 4.8 Power Plant Expected Profit When Outsourcing O&M Services

Assume the approach to calculate the cost of operations and maintenance for power plant operator C_{om}^{pp} is based on a fixed operations and maintenance fee, plus additional fees based on unit usage, using equivalent fired hours and factored starts, given by Equation (4.14):

$$C_{om}^{pp}(T) = h_f(T) * c_h + s_f(T) * c_s + C_{om}^{fixed} \tag{4.14}$$

The parameters H_f and S_f are accumulated factored fired hours and factored starts respectively, and c_h and c_s are the cost per factored fired hours and factored starts respectively.

Let $m_h(t)$ be the maintenance factor of operating hours at time t, and $m_{s,i}$ the maintenance factor of start i. The equivalent life of a system can be defined using two types of matrices, one is the factored fired hours, and the other is factored starts. The factored fired hours h_f during operating period T is defined below:

$$h_f(T) = \int_T m_h(t)dt \tag{4.15a}$$

Similarly the factored starts is defined as

$$S_f(T) = \sum_{i=1}^{N} m_{s,i} \tag{4.15b}$$

The net revenue accumulated for the power plant during time period T can therefore be given by:

$$E(NR^{pp}) = \int_T \begin{matrix} \lfloor P(t) * M_p(t) - F_c(t) * HR(t) * P(t) \rfloor \, dt \\ -\left(H_f(T) * c_h + S_f(t) * c_s + C_{om}^{fixed}\right) - depreciation(T) \end{matrix} \tag{4.16}$$

The services provider collects revenue by providing operations and maintenance services, while taking operational risks. The elements of the operations and maintenance services provider's cost and revenue are shown in Figure 4.9.

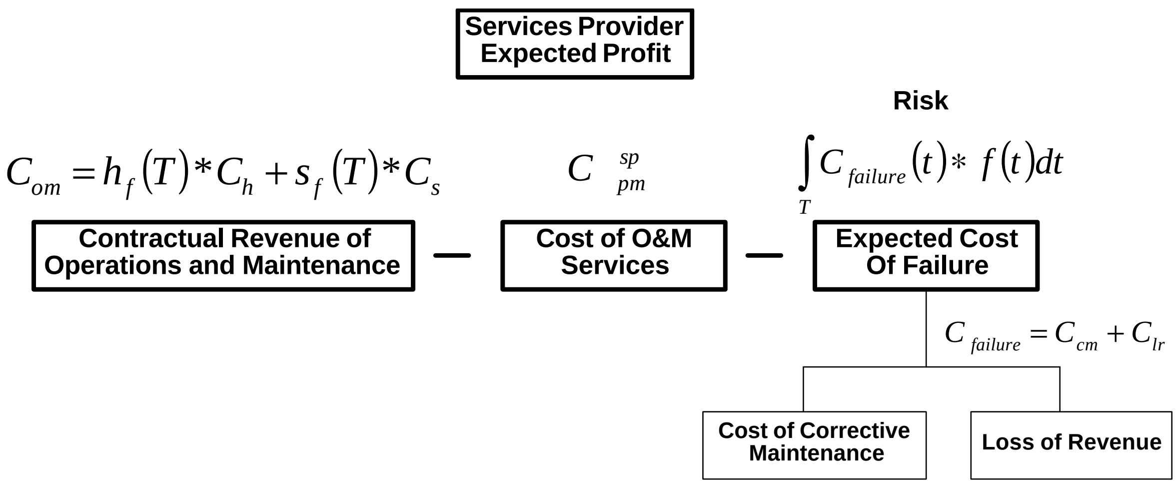

Figure 4.9 Service Provider Expected Profit

Again consider the stochastic nature of failure. The expected cost of preventive maintenance during time period T is

$$E[C_{pm}(T)] = C_{pm}^{sp} \int_{t_{pm}}^{\infty} f(t)dt \tag{4.17}$$

Where C_{pm}^{sp} is the cost of performing preventive maintenance for the services provider.

The consequence or cost of the failure for the customer includes the direct cost to the service provider to the corrective maintenance, and the penalty to the services provider due to the failure of the plant, which leads to the loss of revenue to the power plant due to the unavailability of the plant. Assume the penalty to the services provider equals the loss of revenue to the power plant. The cost of failure can therefore be given as

$$C_{failure}^{sp} = C_{cm}^{sp} + C_{lr} \tag{4.18}$$

Where C_{cm}^{sp} is the cost of corrective maintenance, and C_{lr} is the cost due to loss of revenue.

The risk for the services provider is therefore given by

$$Risk(T) \equiv \int_{T} C_{failure}^{sp}(t) \cdot f(t)dt \tag{4.19}$$

The expected operations and maintenance cost can be given by:

$$E[C_{om}(T)] = E[C_{pm}^{sp}(T) + C_{cm}^{sp}(T)] = C_{pm}^{sp} \int_{t_{pm}}^{\infty} f(t)dt + \int_{T} C_{cm}^{sp}(t) \cdot f(t)dt \tag{4.20}$$

The expected net revenue can be calculated using the following equation:

$$E(NR^{sp}) = \left(H_f(T) * c_h + S_f(t) * c_s + C_{om}^{fixed}\right) - \left[C_{pm}^{sp} \int_{t_{pm}}^{\infty} f(t)dt + \int_{T} C_{cm}^{sp}(t) \cdot f(t)dt\right] \tag{4.21}$$

4.4 2 Multiple Component Systems With Initial Age

The formulated problem introduced above is for a brand new single component system. For multiple component systems with initial age, some special treatment of reliability and risk assessment is required.

The gas turbine engine is a multiple components system, and it can be treated as a series system in that the failure of each of these critical parts will lead to the failure of the whole system. For example, the hot gas path parts include several sets of turbine blades and nozzles. A turbine blade stage with certain number of blades is defined here as a set, and a turbine blade a part of the set. Each part is associated with a unique reliability distribution and aging process.

Scenario (1): Risk taken by the power plant operator

Consider a series system with multiple components. Assuming in the system there are M sets of parts in series, and each set i has N_i parts in series.

Assume the system has an initial age t^0. Each part j of set i has unique initial age $t^0_{i,j}$ when the system has its initial age t^0.

Let $t_{i,j} = t + t^0_{i,j}$, where $t_{i,j}$ is the age of part j of set i. $t^0_{i,j}$ is the initial age of part i of set j. t is the incremental system age since it is put into operation when it has an initial age of t^0. The relationship is shown in Figure 4.10.

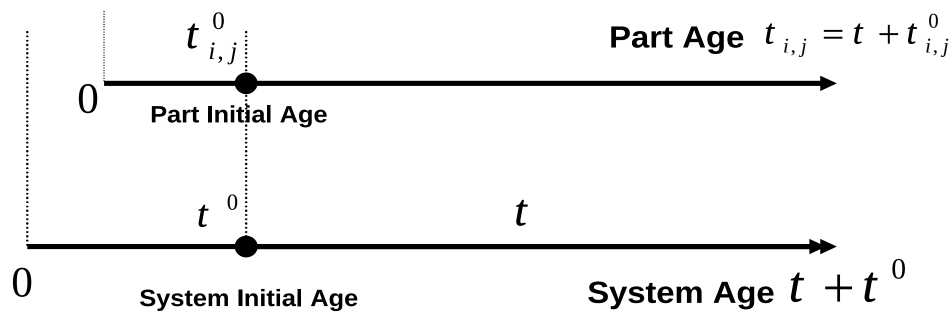

Figure 4.10 System Age and Part Age

Assume the failure rate of part j of set i is $h_{i,j}(t_{i,j})$. For a series system, the failure rate of the system is the summation of all its part failure rates. Therefore the failure rate of set i is therefore

$$h_i(t) = \sum_{j=1}^{N_i} h_{i,j}(t_{i,j}) \tag{4.22}$$

The probability density function of set i is

$$f_i(t) = h_i(t)R_i(t) = R_i(t) * \sum_{j=1}^{N_i} h_{i,j}(t) \tag{4.23}$$

Where $R_i(t) = \prod_{j=1}^{N_i} R_{i,j}(t)$

The probability density function of the system is

$$f(t) = h(t)R(t) = R(t) * \sum_{i=1}^{M} \sum_{j=1}^{N_i} h_{i,j}(t) \tag{4.24}$$

For a series system, the system level reliability at age $t + t^{0}$ for a series system is

$$R(t) = \prod_{i=1}^{M} R_i(t) \tag{4.25}$$

Assume a preventive maintenance is scheduled at age t_{pm}, and corrective maintenance is performed whenever the system fails.

Therefore the expected cost of failure due to the failure of set i in operating period T is:

$$E\left[C_{failure,\,i}(T)\right] = \int_0^{t_{pm}} C_{failure,i}(t) f_i(t) dt \tag{4.26}$$

Where $C_{failure,\,i}$ is cost due to failure of set i. The same method for evaluation of the cost of failure for a single component system is also applicable to the evaluation of the cost of failure of set i.

Assume the failure of each set is independent. The expected cost of failure of the system is the summation of the expected cost of failure of all of its sets.

$$E\left(C_{failure}(T)\right) = \sum_{i=1}^{M} E\left(C_{failure,\,i}(T)\right) = \sum_{i=1}^{M} \int_0^{t_{pm}} C_{failure,i}(t) f_i(t) dt \tag{4.27}$$

Assume the cost of preventive maintenance C_{pm} is time independent. The expected preventive maintenance cost for the operation and maintenance cycle is

$$E\left[C_{pm}(T)\right] = C_{pm} \int_{t_{pm}}^{\infty} f(t) dt \tag{4.28}$$

Where C_{pm} is the cost of preventive maintenance.

The expected operations and maintenance cost is the summation of the expected preventive maintenance cost and the expected cost of failure, given below

$$E[C_{om}(T)] = C_{pm}\int_{t_{pm}}^{\infty} f(t)dt + \sum_{i=1}^{M}\int_{0}^{t_{pm}} C_{failure,i}(t) f_i(t)dt \tag{4.29}$$

The expected net revenue or profit of a power plant over the stated period of time T is therefore given by:

$$\begin{aligned} E(NR^{pp}) = \int_T & \left[P(t) * M_p(t) - F_c(t) * HR(t) * P(t)\right] dt - \\ & \left[C_{pm}\int_{t_{pm}}^{\infty} f(t)dt + \sum_{i=1}^{M}\int_{0}^{t_{pm}} C_{failure,i}(t) f_i(t)dt\right] - depreciation(T) \end{aligned} \tag{4.30}$$

The expected operation and maintenance cycle time is:

$$E(T) = \frac{\int_0^{t_{pm}} tf(t)dt + t_{pm}\int_{t_{pm}}^{\infty} f(t)dt}{R(t_0)} \tag{4.31}$$

The expected maintenance cost per unit operating time is:

$$Z(T) = \frac{E[C_{om}(T)]}{E(T)} = \frac{C_{pm}\int_{t_{pm}}^{\infty} f(t)dt + \sum_{i=1}^{M}\int_{0}^{t_{pm}} C_{failure,i}(t) f_i(t)dt}{\int_0^{t_{pm}} tf(t)dt + t_{pm}\int_{t_{pm}}^{\infty} f(t)dt} R(t_0) \tag{4.32}$$

Scenario (2): Risk transferred to the services provider

The evaluation of the operations and maintenance cost to the power plant operator is the same as introduced for brand new single component system, and the method to calculate power plant expected profit is recalled here.

$$E(NR^{pp}) = \int_T \begin{matrix} \left[P(t) * M_p(t) - F_c(t) * HR(t) * P(t)\right] dt \\ - \left(H_f(T) * c_h + S_f(t) * c_s + C_{om}^{fixed}\right) - depreciation(T) \end{matrix} \tag{4.33}$$

However, special treatment is needed for the calculation of the operations and maintenance cost for the services provider, which is the risk holder. This is because of the difference in the evaluation of reliability distribution and cost of failure introduced above. Assume a preventive maintenance is scheduled at age t_{pm}, and corrective maintenance is performed whenever the system fails.

Therefore the expected cost of failure due to the failure of set i in operating period T is:

$$E\left[C_{failure,i}^{sp}(T)\right]=\int_0^{t_{pm}} C_{failure,i}^{sp}(t)f_i(t)dt \tag{4.34}$$

Where $C_{failure,i}^{sp}$ is cost due to failure of set i. The same method for the evaluation of the cost of failure for a single component system is also applicable to the evaluation of the cost of failure of set i.

Assume the failure of each set is independent. The expected cost of failure of the system is the summation of the expected cost of failure of all of its sets.

$$E\left(C_{failure}^{sp}(T)\right)=\sum_{i=1}^{M} E\left(C_{failure,i}^{sp}(T)\right)=\sum_{i=1}^{M}\int_0^{t_{pm}} C_{failure,i}^{i}(t)f_i(t)dt \tag{4.35}$$

Assume the cost of preventive maintenance to the services provider C_{pm}^{sp} is time independent. The expected preventive maintenance cost for the operation and maintenance cycle is

$$E\left[C_{pm}^{sp}(T)\right]=C_{pm}^{sp}\int_{t_{pm}}^{\infty} f(t)dt \tag{4.36}$$

Where C_{pm}^{sp} is the cost of preventive maintenance to the services provider. A margin is applied to the cost to the services provider so that the services provider for providing the operations and maintenance services obtains a certain profit. The price of the operations and maintenance services set by the services provider is then the cost to the power plant operator.

The expected operations and maintenance cost is the summation of the expected preventive maintenance cost and the expected cost of failure, given below

$$E\left[C_{om}^{sp}(T)\right]=C_{pm}^{sp}\int_{t_{pm}}^{\infty} f(t)dt+\sum_{i=1}^{M}\int_{0}^{t_{pm}} C_{failure,i}^{sp}(t)f_i(t)dt \tag{4.37}$$

The expected net revenue for the services provider can be calculated using the following equation:

$$\begin{aligned}E(NR^{sp}) &= \left(H_f(T)*c_h+S_f(t)*c_s+C_{om}^{fixed}\right)\\ &-\left[C_{pm}^{sp}\int_{t_{pm}}^{\infty} f(t)dt+\sum_{i=1}^{M}\int_{0}^{t_{pm}} C_{failure,i}^{sp}(t)f_i(t)dt\right]\end{aligned} \tag{4.38}$$

Another approach to evaluate power plants economics is to analyze cost of electricity. A formula to evaluate cost of electricity is introduced in Ref.[66]. A detailed introduction to the cost of electricity is introduced in Chapter VIII.

4.5 Summary

In this chapter, a systematic approach to evaluate power plant economics is introduced. The profit equation is first introduced, and then the detailed formulation for each component is derived. The cost of operations and maintenance is derived for multiple components gas turbine systems. The method is a simplification to the practical economic evaluation, with many factors, such as capacity factors, interests rate, inflation rate, etc., neglected.

CHAPTER 5

THE LONG TERM GENERATION SCHEDULING AND PROFIT BASED OUTAGE PLANNING PROBLEM

5.1 Introduction

Performance requirements for modern heavy-duty gas turbines necessitate extreme operating conditions for hot gas path components As a result, these critical components have a limited life span and, more generally, a gas turbine represents an *aging* system experiencing continuous degradation during its operation. This physical degradation manifests itself in performance degradation, as well as in an increased risk of forced outage. Operating conditions of gas turbines determine the aging processes (and degradation rates) of their components and therefore affect both reliability and performance degradation of the power plant. The most important factors influencing operating conditions include starting cycle, power setting, type of fuel, and level of steam or water injection.

Maintenance is the combination of all actions intended to maintain the plant or to restore it to a performance level so that it can perform its required functions [67]. Maintenance activities include inspection, repair and replacement, and they constitute a significant proportion of the varying operating cost.

Timely scheduled (preventive) maintenance can offset the plant degradation, and partially restore/upgrade the system performance as well as improve its reliability by reducing the risk of component failures. On the other hand, preventive maintenance results in significant direct costs as well as in indirect costs due to the loss of revenue during the outage. A trade-off among these conflicting objectives comprises a problem of outage planning (i.e., determination of the timing of power plant shut down for the next preventive maintenance) [68]. The problem is further complicated by the need to plan the outage in advance due to contractual constraints (to minimize loss of revenue) and logistical considerations (to conduct maintenance in a cost- and time-effective manner). Finally, seasonal variations in loss of revenue also contribute to the complexity of the problem. Ideally, preventive maintenance would be done in periods when the demand for electric power is low, typically in the spring and fall months. Recent research on power plant maintenance optimization can be found in Ref. [69][70][71][72][73].

Historically, gas turbine maintenance has been based on a fixed time interval according to recommendations from the power plant supplier. Generally speaking, these recommendations tended to be fairly conservative as minimizing the failure risks carried both financial and reputation-wise incentives for the supplier, while servicing frequent maintenance outages provided a substantial additional source of revenue. Deregulation dramatically changed the nature of the contractual service agreements that effectively provided strong incentives for risk management (as described in the previous paragraph) rather than risk minimization. Since operating conditions for each gas turbine vary from site to site, and from unit to unit, a unit-specific maintenance approach is needed for effective gas turbine maintenance scheduling. For such an approach to be successful, accurate predictions of reliability and performance degradation for each gas turbine is necessary.

In addition, deregulation has also brought new and more complicated means for generating revenue that cannot be reduced to simple cost considerations. Revenue to a power producer can come from fixed contracts, which cover varying periods of time from months to years, or it may come from the spot market, which covers varying periods of time from days to weeks. Thus, revenue models, which is another feature of what may be called market dynamics, is a major part of the optimization problem. While the importance of the market dynamics is well recognized in the problem of unit commitment [74], to date the issue has been largely ignored in outage planning.

The power plant maintenance planning problem is therefore a complex problem involving all of the issues mentioned above: system performance, reliability, operations, maintenance, environment, and market dynamics. The following interdisciplinary modules are pertinent to this profit based approach:

- Power plant system performance and factors that affect this performance (including an ambient conditions model and a performance degradation model)
- Operation and scheduled maintenance considerations, including component and system reliability.
- Economic considerations including power demand and supply, value of power, and price of fuel, etc.

5.2 Coupling of Long Term Generation Scheduling and Outage Planning

The profit-based outage planning approach relies on the knowledge about economic performance of the power plant. However, a projection of the future operating profile is necessary to evaluate power plant output and heat rate, performance degradation and risk assessment, and these factors are pertinent to the evaluation of power plant gross and net revenues. For effective outage planning a projection of the unit usage, which depends on future electric power market and weather conditions in a relatively long-term future time horizon, is required. A profit-based outage planning approach therefore requires long-term generation scheduling.

The simplest approach, which is used in current preventive maintenance planning procedures, is to assume that the operating profile over the time horizon of interest is uniform. This approach is easy to implement and is therefore extensively used in the current engineering practice. In actuality, however, in the market based operating environment, the operating profile shows strong variation due to market dynamics. An inaccurate uniform operating profile assumption leads to inaccurate system degradation estimates and therefore an ineffective outage plan. Thus, a methodology that is capable of capturing the variation of a future operating profile on a long-term basis is therefore necessary for effective outage planning.

5.3 Scenario Description

In the considered scenario a base load combined cycle power plant with single gas turbine is investigated. For this base load gas turbine based power plant, it is assumed that two major preventive maintenances, i.e., a combustion inspection and a hot gas path inspection or major inspection, are scheduled in every three years of operation. It is therefore assumed in this study that the operations and maintenance cycle for this power plant is one and half years or 18 months). It is also assumed that, in the beginning of the time period of concern, the gas turbine has an initial age of 5000 factored fired hours after the last major preventive maintenance. The next scheduled preventive maintenance, which is a hot gas path inspection, is scheduled in the eighth month, and the duration of the maintenance is one month. Furthermore, it is observed that there is a peak demand (wide spark spread--- the difference between the spot market value of natural gas and the electricity at a given time based on the conversion efficiency of a given gas-fired plant.) during the month of scheduled maintenance, so it might be advisable to shift the prescheduled hot gas path inspection to some other time period in order to take advantage of the wide spark spread. For such a decision-making, the tradeoff between risk and reward, i.e., the significance of performance degradation, risk, and spark spread, is very important. In this outage departure problem, the timing of the outage for next preventive maintenance is selected in such a way that the overall expected profit of the power plant during an operations and maintenance cycle is maximized.

5.4 Operational Modeling

This chapter implements a general procedure for integrated power plant modeling introduced in Ref.[75]. Performance and reliability are estimated as functions of operating timelines. Accurate models to analyze quantitatively the relationship between performance, reliability degradation and restoration, unit usage history and maintenance history are necessary.

Recall the operational modeling procedure introduced in Chapter IV. The total expected profit of a gas turbine power plant for a period T can be calculated as

$$E(NR) = \int_T \left[P(t) * M_p(t) - F_c(t) * HR(t) * P(t)\right] dt$$
$$- \left[C_{pm} \int_{t_m}^{\infty} f(t)dt + \int_0^{t_m} C_{failure}(t) \cdot f(t)dt + \int_0^{t_m} q(t)dt \right] \tag{5.1}$$

The first term in the expected profit equation is the integrated over time difference between the value of power, and the cost of fuel, and it can be calculated on a daily basis. This term is here referred to as cumulative spark spread. A definition for spark spread is the difference between the spot market value of natural gas and the electricity at a given time based on the conversion efficiency of a given gas-fired plant. As the conversion efficiency becomes greater, the spread between the market value of the gas and that of power derived by burning the gas becomes wider. The spread also becomes wider as the price of electricity gets higher.

The second term is the expected cost of preventive maintenance, cost of failure, and the depreciation of the power plant in the operation period of time T . The cost of operations and maintenance, and depreciation can be determined once the accumulated age along the operating time line is given. This suggests that the second term in the profit equation can be calculated after the long-term generation scheduling is performed, and it can be calculated once the age of the system during the time period of operation is determined.

5.5 Long Term Generation Scheduling Using a Dual Time Scale Approach

5.5.1 General Method

One of the most challenging problems in the electric power generation business is balancing short-term productivity with the optimal level of production over a long time period. At the level of a single power plant, there are a significant number of control variables that affect the operation of a power plant and its profitability. Most of the involved variables require short-term (weekly or daily) assessment and the corresponding optimization problems are addressed at this small-time scale, i.e., the operator strives to optimize the profits at any given point in time given constraints, demand, and pricing environment. On the one hand, a full-blown long-term optimization of an operating profile is not practical at the same level of detail due to the size of the problem [76][77][78]; on the other hand, the detailed scheduling of long term operation on a daily basis is not reasonable due to the limited accuracy of long term energy market projection.

A dual time scale method for solving the long-term generation scheduling problem is introduced in Ref. [79]. The dual-scale approach allows combining the detailed granularity of the day-to-day operations with global (seasonal) trends, while keeping the resulting optimization model relatively compact. Furthermore, this dual time scale approach can incorporate gas turbine performance, the dynamic electric power market, long term power plant generation scheduling, and outage planning. A brief introduction to the dual time scale long-term generation method is introduced here as follows.

The objective is to maximize the long-term profitability of gas turbine power plant by optimizing the operating profile of gas turbine operation under a dynamic environment, in which the value of power, price of fuel, and plant operating condition are stochastic in nature. The optimization problem is solved in two steps: first a local (e.g., a single day) optimization problem is solved parametrically where accumulated equivalent starts and fired hours are fixed. These two parameters are considered to be the two major factors affecting scheduled maintenance. As a result, at the local level the objective (e.g., net revenue) is expressed as a function of equivalent starts and fired hours, while all the actual plant control variables are embedded (hidden) as a result of the local optimization. Next, a "global" (a time period of certain length till the next scheduled preventive maintenance) problem is posed, where there are only two unknowns (equivalent starts and fired hours) per local time segment.

Operating profile

The operating profile is a control variable, and it is defined on a daily basis. A typical operating profile type defines the starts setting, load setting, fuel type, and power augmentation. The start setting has options such as hot starts, cold starts, and emergency starts. The load setting determines if the system is operating in base load, peak load, or part load. The type of fuel can be natural gas, liquid fuel, etc. Power augmentation defines if steam or water injection is employed. Each combination of these parameters defines an operating profile. To reduce the scale of the problem, operating parameters are converted into a compact description of various scenarios for the daily operation profile of a gas turbine. An example of possible operating profiles for continuous operation is shown in Table 5.1. A similar definition for start up/shut down cycles is given in Table 5.2. Maintenance factors are established for each operating profiles.

It is understood that, in actual engineering practices, a more extensive investigation of the various operating parameters and their corresponding maintenance factors, which affect the life of various components of gas turbine power plants, have to be modeled for effective operational planning. To demonstrate the general method, however, only two operating parameters, the load setting and power augmentation, are investigated in this study. While in this simple case all possible combinations were considered (Table 5.3), in general, design of experiments (DOE) is employed to capture the dependence on operating parameters.

The maintenance factors for each operating profile type are also provided in Table 5.3. These maintenance factors are normalized for the purpose of illustration.

Table 5.1 Parameters for Continuous Operation

Load Setting	Fuel type	Steam Injection	Water Injection
Base load	Natural gas	On	Off
		Off	On
		Off	Off
	Distillate fuel	On	Off
		Off	On
		Off	Off
	Heavy fuel	On	Off
		Off	On
		Off	Off
Peak load	Natural gas	On	Off
		Off	On
		Off	Off
	Distillate fuel	On	Off
		Off	On
		Off	Off
	Heavy fuel	On	Off
		Off	On
		Off	Off

Table 5.2 Parameters for Stats/Stop and Trip

Start/stop Cycle	Part load start/stop cycle(<60%
	Normal base load start/stop
	Peak load start/stop cycle
	Emergency starts
	Fast load starts
Trip	Part load trip
	Full load trip

Table 5.3 Simplified Operating Profiles and Maintenance Factors

Operating Profile Types	Load Mode	Steam Injection	Maintenance Factor
1	Base	Off	1
2	Base	On	1.5
3	Peak	Off	2
4	Peak	On	2.5

Modeling of price of electricity and weather conditions

The variation of ambient temperature for 12 types of day is shown in Figure 5.1. The variation of ambient temperature includes the daily variation and seasonal variation. It is assumed the ambient temperature is relatively low in the early morning, keeps increasing until noon, then decreases, and reaches the minimum at midnight. The seasonal variation shows that the average ambient temperature is relatively low in the spring, keeps increasing in the summer, and then decreases in the fall and reaches the minimum in the winter. Random factors are used to model the stochastic nature of ambient temperature.

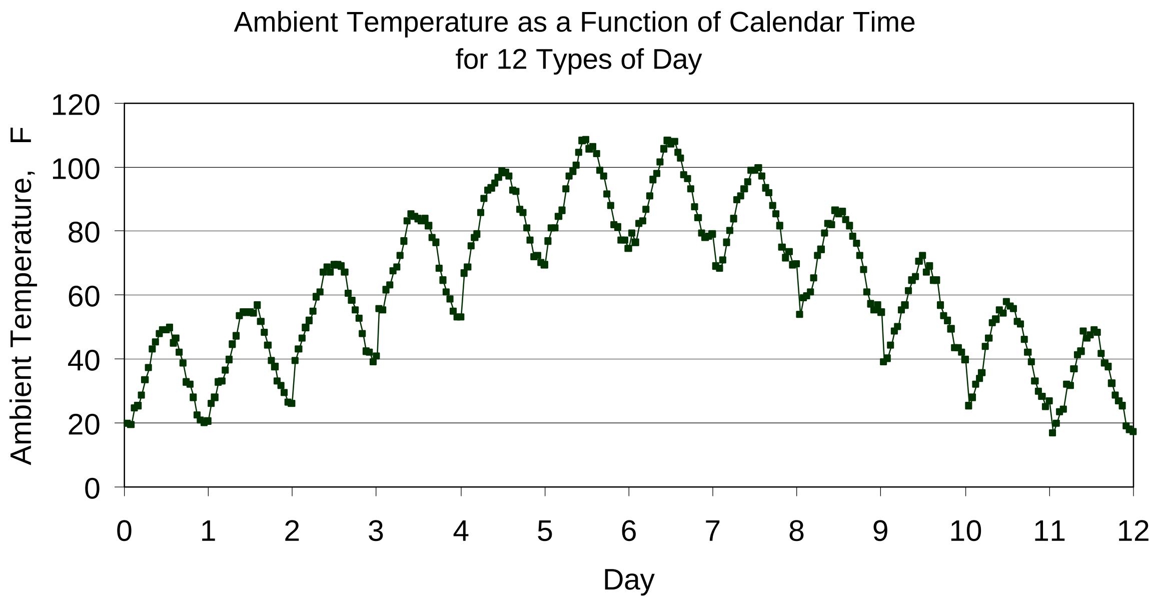

Figure 5.1 Yearly Variation of Ambient Temperature

Similarly, the daily variation of price of electricity is shown in Figure 5.2. The variation of price of electricity also includes the daily variation and seasonal variation. It is assumed that the price of electricity is lower between midnight and early morning than during the day, and the price of electricity is higher in the summer than in the spring, fall and winter, due to high power demand in the summer. Random factors are used to model the stochastic nature of price of electricity. Please note these assumptions do not necessarily match actuality, and what is important here is the variation in a time line [80].

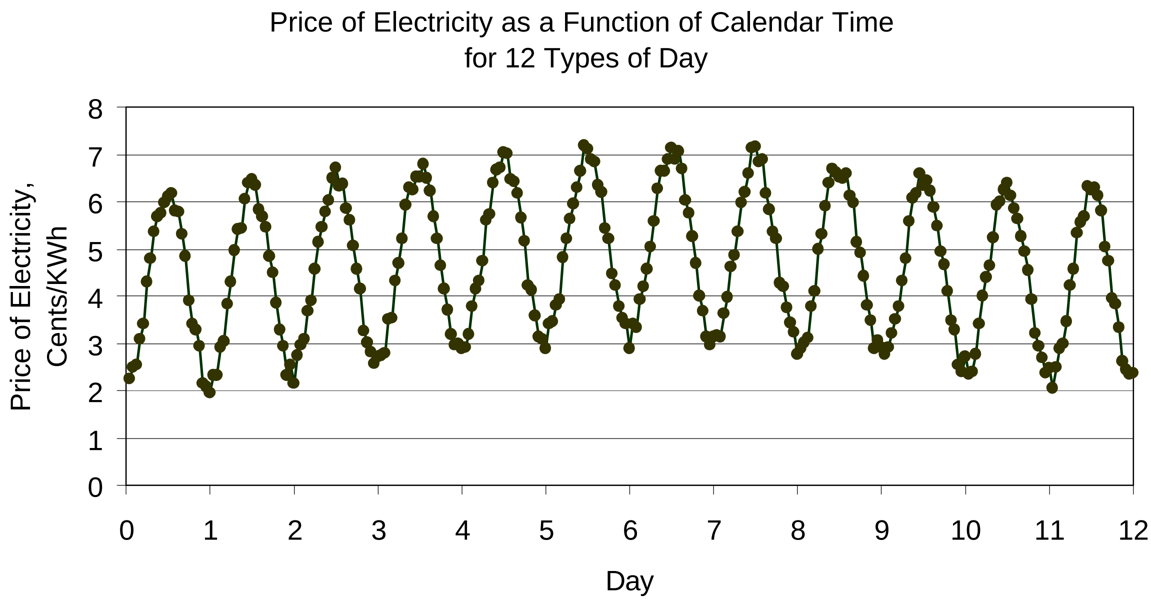

Figure 5.2 Yearly Variation of Price of Electricity

5.5.2 Daily Time Scale Optimization

The strategy for local optimization consists of a separate optimization for each profile with respect to its own parameters followed by a selection of the best profile. The purpose of daily time scale optimization is to construct optimal daily cumulative spark spread profiles as functions of daily usage of the power plant, i.e., daily factored fired hours and factored starts.

Spark spread is determined by price of electricity, price of fuel, and power plant heat rate. Spark spread SS is calculated using the following equation:

$$SS(d,t) = 10 * M_p(d,t) - F_c(d) * HR(d,t)/1000 \tag{5.2}$$

The units here for price of electricity, price of fuel, heat rate, and spark spread are cents/KWh, $/MBTU, BTU/KWh, and $/MWh, respectively. The spark spread depends on the operating profile type O_P since it is a function of the heat rate of the power plant, which is a function of its operating profile type.

The spark spread as a function of calendar time for 12 types of day when the unit is running under operating profile type 1 (based load without power augmentation is shown in Figure 5.3. As expected, the spark spread profile follows the same trend as that of the price of electricity.

Day type 1 is a typical day in January in the winter, when it is assumed the demand of electric power is relatively low and therefore the average price of electricity is low (the situation might be vary depending on a geographical location [80]). The price of electricity in the early morning and midnight is so low that fuel cost is higher than the revenue of selling electricity. As a result the spark spread is negative for that time period, which means money is lost if the power plant is turned on. As the season shifts from spring into summer, the demand of electric power increases, and hence the price of electricity, and therefore the spark spread, becomes wider. This is shown in day type 6 and 7, which is for a typical day in the summer. In this case the spark spread in a summer day is always positive, even in the early morning and midnight. This means the power plant is making profit as long as the plant is in operation.

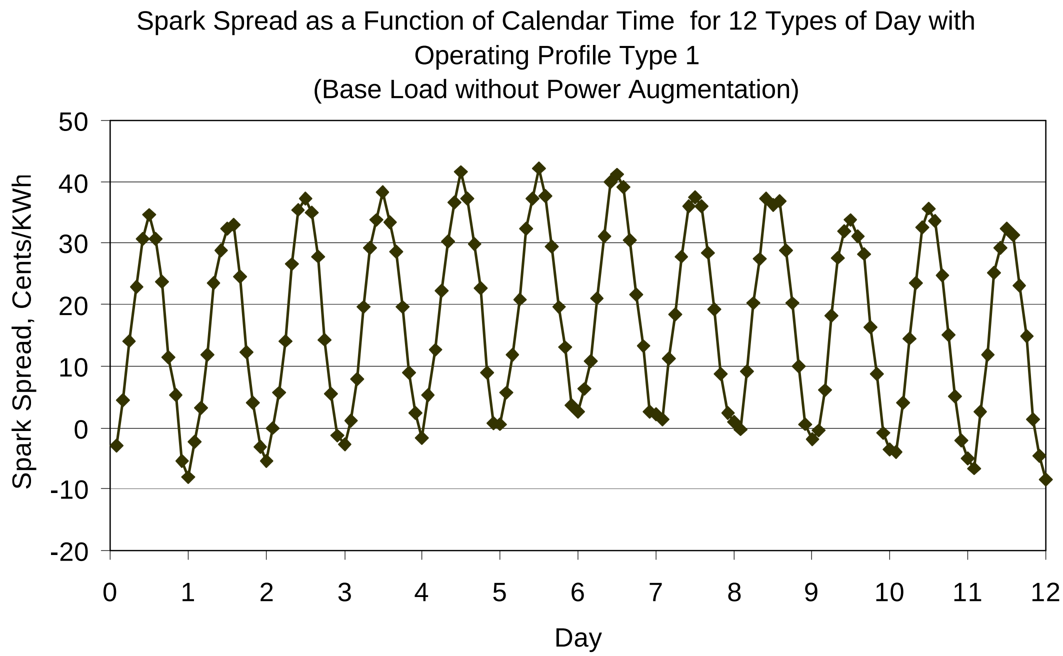

Figure 5.3 Spark Spread as a Function of Calendar Time for the Year

A daily cumulative spark spread is defined and calculated along the time line of daily operation. The daily cumulative spark spread is given by Equation (5.3), which is the difference between the daily gross revenue of selling electricity and daily cost of fuel.

$$DSS = \int_0^{24} P(t) * \left(10 * M_p(d,t) - F_c(d) * HR(d,t)/1000\right) dt \tag{5.3}$$

The parameter, DSS, depends on operating profile type and actual daily operating time, because the heat rate is a function of operating profile type. But, in addition, it also depends on the extraneous parameters, including price of electricity $M_p(d,t)$, price of fuel $F_c(d)$, and ambient conditions $T_a(d,t)$. Note that for a given day during local optimization the ambient condition, price of electricity, and price of fuel are fixed based on forecasting data. The revenue and cost of a plant depend only on the operating profile and actual fired hours and actual starts. Therefore DSS is parametrically expressed as follows:

$$DSS = DSS\left(d, O_p, H_a(d), S_a(d)\right) \tag{5.4}$$

Factored fired hours and factored starts are used as intermediate variables that link long term generation planning and daily generation scheduling. The daily cumulative spark spread can therefore be expressed as a function of type of day, type of operating profile, factored fired hours and factored starts as given below:

$$DSS = DSS\left(d, O_p, H_f(d), S_f(d)\right) \tag{5.5}$$

The daily cumulative spark spread is integrated along the operating time line. As a result, a revenue profile for each operating profile type on a given type of day is calculated as a function of factored fired hours and factored starts. The daily cumulative spark spread profiles for day type 1 and day type 6 are shown in Figure 5.4 and Figure 5.5, respectively.

The cumulative spark spread profiles for day type 1 is shown in Figure 5.4. Day type 1 is a typical day when the price of electricity is relatively low. For each operating profile, as the operating time increases (increases in factored fired hours), the cumulative spark spread increases due to positive spark spread, and reaches the maximum value. It then decreases due to negative spark spread. In this case the daily cumulative spark spread is not wide enough to justify running the power plant all 24 hours per day.

Actually, as shown in Figure 5.4, there is an optimal operating time for each operating profile that optimizes cumulative spark spread for each day, and less cumulative spark spread will be achieved if the plant is run for more time than that optimal operating time.

Figure 5.4 to Figure5.5 show a trend that more cumulative spark spread can be achieved as the time of year shifts from the spring into the summer. As shown in Figure 5.3, the spark spread in a summer day (day type 6) is always positive. For this reason the power producers tend to run the plant more time in summer than in the spring and therefore make more cumulative spark spread each day. This is clearly shown in Figure 5.5.

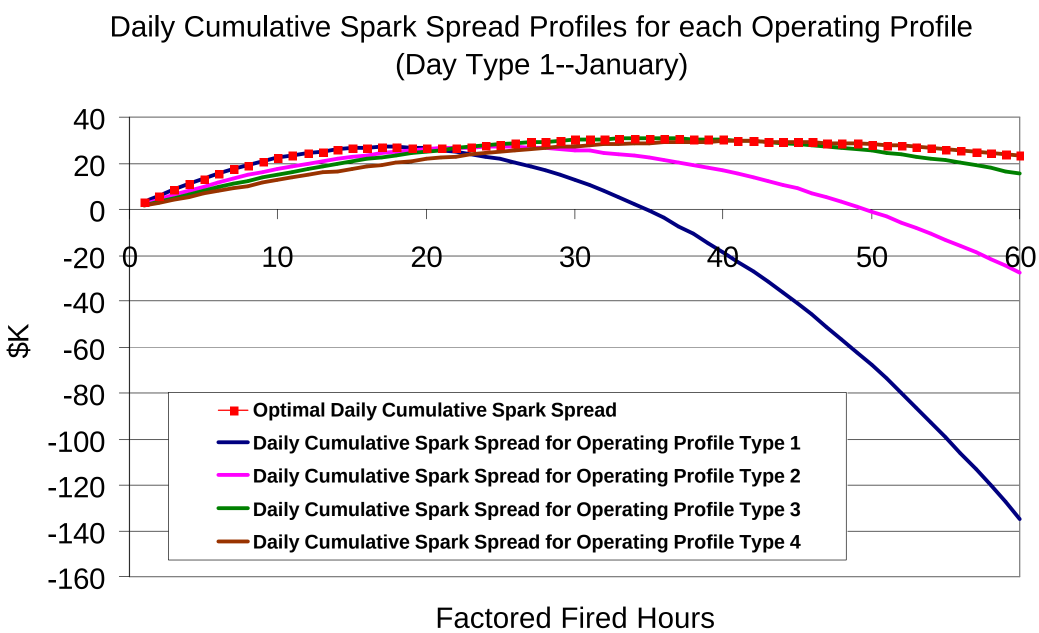

Figure 5.4 Cumulative Spark Spread Profiles--Day 1

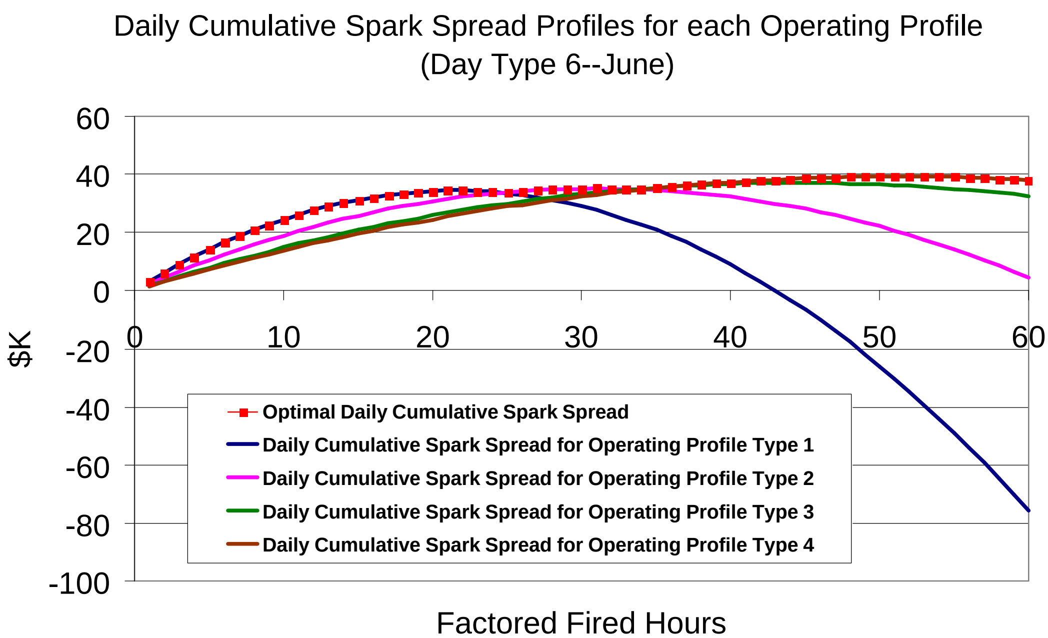

Figure 5.5 Cumulative Spark Spread Profiles--Day 6

For each set of given day, daily factored fired hours H_f and factored starts S_f, an optimal operating profile can be identified which maximizes daily cumulative spark spread. The optimization is formulated as follows:

$$\begin{aligned} DSS^* &= DSS^*\left(d, H_f(d), S_f(d)\right) \\ &= \underset{\text{Profile}}{Max}\left(d, O_p, H_f(d), S_f(d)\right) \end{aligned} \tag{5.6}$$

Here DSS^* is the constrained daily cumulative spark spread.

As a result, for each given day, the optimal daily cumulative spark spread profile is constructed as a function of daily unit usage, i.e., the daily factored fired hours. An optimal daily cumulative spark spread profile is constructed for each day. The optimal daily cumulative spark spread profiles as function of factored fired hours for day types 1-6 are shown in Figure 5.6.

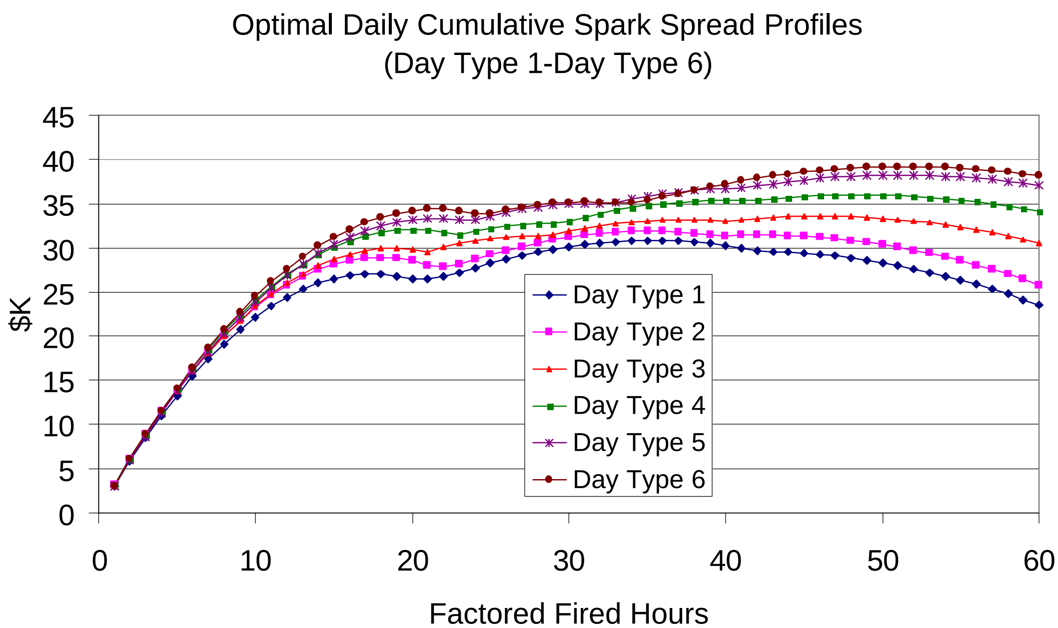

Figure 5.6 Optimal Daily Cumulative Spark Spread

5.5.3 Yearly Time Scale Optimization

The daily (short term) optimization requirement is to maximize daily cumulative spark spread, while the yearly (long term) optimization requirement is to maximize the cumulative profit of the power plant with consideration of long term expected cost of maintenance and depreciation. This is done by optimizing the long term generation scheduling for the given time period of operation.

The power plant will operate until an outage is scheduled for plant maintenance. The long-term economic performance of a plant is the integration of its daily performance over the long-term period. Assume there are a number of D_m days in the operation period T_m, i.e., the next outage is scheduled D_m days away from the current time. For a given future operation profile along the operation period T_m, the aging and consequently the degradation, risk and depreciation of the power plant can be evaluated, and the expected cost of preventive maintenance, cost of failure, and depreciation can be determined.

For a particular future operating profile, suppose the accumulated age (factored fired hours and factored starts) over the operation period T_m is $t_m = (h_f, S_f)$, where h_f and S_f is defined by Equation (3.5-6). The expected cumulative spark spread CSS over the operation period T_m is

$$E(CSS) = \sum_{d=1}^{D_m} DSS^*\left(d, H_f(d), S_f(d)\right) \tag{5.7}$$

Here $DSS^*\left(d, H_f(d), S_f(d)\right)$ is the optimized daily cumulative spark spread profile for each day.

The expected cost of failure and cost of preventive maintenance is therefore

$$\int_0^{t_m} C_{failure}(t)\cdot f(t)dt = C_{failure}\left(1-R\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right)\right) \tag{5.8}$$

$$C_{pm}\int_{t_m}^{\infty} f(t)dt = C_{pm} R\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right) \tag{5.9}$$

Here $R(t) = 1-\int_0^t f(t)dt$ is reliability. The depreciation function Q is defined by the power plant design and configuration, and is a function of age t .

$$Q(t) = Q\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right) \tag{5.10}$$

The expected profit equation is therefore given by:

$$E(NR) = \left(\sum_{d=1}^{D_m} DSS^*\left(d, H_f(d), S_f(d)\right)\right) - \left[\begin{array}{l} C_{failure}\left(1-R\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right)\right) \\ + C_{pm} R\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right) + Q\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right) \end{array}\right] \tag{5.11}$$

The problem now becomes how to assign factored fired hours and factored starts for each day in order to achieve optimized long-term payback for a given time period of operation.

The global problem can be further reduced if individual days of operation with similar characteristics are grouped together. For example, in this study, in order to reduce the number of variables, it is assumed there are k=12 segments of "representative" days at various time of each year. Each segment actually represents a month in a calendar year. Not only are operating conditions assumed to be similar on a representative day, but the global policies are similar as well. In such a setting the 365 days of each year are mapped into the k-types, with $n(d)$ days for each type, which is the number of days of each month. Now, at this point, our 2k optimization parameters are $H_f(d), S_f(d)$, where d=1, 2, ...k.

The formulized yearly time scale optimization is given below:

For a given time period of operation T_m with a number of days D_m, maximize:

$$NR^* = \underset{H_f(d),S_f(d)}{Max}\left(\begin{array}{l}\left(\sum_{d=1}^{D_m} DSS^*\left(d, H_f(d), S_f(d)\right)\right) - \\ \left[C_{failure}\left(1 - R\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right)\right)\right. \\ \left. + C_{pm} R\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right) + Q\left(\sum_{d=1}^{D_m} H_f(d), \sum_{d=1}^{D_m} S_f(d)\right)\right]\end{array}\right) \tag{5.12}$$

Subject to:

$$0 \le H_f(d) \le H_{f,daily}^{Max}$$

$$0 \le S_f(d)$$

$$d = 1, 2, \ldots, k \tag{5.13}$$

Where $H_{f,daily}^{Max}$ is the maximum daily usage of factored fired hours for a given power plant, which corresponds to the cumulative factored fired hours per day when the power plant is operating in 24 hours per day in the operating profile, which results in the highest maintenance factor. $S_f(d)$ is a nonnegative integer.

5.5.4 Results for Long Term Generation Scheduling

As an example, the next outage for preventive maintenance is scheduled 8 months away from the current time of consideration, i.e., the next preventive maintenance is scheduled in this coming August. It is assumed that not only are operating conditions assumed to be similar on each day in a month, but also the global policies are similar as well on each day. As a result, there are 12 different types of days for the entire year. It is also assumed that the current time is in the beginning of the year. A long-term generation scheduling using the dual time scale method is performed, and the optimized future operation profile for these coming 12 months is generated.

The optimized operating profile, the daily factored fired hours, and the daily actual fired hours for this O&M cycle (from the 1st month to the 18th month) are shown in Figure 5.7 and Figure 5.8, respectively. The startup and showdown schedule for each month is shown in Figure5.9.

It is found that the scheduled daily factored fired hours and daily actual fired hours follow the same trend as that of spark spread in the year; and they increase as they go from spring into summer, and decrease from fall into winter. As a result of the dynamics of electric power market, the gas turbine is turned on to the highest output level during the summer, and is scheduled to be in operation 24 hours per day, i.e., the gas turbine is operating under peak load with steam injection (operating profile type 4). During these months, the power plant is running continuously without shutdown. This is the case in the 5th, 6th, 7th, 17th, and 18th month. The power plant is scheduled to operate in a relative low output level, which is peak load without power augmentation (operating profile type 3), during the spring and the winter, and the power plant is start up and shut down on daily basis because the spark spread is not wide enough to justify 24 hours of operation each day.

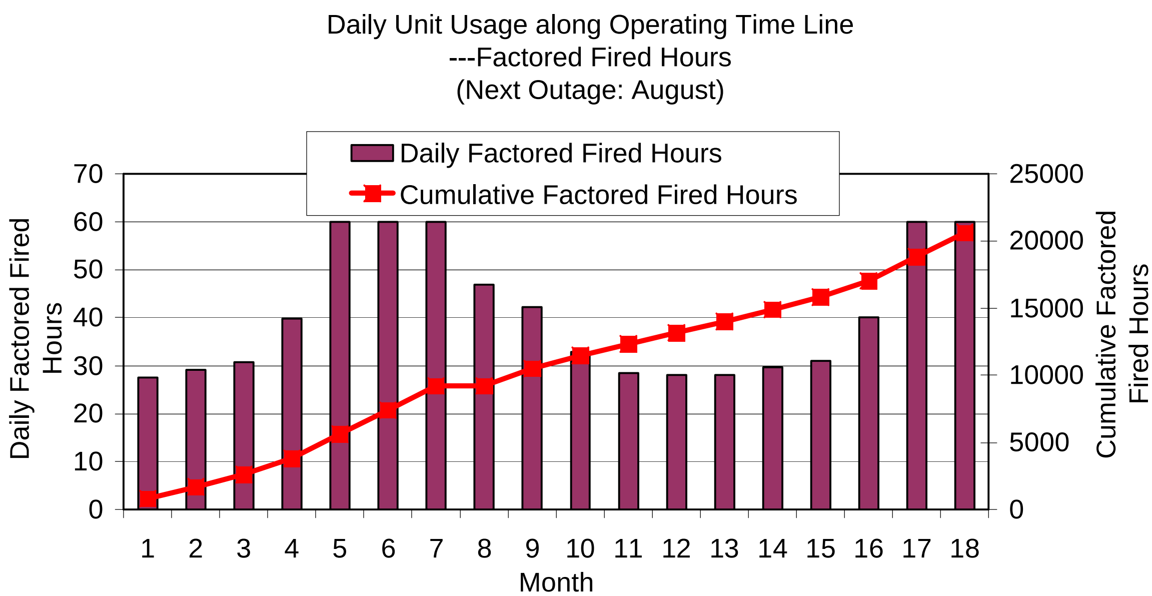

Figure 5.7 Daily Factored Fired Hours Along the Operating Time Line

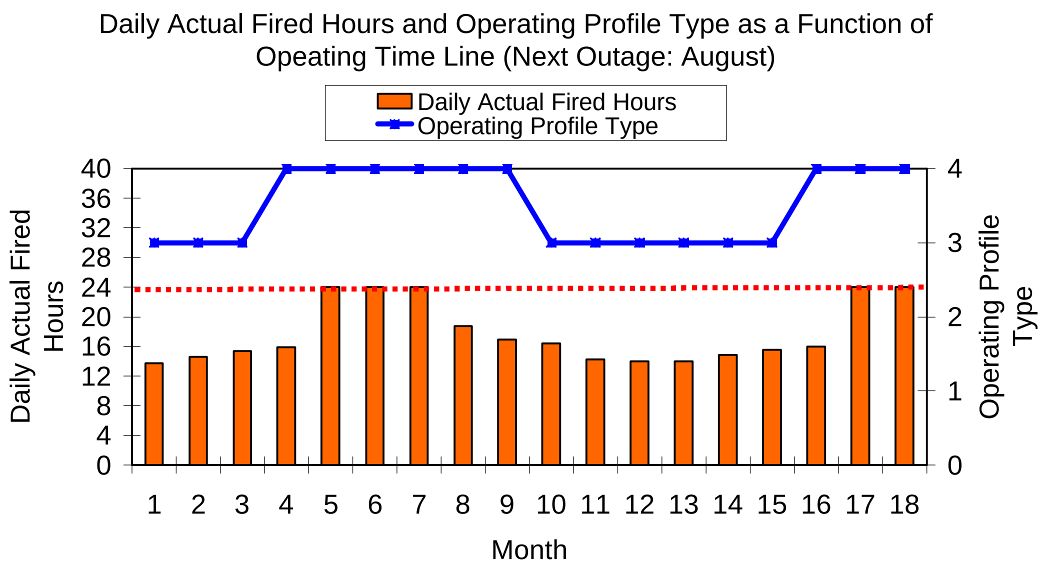

Figure 5.8 Daily Actual Fired hours along the Operating Time

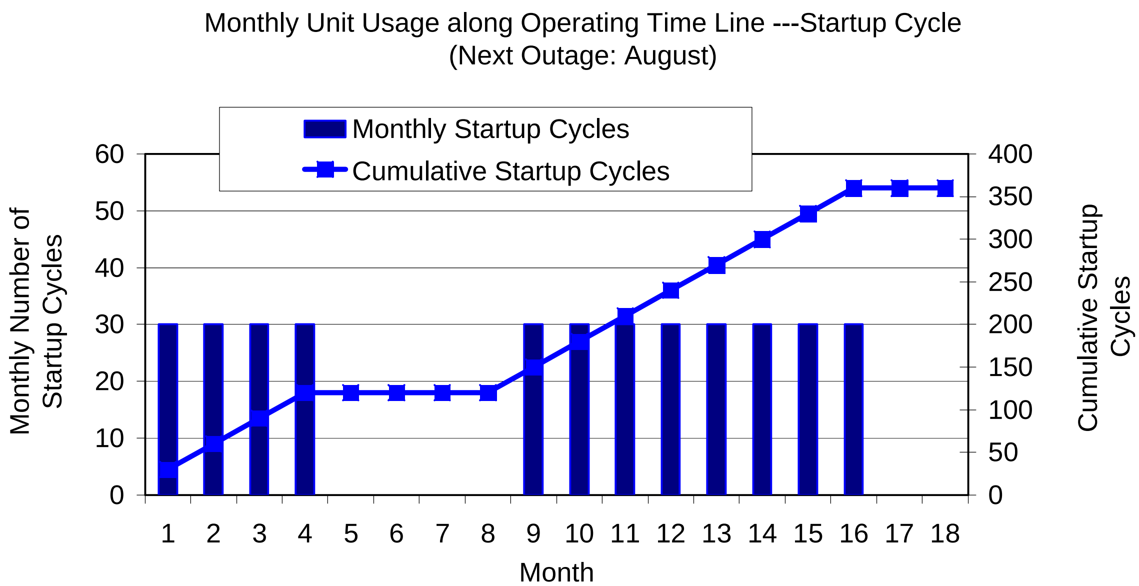

Figure 5.9 Unit Monthly Startup and Shutdown

As a result of the optimized generation schedule, the performance degradation, reliability, and expected cumulative cash flow are shown in Figure 5.10-15.

The power plant performance degradation and restoration as a function of calendar time is shown in Figure 5.10. In this case, perfect maintenance is assumed, which means each type of performance degradation is fully restored as the corresponding type of maintenance is performed. The online water wash and offline water wash is performed with fixed maintenance intervals based on unit cumulative operating hours, which restore partially the performance degradation.

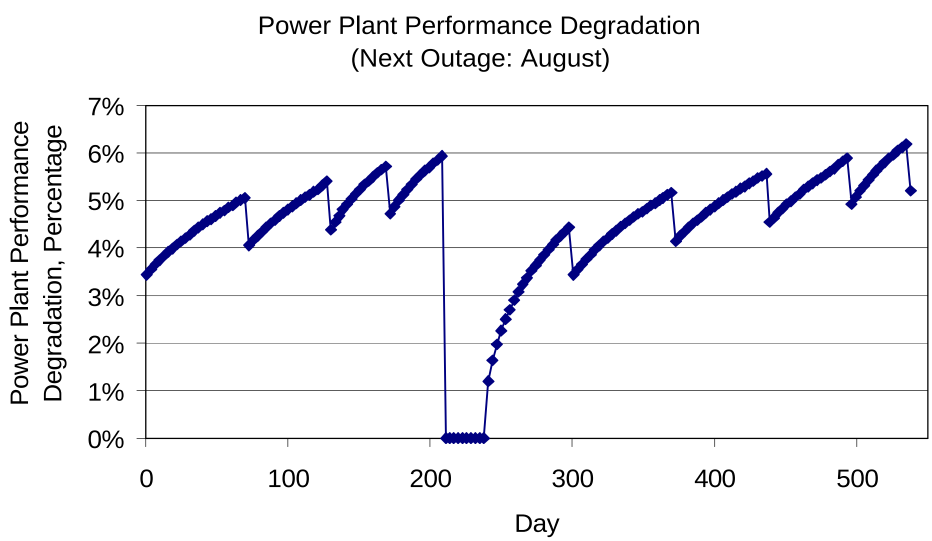

Figure 5.10 Power Plant Performance Degradation and Restoration

The gas turbine system failure rate and reliability is shown in Figure 5.11 and Figure 5.12, respectively. Again perfect maintenance is assumed in this study.

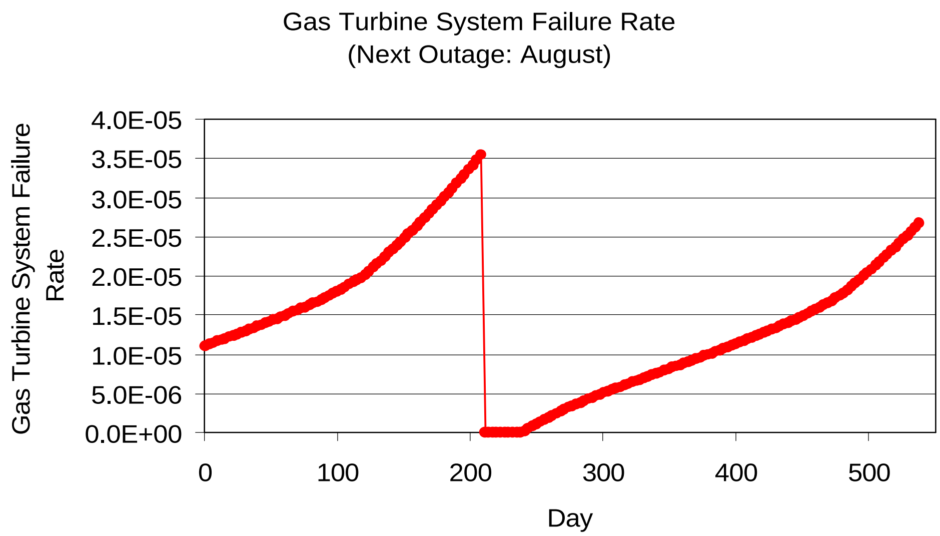

Figure 5.11 Gas Turbine System Failure Rate

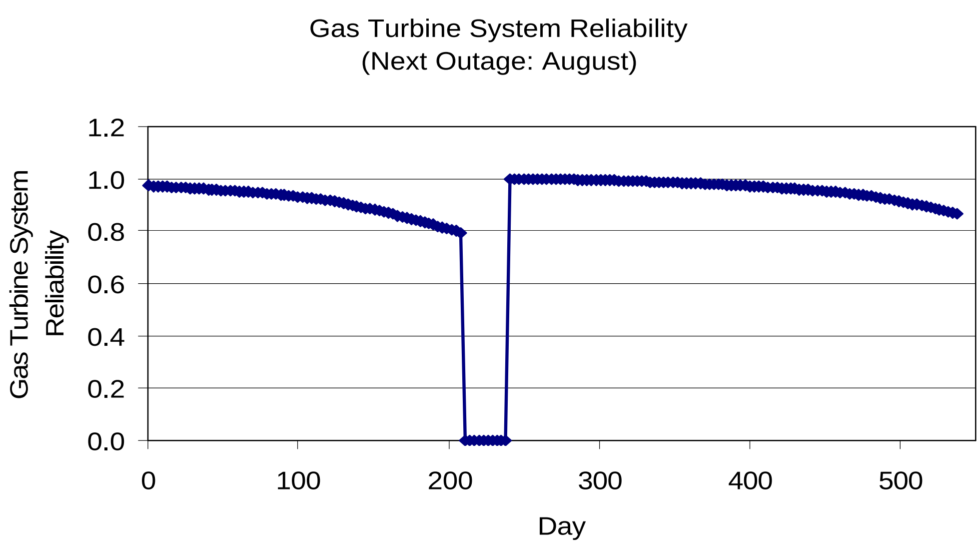

Figure 5.12 Gas Turbine System Reliability

The expected cost of failure, cost of corrective maintenance, and loss of revenue due to outage as a function of calendar time is shown in Figure 5.13. The expected cost of maintenance, cost of corrective maintenance, and cost of preventive maintenance are shown in Figure 5.14. The cumulative spark spread, cost of maintenance, depreciation, and profit for the optimized long term generation scheduling are shown in Figure 5.15. Please note that both cost and revenue are normalized with respect to a fixed reference value.

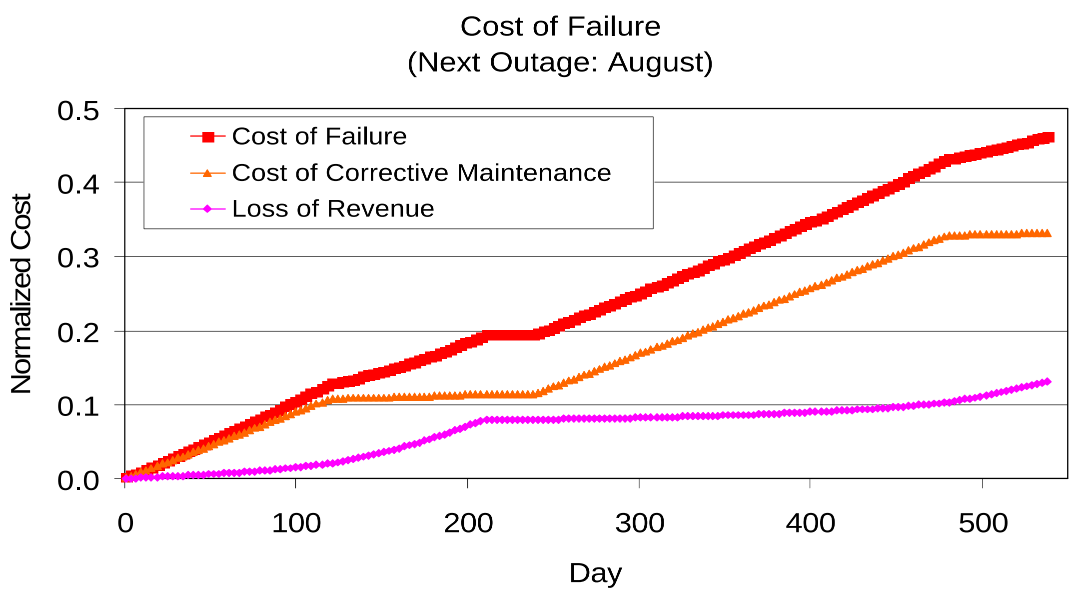

Figure 5.13 Expected Cost of Failure, Cost of Corrective Maintenance, and Loss of Revenue

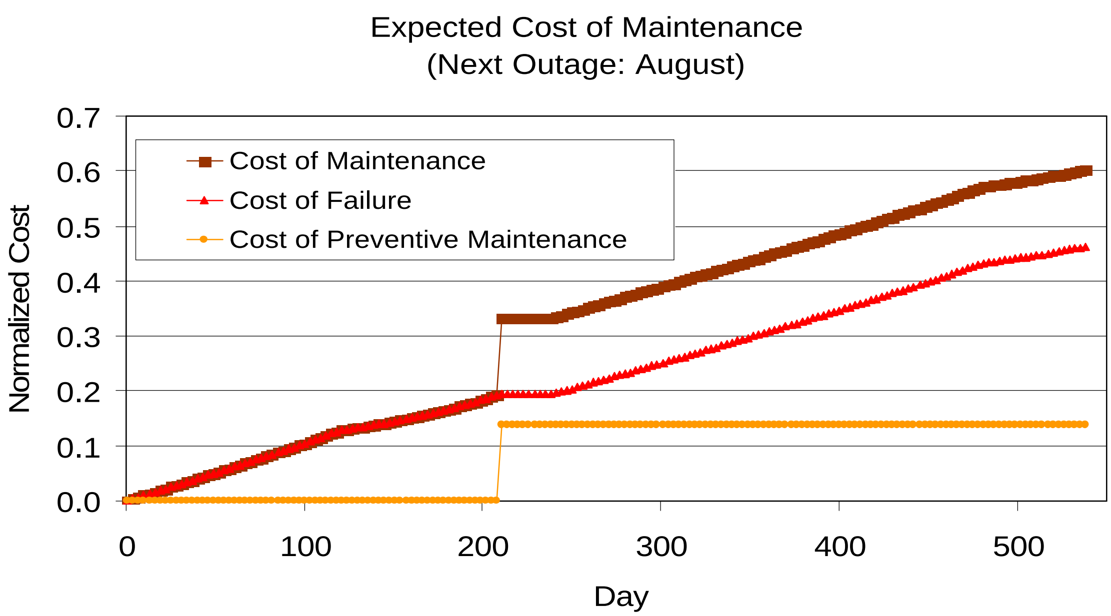

Figure 5.14 Expected Cost of Maintenance, Cost of Failure, and Cost of Preventive Maintenance

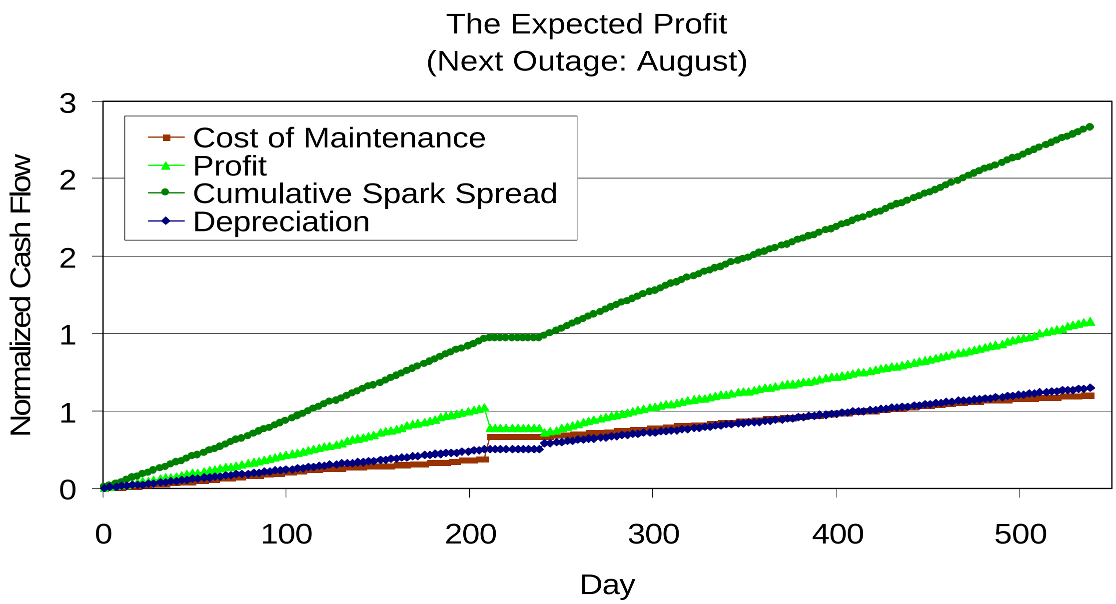

Figure 5.15 Cumulative Spark Spread, Cost of Maintenance, Depreciation, and Profit

5.6 Profit Based Outage Planning

The dual time scale long-term generation scheduling problem is a sub problem for the profit based lifecycle oriented outage planning problem. As a result of the optimization for long term generation scheduling, the optimized expected profit equation is a function of the length of the time period of operation T_m, i.e., the number of days D_m.

$$NR^* = NR^*(D_m) \tag{5.14}$$

The next optimization task is to maximize the expected power plant profit by optimizing the length of the operation period T_m, i.e., the number of days D_m. The outage optimization problem is therefore formulated below:

Maximize:

$$NR^* = NR^*(D_m) \tag{5.15}$$

By optimizing the length of the operation period T_m, i.e., the number of days D_m.

The profit-based outage planning optimization is performed, and the results follow. The normalized expected profit in an Operation and Maintenance (O&M) cycle as a function of outage schedule is shown in Figure 5.16. It is found that, as the next preventive maintenance is postponed, the expected profit increases, and then it reaches the optimal. After that optimal point, the expected profit keeps decreasing if the preventive maintenance is postponed further. The results show that maximized profit over one and half year’s O&M Cycle is achieved when the next outage for preventive maintenance is performed in the 9th month, which is the coming September.

The market dynamics, performance, and reliability all play simultaneously. The spark spread would drive the outage away from a given season when it is wide, when the power plant can gain much profit instantly, to a season when the spark spread is less. This suggests that the next outage occur most likely during the winter, particularly in the 12th and 13th month. However, the impact of gas turbine aging has a different mechanism. When the system is “young” enough, the performance degradation and the risk of running the plant is relatively less significant, and the incremental expected spark spread outweighs the incremental cost (the incremental risk and performance degradation). However, as the gas turbine system ages, the risk increases much faster than does the incremental profit. In this example, the performance degradation and risk associated with postponing the preventive maintenance from the 9th month (September) to the 12th month (December) outweighs the marginal profit.

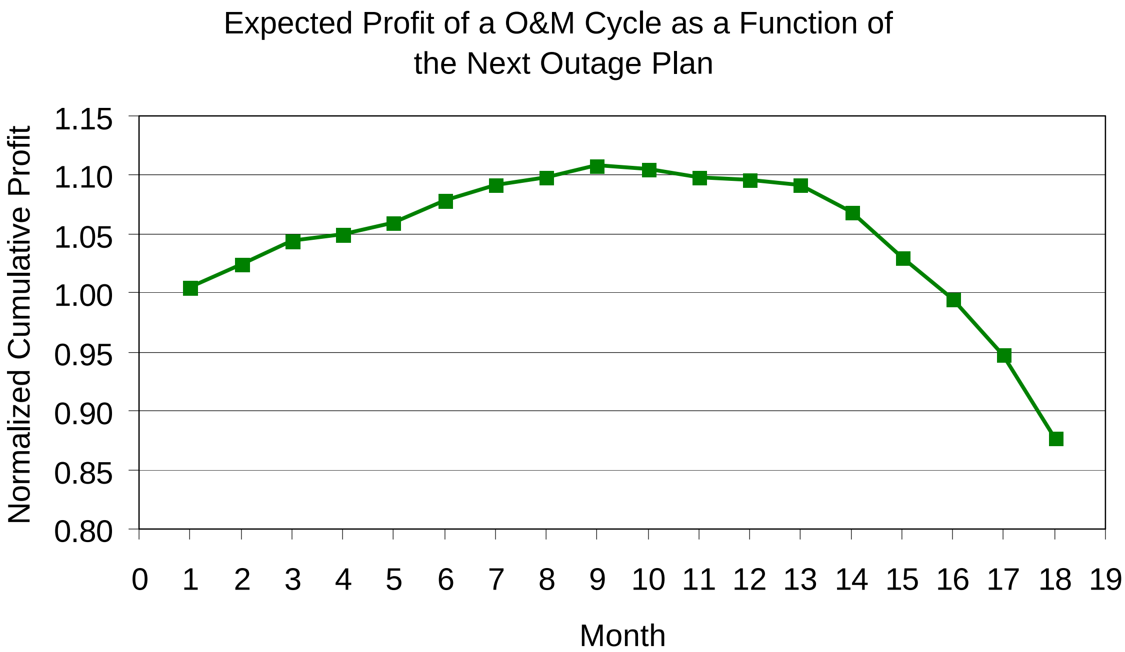

Figure 5.16 Expected Profit as a Function of the Next Outage Time

The detailed optimized generation schedule, including daily factored fired hours, operating profile type for each day, and daily actual fired hours, for this outage schedule is shown in Table 5.4.

The usage of the power plant, the expected cost of maintenance and its percentage change from baseline, and the expected profit and its percentage change from baseline, during the operations and maintenance cycle are shown in Table 5.5. It is shown that, using the optimal outage plan (the 9th month), a 2.78% increase (0.0299 normalized profit) in profit can be achieved than the baseline outage plan (the 6th month). It is also shown that the least profitable outage plan (the 18th month) is 18.65% (0.201 normalized profit) less than the baseline outage plan, and 21.43% (0.231 normalized profit) less than the optimal outage plan (the 9th month).

This example clearly demonstrates that the optimal timing of power plant outage for preventive maintenance is influenced by the power plant performance degradation, reliability, and market dynamics. As a result, outage planning that considers only performance and/or reliability will lead to sub-optimal solution. This provides a strong motivation for pursuing the profit-based approach, where the performance, reliability, and market signals are considered in an integrated fashion.

Table 5.4 Optimized Generation Schedule and Outage Plan

Month	Daily Factored Fired Hours	Operating Profile Type	Daily Actual Fired Hours
1	30.5	3	15.3
2	32.4	3	16.2
3	34.0	3	17.0
4	36.4	3	18.2
5	46.8	4	18.7
6	60.0	4	24.0
7	60.0	4	24.0
8	42.8	4	17.1
9	***Outage***	***Outage***	***Outage***
10	33.4	3	16.7
11	33.3	3	16.7
12	29.9	3	14.9
13	28.0	3	14.0
14	30.6	3	15.3
15	33.6	3	16.8
16	34.3	3	17.2
17	60.0	4	24.0
18	60.0	4	24.0

Table 5.5 Outage Plans and Generation Schedules Summary

Next Outage Schedule (Months)	Factored Fired Hours (Hour)	Factored Starts	Expected Cost of Maintenance	Percentage Change in Cost of Maintenance from Baseline	Expected Profit	Percentage Change in Profit from Baseline
1	15864	510	7.85E-03	2.65%	-7.30E-02	-6.77%
2	16507	510	4.14E-03	1.40%	-5.30E-02	-4.92%
3	18303	450	2.68E-02	9.06%	-3.40E-02	-3.15%
4	18006	480	-1.55E-03	-0.52%	-2.84E-02	-2.64%
5	18913	450	-2.13E-03	-0.72%	-1.81E-02	-1.68%
6	20269	390	0	0.00%	0	0.00%
7	20036	390	-1.52E-02	-5.13%	1.39E-02	1.29%
8	20626	360	-1.01E-02	-3.41%	2.04E-02	1.89%
9	20581	390	-6.83E-03	-2.31%	2.99E-02	2.78%
10	20148	390	-1.62E-03	-0.55%	2.65E-02	2.45%
11	20453	420	9.44E-03	3.19%	2.07E-02	1.92%
12	19031	450	-1.20E-02	-4.07%	1.81E-02	1.68%
13	18926	420	-5.41E-04	-0.18%	1.33E-02	1.24%
14	18981	420	1.45E-02	4.90%	-9.98E-03	-0.93%
15	17639	450	6.60E-03	2.23%	-4.84E-02	-4.49%
16	16473	450	4.57E-03	1.55%	-8.37E-02	-7.77%
17	15281	480	1.67E-02	5.63%	-1.31E-01	-12.13%
18	13412	510	1.35E-02	4.56%	-2.01E-01	-18.65%

5.7 Summary

There is a need for profit-based outage planning for gas turbine power plant as a result of the deregulation of the electric power market. In this study, a systematic approach for profit based outage planning is introduced. The key factors for this profit-based approach include power plant aging, performance degradation, reliability degradation, and, importantly, the energy market dynamics. Outage planning that considers only performance and/or reliability will essentially lead to sub-optimal solution.

A multiple time scale operational scheduling method is developed for coupled generation scheduling and outage planning. The models that are currently being developed for this planning approach have been demonstrated in this study in an example that uses a relatively simple power plant model operating over an 18-month period. It is found that this profit based outage planning approach is capable of coupling power plant performance, reliability, and energy market dynamics, and therefore allows more effective outage planning. Using this multiple time scale profit based outage planning approach, increase in the profitability of a gas turbine power plant is expected.

For practical engineering considerations, more factors and more sophisticated models are required for effective decision making. For example, a more extensive modeling of the operating profiles and their corresponding maintenance factors would be helpful. Also, more sophisticated cost models are needed for sounder decision-making. The price of electricity in the deregulated electric power market is set by rate structures as well as by the spot market. This leads the modeling of price of electricity with regard to time to a very complex problem. Other factors such as power demand, power factor, taxes, etc., are also needed for realistic cost modeling.

The method introduced in this chapter is theoretical, and it is expected that the translation of the method into a computer program with more practical considerations for outage optimization will be helpful for improving gas turbine power plant profitability.

CHAPTER 6

GAS TURBINE POWER PLANT PREVENTIVE MAINTENANCE SCHEDULING

6.1 Introduction

Traditionally the gas turbine power plant preventive maintenances are scheduled with constant maintenance intervals based on recommendations from the equipment suppliers. The preventive maintenances are based on fleet wide experiences, and they are scheduled in a one-size-fit-all fashion. However, in reality, the operating conditions for each gas turbine may vary from site to site, and from unit to unit. Furthermore, the gas turbine is a repairable deteriorating system, and preventive maintenance usually restores only part of its performance. This suggests the gas turbines need more frequent inspection and maintenance as it ages. A unit specific sequential preventive maintenance approach is therefore needed for gas turbine power plants preventive maintenance scheduling. Traditionally the optimization criteria for preventive maintenance scheduling is usually cost based. In the deregulated electric power market, a profit based optimization approach is expected to be more effective than the cost based approach. In such an approach, power plant performance, reliability, and the market dynamics are considered in a joint fashion. In this study, a novel idea that economics drive maintenance expense and frequency to more frequent repairs and greater expense as the equipment and components age is introduced, and a profit based unit specific sequential preventive maintenance scheduling methodology is developed. To demonstrate the feasibility of the proposed approach, this methodology is implemented using a base load combined cycle power plant with single gas turbine unit.

6.2 Gas Turbine Power Plant Preventive Maintenance Scheduling

Gas turbine units are widely used for land electric power generation, and maintenance planning has a strong impact on the profitability of a gas turbine power plant. Performance requirements for modern heavy-duty gas turbines necessitate extreme operating conditions for hot gas path components. As a result, these critical components have a limited life span and, more generally, a gas turbine represents an *aging* system experiencing continuous degradation during its operation. This physical degradation manifests itself in performance degradation, as well as in an increased risk of forced outage. Operating conditions of gas turbines determine the aging processes (and degradation rates) of their components and therefore affect both reliability and performance degradation of the power plant. Timely preventive maintenance is scheduled to stop the power plant from further degradation, and to partially restore its performance and reliability.

Maintenance scheduling problems have been extensively studied in the literature. The questions that a preventive maintenance schedule is trying to answer are:

- When should the next preventive maintenance occur?
- What work scope in the next preventive maintenance period should be carried out?

Today power systems have a large number of units, and the reliability of system operation and production costs are influenced by the maintenance requirements of generating facilities. Traditionally the generator maintenance scheduling problem is to arrange the generating unit for maintenance such that the production costs are minimized, and that certain levels of system security and adequacy are met [81].

To perform generator maintenance scheduling, the maintenance window for each unit should be scheduled first. Each individual unit can have its optimal maintenance window. An outage that takes place too soon wastes money, and an outage that takes place too late can be expensive, since the unit performance degrades as the unit accumulates operating hours, and the probability of forced outage increases as its reliability deteriorates.

Therefore, for power plant maintenance scheduling of multiple units, it is most important to determine the optimal outage time for each unit, and the maintenance window for each unit can be determined. Maintenance windows for each unit are therefore used for multiple units maintenance scheduling.

6.2.1 Gas Turbine Maintenance Considerations

Performance requirements for modern heavy-duty gas turbines necessitate extreme operating conditions for hot gas path components. As a result, these critical components have a limited life span and, more generally, a gas turbine represents an aging system experiencing continuous degradation during its operation. This physical degradation manifests itself in performance degradation, as well as in an increased risk of forced outage. Operating conditions of gas turbines determine the aging processes (and degradation rates) of their components and therefore affect both reliability and performance degradation of the power plant. Timely preventive maintenances are scheduled to stop the power plant from further degradation, and to restore partially its performance and reliability.

The heavy-duty gas turbines are designed to withstand severe duty. The gas turbine hot gas path parts are working under severe environmental conditions, namely, high flow rate, hot gases, and frequent temperature changes due to start-up and shut-down. Therefore they have a relatively short lifespan.

Gas turbine units have been widely used for land electric power generation and marine surface ship power plant, and they show different operating modes due to difference customer needs. Gas turbine units used to meet different customer needs show different start frequency, namely, the ratio between number of starts and number of operating hours. Some land-based gas turbines are utilized to provide electric power on a continuous basis, while others are used only to meet peak consumer demand for a short operation period during each day. If a unit is operating on a continuous basis, and it experiences very few start and stop thermal cycles, this unit is usually called a base load unit. A unit used to meet daily peak loads will accumulate an increased number of starts and stop thermal cycles, and this unit is called a daily start and stop unit. Some gas turbine units may be operated on a weekly start and stop basis to meet some customer needs, and those units are referred as weekly start and stop units.

Maintenance is an important issue for gas turbine power plant. Timely preventive maintenance should be performed to prevent the system from further degradation, and to restore the system performance and reliability to some extent.

Although there is no universal definition for maintenance, some definitions can be identified in the literature. A definition for maintenance is the activities carried out to retain a system in or restore it to an acceptable operating condition [45]. Another definition for maintenance is the combination of all technical and associated administrative actions intended to retain an item in, or restore it to, in which it can perform its required function [67]. Maintenance activities include inspection, repair and replacement, and they constitute a significant proportion of the varying operating cost.

Maintenance and inspection provides not only direct benefits in reduced forced outage and increased starting reliability, but also restores performance, which includes increased power output, and reduced heat rate.

6.2.2 Gas Turbine Power Plant Maintenance Work Scope

Based on an analysis of scheduled outage and forced outage of a simple cycle power plant provided by GER-3620J, the primary power plant maintenance effort is attributed to five basic systems: the control and accessories, turbine section, combustion section, generator, and balance of plant. It is pointed out that the outage due to turbine section, combustion section, generator, and balance of plant usually take long periods, and that due to control and accessories generally takes shorter time periods [13].

The heavy-duty gas turbines are designed to withstand severe duty. The gas turbine hot parts are working under severe environmental conditions, namely, high flow rate, hot gases, and frequent temperature changes due to start-up and shut-down. Therefore they have a relatively short lifespan. The hot gas path parts include combustion liners, end caps, fuel nozzle assemblies, crossfire tubes, transition pieces, turbine nozzles, turbine stationary shrouds, and turbine buckets [13]. These rotating and stationary parts are subject to degradation during normal turbine operation.

The gas turbine's life is affected by many factors, and the mechanism of how these factors affect equipment life has to be well understood for effective maintenance planning. The most important factors include starting cycle, power setting, type of fuel, and level of steam or water injection. These factors have a direct impact on the life of critical gas turbine parts, and therefore influence the maintenance interval.

Gas turbine wears in different ways for different service duties, as addressed in GER-3620J. The crack length of the hot gas parts is used as an indication of the safety index, and it determines the maintenance schedule interval. A certain limit for the crack length is set for a particular type of part, and a hot gas path part whose crack length is beyond this limit is scheduled for repair or replacement. For peaking gas turbine units, thermal mechanical fatigue is the dominant limiter of life. While for continuous duty machines, creep, oxidation, and corrosion are the dominant limiters of life. Intuitively one would imagine that the consideration of interaction between thermal mechanical fatigue, creep, oxidation, and corrosion is necessary for understanding the overall life consumption mechanism for gas turbines [13].

According to GER-3620J, the types of maintenance inspection for gas turbines can be classified as standby, running and disassembly inspections. Disassembly inspection is an inspection that requires opening the turbine for inspection of internal components, and it can be further classified as combustion inspection, hot gas path inspection, and major inspection. An example of gas turbine planned maintenance work scopes is shown in Figure 6.1. The combustion inspection is a relatively short disassembly shutdown inspection, and it concentrates on the combustion liners, transition pieces, fuel nozzles, and end caps, which have relatively short life span due to severe working environment. Hot gas path inspection is an inspection performed to inspect those parts exposed to hot gas discharged from the combustion process, and it includes the full scope of combustion inspection and a detailed inspection of turbine nozzles, stationary stator shrouds, and turbine buckets. Major inspection is a more extensive inspection, and it includes the work scope of combustion and hot gas path inspection. It is to examine all of the major flange-to-flange components of the gas turbine, which are subject to degradation during normal turbine operation [13].

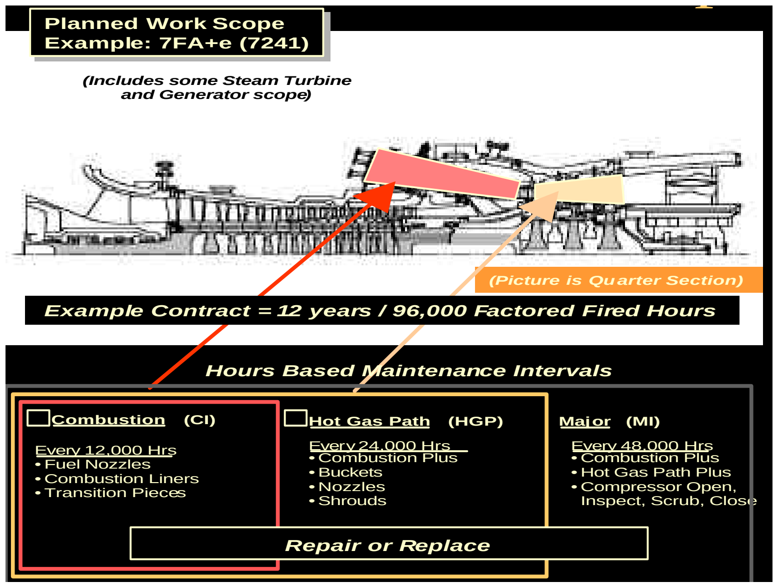

Figure 6.1 Gas Turbine Planned Maintenance Work Scope ([13]GER-3620J)

The effective scheduling of these disassembly inspection/maintenance actions is the primary interest of this study.

The decisions to be made for the maintenance inspection problem is two dimensional, one is to determine when the next inspection should occur, and the other is to determine what maintenance work scope to take, i.e., what maintenance action to take. In this study, the emphasis is on the determination of the optimal timing of preventive maintenance.

6.3 Preventive Maintenance Models

The degradation of gas turbine systems is complex. In the last several decades, maintenance polices for deteriorating systems have been extensively studied [10]. Wang performed a survey of maintenance policies of deteriorating systems, and he points out that although thousands of maintenance models have been published, there is a limited number of maintenance polices on which all maintenance models can be based. Based on Wang's survey, the maintenance polices are categorized as the following:

- Age-dependent policy
- Periodic PM policy
- Sequential preventive maintenance policy
- Failure limit policy.
- Repair limit policy
- Repair number counting and reference time policy

Maintenance can be classified into two major categories: corrective maintenance and preventive maintenance. The corrective maintenance is the maintenance that occurs after a system fails, while preventive maintenance is the maintenance that occurs when the system is operating [10]. There are two commonly used preventive maintenance policies, periodic preventive maintenance and sequential preventive maintenance. Under periodic preventive maintenance policy, a system is maintained at integer multipliers of some fixed period. Under sequential preventive maintenance, the system is maintained at a sequence of intervals that may have unequal lengths of intervals [82].

In the last several decades, numerous models for optimally scheduling inspections and/or maintenance have been published in the literature [82][83][84][85][86][87][88]. The periodic preventive maintenance policy has been extensively used, and one of the reasons for this is that the maintenance is easy to schedule. However, the sequential preventive maintenance policy is more realistic in that most systems need more frequent maintenance as they age, and preventive maintenance is usually imperfect.

Early studies of maintenance models usually assumed that, after corrective or preventive maintenance, the system is in one of the two extreme conditions, either as good as new or as bad as old. Furthermore, down time due to maintenance is negligible and thus discounted, and the aging of the unit is not considered [82][83][84][85][86][87][88]. For real systems such as gas turbine power plants, these assumptions are not true. Realistic reliability modeling and maintenance scheduling for a sophisticated system such as gas turbine power plant has rarely been seen in the literature.

Most preventive maintenance improves or restores the system, but the improvement depends on the age of the system as well as the cost and time of the preventive maintenances [87]. The effect of maintenance usually is somewhere between as good as new and as bad as old. Therefore, most systems need more frequent maintenance due to aging and imperfect maintenance [86]. Reviews and surveys of preventive maintenance models for deteriorating single-unit system have been published in the literature [10][85].

A classification of the maintenance practices based on the maintenance effectiveness is introduced in Ref. [45]. Five categories, according to the degree to which the operating conditions of an item are restored by maintenance, are identified, and they are *perfect, minimal, imperfect, worse,* and *worst* maintenance. The perfect repair or perfect maintenance is an action that restores the system to as good as new. The system has the same reliability distribution as a brand new one after perfect maintenance. Minimal repair or minimal maintenance is an action which restores the system to the failure rate it had when it failed. Then the system operating state is often called as bad as old. Imperfect repair or imperfect maintenance is an action that restores the system operating state to somewhere between as good as new and as bad as old [45].

Minimal repair is a frequently used assumption in the literature [88]. This assumption is acceptable for a complex system with many components, and the failure of each component will lead to the failure of the entire system. The operating status of the whole system will not change much if one or some of its components are replaced or repaired, since it has so many components [89]. It is assumed that in this study, gas turbine power plants are such complex systems with numerous components, and that the corrective maintenance of gas turbine power plant is minimal maintenance.

The preventive maintenance for a gas turbine power plant includes combustion inspection, hot gas path inspection, and major inspection, and it can be classified as a different type of maintenance. In some references, these maintenance actions are referred to as overhauls. The overhaul is scheduled and may act on groups of components, and therefore they can be more effective on the restoration of a system's performance and reliability than would minimal maintenance [88]. For example, the combustion inspection is inspection that concentrates on the combustion liners, transition pieces, fuel nozzles, and end caps. Hot gas path inspection is an inspection performed to inspect those parts exposed to hot gas discharged from the combustion process, and it includes the full scope of combustion inspection and a detailed inspection of turbine nozzles, stationary stator shrouds, and turbine buckets. Major inspection is a more extensive inspection, and it includes the work scope of both combustion and hot gas path inspections. It is to examine all of the major flange-to-flange components of the gas turbine, which are subject to degradation during normal turbine operation [13].

Although the major preventive maintenance actions can rejuvenate the gas turbine power plant system, they cannot restore it to as-good-as-new state, as they do not eliminate all the performance and reliability degradation that has taken place in this complex system. As a result, the major preventive maintenance will restore the gas turbine power plant to be somewhere between as good as new and as bad as old. This is referred to as imperfect maintenance.

6.4 Sequential Preventive Maintenance Scheduling

Traditionally gas turbine power plant preventive maintenance is scheduled with constant maintenance intervals based on recommendations from the equipment suppliers. The preventive maintenances are based on fleet wide experiences, and they are scheduled in a one-size-fit-all fashion. This constant maintenance interval philosophy is referred to as periodic maintenance, and it is not able to take into account the gas turbine system as a repairable aging system.

However, the gas turbine is an aging system, and the aging of the power plant heavily depends on the operating conditions. In reality, the operating conditions of gas turbine power plants vary from site to site and unit to unit. Maintenance performed without regard to the condition of the equipment may result in wasted resources for equipment that is aging less rapidly than expected, or equipment may experience high risk of failure if the equipment ages more rapidly than expected. This suggests that each unit should be treated individually. For such a unit specific approach to be successful, accurate predictions of reliability and performance degradation for each gas turbine is necessary.

Performance and reliability degradation increases as it ages, and, as discussed above, the major maintenance will partially restore performance and improve reliability. As a result, the gas turbine power plant is an aging system in that, for any age x (here x is the elapse age form the end of each major preventive maintenance), its failure rate $h_{m+1}(x)$ during the $(m+1)^{th}$ operations and maintenance cycle is strictly larger than $h_m(x)$ during the m^{th} operations and maintenance cycle[†] (O&M cycle hereafter).

Thus the gas turbine becomes older as more and more maintenance actions are performed, and, intuitively, more frequent maintenance is needed for such a system. This suggests variable maintenance intervals instead of constant maintenance intervals should be scheduled for gas turbine power plants.

To consider the aging of the gas turbine power plant, a sequential preventive maintenance philosophy is needed. In the sequential preventive maintenance schedules, the maintenance intervals are subject to change, and the length of the maintenance intervals are determined by performance degradation, reliability, and market signals in a joint fashion.

[†] An operations and maintenance cycle is the time period which includes a major maintenance (including combustion inspection, hot gas path inspection, or major inspection), and a continuous operating period.

6.5 Optimization Criteria

A first task of preventive maintenance scheduling is to set the optimization objective. Traditionally, for complicated systems such as a gas turbine power plant, maintenance cost and on-line availability are two of the most important concerns to the equipment owner. Several optimization criteria that have been published in the literature [10][83], which follow:

- Minimize system maintenance cost rate
- Maximize system reliability/availability
- Minimize system maintenance cost rate while the system meets its reliability requirement
- Maximize system reliability while the system meets its maintenance cost requirement

Many cost based inspection and preventive maintenance policies have been published in the literature. For the cost based maintenance scheduling, the optimization criterion is usually to minimize the long-run expected cost per unit time (the expected cost rate).

However, in the deregulated electric power market, cost and reliability are not the only concerns. The ultimate goal of the power plant operator in the deregulated electric power market is to make a profit. Furthermore, in a market-based environment, the electricity market shows strong dynamics, and an optimized maintenance cost and maximized plant availability does not necessarily mean optimized profitability, since other factors, such as fuel cost, electricity price, and power demand and supply also play a big role. This suggests that in a market-based environment, the maintenance practices should be optimized to achieve the maximized profit. Any optimization criteria aiming to maximize system availability and/or minimize cost will inevitably lead to sub-optimal solutions.

Constructing a profit function that incorporates availability and cost functions along with the revenue gained per unit operating time was described in Ref. [90]. However, the profit-based approach requires a great deal of information. Although profit based unit commitment has been published [9], profit based preventive maintenance scheduling has rarely been seen in the literature. A framework for a profit based, lifecycle oriented, and unit specific operational optimization for gas turbine based power plant is introduced in Ref. [75], and an implementation of profit based outage planning coupled with generation scheduling is introduced in Ref. [91]. Also in Ref. [91], joint consideration of performance degradation, loss in reliability and market signals is presented. For the unit specific maintenance approach, accurate performance degradation and reliability distribution for each gas turbine power plant is necessary, which requires realistic performance and reliability modeling based on unit operating conditions and maintenance history.

6.6 Problem Formulation

The planning horizon for preventive maintenance is an important issue, since the plant value is directly related to its consumed lifetime. The determination of the planning horizon therefore needs to take into account the high-level plant owner strategies, such as power plant replacement strategy. A desired lifetime is defined here as eight O&M cycles. The problem is to determine the eight optimal preventive intervals $\{T_m\}$, $m = 1, 2, ..., 8$ for this power plant based on the projection of the long term electric power market, power plant performance degradation, and operational risk. For such a decision-making, the tradeoff between risk and reward, i.e., the significance of performance degradation, risk, and spark spread[‡], is very important.

One approach to evaluate the economic performance of the power plant is to calculate the profit rate or cost rate over its entire service life. In this situation, the profit rate or cost rate is calculated by summing up the cumulative profit or maintenance cost over its entire service life (eight O&M cycles), and dividing it by the entire service life of the power plant.

A second approach is to calculate the profit rate or cost rate of maintenance of each O&M cycle separately. This approach allows that the power plant economic performance be evaluated on a shorter-term basis. This approach is employed in this study.

In the integrated framework introduced in Chapter III and IV, the power pant performance, reliability, and market dynamics are considered in an integrated fashion. This method is applicable to different categories of operational optimization problems, and it is employed here for the modeling of power plant operations and maintenance. A brief summary to the method is given in the section below. The key elements that define the power plant profit is the value of power or gross revenue due to the selling of electricity and the cost of electricity, which includes cost of fuel, cost of operations and

[‡] A definition for *spark spread* is the difference between the spot market value of natural gas and the

maintenance (excluding cost of fuel), and depreciation of the power plant investment. The following factors are pertinent to the cost and revenue of power plant operations.

In a market based operation environment, price of electricity and price of fuel are major driving factors for power plant operational planning. In this study, three major external factors are investigated: price of electricity, price of fuel, and ambient temperature. Let t be the calendar time. The price of electricity, $M_p(t)$, price of fuel $F_c(t)$, and ambient temperature, $T_a(t)$, are all functions of calendar time. It is understood that a relatively simplistic dynamic model employed here captures the essential dynamics expressed as daily variance, seasonal trend, and long-term trend.

To evaluate the aging of a gas turbine power plant is an important task for the evaluation of power plant performance and reliability degradation. It is assumed that the system ages only when it is in operation, and it ages as it accumulates its operating hours. The independent starts and hours method is employed here in this study.

Power plant performance (output power rate and heat rate) is a function of power plant design, technology upgrades, operating mode, ambient conditions, and degree of degradation. The actual output rate and heat rate of the power plant must include the effects of the degradation.

Performance degradation is a function of system design and unit usage history, with the latter including both unit operating history and maintenance activities. In this study, performance degradation of the power plant is modeled as a function of its actual operating hours.

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electricity at a given time based on the conversion efficiency of a given gas-fired plant.

The virtual age method is employed to model the effectiveness of maintenance.

Recall the procedure to evaluate the power plant economics introduced in Chapter IV. The key elements that define the power plant profit are the value of power or gross revenue due to the sale of electricity, and the cost of electricity, which includes cost of fuel, cost of operations and maintenance (excluding cost of fuel), and depreciation of the power plant.

Consider an O&M cycle T_m. The expected duration of this O&M cycle $E(T_m)$ is

$$E(T_m) = \int_0^t tf(t)dt + t\int_t^\infty f(t)dt = \int_0^t tf(t)dt + tR(t) \tag{6.1}$$

The expected cost rate of maintenance $E[c_{om}(T_m)]$ for the m^{th} O&M cycle T_m, is therefore given by

$$E[c_{om}(T_m)] = {E[C_{om}(T_m)]} \big/ {E(T_m)} \tag{6.2}$$

Recall the expected profit of a power plant over the stated period of time T:

$$\begin{aligned} E(NR(T)) &= \int_T [P(t) * M_p(t) - F_c(t) * HR(t) * P(t)]dt \\ &- \left[C_{pm}\int_T^\infty f(t)dt + \int_T C_{failure}(t)\cdot f(t)dt + \int_T q(t)dt \right] \end{aligned} \tag{6.3}$$

The expected profit rate for the m^{th} O&M cycle T_m is therefore given by

$$E[nr(T_m)] = {E[NR_{om}(T_m)]} \big/ {E(T_m)} \tag{6.4}$$

For preventive maintenance scheduling in this study, the optimization criteria employed includes both the expected profit rates, which is defined in Equation (6.4), and the expected cost rate of maintenance, which is defined in Equation (6.2), for each O&M cycle.

The formulized profit based sequential preventive maintenance scheduling problem is therefore given below:

Maximize:

$$E[nr(T_m)] = E[NR_{om}(T_m)] / E(T_m) \tag{6.5}$$

By optimizing T_m,

Where $m = 1, 2, ..., 8$.

The formulized cost based sequential preventive maintenance scheduling problem is therefore given below:

Minimize:

$$E[c_{om}(T_m)] = E[C_{om}(T_m)] / E(T_m) \tag{6.6}$$

By optimizing T_m,

Where $m = 1, 2, ..., 8$.

As addressed in Ref. [91], the profit-based approach relies on knowledge about the economic performance of the power plant. However, a projection of the future operating profile is necessary to evaluate power plant output and heat rate, performance degradation and risk assessment; also the projection of future electric power market, such as price of electricity, is also necessary, since these factors are pertinent to the evaluation of power plant gross and net revenues.

Since the time horizon for this sequential preventive maintenance scheduling involves the entire service life of the gas turbine power plant, which is a time period up to even more than a decade or more. For the preventive maintenance scheduling problem involving such a long term period, the variations of the electric power market in a relatively short term timeline, i.e., daily variation, are essentially noise variables, and the detailed modeling of electric power market and weather conditions on daily basis are not necessary. However, models to predict the seasonal and long term trends of the dynamic electric power market is important for effective profit based preventive maintenance scheduling. Therefore, in this study, the daily variations of the electric power market and weather conditions are not taken into account. For simplicity, only the long-term trend of price of electricity and price of fuel are modeled, with the seasonal trend of the electric power market and weather conditions not considered. For the same reason, a uniform future operating profile over the entire service life of the power plant is assumed.

The following assumptions for the sequential preventive maintenance problem are used:

1. The gas turbine power plant is brand new at the beginning of its service
2. The planning horizon is eight operations and maintenance cycles

3. The preventive maintenance actions are performed at a sequence of fixed intervals T_k , and preventive maintenance is imperfect maintenance, as defined previously

4. Corrective maintenance is performed whenever the system fails, and the corrective maintenance is minimal maintenance, as defined previously

5. The duration for preventive maintenance is one month

6. The gas turbine system reliability functions, including hazard rate, probability density function, and reliability, are defined only when it is in operation

7. The gas turbine components and system reliability are Weibull distributions.

6.7 Numerical Results Analysis

6.7.1 Scenario Description

A numerical example is introduced here to demonstrate the feasibility of the proposed approach. In this example, both the profit based sequential preventive approach and the cost based sequential preventive maintenance approach are employed to determine the eight optimal preventive intervals over the entire service life of a base load combined cycle power plant. A base load combined cycle power plant with single gas turbine is investigated. This base load power plant runs 24 hours per day continuously during its normal operation. A uniform future operating profile over the entire service life of the power plant, which is base load, natural gas fuel, and without power augmentation, is assumed.

6.7.2 Preventive Maintenance Scheduling for the First O&M Cycle

A parametric study on the impact of the timing of the preventive maintenance schedule on power plant economic performance over each O&M cycle is performed, by manipulating the maintenance interval for the O&M cycle. The power plant economic performance, which includes expected cost of maintenance, the expected cost of maintenance per unit time, the expected profit and the expected profit per unit time are investigated. The optimal timing of the preventive maintenance schedule is then determined, and the detailed operation for the power plant under this optimal preventive maintenance schedule is illustrated.

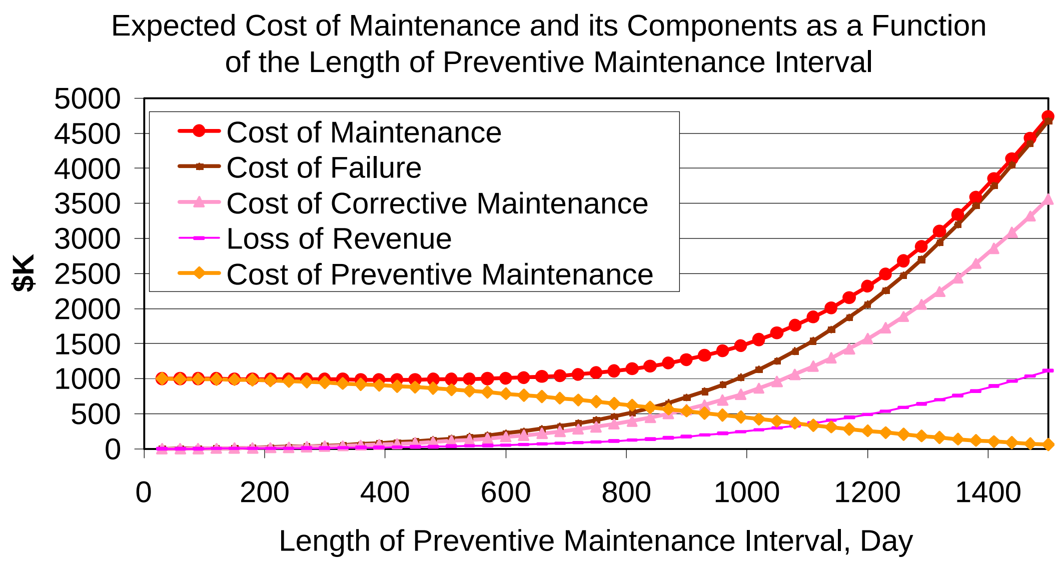

Figure 6.2 Expected Costs of Maintenance and its Components as a Function of the Length of Preventive Maintenance Interval for the First O&M Cycle

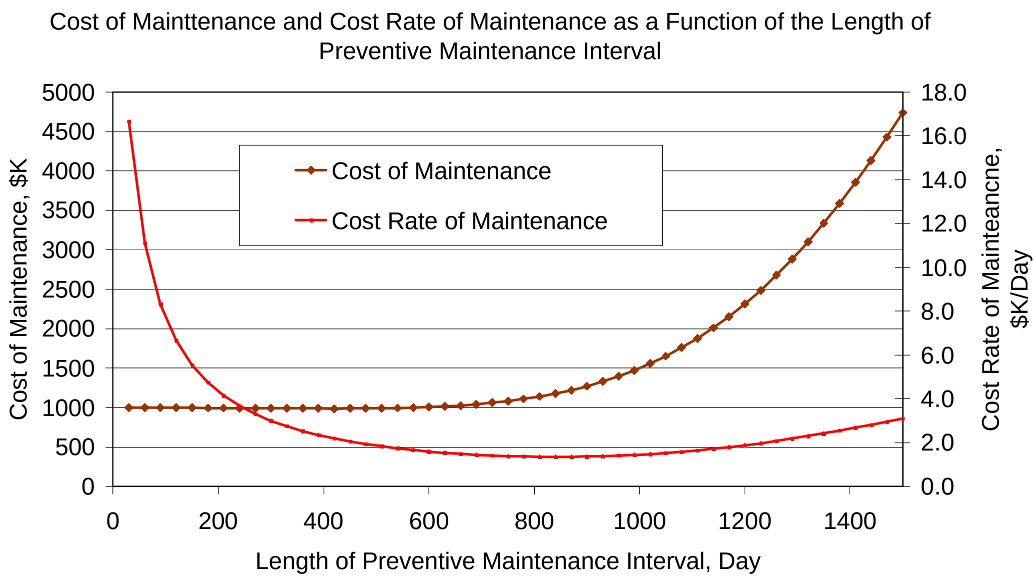

Figure 6.3 Cost of Maintenance and Cost Rate of Maintenance as a Function of the Length of Preventive Maintenance Interval for the First O&M Cycle

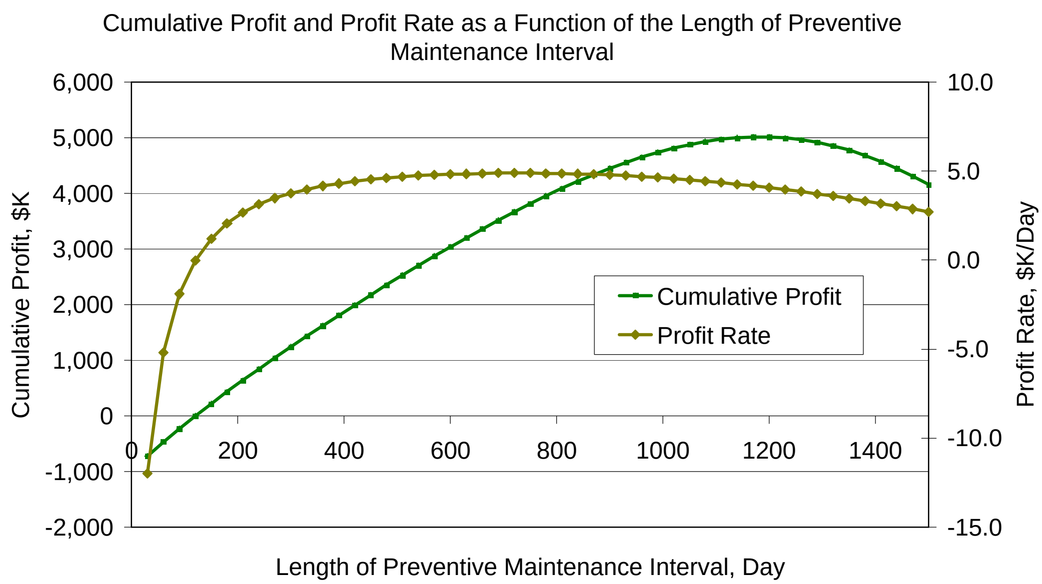

Figure 6.4 Expected Profit and Profit Rate as a Function of the Length of Preventive Maintenance Interval for the First O&M Cycle

The variation of power plant expected cost of maintenance, revenue and profit as functions of the length of the preventive maintenance interval is investigated. The length of the maintenance interval for the first O&M cycle varies from 30 days to 1500 days. The results are shown in Figure 6.2 to Figure 6.4.

It is shown that, the expected cost rate of maintenance is very high when the maintenance interval is very small, say, 30 days. The cost of preventive maintenance dominates the total cost of maintenance, and the relatively short time span results in a high cost rate. As the maintenance interval increases, the expected cost of failure keeps increasing, and the expected cost of preventive maintenance keeps decreasing. As a result, the expected maintenance cost decreases slightly, reaches its minimum, and then climbs up fast as the maintenance interval increases further. The cost rate of maintenance decreases rapidly as the maintenance interval increases, reaches it minimum, and then climbs up. Please note that the optimal maintenance interval for the cost rate of maintenance lags behind that for the total cost of maintenance. The variation of cost rate of maintenance (cost of maintenance per day here) as a function of the length of preventive maintenance interval is shown in Figure 6.3.

It is shown in Figure 6.4 that, the cumulative profit, and the therefore the profit rate (average profit per day) for the operations and maintenance cycle are negative, when the maintenance interval is very small, say, 30 days. The length of operation time period is so small that the revenue collected is less than the cost of operations and maintenance.

As the maintenance interval increases, the expected revenue and cost of operations and maintenance keeps increasing, but the incremental revenue outweighs that of the cost of operation. As a result, the expected profit increases as the maintenance interval increases. It climbs up and reaches its maximum value. As the length of maintenance interval increases further, the incremental cost of operation outweighs the incremental revenue, and the value of cumulative profit goes down. The profit rate follows the seam trend of the cumulative profit, however, the optimal maintenance interval for the profit rate is smaller than that for the cumulative profit.

6.7.3 Sequential Preventive Maintenance Scheduling

The method to optimize the maintenance interval for a single O&M cycle can be used to optimize sequentially the preventive schedules over the entire service life of the power plant. A sequential preventive maintenance optimization, which determines the eight optimal maintenance intervals for the entire service life of the power plant, is then performed.

Profit based sequential preventive maintenance scheduling

A series of eight preventive maintenance actions is scheduled using the profit rate for each O&M cycle as the objective function. The impact of unit age on cost rate and profit rate of each O&M cycle is shown in Figure 6.5. The cost rate increases and the profit rate decrease as the unit ages.

The optimized preventive maintenance schedules are shown in Table 6.1, and the power plant aging, reliability and performance degradation, and cost and profit information under these optimal preventive maintenance schedules are shown in Figure 6.6 to Fig 6.10. The results show that as the power plant ages, the optimal maintenances interval becomes smaller. This is because as the unit becomes “older”, the performance degradation and probability of failure of the power plant become more significant, i.e., the performance loss and the risk increase.

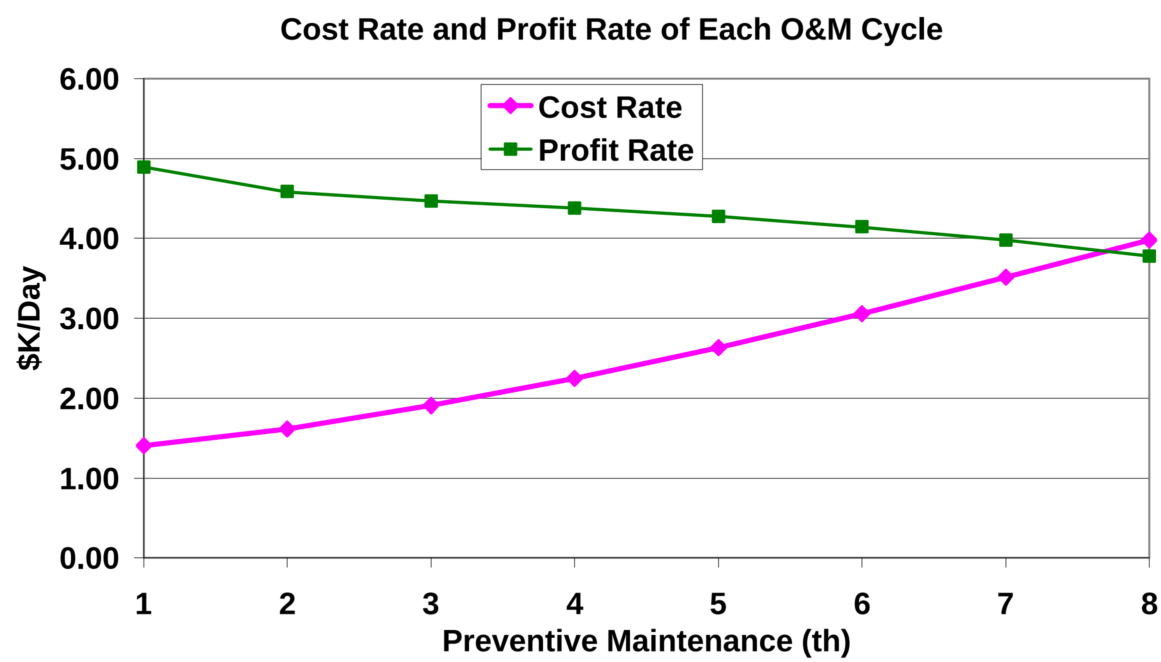

Figure 6.5 Cost Rate and Profit Rate of Each O&M Cycle as Unit Ages

Table 6.1 Results of Profit Based Sequential Preventive Maintenance Scheduling

Preventive Maitenance	Preventive Maintenance Intervals (day)	Date of Scheduled Preventive Maintenance (day)	Cost Rate of Each O&M ($K/day)	Profit Rate of Each O&M ($K/day)
1st	729	729	1.41	4.89
2nd	692	1451	1.61	4.58
3rd	622	2103	1.91	4.46
4th	552	2685	2.25	4.38
5th	490	3205	2.63	4.28
6th	438	3673	3.06	4.14
7th	393	4096	3.51	3.98
8th	353	4479	3.98	3.78

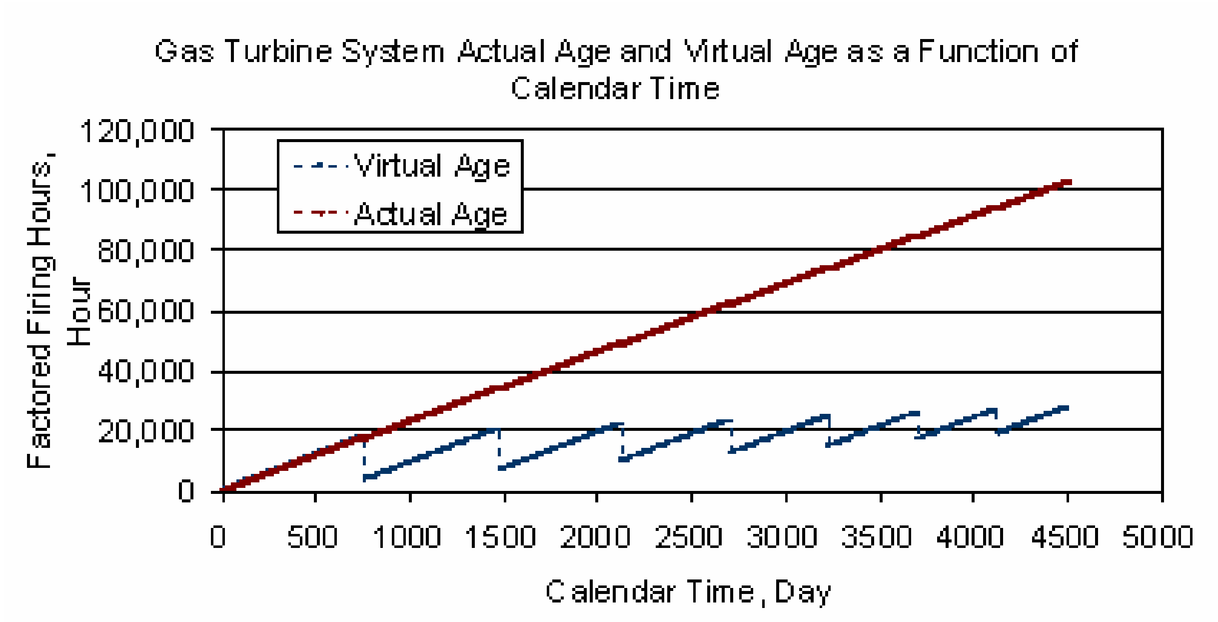

Figure 6.6 Gas Turbine System Actual Age and Virtual Age for the Sequential Preventive Maintenance Schedule

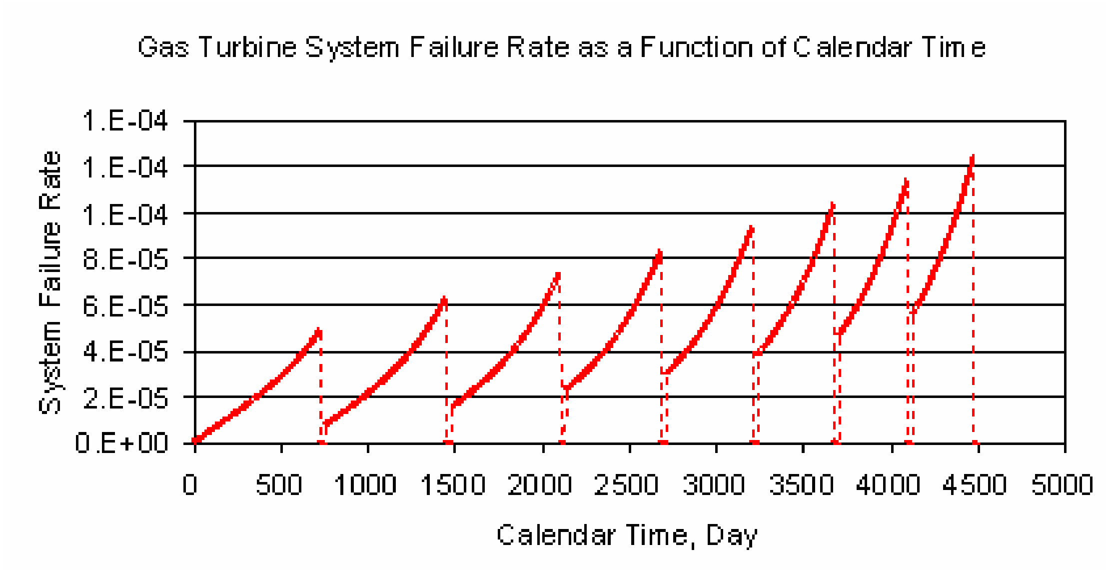

Figure 6.7 Gas Turbine System Failure Rate for the Sequential Preventive Maintenance Schedule

The actual age and virtual age of the gas turbine power plant in factored fired hours are shown in Figure 6.6, and the failure rate of the gas turbine as a function of calendar time is shown in Figure 6.7. The performance degradation as a function of calendar time is shown in Figure 6.8. These figures show that the gas turbine power plant is an aging system. The preventive maintenance is imperfect in that each preventive maintenance action partially reduces the age of the gas turbine. Therefore the reliability and performance degradation are partially restored whenever a preventive maintenance is performed.

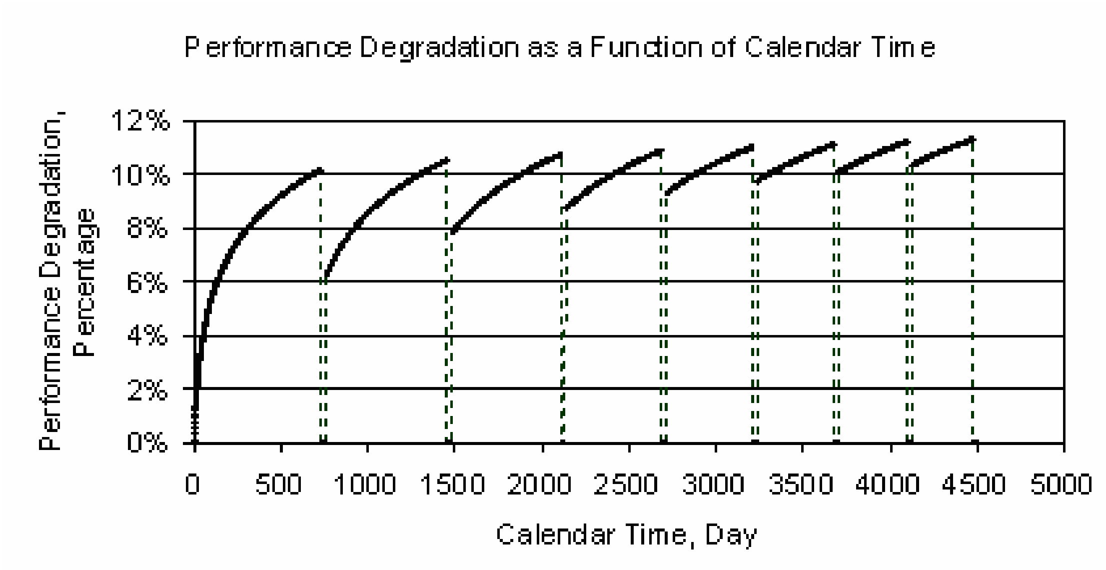

Figure 6.8 Power Plant Performance Degradation for the Sequential Preventive Maintenance Schedule

The cumulative cost of maintenance and its components, which include the cost of preventive maintenance, the loss of revenue due to unavailability of the plant, the cost of corrective maintenance to repair plant, and the cost of failure of the damage due to failure, are shown in Figure 6.9. It is shown that the cost of preventive maintenance and therefore the cost of maintenance jump whenever a scheduled preventive maintenance is performed.

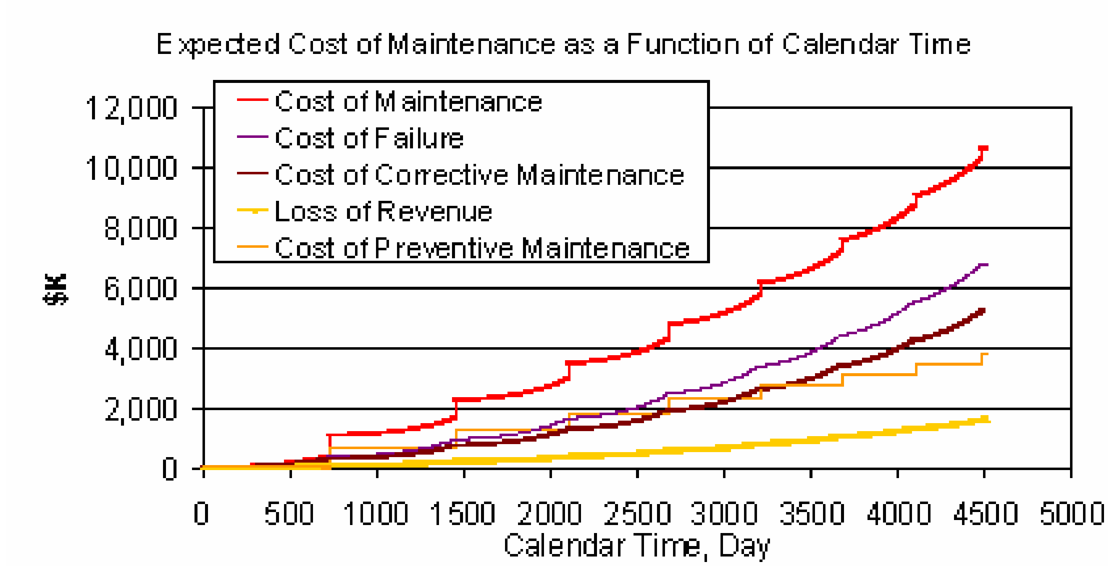

Figure 6.9 Power Plant Expected Cost of Maintenance and its Components for the Sequential Preventive Maintenance Schedule

The cumulative cash flow of the power plant, which includes the cost of maintenance, revenue, cumulative spark spread, profit, and depreciation, are shown in Figure 6.10.

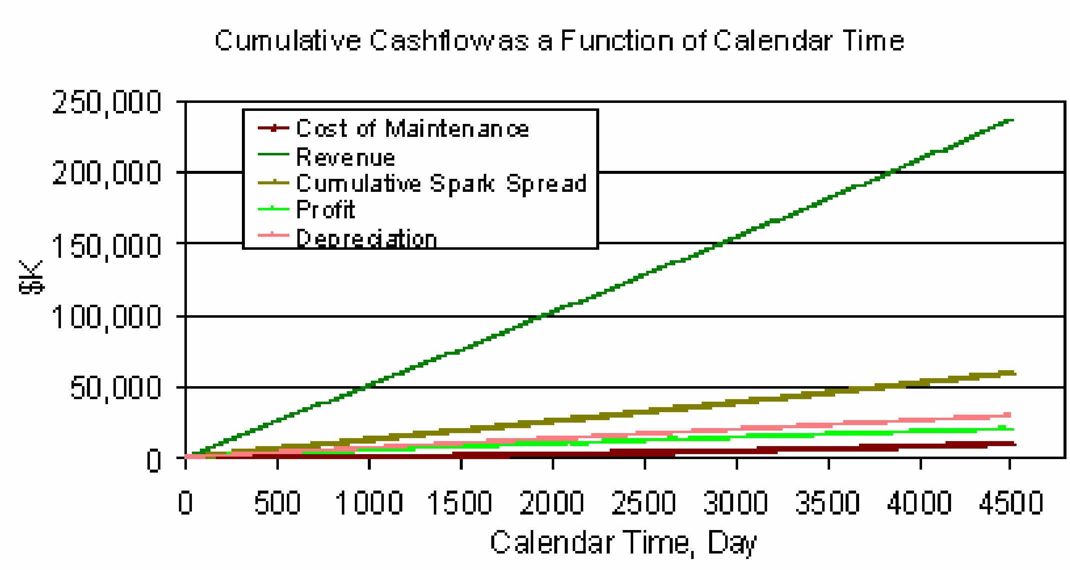

Figure 6.10 Power Plant Cumulative Cash Flow for the Sequential Preventive Maintenance Schedule

<u>Cost based sequential preventive maintenance scheduling</u>

A cost based sequential preventive maintenance scheduling is also performed, and the expected cost rates of maintenance for each O&M cycle is used as the objective function. The optimized preventive maintenance schedules are shown in Table 6.2.

Table 6.2 Results of Cost Based Sequential Preventive Maintenance Scheduling

Preventive Maintenance	Preventive Maintenance Intervals (day)	Date of Scheduled Preventive Maintenance (day)	Cost Rate of Each O&M ($K/day)	Profit Rate of Each O&M ($K/day)
1	842	842	1.35	4.84
2	713	1585	1.65	4.55
3	609	2224	1.97	4.44
4	523	2777	2.32	4.35
5	455	3262	2.70	4.24
6	399	3691	3.10	4.10
7	351	4072	3.51	3.94
8	313	4415	3.91	3.75

The periodic preventive maintenance scheduling

To develop a benchmark for the sequential preventive maintenance approach, a periodic preventive maintenance scheduling is performed. In this example, the following assumptions are made for the periodic preventive maintenance scheduling:

- The length of the time frame is the same as that of the sequential preventive maintenance scheduling, i.e., 5409 days.
- Eight preventive maintenance actions are equally distributed, with the maintenance interval 534 days.
- Imperfect maintenance is assumed, with the restoration factor as 0.8.

A summary for periodic preventive maintenance schedule is given in Table 6.3.

Table 6.3 Results of Periodic Preventive Maintenance Scheduling

Preventive Maintenance	Preventive Maintenance Intervals (day)	Date of Scheduled Preventive Maintenance (day)	Cost Rate of Each O&M ($K/day)	Profit Rate of Each O&M ($K/day)
1st	534	564	1.76	4.73
2nd	534	1128	1.80	4.47
3rd	534	1692	1.88	4.42
4th	534	2256	2.03	4.42
5th	534	2820	2.31	4.38
6th	534	3384	2.75	4.25
7th	534	3948	3.40	3.97
8th	534	4512	4.28	3.52

A summary of the results of preventive maintenance scheduling using the 3 different maintenance scheduling approaches is shown in Table 6.4. In this example, the overall profit rate of the profit based sequential approach is slightly high than that of the cost based sequential approach, which is in turn higher than the traditional periodic approach.

Table 6.4 Comparison of Periodic, Cost Based Sequential, and Profit Based Sequential Preventive Maintenance Scheduling

	Periodic Approach			**Cost Based Sequential Approach**			**Profit Based Sequential Approach**		
Preventive Maitenance	Profit Rate ($K/day)	Cost Rate ($K/day)	Cumulative Profit ($K)	Profit Rate ($K/day)	Cost Rate ($K/day)	Cumulative Profit ($K)	Profit Rate ($K/day)	Cost Rate ($K/day)	Cumulative Profit ($K)
1	4.73	1.76	2669.6	4.84	1.35	4224.8	4.89	1.41	3712.4
2	4.47	1.80	5192.0	4.55	1.65	7605.8	4.58	1.61	7021.5
3	4.42	1.88	7687.2	4.44	1.97	10444.0	4.46	1.91	9932.6
4	4.42	2.03	10180.3	4.35	2.32	12849.8	4.38	2.25	12480.3
5	4.38	2.31	12652.7	4.24	2.70	14906.9	4.28	2.63	14703.6
6	4.25	2.75	15051.1	4.10	3.10	16667.7	4.14	3.06	16642.4
7	3.97	3.40	17292.9	3.94	3.51	18167.9	3.98	3.51	18324.1
8	3.52	4.28	19277.9	3.75	3.91	19455.3	3.78	3.98	19771.3
Overall Profit Rate	4.273 $K/day			4.377 $K/day			4.385 $K/day		

Please note that the seasonal trends of the price of electricity, price of fuel, and weather conditions are not taken into account in the example introduced above, and a uniform future operating profile is assumed in this example. In actuality, however, the seasonal variations of the market signals are important factors, and the operating profile of the gas turbine power plant does change along the time line due to the dynamic electric power market.

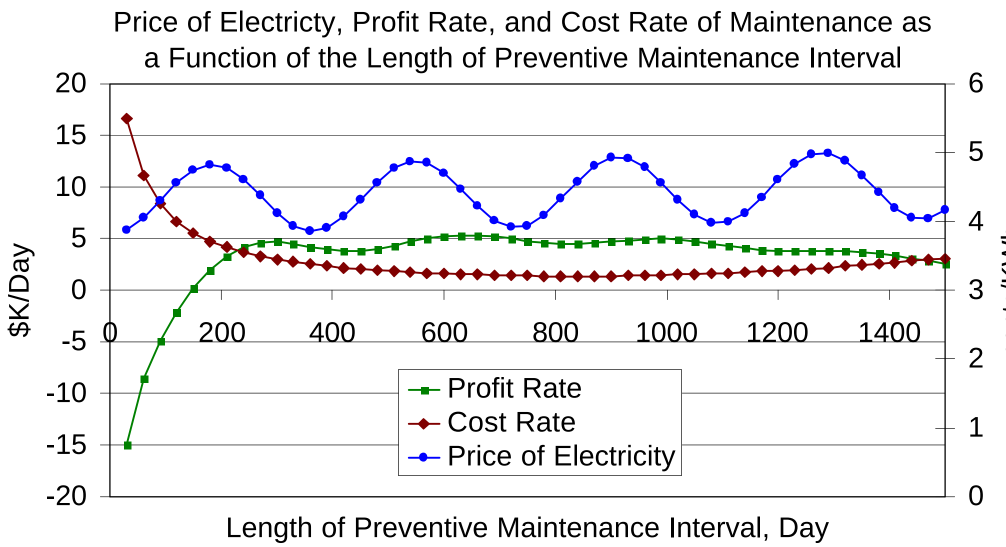

Figure 6.11 The Price of Electricity, Profit Rate, and Cost Rate of Maintenance (With Consideration of the Seasonal Trend of the Price of Electricity)

To illustrate the impact of seasonal trends of the dynamic electric power market, the expected profit per day as a function of preventive maintenance interval with consideration of seasonal trend of price of electricity is created and is shown in Figure 6.11. In this example, the price of electricity is assumed to be of a seasonal trend, and the price of electricity is higher in the summer than in the spring, fall and winter, due to high power demand in the summer. The results clearly show that the impact of the price of electricity on the profit rate of the power plant. The seasonal trend of price of electricity does affect the revenue profile and therefore the profit rate. This is different from the profit rate distribution shown in Figure 6.4. A more complicated pattern of profit rate distribution is expected if the variation of future operating profile is taken into account.

The mechanism of this effect is complicated. A full consideration of the dynamic electric power market, and hence the varying future operating profile, is therefore needed for more effective preventive maintenance scheduling. A profit based methodology for gas turbine power plant outage planning is developed to meet this need [91], and outage planning and long term generation scheduling is performed in a coupled fashion.

6.8 Summary

In this chapter, a novel approach for gas turbine based power plant maintenance scheduling is introduced, and a profit based sequential preventive maintenance scheduling is developed for more effective maintenance scheduling. A numerical example for the profit based sequential preventive maintenance scheduling is introduced. The procedure is implemented using a base load combined cycle power plant with single gas turbine and the results demonstrate the feasibility of the proposed approach. Sequential preventive maintenance planning is performed for the gas turbine power plant with eight operations and maintenance cycles over its entire service life. The objective function for optimization is the profit rate or cost rate for each O&M cycle. The results show decreasing maintenance intervals as the power plant ages. By implication, new equipment should be more reliable with lower maintenance costs.

With the use of the profit based sequential preventive maintenance scheduling, the power plant maintenance decisions depend not only on the maintenance cost, but also on the plant performance and the dynamic electric power market. Using this profit based sequential approach instead of the traditional cost based periodic preventive maintenance approach, it is expected that the cost of operations and maintenance be reduced, and the power plant profit be increased.

It is understood that, in reality, many more factors are involved in the power plant maintenance scheduling, and the problem is much more complicated than the one addressed in this study. However, even this relatively simple example demonstrates the importance of not previously modeled effects for gas turbine power plant sequential preventive maintenance scheduling. A more sophisticated method can be developed using the methodology presented in this study for preventive maintenance scheduling for heavy-duty gas turbine power plant. With the implementation of these methods, improved profitability for gas turbine power plant systems is expected.

CHAPTER 7

GAS TURBINE POWER PLANT UPGRADE PACKAGES EVALUATION AND SELECTION

7.1 Power Plant Upgrades Evaluation and Selection Problem

An important issue for power plant optimization is the evaluation and selection of the power plant upgrade packages. A benefit analysis for each upgrade package combination is required for upgrade packages selection optimization, and a classic procedure to perform this type of analysis follows [29]:

1. Develop power plant performance and reliability models

2. Perform model validation and calibration test

3. For a given power plant configuration and combination of upgrade packages, perform economics analysis

4. Analyze the system level economic metrics of the power plant

Step 3 and step 4 of the above procedure are performed for each case of an upgrade scenario. In actuality, there may be numerous technology upgrade packages available, and the power plant operator may consider infusing a combination of them to obtain the maximum benefit. If this is the case, an efficient and accurate method to identify the best combination of upgrade packages is extremely helpful.

It is recognized that there is uncertainty connected with the implementation of technology and/or new ideas of any kind. For an existing power plant, uncertainty primarily concerns the day-to-day operation, but with new engine models, uncertainty expands to include the power plant design itself. To be effective, modern analysis techniques must include probabilistic methods that address all unknown factors and apply a probability distribution to all estimates.

In reality, a pool of technology options for power plant upgrades is usually available, and the complexity of the problem increases with the number of the available technology options. An upgrades selection problem with 10 upgrades options would require 2^{10} evaluations, and an upgrades selection problem with 20 upgrades options would require 2^{20} evaluations. To evaluate each of these options is computationally prohibitive.

In this study, there is a set of 10 upgrade packages available for operational power plants. The purpose of this study is to identify the optimal combination of upgrade packages that has the highest long-term payback to the power plant operator and equipment/services provider. To achieve this goal, a computational efficient methodology must be employed.

7.2 Technology Identification, Evaluation, and Selection Method

Methodologies that provide the decision maker with an ability to easily assess and trade-off the impact of various technologies in the early phases of design have been well established in the literature. The Technology Identification, Evaluation, and Selection (TIES) method provides a comprehensive, structured, and robust methodology for decision making in the early phase of design [92][93]. The TIES methodology has been successfully applied to numerous applications for conceptual level decision-making with regard to technology infusion. The applications of the TIES methodology for technology selection in the conceptual level of design can be found in References [94][95] [96]. The key framework and techniques described in these references are applicable to the selection of upgrade packages for gas turbine based power plants.

TIES is a method for selecting technologies. The method identifies a need, develops a physics-based meta-model to represent technologies, evaluates technology concepts, and selects those concepts that are the most beneficial to a given set of design objectives. The fundamental premise of TIES is that the impact of all technologies can be quantified in terms of a small number of key parameters—“technology metrics” or figures of merits. By quantifying a technology in terms of these technology metrics and the relationships among them, the impact of each technology can be evaluated without the need to create an explicit model of the technology. Instead, the incremental delta in the technology metric is determined and then reviewed. Probabilistic methods are included to address unknown factors, and a probability distribution is applied to all estimates [95].

For each particular power plant, Response Surface Equations (RSEs) are created to evaluate power plant performance as functions of technology upgrades, operating mode, ambient conditions, and degradation. These performance RSEs are the meta-models of the system, and they allow the fast evaluation of gas turbine performance with sufficient accuracy.

Although initially TIES was developed for system level design analysis, its framework and techniques provide a good basis for efficient evaluation of upgrade selection for operational power plant systems. In this study a framework for power plant upgrades evaluation and selection using the TIES methodology is introduced and applied.

7.2.1 Probabilistic Analysis Method

Due to the inherent uncertainty of future electric power market and operational conditions, the evaluation of the long-term economic performance of power plant is necessarily probabilistic in nature. For example, the profitability of gas turbine based power plants depends heavily on the price of fuel. A multiple-year (say, 15 years) forecast of fuel price is necessary to perform upgrades selection effectively, but to achieve such a forecast with high accuracy is almost impossible [97]. Thus, uncertainty essentially plays an important role in the decision-making of power plant upgrades selection.

On a long term basis, the presence of uncertainty in the price of fuel, value of power, and system reliability results in an inability to predict the exact operating profile, and therefore the inability to predict the exact long term economic performance of the power plant. The price of fuel, price of electricity, and ambient conditions are noise variables in the power plant operations modeling, and they are inherently random phenomenon. This suggests that the power plant economic performance subject to uncertainty cannot be expressed as a single, deterministic solution. A probabilistic analysis method is therefore needed.

In this study, the major sources of uncertainties include the following:

- Ambient conditions
- Cost of Fuel
- Value of Power
- Degradation
- Operating Modes
- Reliability

Mavris and his co-workers has developed a robust design and simulation methodology for conceptual level system design optimization [98], and it provides an efficient evaluation approach for conceptual level design concept selection. The basic framework of this methodology is used throughout this study.

For probabilistic analyses, a Monte Carlo Simulation coupled with the response surface method is employed. A Monte Carlo Simulation is a commonly used technique to simulate uncertainty by randomly generating values in a specified range. It is effectively a random number generator that creates values for each noise variable within specified ranges and with a frequency proportional to the shape of distribution associated with each noise variable. Probability distributions are defined for parameters that are considered uncertain, and cumulative distribution functions are obtained for desired objectives. The accuracy of Monte Carlo Simulation increases as the number of simulations increases. A Monte Carlo Simulation can be performed using Crystal Ball with Microsoft Excel [99].

7.2.2 Design of Experiments and Response Surface Method

Design of Experiments (DoE) techniques and the response surface method (RSM) are employed for efficient computation of power plant performance. For each particular power plant, Response Surface Equations (RSEs) are created to evaluate power plant performance as functions of technology upgrades, operating modes, ambient conditions, and degradation. The performance RSEs allow fast evaluation of gas turbine performance with sufficient accuracy.

“The response surface methodology compromises a group of statistical techniques for empirical modeling building and model exploitation. By careful design and careful analysis of the experiments, it seeks to relate a response, or output variable, to a number of predictors, or input variables, that affect it.” [100] The resulting are the response surface equations, and they provide a significant insight to a previously unknown or complicated response behavior in an efficient manner [101].

RSM is a multivariate regression technique developed to model the response of a complex system using a simplified equation. Regression data are obtained intelligently through the DoE techniques, and RSM is based on these techniques to give the maximum power for a given amount of experimental effort. Typically, the response is modeled using a second-order quadratic equation of the form:

$$R = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i=1}^{k-1} \sum_{j=i+1}^{k} b_{ij} x_i x_j + e \qquad (7.1)$$

Where,

R is the response of interests

b_0 is the interception term.

b_i are regression coefficients for the first-degree terms

b_{ii} are coefficients for the pure quadratic terms

b_{ij} are the coefficients for the cross-product terms

x_i : main effect of independent variables

x_i^2 : quadratic effect of independent variables

$x_i x_j$: second order interaction of independent variables

e : error associated with second order approximation

Since the response is in a polynomial form, the response surface equations can be used in lieu of more sophisticated, time consuming computations to predict and optimize the response.

7.2.3 Upgrade Packages Selection Methods

The decision making of upgrade packages selection problem sometimes involves multiple objectives. For example, a successful contractual agreement will be one that maximizes the profitability of both the power plant operator and equipment/services provider. Optimizing only the profitability of power plant usually leads to sub-optimal solution to the equipment/services provider. Several decision-making techniques can be employed for the selection of optimal set of upgrade packages. These techniques are described below.

TOPSIS

TOPSIS is the abbreviation of the Technique for Order Preference by Similarity to Ideal Solution. It is a simple and easy to implement, multi-attribute decision-making technique. The key concept of TOPSIS is that the best alternative amongst a finite set should have the shortest Euclidean distance to the ideal solution, and farthest to the negative-ideal solution [101]. TOPSIS results in a ranking of best alternatives.

Technology Pareto Frontier

Power plant upgrade packages selection is essential a combinatorial optimization problem, which involves combinations of alternatives. The objective is to select an optimal combination of upgrade packages, subject to certain constraints.

A Pareto Frontier represents the range of optimal solutions achievable with a given set of upgrade alternatives [95]. The Pareto Frontier technique does not need explicit objective weightings, which are required for the TOPSIS technique. In addition, the "Pareto Front goes beyond a simple technology ranking by showing how the set of optimal technologies changes with shifting objectives".

Genetic Algorithm

As the number of the available upgrades packages increases, the size of the combination problem can be enormous. This is the so-called "curse of dimensionality". Assuming that all upgrade packages are compatible, the size of the combinatorial optimization problem is 2^n. If the number of available upgrade packages is 10, there are $2^{10} = 1024$ combinations of upgrade packages. The computational expense is acceptable if the evaluation of each combination of upgrade packages is efficient enough, for example, using response surface equations. However, if the number of available upgrade packages reaches 30 or more, the computational cost even with meta-models is not acceptable to evaluate all of the possible combinations.

Roth [96], etc, Kirby and Mavris [102] have shown that the Genetic Algorithm is an efficient means to solve this type of combinatorial optimization problem. The Genetic algorithm is based on the theory of evolution. It begins with a set of random set of seeds, and each seed is evaluated based on a given fitness function. Through generations of reproduction and mutation, it will converge to a population which best satisfies the specified objective function. The Genetic Algorithm used with in the TIES method are "an extremely effective means" to identify the most promising set of technologies subject to constraints. It allows the user to visualize the technology frontier, and intuitively make decisions. The technology impact to system level metrics or figures of merit is represented using response surface equations.

7.3 Modeling of Impact of Upgrade Packages on Performance and Reliability

The infusion of power plant upgrade packages may affect both the plant performance and reliability. Therefore, methods to analyze the impact of upgrade packages on both power plant performance and reliability are essential for the evaluation of the economics of upgrade packages. However, the mechanisms that are used to compute the effect of upgrade packages and maintenance on performance and reliability are modeled with different approaches.

Upgrade is the introduction of a new or enhanced version of a hardware or software product designed to replace an older version of that same product. Upgrade is usually a new design using advanced technology, and it will change the lifespan of the item. Therefore, the characteristics inherent to the item do change.

In contrast, maintenance actions do not change the design life of an item, and therefore the characteristic inherent to the item does not change. This suggests that the reliability distribution of the item will remain the same. However, the maintenance action may change the status (age) of the item, i.e., it may restore the performance and reliability of the item. Maintenance is therefore an improvement of the equipment status.

In this study, the impact of upgrade packages on power plant performance is analyzed using technology impact factors. This is introduced in section 7.5.

On the modeling of the reliability impact of upgrades packages, two different mechanisms are considered:

(1) The infusion of upgrade packages improves the design life span or repair lifespan, which will result in the changes of maintenance intervals. This is the scenario when the upgrade packages are specifically designed to improve power plant reliability.

(2) The infusion of upgrade packages improves plant performance. However, the introduction of the upgrade packages still affects component reliability. For example, the introduction of a certain brush seal will reduce the leakage in compressors or turbine stages. This leads to the improvement of compressor or turbine efficiency.

The infusion of upgrade packages may also change the operating condition of a component, which will affect the degradation rate of the power plant. For example, the infusion of certain upgrade may change the geometry of the flow path, which results in a change in the firing temperature. Firing temperature is the highest temperature reached in the entire thermal cycle of the gas turbine, and it is an important parameter to assess the degradation of components subject to hot gas. A quantitative relationship between firing temperature and maintenance factors can be developed. The unit aging can therefore be modeled using the maintenance factors, which is introduced in Chapter III. In so doing, the impact of upgrade on reliability can be evaluated.

Assume the reliability distribution is Weibull distribution, and the reliability is given as:

$$h = h(b, h, t) \tag{7.2}$$

The parameters b and h are characteristics of the design, and t is the cumulative age of the item, which is a representation of the status of the item. The change in the shape parameter b and the scale parameter h are provided by the equipment provider. The cumulative age t is evaluated using the method introduced in section 3.3.

7.4 The Baseline Combined Cycle Power Plant

A power plant can be either a simple cycle gas turbine engine or it can be a combined cycle with a gas turbine engine, heat recovery steam generator and steam turbine included in the complete plant. In this study, the baseline power plant is a generic combined cycle gas turbine based power plant, and the gas turbine engine is a current-technology heavy-duty gas turbine engine. A representation of the combined cycle model using program GateCycle is given in Figure 7.1.

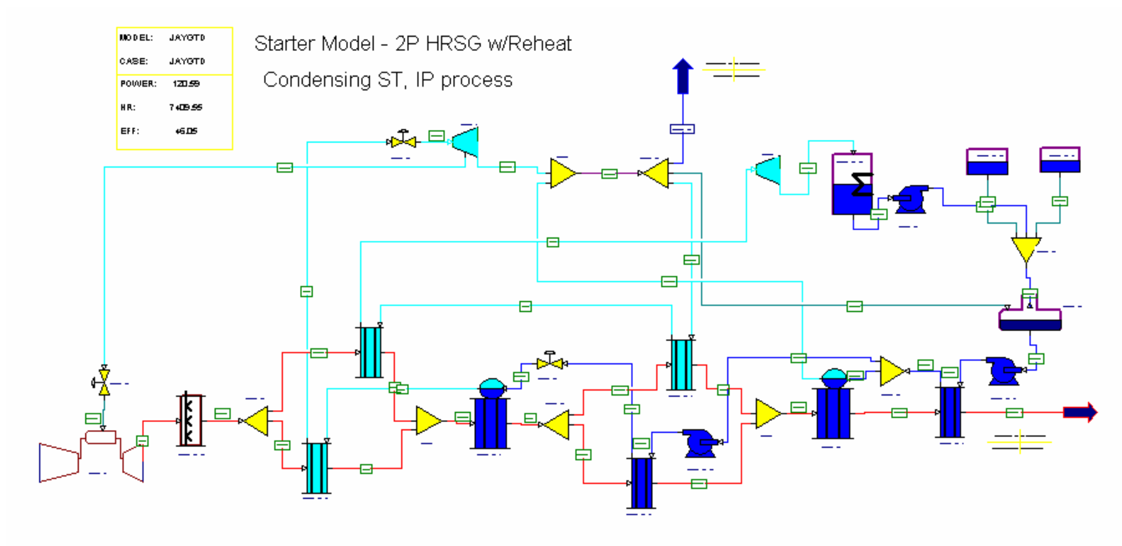

Figure 7.1 The Combined Cycle Power Plant

Two parameters are used to evaluate the power plant performance, the power output rate and heat rate. Heat rate is a measure of the quantity of heat in Btu/hr required to produce a Kilowatt of power, and thus a reduction in heat rate is desirable.

The equipment/services provider provides not only power plant equipment, but also operations and maintenance services through a long-term services agreement with power plant operators. To achieve a win-win strategy, an appreciation of the economics of both the power plant operators and the equipment providers is required.

The revenue to the equipment provider includes the revenue resulting from the operations and maintenance services that are provided to the power plant operator, and the revenue from selling the upgrade packages to the power plant operator.

In this study, the gross revenue to the power plant operator is the result of selling electricity. Net revenue is the gross revenue minus operating costs, which include the following components:

- Cost of fuel
- Cost of operations and maintenance
- Cost of upgrade packages
- Cost of power plant capital requirement

The time frame considered here is eight operations and maintenance cycles.

7.5 Creation of a United Forecasting Environment

Plant Performance Meta-modeling

Operational optimization requires the efficient evaluation of power plant performance, because numerous evaluations are required. Thus, a performance evaluation using physics based models is extremely computationally expensive for optimization purposes, and meta-models, such as response surfaces equations, are therefore very helpful for power plant operational optimization.

The response surface method requires that the design space under investigation must be homogeneous using either continuous or discrete variables. For this reason, for each specific design of power plant running under a specific operating mode, a response surface equation for plant operation is created as a function of ambient conditions, technology impact factors, and degradation. The performance RSEs are created as a function of operating profile, ambient conditions, and unit degradation coefficients.

Table 7.1 Power Plant Operating Parameters

Level	Load Setting	Power Augmentation	Fuel Type
0	Base Load	Steam Injection On	Natural Gas
1	Peak Load	Steam Injection Off	Distillate fuel

In this study, three parameters that define the operating mode are investigated, and they are load setting, steam injection setting, and fuel type. There are two discrete levels of load setting, base load and peak load; two discrete levels of steam injection, on and off; and two types of fuel, natural gas and distillate fuel. The operating mode of the power plant is designated as O, where O is a vector $O = O(o_1, o_2, o_3)$, and o_1 is the index for load setting, o_2 the index for power augmentation, o_3 the index for type of fuel. An example of the operating parameters under investigation in this study is given in Table 7.1, and the corresponding operating modes are given in Table 7.2.

As a result, eight operating modes O_i, $i = 1, 2, ...8$ are defined, and they are shown in Table. 7.2.

Table 7.2 Operating Modes for Gas Turbine Power Plant

Oeprting Modes	Load Setting	Steam Injection	Fuel Type
1	Base	Off	Natural Gas
2	Base	On	Natural Gas
3	Peak	Off	Natural Gas
4	Peak	On	Natural Gas
5	Base	Off	Distillate
6	Base	On	Distillate
7	Peak	Off	Distillate
8	Peak	On	Distillate

Response surface equations for the power plant performance evaluation are created for each of these operating modes.

Identify Critical Parameters

Power plant operational optimization requires an efficient evaluation of power plant performance. This requires performance meta-models to evaluate the plant performance when the power plant is running under various operating conditions. Further more, power plant degradation and technology status also affects plant performance. As a result, the following critical parameters are identified:

- Ambient conditions, including ambient temperature, ambient pressure, and relative humidity

- Degradation factors, including compressor flow rate coefficient, compressor efficiency coefficient, and turbine efficiency coefficient

- Gas turbine technology parameters

The ranges for these critical parameters associated with power plant performance are shown in Table 7.3.

<u>RSE generation</u>

A gas turbine performance model is employed to perform the gas turbine performance analysis. The system level performance of gas turbine is generated based on the parameters shown in Table 7.3. For a combined cycle power plant, these gas turbine performance data are then fed into as input a combined cycle performance analysis code, and the performance data for the combined cycle power plant is therefore calculated. The analysis process flow is shown in Figure 7.2.

Table 7.3 Critical Parameters for Performance Meta-modeling

Variable	Description	Units	Min	Norminal	Max
x1	Ambient Temperature	F	-1.7000E+01	4.5000E+01	1.0700E+02
x2	Ambient Pressure	inHg	2.9002E+01	2.9851E+01	3.0700E+01
x3	Humidity	Kgw/Kga	1.0000E-03	1.2500E-02	2.4000E-02
x4	Degradation Factor 01	N/A	8.9411E-01	9.2680E-01	9.5950E-01
x5	Degradation Factor 02	N/A	9.6342E-01	9.6451E-01	9.6560E-01
x6	Degradation Factor 03	N/A	9.8410E-01	1.0005E+00	1.0168E+00
x7	Technology Factor k1	N/A	1.0768E+00	1.0768E+00	1.0768E+00
x8	Technology Factor k2	N/A	1.0096E+00	1.0096E+00	1.0096E+00
x9	Technology Factor k3	N/A	2.6862E-02	2.7631E-02	2.8400E-02
x10	Technology Factor k4	N/A	3.0891E-02	4.5053E-02	5.9215E-02
x11	Technology Factor k5	N/A	5.6530E-01	5.9003E-01	6.1477E-01
x12	Technology Factor k6	N/A	6.8165E-01	7.8888E-01	8.9611E-01
x13	Technology Factor k7	N/A	2.5740E-01	2.5740E-01	2.5740E-01
x14	Technology Factor k8	N/A	1.0380E-01	1.9355E-01	2.8331E-01
x15	Technology Factor k9	N/A	1.0047E+00	1.0217E+00	1.0387E+00
x16	Technology Factor k10	N/A	1.0230E+00	1.0288E+00	1.0347E+00
x17	Technology Factor k11	N/A	1.0006E+00	1.0075E+00	1.0145E+00
x18	Technology Factor k12	N/A	9.7182E-01	9.8703E-01	1.0022E+00
x19	Technology Factor k13	N/A	1.0019E+00	1.0112E+00	1.0205E+00
x20	Technology Factor k14	N/A	1.0124E+00	1.0182E+00	1.0240E+00

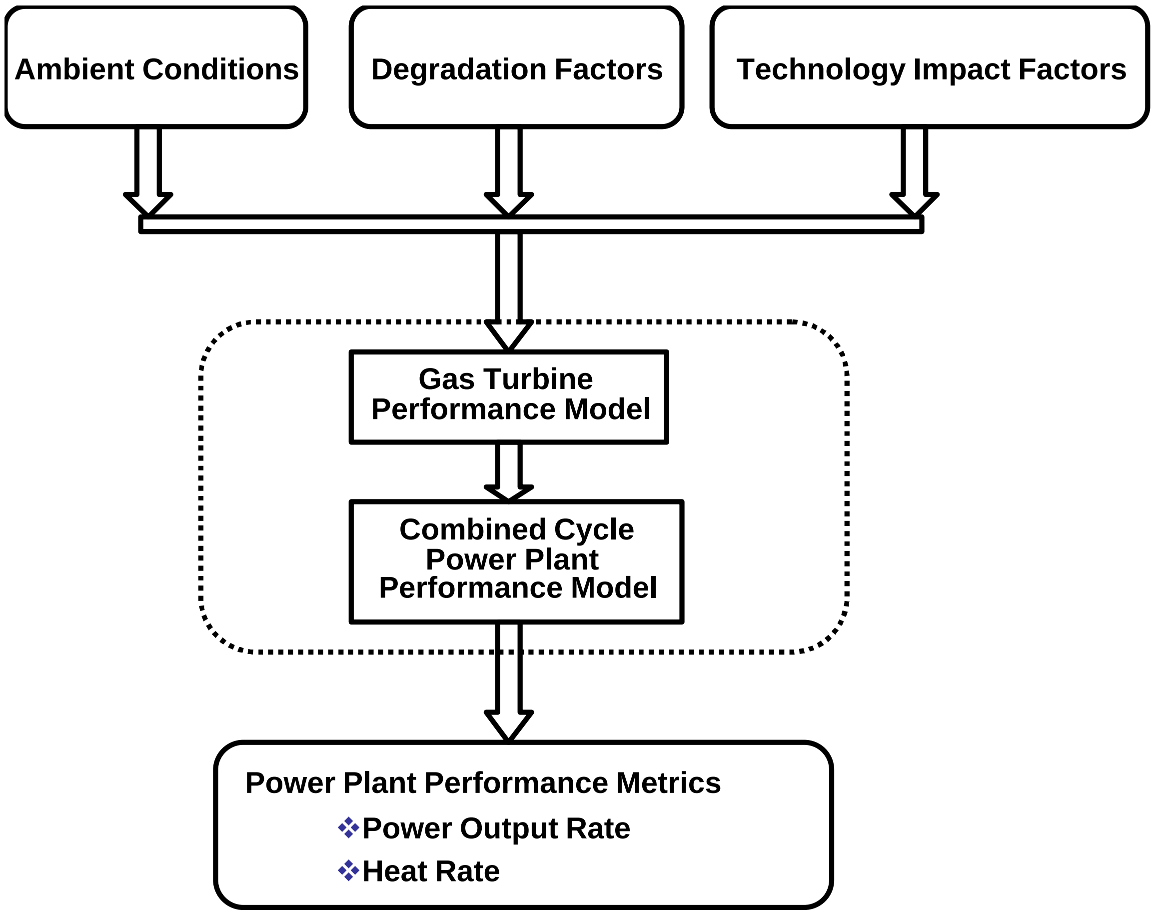

Figure 7.2 Analysis Procedure to Generate Response Surface Equations for Performance Evaluation

The ranges of the gas turbine technology metrics are first established based on empirical data or test data. The responses equations, which link the input parameters defined in Table 7.3 and the power plant performance metrics, are then created using a design of experiment approach. The equations for power plant system level responses are listed below:

$$P = P(x_1, x_2, x_3, ..., x_{20}) \tag{7.3}$$

$$HR = HR(x_1, x_2, x_3, ..., x_{20}) \tag{7.4}$$

Once the ranges of the critical parameters are identified, the Design of Experiment can be set up and the response surface equation can be generated. This is done using the statistical software package JMP [103]. In this study, 20 critical design variables are identified, and a customized design of experiment with 257 cases is generated. These 257 cases are executed using the combined cycle power plant performance model, and the responses (power plant performance metrics) of output rate and heat rate are obtained. A response surface equation for each of these two responses is generated. Prediction profilers for these two responses are shown in Figure 7.3. This prediction profiler provides a united tradeoff environment for power plant performance evaluation as a function of ambient conditions, degradation, and technology.

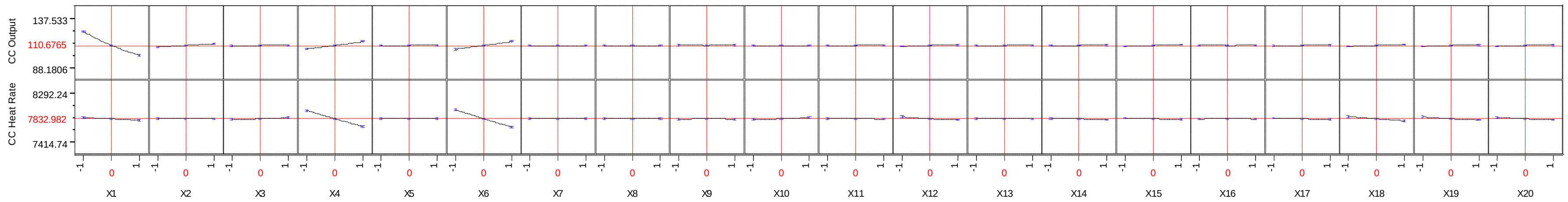

Figure 7.3 Prediction Profilers for Power Plant Output Rate and Heat Rate

RSE verification

A summary of fit analysis using the R^2 parameter is performed to ensure that the accuracy of the response surface equations is acceptable. R^2 estimates the proportion of the variation in the response around the mean that can be attributed to terms in the model rather than to random error. In this example, the values of R^2 for power output rate and heat rate are 1.0. This suggests a very good model fit for both parameters. The actual versus predicted plots for power output rate and heat rate are shown in Figure 7.4. Good accuracy and over the full range of power and heat rate is demonstrated.

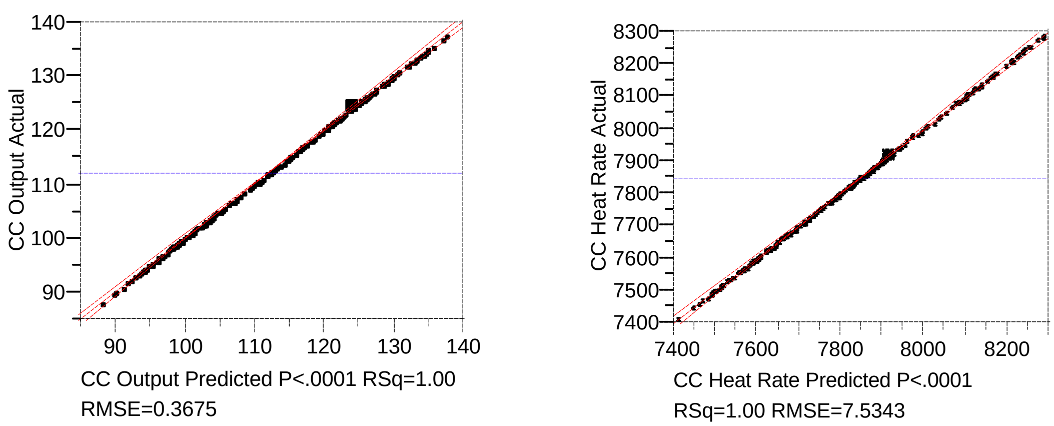

Figure 7.4 Response Surface Equations Accuracy Determination---Performance

Power Plant Long Term Economics Forecasting Environment

The evaluation of power plant economics is much more complicated than for the performance evaluation. In this study, for each combination of upgrade packages, a sequential preventive maintenance schedule is established to evaluate the optimal economic performance of the plant with each upgrade package. The development of this schedule is therefore a sub-problem for the upgrade selection problem. The optimal economics performance for each combination of upgrade packages is then used to perform a deterministic and probabilistic economics analysis. The methodology for sequential preventive maintenance scheduling is introduced in Chapter VI.

Power plant economics model

One element in the evaluation of power generation economics is to evaluate cost of electricity. The cost of electricity addresses only the cost side of the power plant. Another approach is to evaluate the expected profit of the power plant. The power plant economics model developed in Chapter III uses this approach, and it can be used here to evaluate the economic performance of power plant with given upgrades combinations.

Recall the evaluation of power plant economics introduced in Chapter III. The key elements that define the power plant profit are the value of power or gross revenue due to the sale of electricity, and the cost of electricity, which includes cost of fuel, cost of operations and maintenance (excluding cost of fuel), and depreciation of the power plant.

The expected profit of a power plant over the stated period of time T is therefore given by:

$$\begin{aligned} E(NR(T)) &= \int_T \left[P(t) * M_p(t) - F_c(t) * HR(t) * P(t)\right] dt \\ &- \left[C_{pm} \int_T^{\infty} f(t)dt + \int_T C_{failure}(t) \cdot f(t)dt + \int_T q(t)dt\right] \end{aligned} \tag{7.5}$$

The depreciation for the entire service life in the profit equation is the capital cost of the combine cycle power plant, which includes the total capital requirement of the power plant and the cost of power plant upgrade packages. The total depreciation during the entire services life is outlined below:

- Cost of gas turbine
- Cost of steam turbine
- Cost of balance of plant, which includes electric generators, sub-system equipment, engineering construction services, plant startup and commissioning
- Other cost including construction interests and owners cost
- Cost of upgrade packages

In this study, the cost of upgrade packages is the only variable parameter that is under investigation. The capital cost of the total power plant excluding the cost of upgrade packages is fixed.

<u>Identify Critical Parameters</u>

The dynamics of the electric power market has a strong impact on the economic performance of power plant. The price of fuel and price of electricity are stochastic in nature, and they are critical parameters for an economic analysis. It is recognized that it is not possible to have accurate long term forecasting for price of fuel and price of electricity. It is therefore more reasonable to model these parameters in a probabilistic fashion.

The following 25 parameters given in Table 7.4 are identified as critical, and they include ambient conditions, price of fuel, price of electricity, technology impact factors, and the lifespan of several major components. The values of ambient conditions, price of fuel, and price of electricity, are estimated based on historic data.

As introduced in section 4.2, the price of electricity is modeled using long term, seasonal, and daily trends with random effects applied. In the upgrade selection problem, the time horizon involved in is measured in decades. For this reason, the price signals, such as price of fuel and price of electricity, are estimated using average values, and only the long-term trend is modeled, with the seasonal, daily, and random effects neglected.

RSE generation

The power plant economics model introduced in section chapter IV is employed to perform the gas turbine power plant economic analysis. The system level economic metrics are generated based on the input defined in Table 7.4. The analysis process flow is shown in Figure 7.5.

Table 7.4 Nominal Values and Ranges for Critical Parameters of Economics Analysis

Variable	Description	Units	Min	Norminal	Max
x1	Price of Fuel	$/MBTU	3.5000E+00	4.0000E+00	4.5000E+00
x2	Price fo Electricity	Cents/KWh	5.0000E+00	6.0000E+00	7.0000E+00
x3	Ambient Temperature	F	-1.7000E+01	4.5000E+01	1.0700E+02
x4	Ambient Pressure	inHg	2.9002E+01	2.9851E+01	3.0700E+01
x5	Humidity	Kgw/Kga	1.0000E-03	1.2500E-02	2.4000E-02
x6	Degradation Factor 01	N/A	8.9411E-01	9.2680E-01	9.5950E-01
x7	Degradation Factor 02	N/A	9.6342E-01	9.6451E-01	9.6560E-01
x8	Degradation Factor 03	N/A	9.8410E-01	1.0005E+00	1.0168E+00
x9	Technology Factor k1	N/A	1.0768E+00	1.0768E+00	1.0768E+00
x10	Technology Factor k2	N/A	1.0096E+00	1.0096E+00	1.0096E+00
x11	Technology Factor k3	N/A	2.6862E-02	2.7631E-02	2.8400E-02
x12	Technology Factor k4	N/A	3.0891E-02	4.5053E-02	5.9215E-02
x13	Technology Factor k5	N/A	5.6530E-01	5.9003E-01	6.1477E-01
x14	Technology Factor k6	N/A	6.8165E-01	7.8888E-01	8.9611E-01
x15	Technology Factor k7	N/A	2.5740E-01	2.5740E-01	2.5740E-01
x16	Technology Factor k8	N/A	1.0380E-01	1.9355E-01	2.8331E-01
x17	Technology Factor k9	N/A	1.0047E+00	1.0217E+00	1.0387E+00
x18	Technology Factor k10	N/A	1.0230E+00	1.0288E+00	1.0347E+00
x19	Technology Factor k11	N/A	1.0006E+00	1.0075E+00	1.0145E+00
x20	Technology Factor k12	N/A	9.7182E-01	9.8703E-01	1.0022E+00
x21	Technology Factor k13	N/A	1.0019E+00	1.0112E+00	1.0205E+00
x22	Technology Factor k14	N/A	1.0124E+00	1.0182E+00	1.0240E+00
x23	Part 1 Design Life	Hour	1.0000E+05	1.5000E+05	2.0000E+05
x24	Part 2 Design Life	Hour	1.0000E+05	1.5000E+05	2.0000E+05
x25	Part 3 Design Life	Hour	1.0000E+05	1.5000E+05	2.0000E+05

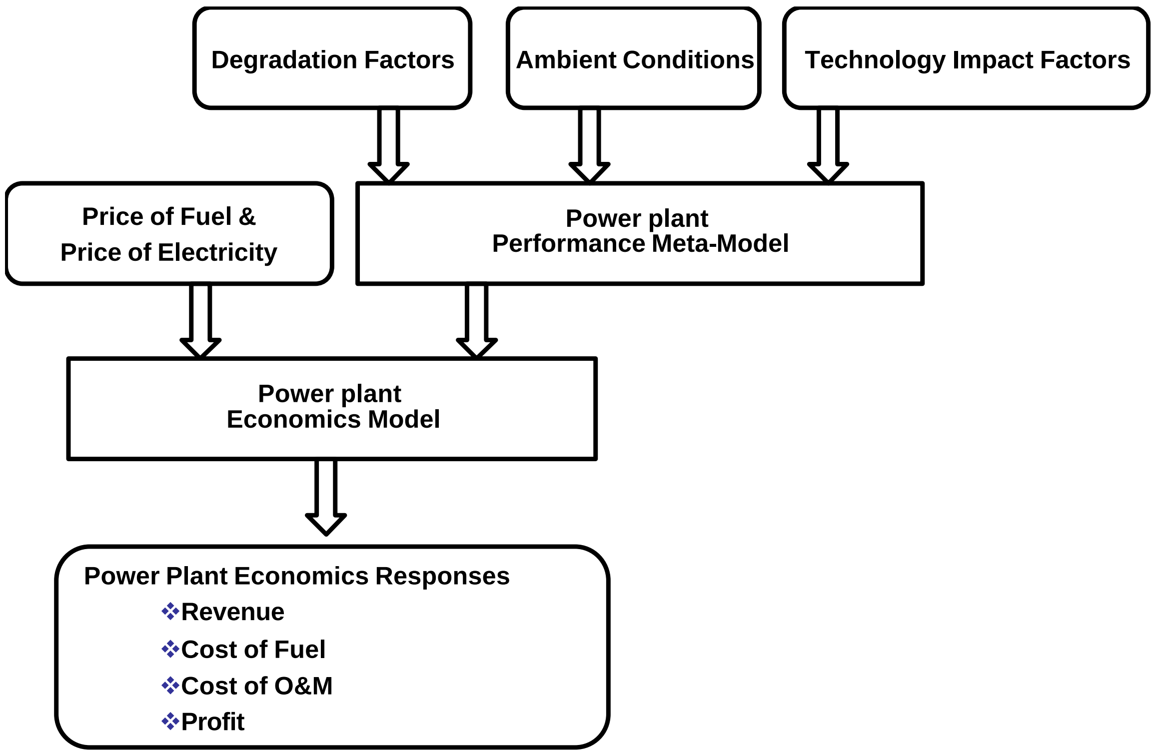

Figure 7.5 Analysis Process Flow for Power Plant Economics

Once the ranges of the critical parameters are identified, the Design of Experiment can be set up and the response surface equation can be generated. This is done using the statistical software package JMP [103]. For the 25 critical design variables given in Table 7.4, a design of experiment with 513 cases is generated. These 513 cases are executed using the power plant sequential preventive maintenance scheduling approach. The optimal economics performance for each case is then obtained, with the responses of power plant revenue, fuel cost, cost of O&M, and profit. A response surface equation for each of these responses is generated. Prediction profilers for these three responses are shown in Figure 7.6. These prediction profilers provide a united tradeoff environment for power plant economic performance evaluation as a function of market signals, ambient conditions, degradation, and technology. The actual versus predicted plots for power plant economics metrics are shown in Figure 7.7. The results suggest good model fit for all of the four economics metrics.

The ranges of the gas turbine technology metrics are first established based on empirical data or test data. Response equations that link the gas turbine technology metrics and the power plant system level responses are then created using a design of experiment approach. The equations for power plant system level responses are listed below:

$$\mathrm{Re}\,venue = f_1(x_1, x_2, x_3, ..., x_{25})$$

$$Fuel\,\cos t = f_2(x_1, x_2, x_3, ..., x_{25})$$

$$O\,\&\,M\;\; price = f_3(x_1, x_2, x_3, ..., x_{25})$$

$$O\,\&\,M\;\; Cost = f_4(x_1, x_2, x_3, ..., x_{25})$$

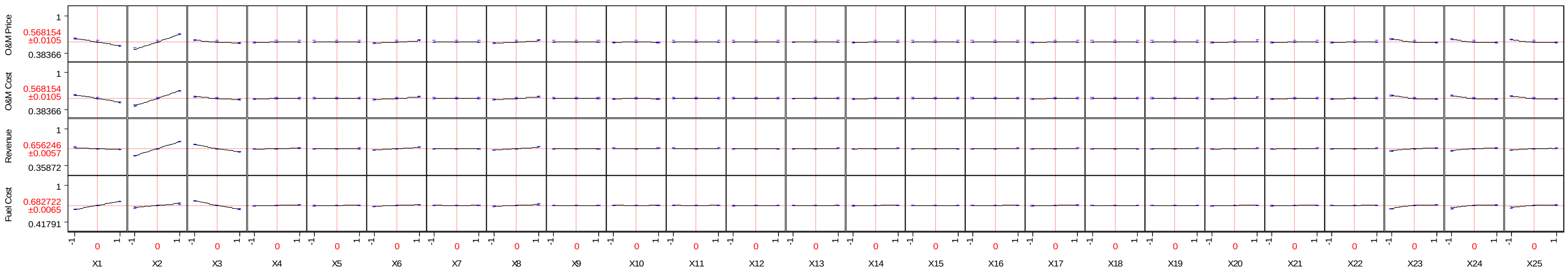

Figure 7.6 Prediction Profilers for Power Plant Economics Evaluation (Normalized)

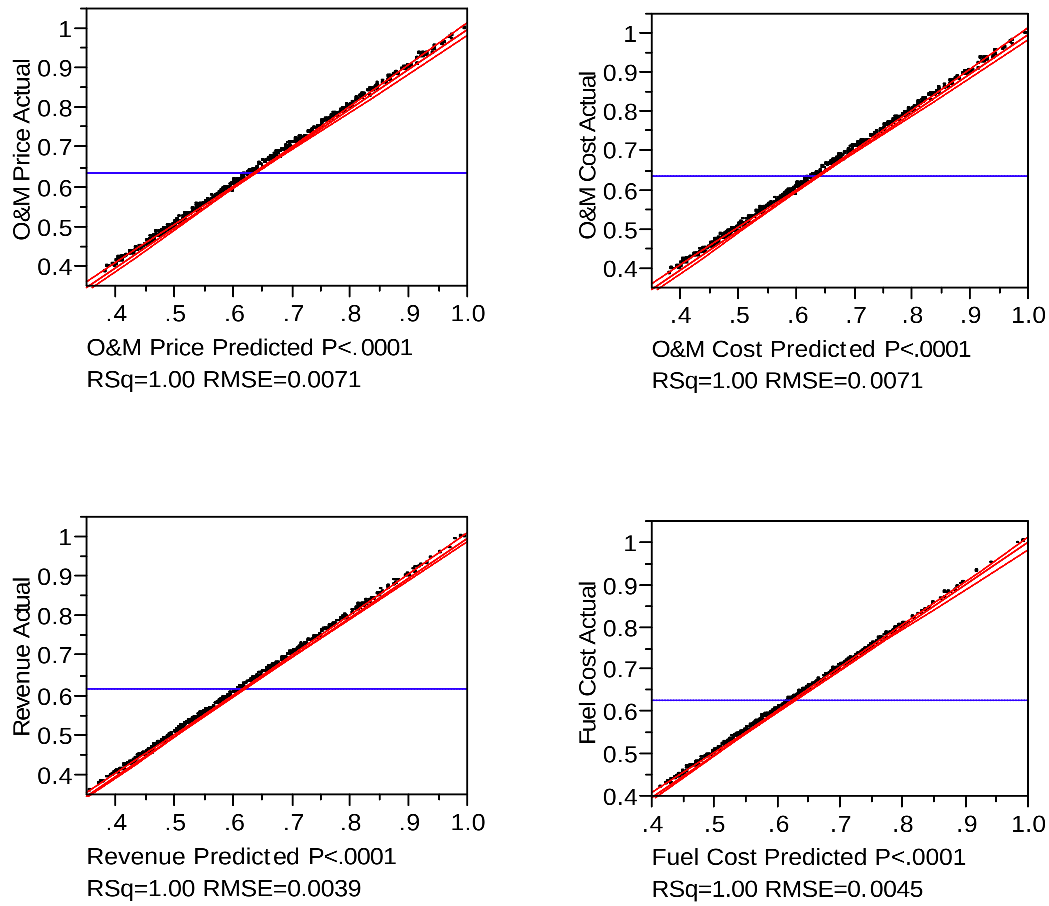

Figure 7.7 Response Surface Equations Accuracy Determination---Economics

7.6 Power Plant Upgrade Packages Alternatives

There are a series of gas turbine classes and for each gas turbine class there is a pool of potential upgrade alternatives, which are designed to improve the performance or reliability of the gas turbines. A pool of upgrades with 10 options is identified and they are shown in Table 7.5. The cost of the upgrades packages is a component of the depreciation that has been defined in Equation (7.5).

Table 7.5 Power Plant Upgrades Packages

Upgrade Packages	Description
t1	Upgrade 1
t2	Upgrade 2
t3	Upgrade 3
t4	Upgrade 4
t5	Upgrade 5
t6	Upgrade 6
t7	Upgrade 7
t8	Upgrade 8
t9	Upgrade 9
t10	Upgrade 10

A set of upgrade packages can therefore be represented as a technology vector T, and here $T = T(t_1, t_2, t_3, ..., t_{10})$.

Where $t_i = \begin{cases} 1, & if\ upgrade\ t_i\ is\ used \\ -1, & if\ upgrade\ t_i\ is\ not\ used \end{cases}$

7.6.1 Upgrades Compatibility Matrix

There are a variety of interrelationships that can exist between upgrade packages. Several technology interrelationships are introduced by Roth and his coworkers [96]. They include independent, enabling, two-way inclusivity, and two-way exclusivity.

Let c_{ij} be the interrelationship between two upgrade packages t_i and t_j. For this study they are defined below:

$$c_{ij} = \begin{cases} 1, \; if \; t_i \; and \; t_j \; are \, independent \\ 0, if \; t_i \; and \; t_j \; are \, two - way \; exclusive \\ -1, if \; the \, use \, of \; t_i \; requires \, the \, use \, of \; t_j \end{cases}$$

Therefore the interrelationship between upgrade packages can be represented as a matrix, with each element defining an interrelationship between two upgrade packages.

In this study, all the upgrade packages are assumed to be independent with two exceptions: t_2 and t_9 are two-way exclusive, and upgrade package t_3 is an enabling technology package that allows the use of upgrade packages t_8 and t_{10}. The upgrades compatibility matrix is shown in Table 7.6.

Table 7.6 Upgrade Packages Impact Matrix

		t1	*t2*	*t3*	*t4*	*t5*	*t6*	*t7*	*t8*	*t9*	*t10*
	Upgrade Packages Compatibility Matrix	Upgrade 1	Upgrade 2	Upgrade 3	Upgrade 4	Upgrade 5	Upgrade 6	Upgrade 7	Upgrade 8	Upgrade 9	Upgrade 10
t1	Upgrade 1	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
t2	Upgrade 2	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**
t3	Upgrade 3	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**-1**	**1**	**-1**
t4	Upgrade 4	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
t5	Upgrade 5	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
t6	Upgrade 6	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
t7	Upgrade 7	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
t8	Upgrade 8	**1**	**1**	**-1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
t9	Upgrade 9	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
t10	Upgrade 10	**1**	**1**	**-1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**

7.6.2 Upgrade Impact Matrix

The impact of each upgrade package on power plant performance is quantified in terms of a multiplier that measures the impact on plant performance. The impact is usually based on an expert opinion or through a test. Let $k_{i,j}$ be the impact of upgrade package i on technology impact factor j. A representation of matrix of power plant upgrade impact is shown in Table 7.7. There are 10 upgrade options t_j listed on the top of the matrix, and 14 engine parameters, k_j, which are used in the prediction of engine performance. For example, the application of upgrade package t_1 will increase the value of technology impact factor k_3 by 5.73 percent.

Table 7.7 Power Plant Upgrades Technology Impact Metrics

		t1	*t2*	*t3*	*t4*	*t5*	*t6*	*t7*	*t8*	*t9*	*t10*
	Upgrade Impact Factor Vector	Upgrade 1	Upgrade 2	Upgrade 3	Upgrade 4	Upgrade 5	Upgrade 6	Upgrade 7	Upgrade 8	Upgrade 9	Upgrade 10
k1	Technology Factor k1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
k2	Technology Factor k2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
k3	Technology Factor k3	1.0573	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
k4	Technology Factor k4	1.0000	1.0000	0.8932	0.8753	1.0000	1.0000	0.8094	0.8699	1.0000	0.9478
k5	Technology Factor k5	1.0875	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
k6	Technology Factor k6	1.0000	1.0000	0.9614	0.9542	1.0000	1.0000	1.0400	1.1392	1.0000	0.9823
k7	Technology Factor k7	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
k8	Technology Factor k8	1.0000	1.0000	1.1233	1.1330	1.0000	1.0000	1.0000	0.4663	1.0000	1.0000
k9	Technology Factor k9	1.0000	0.9938	1.0108	1.0013	1.0000	1.0000	1.0004	1.0000	1.0147	1.0000
k10	Technology Factor k10	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9889	1.0000	0.9998	1.0000
k11	Technology Factor k11	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.9867	1.0000	0.9995	1.0000
k12	Technology Factor k12	0.9914	1.0084	1.0000	1.0022	1.0000	1.0000	1.0020	1.0000	0.9919	1.0015
k13	Technology Factor k13	1.0000	1.0000	1.0029	1.0000	1.0088	1.0000	1.0028	1.0039	1.0001	1.0000
k14	Technology Factor k14	1.0000	1.0000	1.0000	1.0000	1.0000	1.0030	1.0083	1.0000	1.0002	1.0000

For a given single upgrade package or combination of upgrade packages, a set of technology impact factors is defined, and this set forms a technology impact vector. With the technology impact vector as input, the long-term economic performance metrics can therefore be calculated using the response surfaces equations.

The technology impact vector $\vec{K}$ associated with a given set of N upgrade packages T can therefore be given by

$$\vec{K} = \left(k_1, k_2, k_3, ..., k_M\right)$$

Where the technology impact factor k_i is given by

$$k_i = \prod_{j=1}^{N} k_{ji} \ , \qquad i = 1, ,2, 3, \ldots, M \tag{7.6}$$

7.7 Upgrades Evaluation and Selection Based on Plant Performance

7.7.1 Deterministic Performance Evaluation

For simplicity, the following assumptions are made for the deterministic performance evaluation:

- The power plant is brand new and in clean condition
- The power plant is evaluated with ISO standard day conditions, with ambient temperature 59F, ambient pressure 14.7 PSI, and relative humidity 0.6
- The power plant is operating in base load condition without power augmentation

<u>Technology sensitivities analysis</u>

The sensitivity analysis for combined cycle power plant performance is shown in Figures 7.8-7.9.

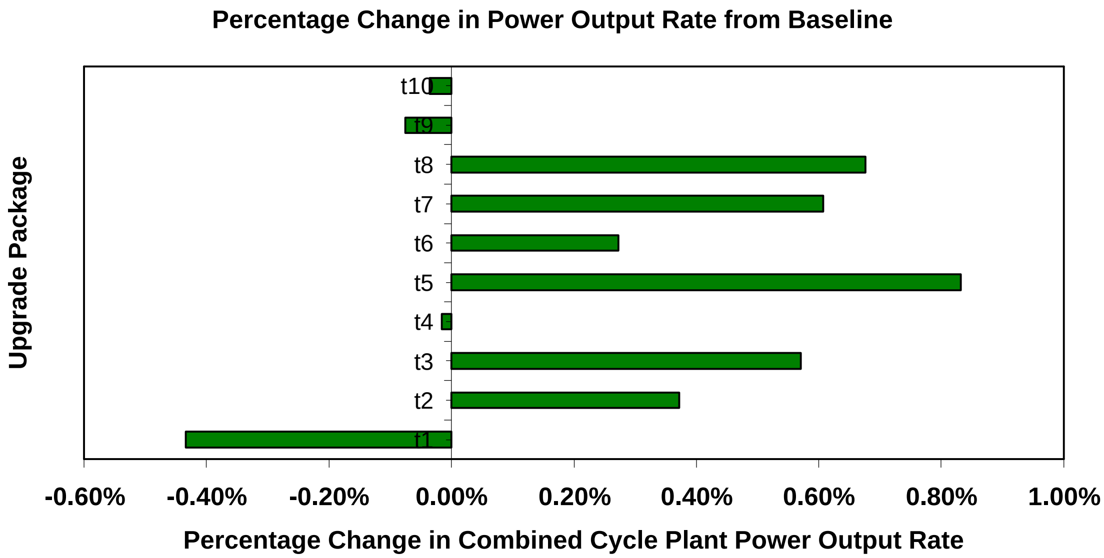

Figure 7.8 Percentage Change in Combined Cycle Power Plant Output Rate Measured from the Baseline

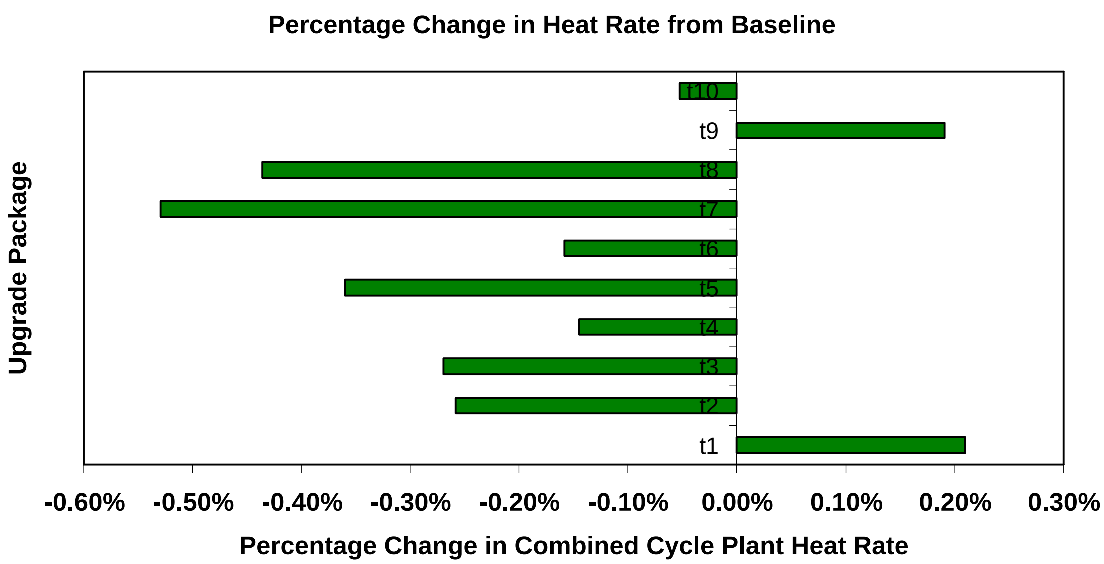

Figure 7.9 Percentage Change in Combined Cycle Power Plant Heat Rate Measured from the Baseline

Please note that the introduction of technology t5 results in highest increase in output rate, while the introduction of t7 results in the highest decrease in heat rate.

A Pareto Frontier for power plant performance without consideration of uncertainty is shown in Figure 7.10. Decisions can be made which concern power output rate and heat rate simultaneously. From the performance point of view, the ideal solution is to keep the output rate as high as possible and heat rate as low as possible. Each dot shown in Figure 7.10 represents a combination of upgrade packages. The red ones are those that are not compatible, and the green ones are those that are compatible combinations. The top solutions based on performance are those in the green circle.

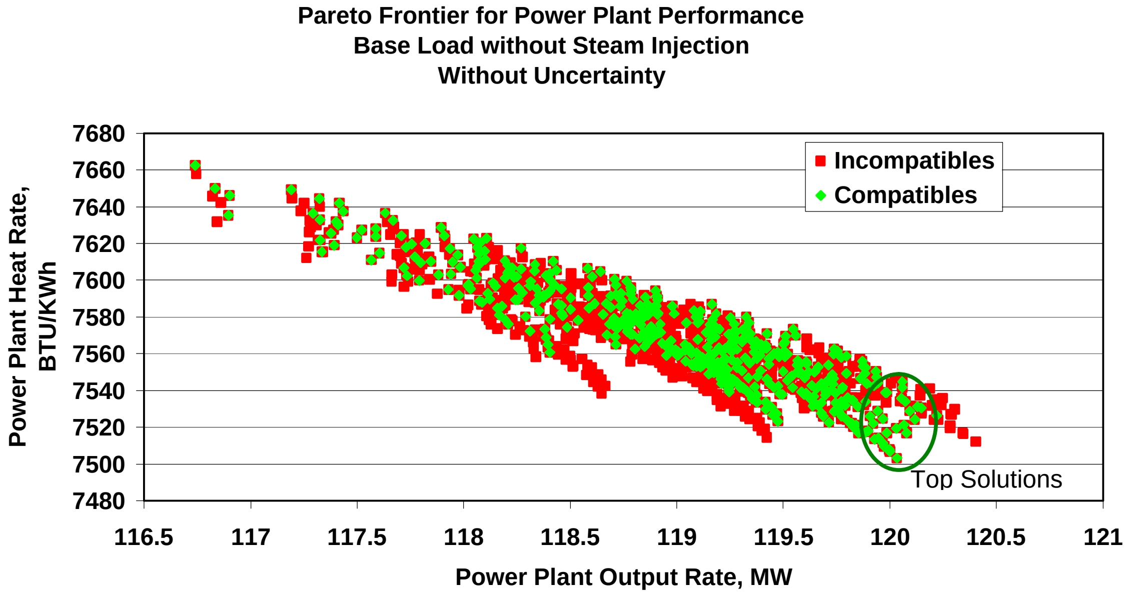

Figure 7.10   Pareto Front for Power Plant Upgrade Packages Selection

7.7.2 Probabilistic Performance Evaluation

The following assumptions are made for the deterministic performance evaluation:

- The power plant is brand new and clean condition
- The power plant is operating in base load condition without power augmentation

The uncertainty investigated here includes the variation of ambient conditions, and performance degradation. The ranges for these parameters are given in Table 7.8.

Table 7.8 Ranges for Ambient Conditions and Degradation Parameters

Variable	Units	Min	Norminal	Max
Ambient Temperature	F	17	62	107
Ambient Pressure	inHg	30	30	31
Humidity	Kgw/Kga	0.00	0.50	1.00
Degradation Factor 01	N/A	0.8941	0.9268	0.9595
Degradation Factor 02	N/A	0.9634	0.9645	0.9656
Degradation Factor 03	N/A	0.9841	1.0005	1.0168

A probabilistic analysis is performed for each compatible combination of upgrade packages, and cumulative distribution functions (CDFs) are generated for power output rate and heat rate. As an example, the CDFs for the power output rate of the baseline and the top combination of upgrade packages based on a deterministic evaluation are shown in 7.11, and the CDFs for the heat rate of the baseline and the top combination of upgrade packages again based on a deterministic evaluation are shown in Figure 7.12.

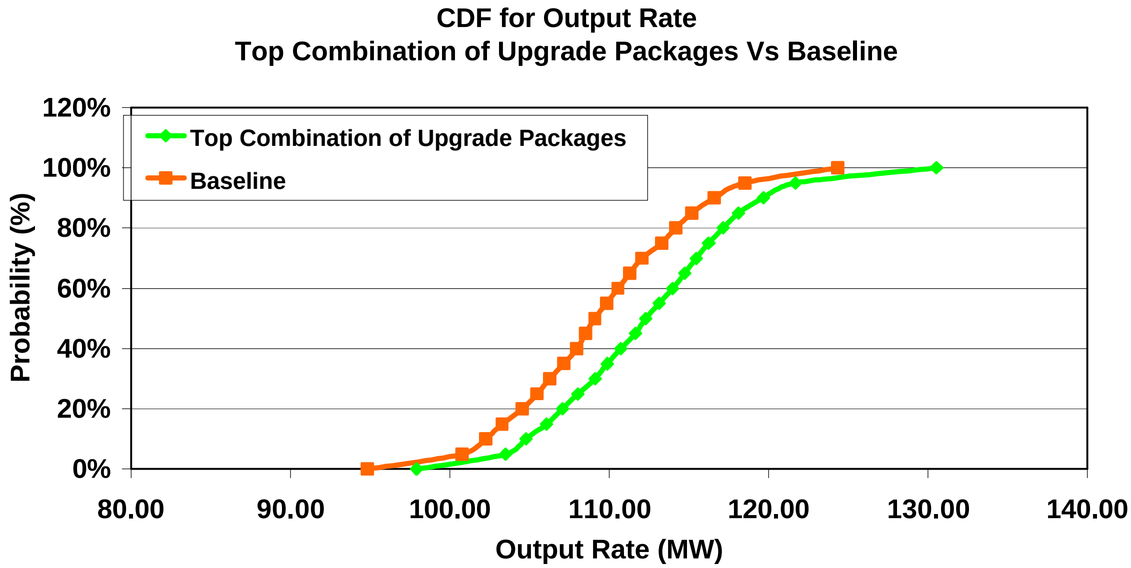

Figure 7.11 CDFs for Power Plant Output Rate

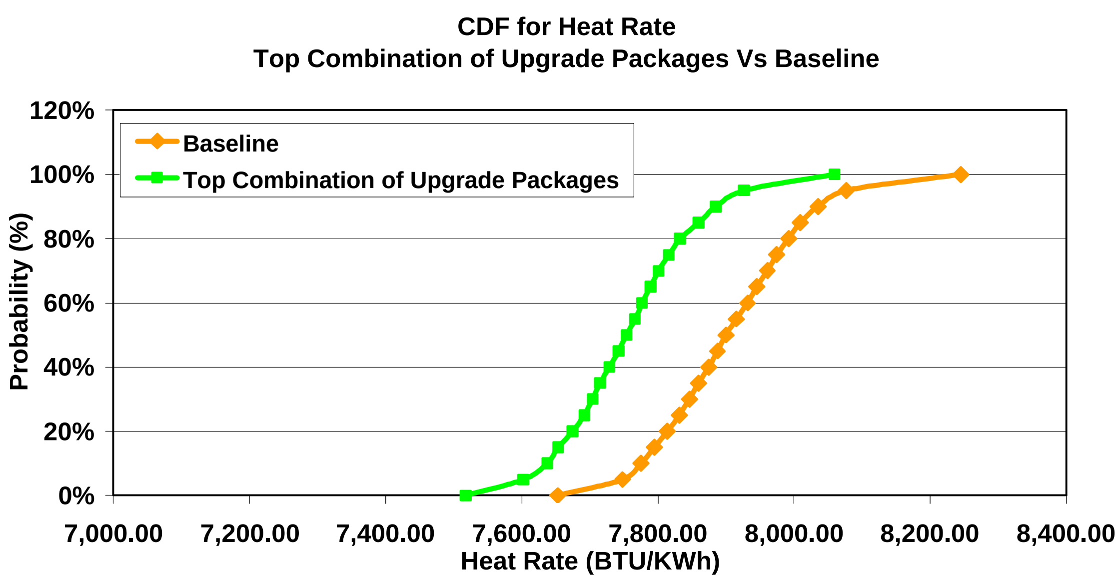

Figure 7.12 CDFs for Power Plant Heat Rate

The performance Pareto Frontiers for upgrade packages with consideration of uncertainty are shown in Figure 7.13. Each dot in Figure 7.13 represents a compatible combination of upgrade packages. Each group of data points (represented by the points in the same color) represents a Pareto Frontier with given uncertainty (confidence level). In Figure 7.13, 95% uncertainty corresponds to 5% confidence level; 85% uncertainty corresponds to 15% confidence level, etc. As the confidence level increases (less uncertainty level), the expected optimal performance decreases.

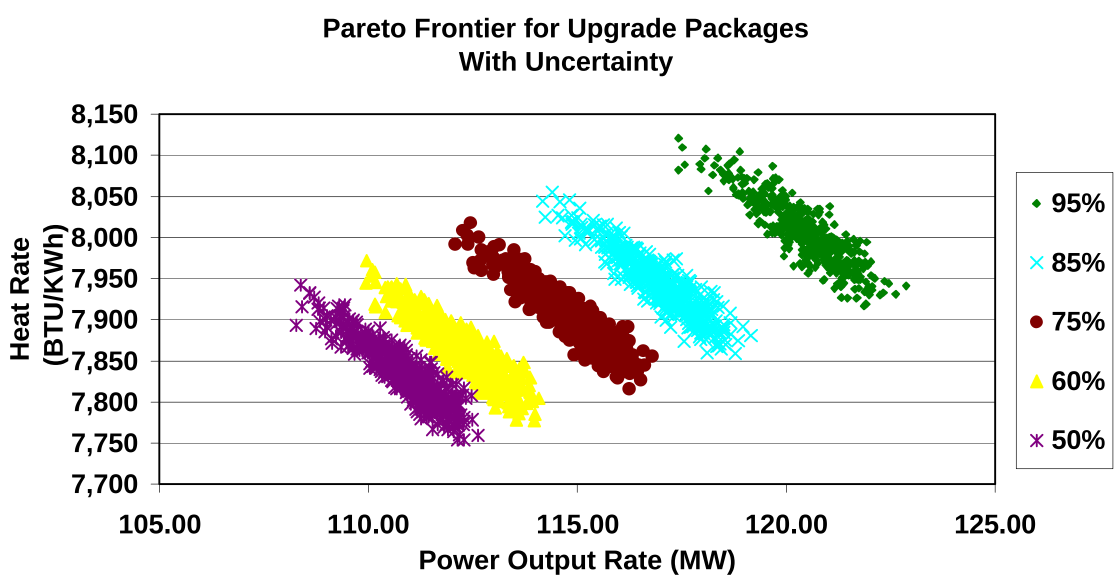

Figure 7.13 Performance Pareto frontier for Upgrade Packages with Consideration of Uncertainty

7.8 Upgrade Packages Evaluation and Selection Based on Economics

The procedures to analyze the effectiveness of upgrade packages based on performance can also be used to perform economics analysis. The only difference lies in the model used to analyze economics.

A base load operational profile is assumed for the power plant, and the power plant is operating continuously under a constant operating profile. The expected payback for an infusion of upgrade packages is the difference between the expected profit associated with a given set of upgrade packages and that of the baseline.

7.8.1 Deterministic Economics Evaluation

The sensitivity analysis for the payback of equipment/services provider is shown in Figure 7.14, and the sensitivity analysis for the payback of the power plant operator is shown in Figure 7.15. Please note that the introduction of *t9* has the highest payback to the equipment provider, while the introduction of upgrade package *t7* has the highest payback to the power plant operator. It is found in this example that the introduction of upgrade package *t1* has negative payback to the equipment/services provider but not to the plant operator. One possible reason for this is that the introduction of upgrade package *t1* leads to an extension of maintenance intervals, and less maintenance actions are required. This results a decrease of revenue for the equipment/services provider. The opposite situation exists for upgrade packages t9 and t10, which shows negative paybacks for the plant operator but large paybacks for the equipment/services provider. Such tradeoffs are to be expected because factors that affect maintenance costs can opposite effects for the services provider and the plant operator.

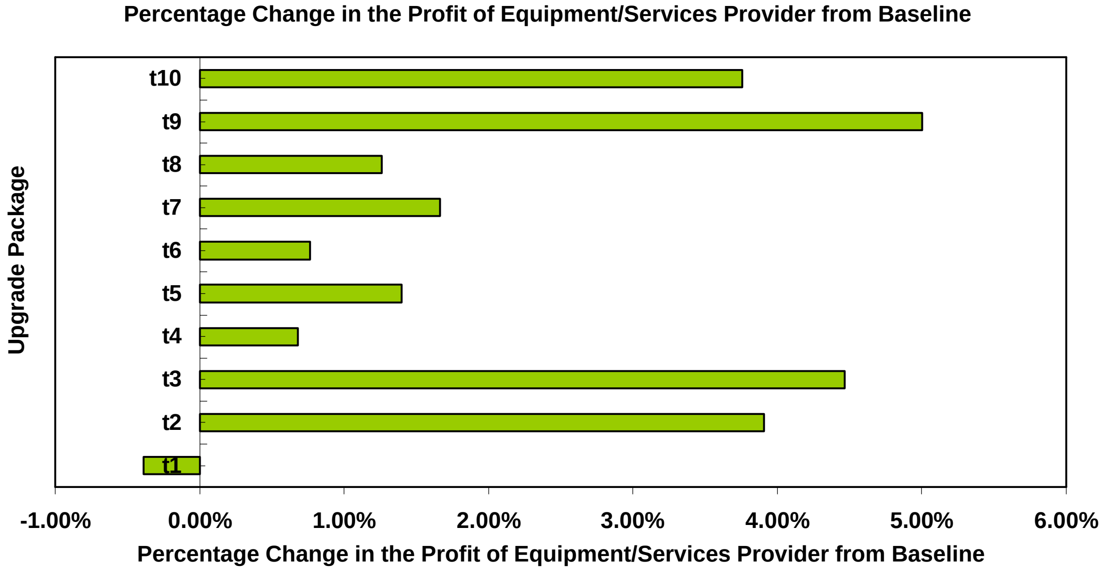

Figure 7.14 Percentage Change in the Profit of Equipment/Services Provider from Baseline

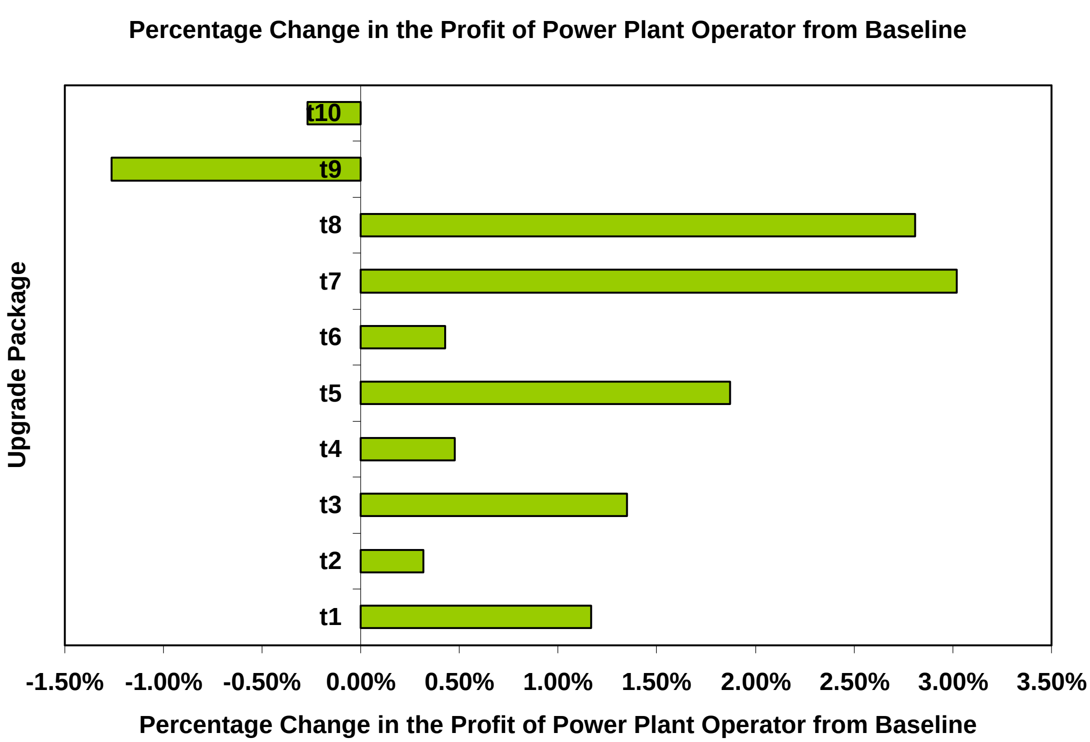

Figure 7.15 Percentage Change in the Profit of Power Plant Operator from Baseline

A full evaluation of upgrade packages requires the examination of the economic performance of all possible combinations of each upgrade package. A full factorial design of experiments based on two levels of “On” and “Off” is generated for this purpose. There are two scenarios for each upgrade, either the upgrade is employed, or not employed. Consequently there are two discrete levels of values for the parameter representing the upgrade package, which is -1 or 1, with 1 representing that the upgrade package is employed, and -1 not.

1024 cases of full factorial design of experiments are generated with 10 upgrade packages. For each case, the power plant long-term economic metrics are calculated using the response surface equations. The long term economic metrics of each case is then compared to the baseline, and the incremental revenue, cost, and profit are then calculated. The top ranking combinations of upgrade packages are then identified.

The top 10 combinations of upgrade packages for equipment/services provider are shown in Figure 7.16; and those for power plant operator are shown in Figure 7.17.

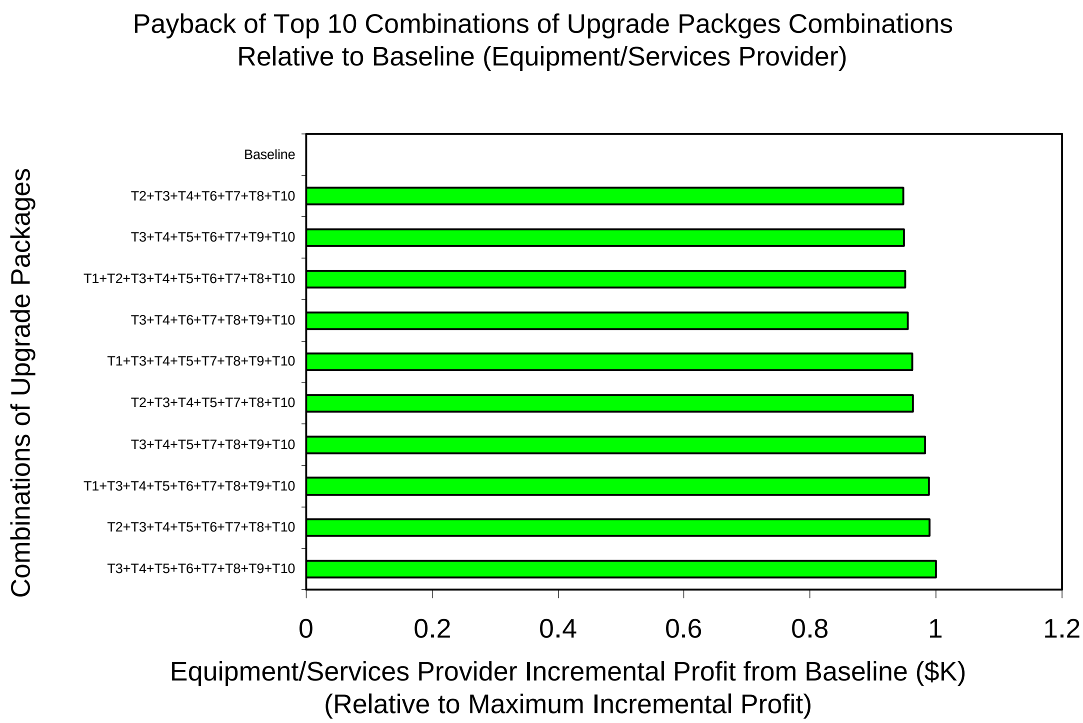

Figure 7.16 Increment Profit of Top 10 Combinations of Upgrade Packages for the Equipment/Services Provider

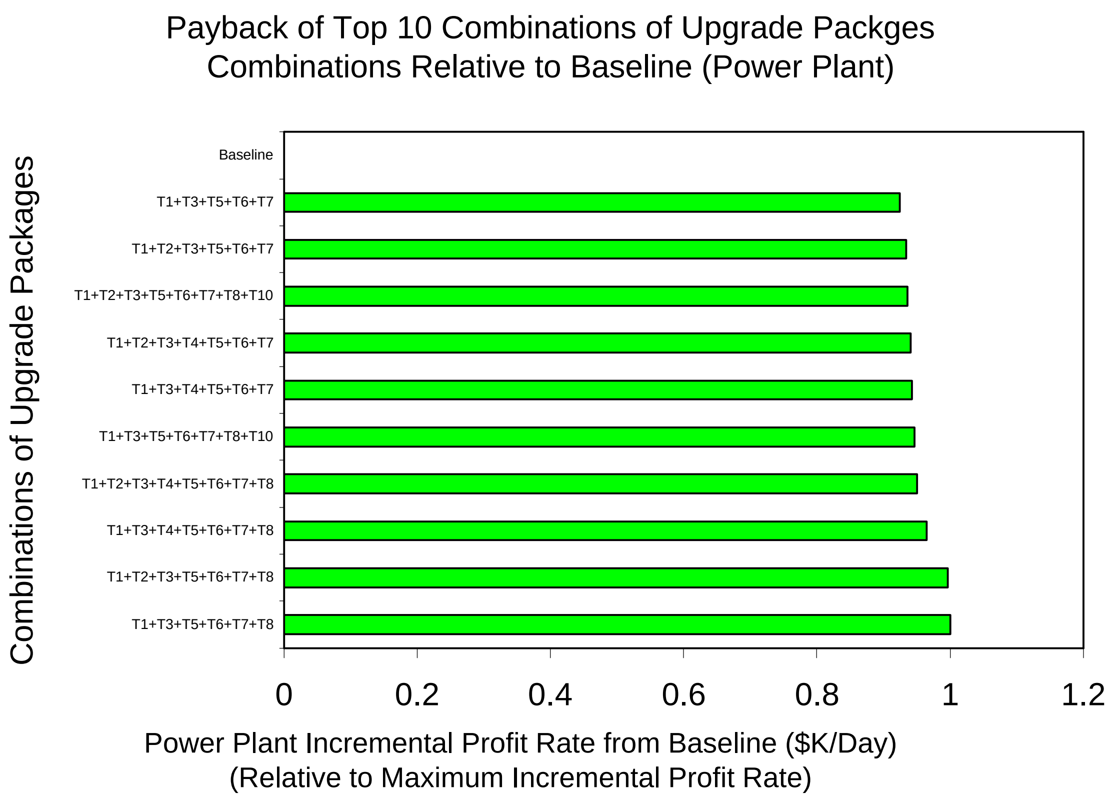

Figure 7.17 Increment Profit of Top 10 Combinations of Upgrade Packages for the Power Plant Operator

A Pareto Frontier for upgrade packages economics without consideration of uncertainty is shown in Figure 7.18. Decisions can be made with consideration of the payback for both the equipment/services provider and the power plant operator simultaneously. To achieve a win-win strategy, the ideal solution is to maximize the payback for both. Each dot shown in Figure 7.18 represents a combination of upgrade packages. The red ones are those that are not compatible, and the green ones are compatible combinations. The top solutions based on economics are those in the green circle.

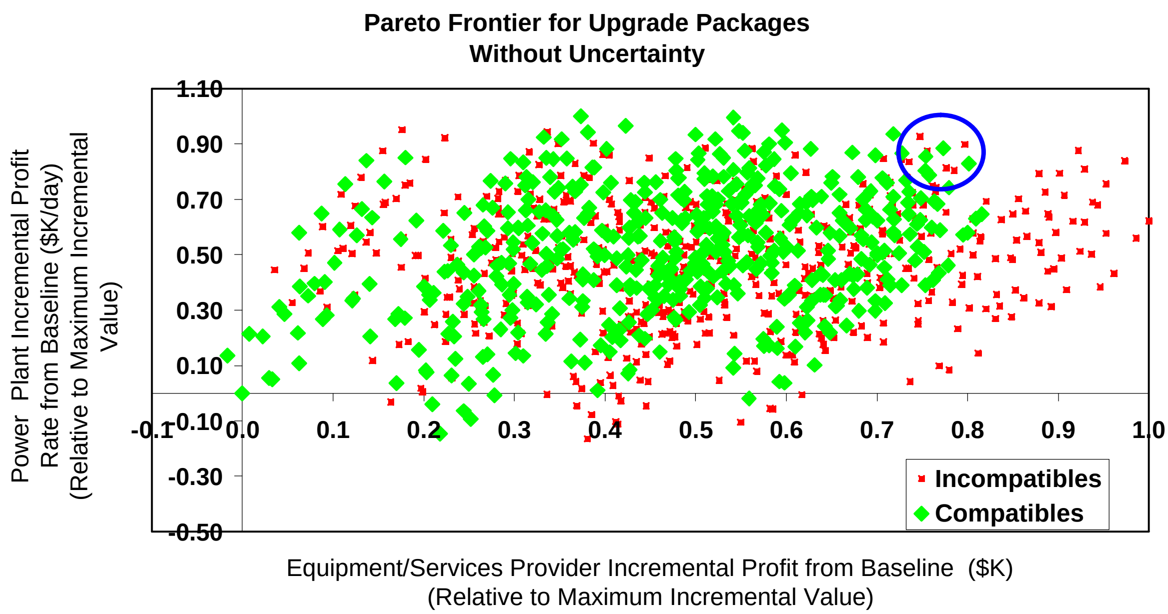

Figure 7.18 Pareto Frontier for Upgrade Packages without Consideration of Uncertainty

7.8.2 Probabilistic Economics Evaluation

The following assumptions are made for the deterministic performance evaluation:

- The power plant is brand new and clean condition at the beginning of its operation
- The uncertainty investigated here includes the variation of price of fuel, price of electricity, ambient conditions, performance degradation, and component service life. The ranges for these parameters are given in Table 7.9.

Table 7.9 Ranges of Parameters for Probabilistic Economics Evaluation

Variable	Units	Min	Norminal	Max
Price of Fuel	$/BTU	3.5	4	4.5
Price of Electricity	c/KWh	5	6	7
Ambient Temperature	F	17	62	107
Ambient Pressure	inHg	30	30	31
Humidity	Kgw/Kga	0.00	0.50	1.00
Degradation Factor 01	N/A	0.8941	0.9268	0.9595
Degradation Factor 02	N/A	0.9634	0.9645	0.9656
Degradation Factor 03	N/A	0.9841	1.0005	1.0168
Part 1 Design Life	Hour	100000	150000	200000
Part 2 Design Life	Hour	100000	150000	200000
Part 3 Design Life	Hour	100000	150000	200000

A probabilistic analysis is performed for each compatible combination of upgrade packages, and cumulative distribution functions (CDFs) are generated for the payback for both the equipment/services provider and the power plant operator. The CDFs for the power plant operator profit of the baseline and the top combination of upgrade packages based on deterministic evaluation are shown in Figure 7.19, and the CDFs for the profit equipment/services provider of the baseline and the top combination of upgrade packages based on deterministic evaluation are shown in Figure 7.20.

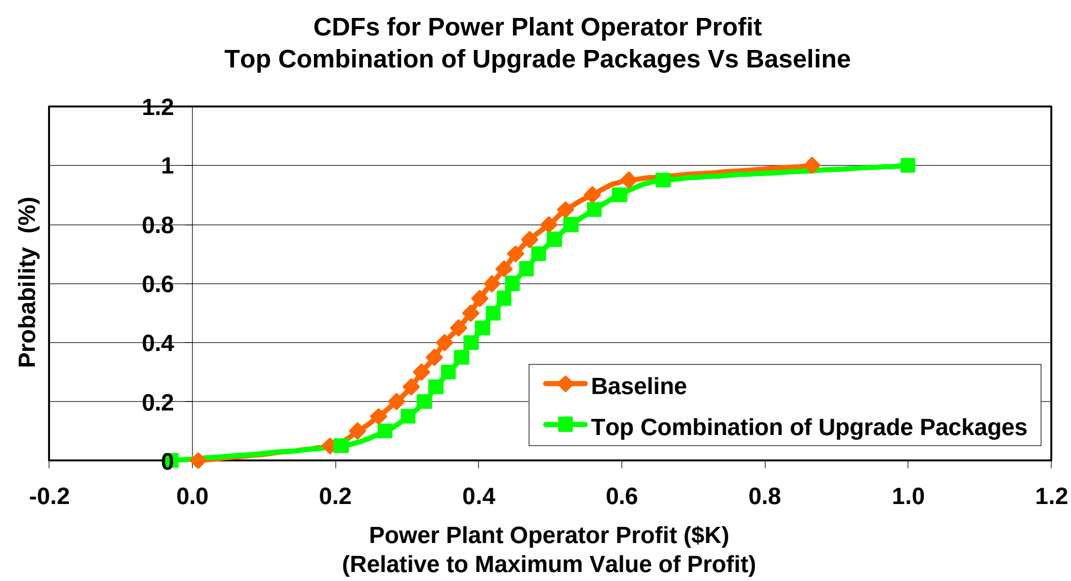

Figure 7.19 CDFs for Power Plant Operator Profit of Best Combination of Upgrade Packages and Baseline

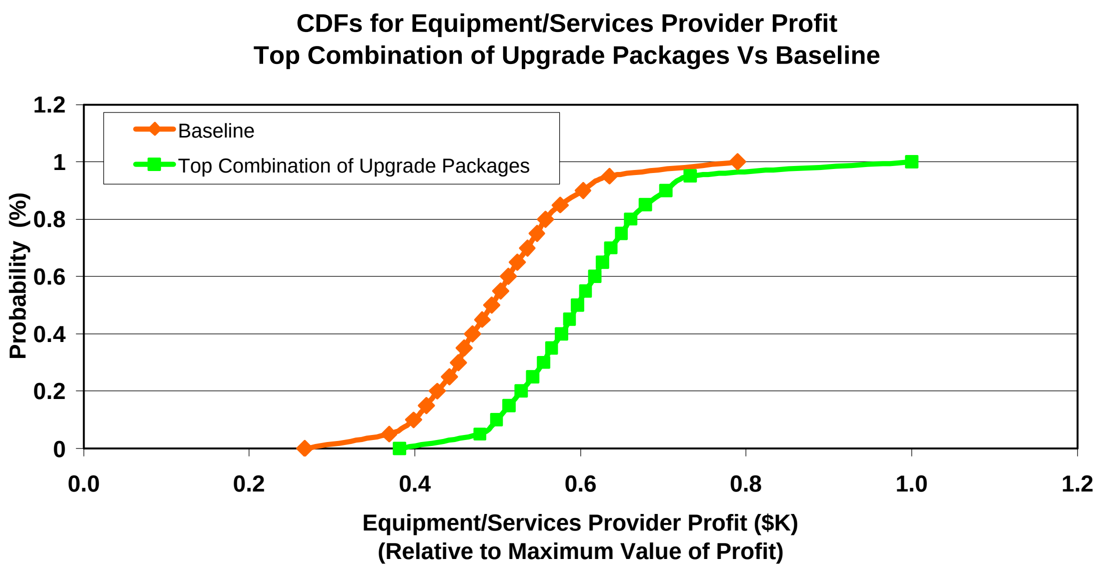

Figure 7.20 CDFs for Equipment/Services Provider Profit of Best Combination of Upgrade Packages and Baseline

The economics Pareto Frontiers for upgrade packages with consideration of uncertainty are shown in Figure 7.21. Each dot in Figure 7.21 represents a compatible combination of upgrade packages. Again, each group of data points (represented by the points in the same color) represents a Pareto Frontier with given uncertainty (confidence level). In Figure 7.21, 95% uncertainty corresponds to 5% confidence level; 85% uncertainty corresponds to 15% confidence level, etc. As the confidence level increases (less uncertainty level), the expected optimal payback decreases.

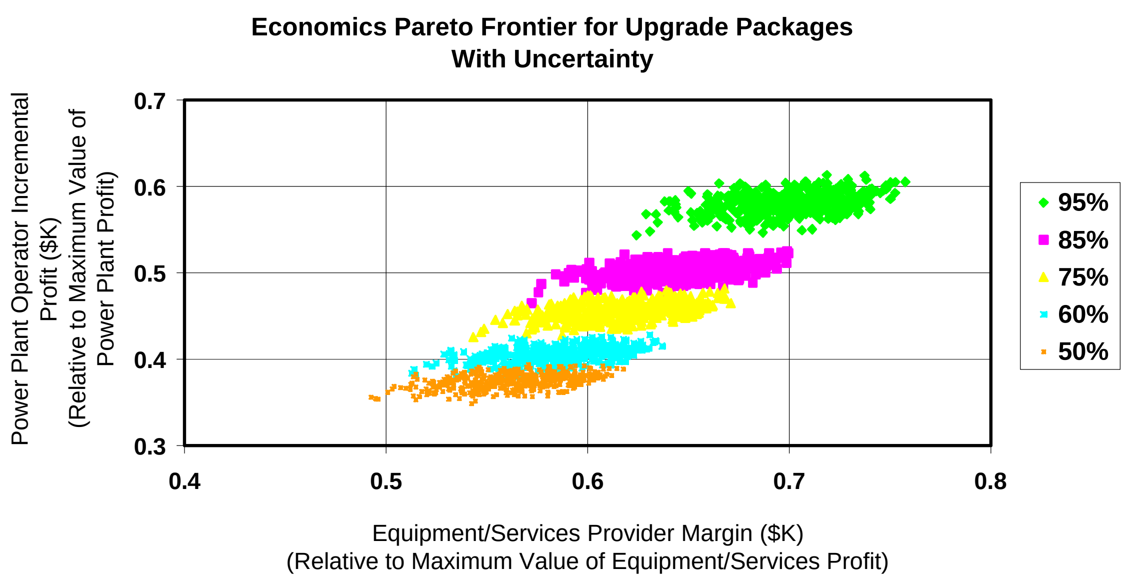

Figure 7.21 Economics Pareto Frontier for Upgrade Packages with Consideration of Uncertainty

7.9 Summary

It is understood that, in reality, many more factors are involved in the evaluation of power plant upgrade packages, and the problem is much more complicated than the one addressed in this study. However, a generic method is introduced in this chapter for both performance and economics analysis, and quantitative tradeoffs and benefits of introducing technology upgrades packages are demonstrated for both the equipment/services provider and the power plant operator. This generic method can be applied to the following practical problems if more sophisticated models are employed.

- Power plant performance guarantee analysis: to analyze probability of success for existing/to be designed plant to meet customer output requirement on point performance and a time period.

- Economic viability analysis and risk assessment for the infusion of upgrade packages. Identify the optimal combination of upgrades packages for both equipment providers and the power plant operator to achieve win-win strategies.

CHAPTER 8

OPTIMIZATION OF COMBINED CYCLE POWER PLANT HEAT RECOVERY STEAM GENERATOR SYSTEM

8.1 Introduction

In this study, the combined cycle power plant is made up of three major systems, the gas turbine engine, the heat recovery steam generator and the steam turbine. Of the major systems the gas turbine engine is a fixed design offered by a manufacturer, and the steam turbine is also a fairly standard design available from a manufacturer, but it may be somewhat customized. In contrast, the heat recovery steam generator (HRSG) offers many different design options, and its design is highly customized and integrated with the steam turbine.

A HRSG is a series of heat exchangers – economizers to heat water close to saturation, evaporators to produce saturated steam and superheaters to produce superheated steam. A relatively simple HRSG design will operate at a single water/steam pressure through the Rankine cycle circuit, but in an effort to extract the maximum amount of energy from the gas turbine exhaust gas there may be one or two higher pressure circuits added to the system. Each added pressure level increases power output from the steam turbine, but the complexity and cost of the HRSG system and the steam turbine are also increased.

The economic viability of a combined cycle power plant depends primarily on how it is to be used. Power and efficiency are improved, but there will be an increase in the plant investment due to the added equipment. Thus, this type of plant is typically used as a "base" plant operating continuously, perhaps 8000 hours per year, with down time only for required maintenance. The basis for an economic study of a combined cycle power plant is the "cost of electricity -- COE," which is a measure of the operating cost of the plant. The elements that are included in the COE are fuel cost, depreciation cost of the investment and maintenance costs. A complete economic study would also consider the revenues to be produced from the generated power, which requires knowing the value of power. This is a parameter that varies not only with the time of day but also with the time during the year – consider the demand and resulting price for power on hot summer afternoons. However, in this study only costs are evaluated, not revenues.

This study is different from the previous study, in that, it studies the design aspect of combined cycle power plant, while previous study in this thesis is on the operational aspect of gas turbine power plant. The objective of this study is to evaluate the impacts of HRSG exhaust gas pressure drop and system complexity on the overall COE of a combined cycle power plant. The study uses a fixed gas turbine engine and steam turbines that differ depending on the number of pressure levels in the system. With the emphasis placed on the HRSG design, numerous parameters are varied to optimize the HRSG design. For this study, the design parameter chosen for evaluation is the exhaust gas pressure drop across the HRSG. This parameter affects the performance of both the gas turbine and steam turbine and the size of the heat recovery unit. HRSG and steam turbine designs with one, two and three circuit pressures are evaluated in the study. A genetic algorithm (GA) is used in the optimization process, and advanced design methods are used in the analysis.

Several system level metrics are employed to evaluate a design. They are gas turbine net power, steam turbine net power, fuel consumption of the power plant, net cycle efficiency of the power plant, HRSG investment cost, total investment cost of the power plant and the operating cost measured by the cost of electricity (COE). The impacts of HRSG exhaust gas pressure drop and system complexity on these system level metrics are investigated.

8.2 Approach

8.2.1 Combined Cycle Power Plant Models & Software Programs

Three HRSG—steam turbine models, HRSG01, HRSG03, and HRSG05, are used in the study. These models are built-in with the GateCycle program [34] and they are considered to be representative of a single-pressure, two-pressure, and three-pressure steam turbine and HRSG systems, respectively. These three configurations all use the same gas turbine — the GE MS7231(FA), an engine widely used in industrial power generation.

GateCycle does not provide enough information on the cost and physical design of a HRSG. Instead, the HXDSN program [104] is used for this purpose. This program is an analysis tool based on proven methods, which will develop an accurate physical design and investment cost estimate of the HRSG. The analysis is then carried on to give a detailed estimate of the cost of the system In this research, the required thermodynamic inputs for HXDSN are generated using GateCycle [105], and additional geometric data for the HRSG design are also input for use in HXDSN. The modeling program iSIGHT is used to couple GateCycle and HXDSN. iSIGHT is a generic software shell that improves productivity in the design process, and its role is to automate the design-evaluate-redesign cycle, which is an essential characteristic of design [106].

System Metrics — Several system level metrics are employed to evaluate a design. They are gas turbine net power, steam turbine net power, fuel consumption of the power plant, net cycle efficiency of the power plant, HRSG investment cost, total investment cost of the power plant and the operating cost measured by the cost of electricity (COE). For investment cost, the gas turbine engine is a fixed parameter in this study, and thus the engine cost is fixed. Steam turbine cost changes depending on the number of pressure levels in the system, and as the HRSG is being resized its cost is recomputed for each design.

8.2.2 Cost of Electricity Model

The cost of electricity model is based on Reference [66]. The following elements are included as part of the cost of electricity:

- Capital cost
- Cost of fuel
- Variable maintenance and operation costs
- Fixed maintenance and operation costs

Throughout this study, cost will be discussed, but it should be understood that it is price that is being presented in US$ for the year 2002.

Costs of Electricity (COE) is computed in units of US$/MW-hour ($MWh), which is the cost per unit energy. Following the format given in References [107] and [108], the equation for computing COE is given by

$$COE = \frac{TCR \cdot y}{P \cdot T_{eq}} + \frac{M_p}{h} + \frac{U_{fix}}{P \cdot T_{eq}} + u_{\text{var}} \tag{8.1}$$

Where,

TCR: Total capital requirement

y : Capital charge factor

P : Rated power output

T_{eq} : Equivalent annual utilization at rated power output hours/annum

M_p : Price of fuel

h : Average plant efficiency

U_{fix} : Fixed cost of operation, maintenance and administration

u_{var} : Variable cost of operation, maintenance and repair $/MWh

For this study it is important to have a breakdown in of the capital investment of the plant into the major elements – gas turbine, steam turbine, HRSG and balance of plant (BOP). The gas turbine is fixed, and with a nominal size of 166 MW (to be shown), cost is set at $32M. The steam turbine will vary depending on the number of pressure levels in the design, and its cost is determined from a database in the HXDSN program. To determine a cost for BOP, data from Reference [109] was used. BOP includes electric generators, sub-system equipment, engineering construction services, plant startup and commissioning. Finally, the HRSG cost is computed for each case using the methodology from the HRSG program. Actual cost is computed in this program, and a profit of 10% is assumed to convert to a price for the HRSG. The capital charge factor, y ? the annuity present worth factor, is used to write off the investment of capital. It accounts for the discount rate, i, on capital and the life of the plant, N years. For this study, i = 8% and N = 25 years.

Maintenance cost models for both U_{fix} and u_{var} were taken directly from Reference [107] for combined cycle power plants. Both of these parameters are modeled as a function of the rated power output of the plant. Thus, as the HRSG design is changed from 1-pressure to 2-pressure and 3-pressure, more power is developed by the system, so slightly higher maintenance costs will be computed. However, it is likely that the true complexity and increased maintenance requirements of going to increased number of pressures and higher pressure levels is not captured adequately by this model. For this study this level of complexity is deemed to be of secondary importance.

For the remaining parameters, fuel price is assumed to 30 US$/bbl. A heating value of 18,400 Btu/lb is assumed to convert to $/MWh. Also, the combined cycle is assumed to a base load plant, and an annual utilization of 8000 hours is assumed. Rated power and plant efficiency is computed for each run of the GateCycle program.

8.3 HRSG Design and Optimization

Before the three HRSG configurations are evaluated, it is necessary to make sure that the optimal design of each configuration is achieved. Therefore, the design and optimization of each HRSG is an important step. There are numerous parameters and constraints that must be considered in a complete design study of a HRSG, and to evaluate them all in an optimization study is beyond the scope of this study. However, the gas side pressure loss across the HRSG is an important parameter in the design of a HRSG, and its effect on HRSG design and cost and the overall effect on COE will be demonstrated. A higher gas side pressure loss will result in a higher exhaust pressure of gas turbine engine, and, therefore, less power output from gas turbine. On the other hand, a higher gas side pressure loss also results in a higher exhaust gas temperature of the gas turbine, and therefore more steam will be produced by the HRSG and more power will be produced from the steam turbines. Therefore, with regard to gas side pressure loss, there is a tradeoff between the power output of the gas turbine and the steam turbine, and, as will be shown, the effect on power output is not major.

However, the gas side pressure loss does have a significant effect on the HRSG design. A decrease in the pressure loss through the HRSG can only be achieved with a reduction in the flow velocities through the heat exchangers, and this is done by increasing cross section flow area. Also, reduced velocity decreases the heat transfer coefficients and increased heat transfer surface areas are thus required. The result is an increase in the size and cost of the HRSG.

Five levels of gas side pressure loss are selected in the design process. They are 12, 16, 20, 24 and 28 inches of water. For each gas side pressure loss, a HRSG design is optimized using a genetic algorithm. The objective of the optimization is to minimize the investment cost of the HRSG, including the heat exchangers, insulated casing panels and all related components such as the condenser, deaerator and pumps. The optimization is done for a standard day design condition at sea level where the ambient temperature is set as 60 °F, the ambient pressure 14.7 PSIA, and the relative humidity 0.6.

Numerous design variables are identified. They are HRSG face width, tube outside diameter of each heat exchangers, fin height of each heat exchanger, fin density of each heat exchanger, and minimum allowable tube spacing/tube diameter of each heat exchanger. For this last parameter, tube spacing is the tip to tip spacing of adjacent finned tubes in a row. A screening test is performed to identify those design variables with significant effects on the responses. For a three-pressure HRSG system, a set of 45 design variables are used in the screening test, and 13 design variables are selected as important design variables, which are manipulated in the optimization. For a two-pressure HRSG system, a set of 25 design variables is identified, and again, 13 of them are chosen for the optimization process. For a single-pressure HRSG system, 13 design variables are identified, and all of them are used in the optimization process.

It is important to choose the robust optimization technique for this problem since there are as many as 13 design variables being changed, and these design variables are of different type. Some of them are discrete variables; some of them are integers, while others are real. The genetic algorithm (GA) used to optimize the design is a built-in technique in iSIGHT. GA is an optimization technique that mimics biological reproduction and evolution [110]. In this research it takes advantage of the integration environment of iSIGHT and does not need to create response surface equations (RSEs) to produce responses. Also, it is especially applicable to problems with discrete design variables. It was found that the time consumed in the optimization process was affordable.

8.4 Single Pressure System

8.4.1 System Description

The single-pressure heat recovery system chosen for investigation is the HRSG01, a built-in model in GateCyle program. The system has a gas turbine, the GE MS7231(FA), and three heat exchangers, including a superheater (SH), an evaporator (EV), and an economizer (EC). In addition, there is a single section condensing steam turbine. The detailed GateCycle model shown in Figure 8.1 is taken from the GateCycle manual [34].

8.4.2 Screening Test

The purpose of this screening test is to identify the design variables that have the most significant effects on the responses. Thirteen design variables are identified and selected as inputs, and the descriptions of those parameters are listed in Table 8.1. HRSG investment cost, height of the HRSG and total surface area of heat exchangers are selected as responses. The gas side pressure loss is set as 20 inches of water for the screening test. Standard ambient (ISO) conditions are used, and a design of experiment (DoE) with 129 cases is run.

A sample prediction profiler for one of the responses with 7 of the 13 design variables is shown in Figure 8.2. This figure is produced in the JMP program. In actual use, this profile links all input parameters dynamically, and change in the value of any parameter (achieved by moving any one of the vertically dotted lines) will affect the slopes and values of all responses shown in the figure. The slopes of the prediction traces inform the designer which designs variables may have significant effect on the design matrices. A detailed explanation of the use of this program and the complete methodology is given in Reference [103]. It is shown in Figure 8.2 that WFACEI (HRSG face width) has strong effect on the investment cost of single pressure HRSG. An increase of HRSG face width will increase the HRSG investment cost substantially, given other design parameters kept constant.

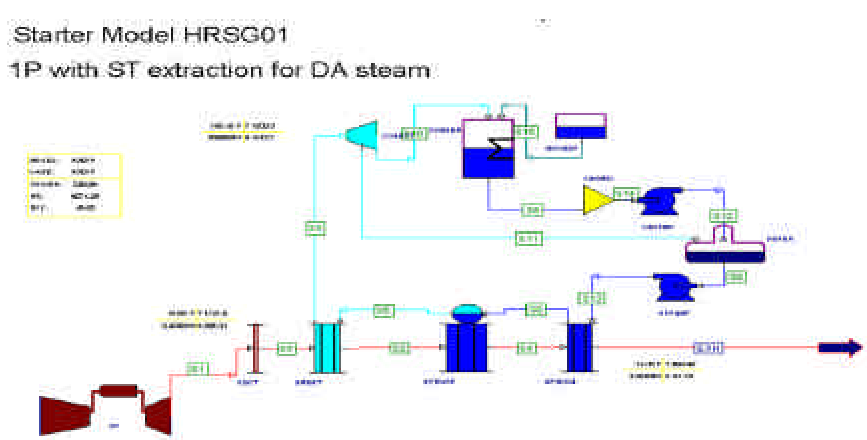

Figure 8.1 GE MS7231 (FA) Gas Turbine & HRSG with Single-Pressure

A Pareto plot is a statistical tool that enables the designers to identify the most significant design variables. The design variables are ordered based on the significance to the responses in a decreasing order. This allows the designers to reduce the number of design variables, and only those significant design variables are kept in the design optimization. A Pareto plot for total investment cost is shown in Figure8. 3.

Table 8. 1 Design Variables for Single Pressure System

Design Variables	Description	Unit
WFACEI	HRSG face width	Inches
DOUT01, DOUT02, DOUT03	Tube outside diameters of SH, EV & EC	Inches
HFIN01, HFIN02, HFIN03	Fin heights of SH, EV & EC	Inches
FINPI01, FINPI02, FINPI03	Fin Density of SH, EV & EC	Fins/inch
SQDMIN01, SQDMIN02, SQDMIN03	Min allowable tube spacing /	
Tube outside diameters of SH, EV & EC	N/A	

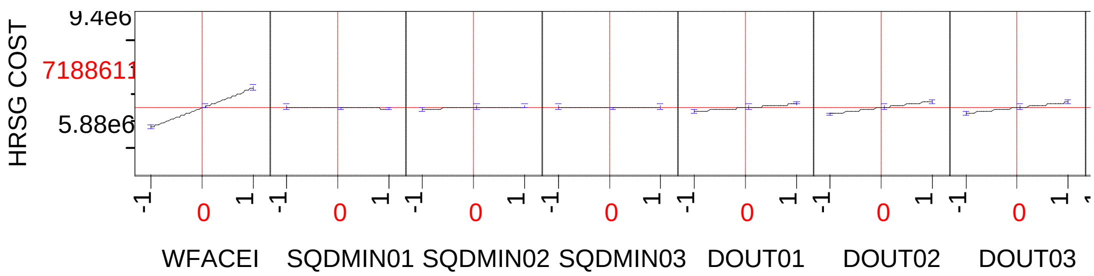

Figure 8.2 A Sample Prediction Profiler for Single-Pressure System

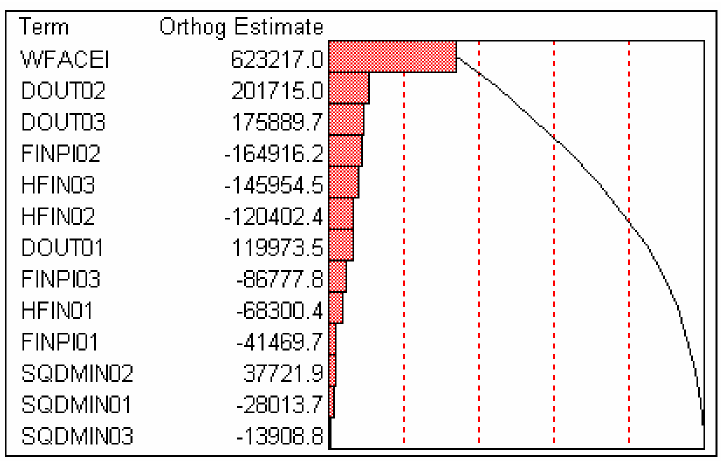

Figure 8.3 Pareto Plot for HRSG Investment Cost for a Single-Pressure System

An important feature of the Pareto diagram is the length of the horizontal bars. This indicates the relative magnitude of each parameter on the response, in this case the HRSG investment cost. The orthogonal estimate is a mathematical transformation that allows an independent evaluation of each parameter. If the estimate value is positive, an increase in the parameter increases investment cost and vice versa. It is shown in Figure 8.3 that HRSG face width has the most significant effect on HRSG investment cost.

8.4.3 Design Optimization

The pressure drop across the HRSG is set for each design case, and the task is to optimize the design of the HRSG using the design variables identified in the screening test. The objective is to minimize the total investment cost of the HRSG, and there are three constraints that the HRSG is required to satisfy: the height of HRSG cannot exceed 60 feet; the fin tip temperature of the SH cannot exceed 1200 °F; and steam/water pressure loss of each heat exchanger cannot exceed 30 PSI. The genetic algorithm is employed with a population size of 100 and a maximum evaluation number of 1000.

The ranges for optimization are a little broader than those used for screening test. HRSG face width can vary between 10 feet and 40 feet. Tube outside diameters are set as discrete variables, and only 5 values are valid (1.0, 1.5, 2.0, 2.5, 3.0 inches). Also fin heights are set as discrete variables, and 4 valid values are available (0.25, 0.5, 0.75, 1.0 inches). Fin density is set as integer, and can vary from 6 to 10. Minimum allowable tube spacing/tube diameter ratios are set as continuous variables and vary from 0.125 to 0.5. The optimization results for single-pressure system are shown in Table 8.2 for a range of HRSG pressure loss from 12 to 28 inches of water. The HRSG width and height both vary such that the HRSG frontal area is reduced as the pressure drop increases. With increased HRSG pressure drop (engine back pressure increasing), the gas turbine power is reduced, but with a higher exhaust temperature more steam is generated in the HRSG and steam turbine power increases. The net result is a slight reduction is total power and power plant efficiency with increased pressure drop. The reduced size of the HRSG with increased pressure drop results in a reduced cost of the HRSG as shown in the table. This reduction is a significant fraction of the HRSG cost, but compared to the total capital requirement of the plant (TCR) it is a small reduction. Although TCR is reduced, there is a slight increase in the COE with increased pressure drop due to the decrease in power output. The steam turbine cost is $14.1M, and it is based on the maximum ST net power shown in the table. Data from Table 8.2 are plotted for total output power, HRSG investment cost, TCR and COE in Figures 8.4, 8.5, 8.6 and 8.7, respectively.

Table 8.2 Design Results for Single Pressure System

HRSG Gas Side Pressure Loss (Inches of Water)	GT Net Power (MW)	ST Net Power (MW)	Total Net Power (MW)	Combined Cyce Efficiency	HRSG Width (feet)	HRSG Height (feet)	HRSG Investment Cost (Million Dollars)	TCR (Million Dollars)	COE (Dollars per MWh)
12	166.1	68.6	234.7	50.10	21.5	57.7	6.1	116.4	48.05
16	165.1	69.1	234.2	50.00	20.0	56.2	5.9	116.1	48.13
20	164.4	69.4	233.8	49.91	22.2	44.1	5.7	115.9	48.20
24	163.6	69.8	233.4	49.82	21.5	42.3	5.6	115.8	48.20
28	162.8	70.2	233.0	49.73	20.6	41.0	5.5	115.7	48.35

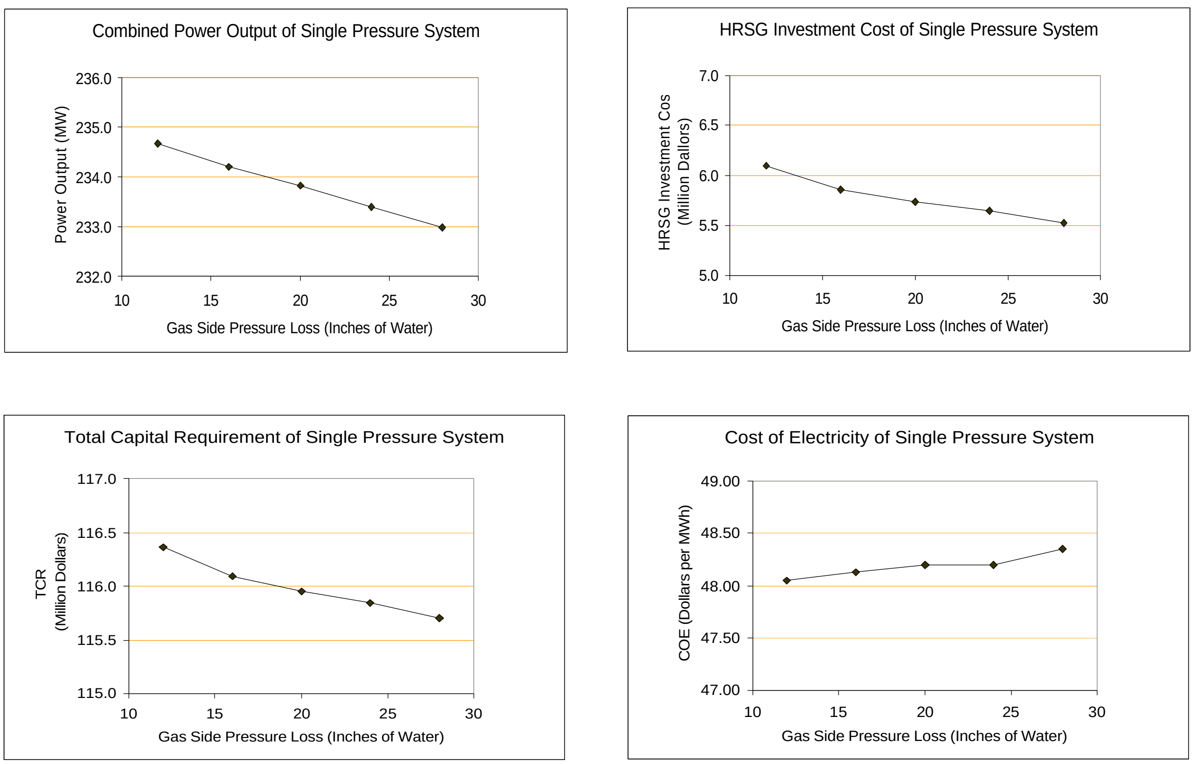

Figure 8.4-7 Effects of Gas Side Pressure Loss on Power Plants Performance and Cost of Single-Pressure System

8.5 Two Pressure System

8.5.1 System Description

The two-pressure system chosen for investigation is the HRSG03, which is also a built-in model in the GateCyle program. The system has a gas turbine GE MS7231 (FA), the same engine used in the Single-Pressure system, and a six heat exchanger HRSG. The HRSG includes two super heaters, two evaporators, one economizer, and one condensate water preheater. Also, there are two steam turbine sections. The detailed GateCycle model shown in Figure 8.8 is taken from the GateCycle manual.

8.5.2 Design Optimization

A simulation of the HRSG pressure drop, the screening test and Pareto plot necessary to identify the most important 13 design variables was conducted just as described for the single pressure system. Then the HRSG design is optimized with the objective of minimizing the investment cost of the HRSG. The same constraints of HRSG height, first SH fin tip temperature and internal pressure drop are applied as before using the genetic algorithm, and values for 13 design variables were obtained using the genetic algorithm are similar to those found for the 1-pressure system. The 13 design variables for this system changed slightly for this HRSG design, but again, the width of the HRSG is a dominant parameter.

The optimization results for two-pressure system are shown in Table 8.3 over a range of HRSG pressure drop from 12 to 28 inches of water, and the results show the same trends as given for the 1-pressure system. Data from Table 8.3 are plotted for total output power, HRSG investment cost, TCR and COE in Figures 9, 10, 11, and 12, respectively. The steam turbine cost is $16.5M, and it is based on the maximum ST net power shown in the table.

The comments given above for the Single-Pressure system apply to these results as well. With increased HRSG pressure drop, HRSG investment cost and total investment cost are reduced, but with the reduction in total output power the COE increases. It is interesting to note that adding the more complicated two-pressure system has increased the power output by approximately 5% over the single pressure system. This is because of the greater production of steam for the steam turbines. However, the cost of the HRSG has increased by approximately 25-28%. Also, the face areas (height * width) of the HRSGs shown in Table 8.3 are greater than the corresponding HRSG heights shown for the single pressure system. There are more heat exchangers in the two pressure system, and thus for a given pressure drop, the HRSG cross-section area must be increased to reduce flow velocity. The reduced flow velocities will result in a reduction in heat transfer coefficients for each heat exchanger, which has the effect of increasing heat exchanger surface areas. This effect is modeled in the HXDSN program.

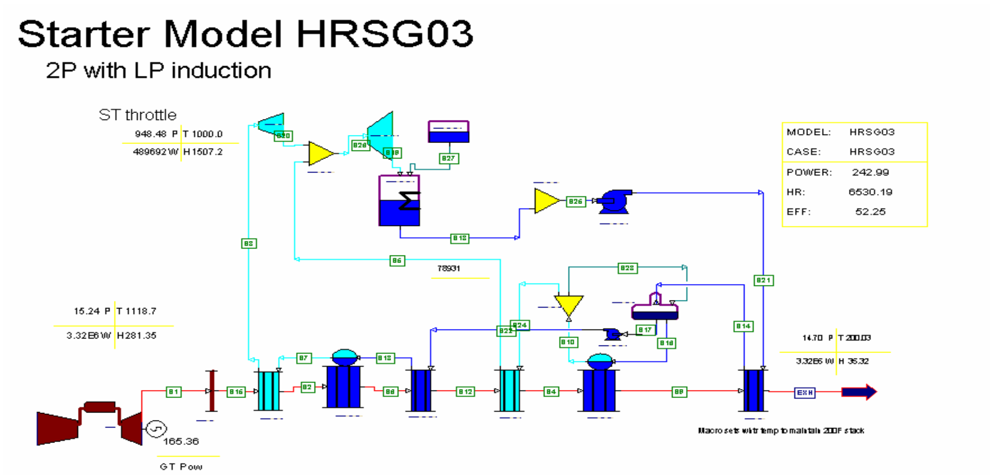

Figure 8.8 GE MS7231 (FA) Gas Turbine & HRSG with Two-Pressures

Table 8.3 Design Results for Two-Pressure System

HRSG Gas Side Pressure Loss (Inches of Water)	GT Net Power (MW)	ST Net Power (MW)	Total Net Power (MW)	Combined Cycle Efficiency	HRSG Width (feet)	HRSG Height (feet)	HRSG Investment Cost (Million Dollars)	TCR (Million Dollars)	COE (Dollars per MWh)
12	166.0	79.1	245.1	52.32	26.5	54.4	8.8	119.6	46.33
16	165.2	79.5	244.7	52.23	24.7	51.0	8.1	119.3	46.39
20	164.4	79.9	244.2	52.13	22.1	51.4	7.8	118.9	46.46
24	163.6	80.2	243.8	52.04	21.7	49.3	7.8	118.9	46.53
28	162.7	80.6	243.4	51.94	21.9	46.8	7.7	118.8	46.60

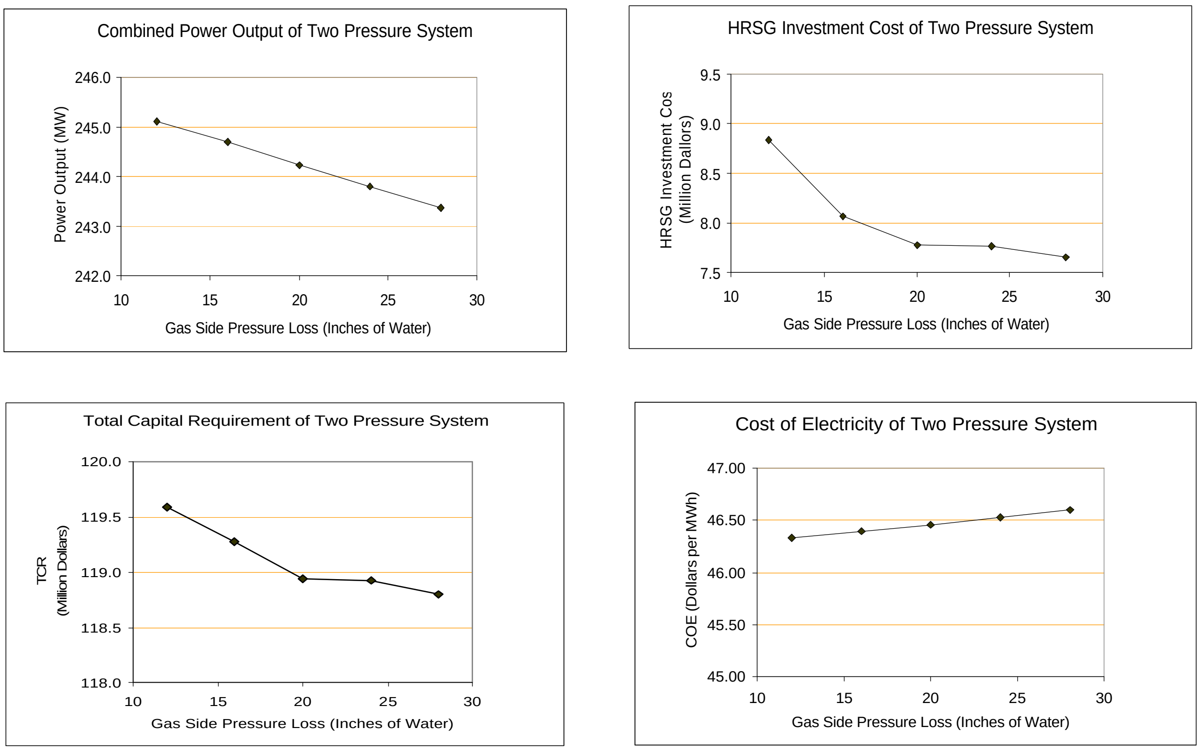

Figure 8.9 -12 Effects of Gas Side Pressure Loss on Power Plants Performance and Cost of Two-Pressure System

8.6 Three Pressure System

8.6.1 System Description

The three-pressure system chosen for investigation is the HRSG05, also a built-in model in GateCyle program. Once again the system has the GE MS7231 (FA) gas turbine engine. But in this case there are eleven heat exchangers, including four super heaters, three evaporators, three economizers, and a condensate water pre-heater. In addition, there are three steam turbine sections. The detailed GateCycle model shown in Figure 8.13 is taken from the GateCycle manual.

8.6.2 Design Optimization

Again, a simulation of the HRSG pressure drop was conducted, and a screening test and Pareto plot necessary to identify the most important 13 design variables were developed just as described for the single pressure system. Then the HRSG design is optimized with the objective of minimizing the investment cost of the HRSG. The same constraints of HRSG height, first SH fin tip temperature and internal pressure drop are applied as before using the genetic algorithm, and values for 13 design variables were obtained using the genetic algorithm are similar to those found for the 1-pressure and 2-pressure systems. The 13 design variables for this system changed slightly for this HRSG design, but the width of the HRSG remains as the dominant parameter.

The optimization results for three-pressure system are shown in Table 8.4 over a range of HRSG pressure drop from 12 to 28 inches of water, and the results show the same trends as given for the 1-pressure and 2-pressure systems. The steam turbine cost is \$19.5M, and it is based on the maximum ST net power shown in the table. Data from Table 8.4 are plotted for total output power, HRSG investment cost, TCR and COE in Figures 8.14, 8.15, 8.16 and 8.17, respectively.

This Three-Pressure system has increased the power even further, again due to increased output of the steam turbines. Now the total power output is increased by approximately 7% over the single pressure system, but the investment cost of the HRSG and steam turbines is increased by almost 50%. A more complete comparison of the three HRSG configurations is given in the following section.

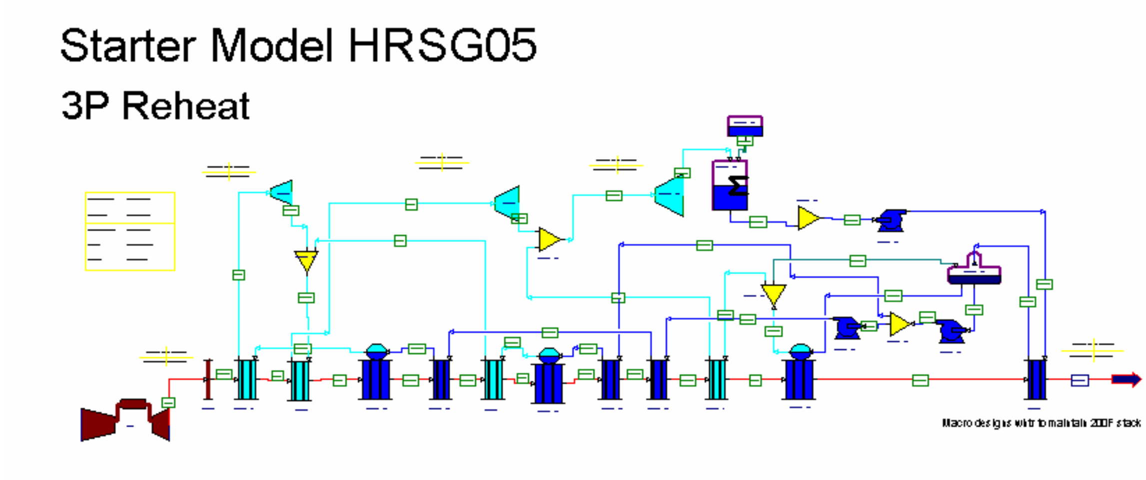

Figure 8.13 GE MS7231 (FA) Gas Turbine & HRSG with 3-Pressures

Table 8.4 Design Results for the Three-Pressure System

HRSG Gas Side Pressure Loss (Inches of Water)	GT Net Power (MW)	ST Net Power (MW)	Total Net Power (MW)	Combined Cyce Efficiency	HRSG Width (feet)	HRSG Height (feet)	HRSG Investment Cost (Million Dollars)	TCR (Million Dollars)	COE (Dollars per MWh)
12	166.0	85.5	251.5	53.69	30.6	54.4	10.5	130.5	45.75
16	165.2	85.9	251.1	53.61	27.3	52.8	9.9	129.9	45.79
20	164.4	86.3	250.7	53.52	24.8	50.6	9.1	128.9	45.82
24	163.6	86.7	250.3	53.43	23.2	52.2	8.9	128.7	45.87
28	162.8	87.1	249.9	53.34	21.1	53.6	8.6	128.3	45.93

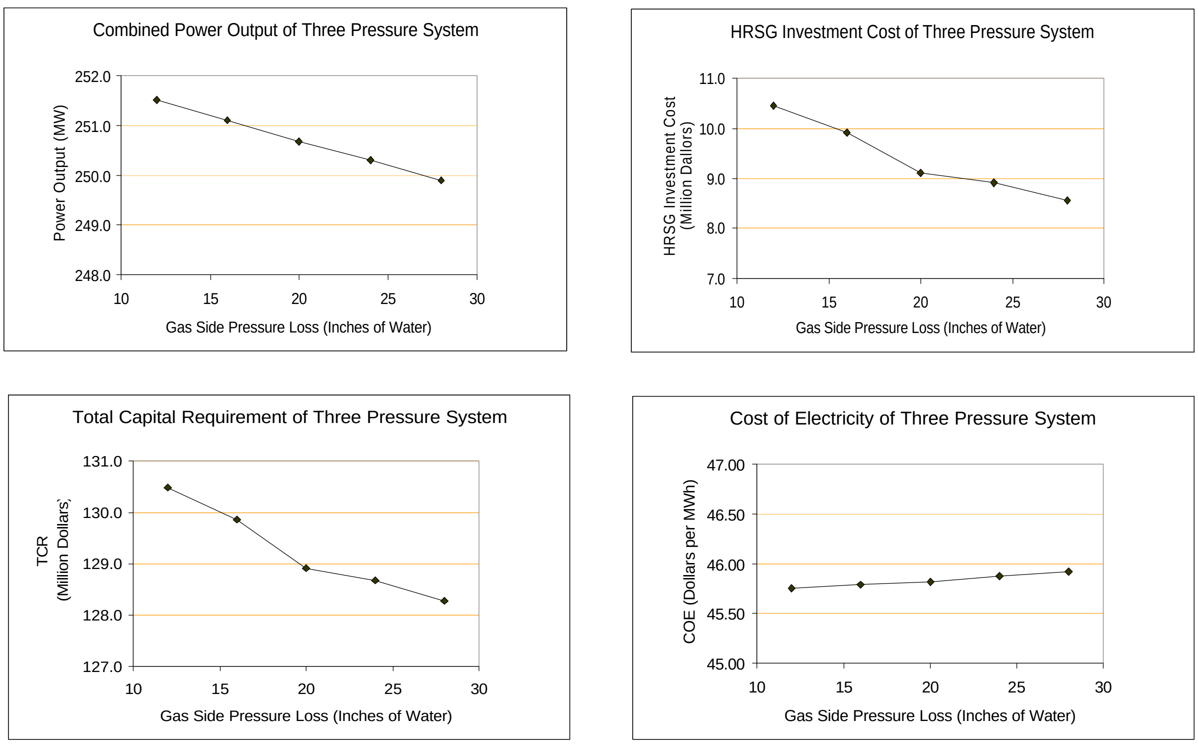

Figure 8.14-17 Effects of Gas Side Pressure Loss on Power Plants Performance and Cost of Three-Pressure System

8.7 Evaluation of the Three HRSG Configurations

The three different HRSG configurations are evaluated on the basis of the tradeoff between the power produced by the total system, the thermal efficiency of the power plant, the HRSG and total plant investment costs and the COE of the power plant. These parameters are shown in Figures 8.18-23 in the form of bar charts, which compare a single-pressure, two-pressure and three-pressure combined cycle power plant. The HRSG pressure drop for these comparisons is 16 inches of water.

It can be seen that the simple one pressure system has less net power output and lower cycle efficiency than the two and three pressure systems, but the HRSG investment cost is much less than that of the more complicated systems. However, when the total COE is considered, the three-pressure system is the lowest, which again reflects the fact that the HRSG cost is a relatively small fraction of the total plant cost, and that plant efficiency is a more important parameter.

8.8 Summary

In this study, the GateCycle and HXDSN programs have been linked together using iSIGHT, a generic software shell that improves productivity in the design process, and its role is to automate the design-evaluate-redesign cycle, which is an essential characteristic of design. The genetic algorithm used to optimize the design is a built-in technique in iSIGHT, and it takes advantage of the integration environment of iSIGHT and does not need to create response surface equations (RSEs) to produce responses. It was found that the optimization process that was developed with these programs was very efficient.

There are numerous design parameters and constraints that must be considered in the design of the HRSG. This is the initial study of a much larger project to investigate HRSG design, and the key parameter chosen for the analysis is the HRSG total pressure drop. This parameter was used as a design requirement, and it is a critical parameter because it affects the performance of both the gas turbine engine and the steam turbine. HRSG designs with an overall pressure drop ranging from 12 to 28 inches of water were investigated. Using HRSG designs available from GE Enter Software using GateCycle, this range of HRSG pressure drop was evaluated for one-pressure, two-pressure and three-pressure HRSG-steam turbine systems. The multiple pressure systems are reheat systems and all designs use condensing steam turbines.

It was found that increasing the allowable pressure drop through the HRSG has a significant effect on the size and cost of the HRSG. HRSG cost is reduced by 20-25% when the allowable pressure drop is increased from 12 to 28 inches of water. However, the HRSG represents less than 10% of the total cost of a combined cycle power plant, so the effect on the total cost of the system and the resulting cost of electricity is minimal. The decrease in power over the range of pressure drops evaluated is approximately 1.7 MW for each system, less than 1% of the power output of the power plants. The true economic effect can only be measured by the resulting loss in revenue from the sale of energy, and such an evaluation was beyond the scope of this study.

A comparison of one-pressure, two-pressure and three pressure HRSG/steam turbine systems demonstrates that HRSG costs increase very significantly as pressure levels are added to the system, but again these costs are a relatively small fraction of the total plant costs. More significant is the increase in power output, and the result is a reduction in the

COE with added pressure levels. However the effect is non-linear; e.g., with the design pressure drop set at 16 inches of water, COE is shown in Table 8.5.

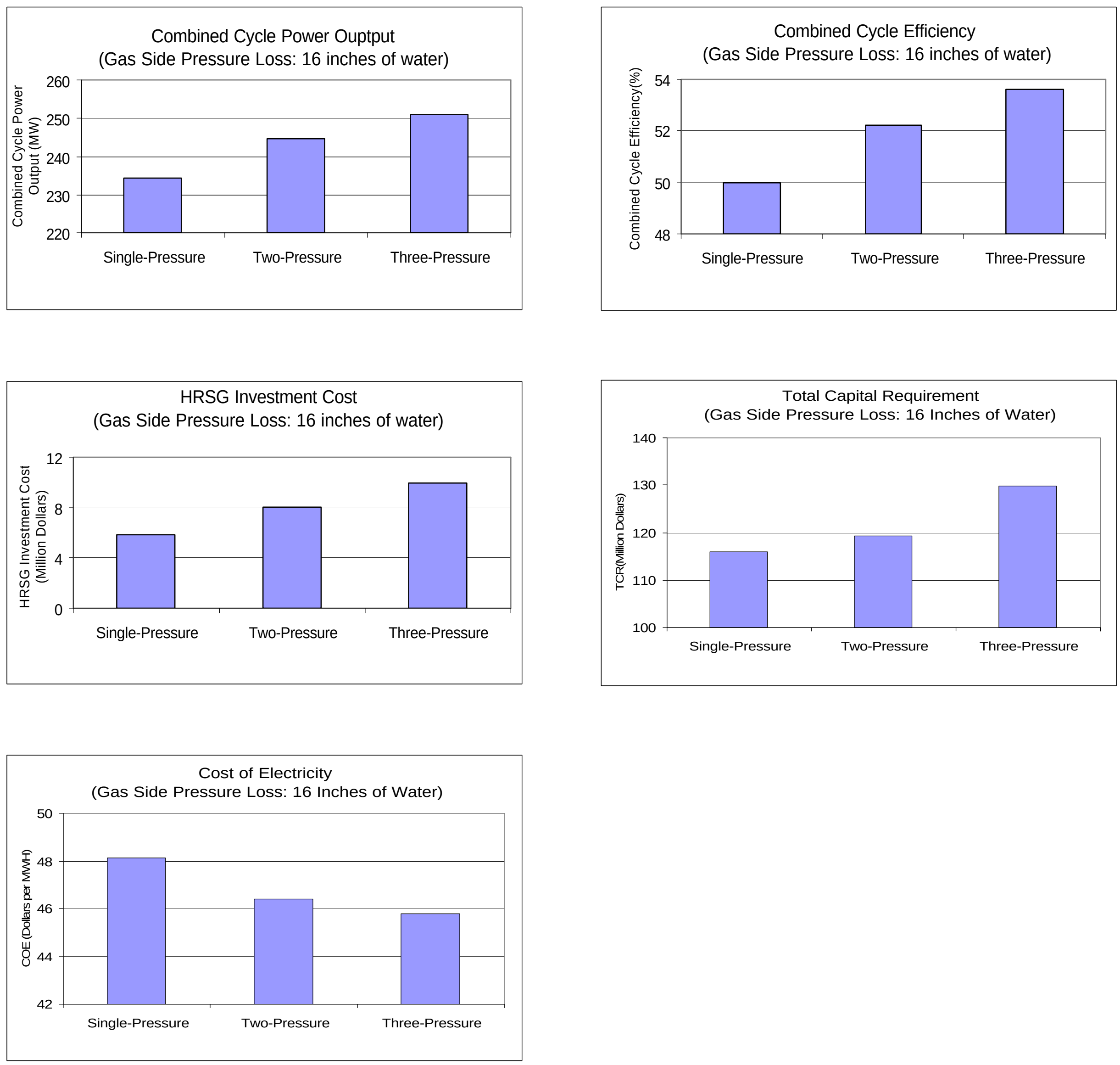

Figure 8.18-23 Performance and Cost for 3 Configurations (Gas Side Pressure Loss: 16 Inches of Water)

Table 8.5 COE for the Three Pressure Systems

1 pressure system	48.13 $/MWh
2 pressure system	46.39 $/MWh
3 pressure system	45.79 $/MWh

These results are not sufficient to determine an optimum design. To do so will require a more complete evaluation of the cost of electricity (COE), which will include more details on maintenance costs, coupled with a study of power demand and value. In addition, other HRSG design parameters besides the exhaust gas pressure drop must be evaluated. These parameters include the following:

- Temperature increments between the exhaust gas temperature and the water/steam temperatures such as the pinch point temperature increment in evaporators and approach temperature increments in superheaters and reheaters.

- Pressure levels for one-pressure, two pressure and three pressure systems.

- Integration of catalysts for NOx and CO reduction (these components add to the exhaust gas pressure drop)

- Off design conditions emphasizing the change in exhaust gas temperature and flow rates. In addition, supplementary burning (SB) in the HRSG is a viable off design option. Whether on or off an SB will also affect the exhaust gas pressure drop, and the added steam production when it is on will affect the size of the steam turbine.

Each of these parameters is important design consideration that will affect the size and cost of the heat exchangers in the HRSG, and the economics of the total combined cycle power plant [111]. However, the results presented herein are considered to be an important part of that more complete optimization study.

CHAPTER 9
CONCLUSIONS AND RECOMMENDATIONS

The deregulation of the electric power market has introduced a strong element of competition. To meet this challenge, power plant operators must strive to develop advanced operational strategies to maximize the profitability in the dynamic electric power market. The objective of this research is to create an integrated operational modeling and optimization environment for gas turbine based power plants. This environment is intended to maximize power plant lifecycle profitability through intelligent generation scheduling, outage planning, maintenance scheduling, and upgrade packages selection. This approach matches the evolving electric power market and is capable of performing operational optimization with complex situations.

9.1 Research Questions

The research questions motivated this study are now revisited and answered based on the findings of the research work. The questions and their answers are as follows:

1. are the limitations of the current adopted philosophies and methods for power plant operational optimization? What are the needs for change to achieve power plant operational optimization in the deregulated electric power market?

- There has been intensive research on power system level optimization. The methods are based on system wide or fleet wide approach. Simplified assumptions on plant performance, reliability, and maintenance effectiveness are made, and the complexity of gas turbine based power plant operation and maintenance is not well addressed. Traditionally, the objective of operational optimization is usually to minimize cost. Generation scheduling and outage planning optimization are performed separately, which means that short term and long-term productivity are not coordinated, and the impact of generation scheduling on power plant entire service life is not addressed.

- A profit based, lifecycle oriented, unit specific power plant operational modeling and optimization methodology is needed for gas turbine based power plant operation to enhance operational decision making, and therefore to maximize power plant profitability by reducing operations and maintenance cost and increasing revenue.

2. Is it possible to develop a profit based, lifecycle oriented, and unit specific approach for gas turbine power plant operational modeling and optimization, which considers performance, reliability, and market signals simultaneously?

- Yes. This research creates an integrated operational modeling and optimization environment for gas turbine based power plants. A integrated operational modeling environment for gas turbine power plant is created, and various operational optimization problems, including long term generation scheduling, outage planning, preventive maintenance scheduling, upgrade packages selection, and power plant design optimization problems are solved using this integrated operational modeling. This approach matches the evolving electric power market and is capable of performing operational optimization with complex situations.

3. What are the key elements for the proposed operational modeling and optimization approach?

- A profit based lifecycle oriented operational optimization considers all the factors that are involved in producing power plant revenue and associated cost. There are two main issues, and they are to be addressed simultaneously: 1) the generation of revenue from both long-term fixed contracts and the short-term spot market; 2) technical drivers such as power plant performance and its degradation and restoration, and reliability and its restoration. Unit specific performance and reliability modeling with consideration given to changing operating conditions and maintenance activities provides accurate information to treat plants or units individually. This requires the development of models to quantitatively analyze the relationships between unit aging rate and operating conditions. All of the key elements are modeled using a generic profit equation. Lifecycle oriented operational modeling and optimization requires coupled generation scheduling, outage planning, maintenance scheduling, and upgrade packages selection.

4. How are the quantitative relationships between power plant degradation (aging) rate and unit operating modes evaluated? How are the quantitative relationships between performance and reliability degradation and operating conditions

evaluated? How to evaluate the quantitative relationships between performance and reliability restoration and maintenance activities?

- The concept of maintenance factors is used to evaluate power plant aging rate and its operating modes. A baseline condition for operating hours is defined as a gas fuel unit operating at continuous duty with no water or steam injection. The maintenance factor for this baseline is defined as 1. For operation that differs from the baseline, maintenance factors reflect the changed level of maintenance that is required. In so doing, the influence of factors such as fuel type and quality, firing temperature setting, and the amount of water or steam injection are considered with regard to hours based criteria. Similarly a baseline condition for starts can be defined, and maintenance factors can be defined based on the attributes of an actual start. Start up rate and the number of trips are considered for the start-based criteria. Therefore the maintenance factor converts the effects of operating conditions that deviate from the baseline to that of the baseline. Cumulative factored fired hours and factored starts can be obtained along the unit operating timeline.

- The power plant performance and reliability degradation can therefore be evaluated using empirical models based on historical operational data. The effectiveness of maintenance, i.e., the quantitative relationships between performance and reliability restoration and maintenance activities is evaluated using the virtual age method.

5. How is the coupled long term generation and profit based outage planning problem formulated and solved?

- The cumulative factored fired hours and factored starts are used as the intermediate parameters to couple the long term generation scheduling and outage planning problem. A multiple time scale optimization technique is developed to solve the long-term generation scheduling problem to identify the optimal long-term generation profile. This profile will be subject to the constraint of next outage plan. In the profit-based outage planning problem, the long term generation scheduling is a sub-problem, and the optimal generation schedule and outage plan are achieved simultaneously, with joint consideration of power plant performance, reliability, and market signals. The optimization algorithm is implemented using a combination of a Genetic Algorithm and gradient based optimizer.

6. How is a sequential preventive maintenance scheduling method different from the current adopted periodic preventive maintenance scheduling method? How is it formulated and solved?

- Traditionally gas turbine power plant preventive maintenances are scheduled with constant maintenance intervals based on recommendations from the equipment suppliers, and the preventive maintenances are scheduled in a one-size-fits-all fashion. However, in reality, the operating conditions for each gas turbine may vary from site to site, and from unit to unit. Furthermore, the gas turbine is a repairable deteriorating system, and preventive maintenance usually restores only part of its performance. This suggests the gas turbines need more frequent inspection and maintenance as they age. Traditionally the optimization criteria for preventive maintenance scheduling are usually cost based. In the deregulated electric power market, a profit based optimization approach is expected to be more effective than the cost based approach. In such an approach, power plant performance, reliability, and the market dynamics are considered in a joint fashion.

- A profit based sequential preventive maintenance scheduling method is developed in this study. Imperfect maintenance is assumed and the virtual age method is employed to model maintenance effectiveness. The objective of the maintenance scheduling is to maximize the profit rate of the power plant, instead of the traditional approach to minimize the cost of maintenance.

7. How is an upgrade packages evaluation and selection problem formulated and solved with consideration of power plant operational decisions?

- The impact of upgrade packages on power plant performance is modeled using technology impact factors (tuning constants). Two different mechanisms are used to model the impact of upgrade packages on reliability. One mechanism is that the introduction of upgrade packages results in a change in the operating conditions (firing temperature), which results in a maintenance factor for each critical component. The other mechanism is that the introduction of upgrade packages changes the design of certain critical components, which results in a change in their design life, and therefore a change in their reliability.

- The technology identification, evaluation, and selection method is employed to develop an effective method for power plant upgrade packages evaluation and selection.

8. How is a combined cycle power plant design optimization problem formulated and solved?

- As an example, a study to evaluate the impact of HRSG exhaust gas pressure drop and system complexity on the overall COE of a combined cycle power plant is performed. The study uses a fixed gas turbine engine and steam turbines that differ depending on the number of pressure levels in the system. With the emphasis placed on the HRSG design, numerous parameters are varied to optimize the HRSG design. For this study, the design parameter chosen for evaluation is the exhaust gas pressure drop across the HRSG. This parameter affects the performance of both the gas turbine and steam turbine and the size of the heat recovery unit. HRSG and steam turbine designs with one, two and three circuit pressures are evaluated in the study. Techniques such as Design of experiments, screening test, and Genetic Algorithm are employed to implement this parametric study.

9.2 Summary of Contributions

The focus of this study is to develop an integrated framework for gas turbine power plant operational optimization that matches the changing environment of the deregulated electric power system. This framework is unique and novel in that it matches the needs of improving power plant profitability by integrating power plant performance, reliability, and market dynamics. However, the development of the integrated framework is only one of the several contributions made in this study. Several specific operational optimization problems are formulated and solved with novel philosophies and methods.

There are three major thrusts in this thesis work.

1. The first thrust is the development of the profit based, lifecycle oriented, and unit specific operational modeling and optimization approach. This thrust involves with simultaneous consideration given to power plant performance, reliability, maintenance, and market models. The developed method is applicable for a variety of operational optimization problems.

2. The second thrust is the development of specific optimization problems using the integrated operational modeling environment. The development of models is achieved for the profit based, coupled generation and maintenance scheduling, and the sequential preventive maintenance approach. Specific operational and maintenance strategies are developed.

3. The third thrust is the application of TIES method for power plant upgrade packages evaluation and selection and power plant design optimization.

The contributions of this study are summarized as follows:

1. Development of a systematic and integrated approach for gas turbine based power plant operational modeling and optimization. A profit based, lifecycle oriented, and unit specific methodology for gas turbine based power plant operational modeling is developed with the power plant performance, reliability,

maintenance, and market dynamics considered simultaneously. The generic methodology is applicable for a variety of optimization problems, and several applications are implemented in the study using this method.

2. Development of a dual time scale method for gas turbine power plant long term power generation scheduling. This dual-scale approach allows combining the detailed granularity of the day-to-day operations with global (seasonal) trends, while keeping the resulting optimization model relatively compact.

3. Development of a method for gas turbine power plant profit based outage planning. Outage planning that considers only performance and/or reliability will essentially lead to a sub-optimal solution. A systematic approach for profit based outage planning is introduced, and the key factors for this profit based approach include power plant aging, performance degradation, reliability degradation, and, importantly, the energy market dynamics. The profit-based outage planning problem is solved with the long term generation scheduling as a sub-problem.

4. Development of a profit based sequential approach for gas turbine power plant preventive maintenance scheduling. A novel approach for gas turbine based power plant maintenance scheduling is introduced, and a profit based sequential preventive maintenance scheduling method is developed for more effective maintenance scheduling. The objective function for optimization is the profit rate for each O&M cycle. The results show decreasing maintenance intervals as the power plant ages.

5. Application of the TIES methodology for effective selection of gas turbine power plant upgrade packages, and application of the TIES method for gas turbine based power plant design optimization using a HRSG design optimization as an example.

9.3 Recommendations for Future Development

The following are recommendations for future research based on this thesis study.

Maintenance actions and upgrade packages show strong similarity in the operational modeling and optimization. They both restore or improve power plant performance and reliability, and they are both discrete events. The development of an integrated approach to model maintenance actions and upgrade packages would be helpful for planning maintenance actions and infusion of upgrade packages in a joint fashion.

As addressed before, the unit specific approach for gas turbine based power plant operational modeling and optimization requires numerous historical operational data. In this study, several specific models for plant aging, performance and reliability degradation are proposed, however, the data required to implement and validate these models are not accessible. Future work is recommended for further development of these advanced models, as long as the historical data are available.

The reliability functions for the equivalent age reliability modeling method addressed in Chapter III is based on the regression from a fleet wide data analysis. However, the unit history of a specific unit may differ substantially from the "normal" usage history. For example, the aging of a specific unit may differ from the "normal" condition in that it may suffer from poor quality fuel, wrong operation, and long time peak load operation. This kind of unit specific operation is not obtainable from the equivalent age based approach. These types of constraints can be overcome by employing the covariates based approach. Other proposed approaches for operating conditions modeling include the accelerated life mode (ALF) and the proportional hazards model. These models have been used in the study of lifetime in medicine, reliability and economics. In these approaches, operating conditions are defined using covariates.

Another important task is to model performance degradation with consideration given to varying operating conditions. In this study, the actual operating hours approach is employed to model the accumulative performance degradation. The actual operating hours approach assumes specific operating conditions, and therefore, the performance degradation is only a function of service life. This implies that the engine is running at a uniform operating profile and constant external environment. These assumptions are not true in that the external environment, such as the ambient conditions varies substantially with a strong seasonal and daily trend. Furthermore, the operating modes, which define the load setting, fuel type, and power augmentation, vary substantially due to the dynamic electric power market. The operating conditions significantly affect the engine degradation rate. To capture the effect of operating conditions on engine performance degradation, a model which does not only consider engine service life, but also its operating conditions, which include external operating environment and usage history, would be helpful The model should be able to link performance degradation rate and operating conditions. Obviously, such a model would be extremely useful for the determination of operating decisions when performance and economics are considered.

Similar to the method for reliability modeling, a proportional degradation rate model can be developed for this purpose.

In this study, operations modeling and optimization are based on unit specific approach, and only one unit is assumed in the optimization problem. In actuality, electric power producers may have multiple units in a single plant or site. This requires the development of a plant/site specific approach. The unit specific approach developed in this study provides a good basis for plant/site specific approaches.

In this study, the dynamic electric power market is modeled using a forward forecasting of price of electricity and price of fuel. However, the mechanism of electricity pricing has not been investigated. A further development would be to investigate the dynamics of electricity markets, and agent based economics can be employed to study the dynamic behavior, i.e., the interaction of the key players in the deregulated electric power market.

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