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Degradation Modelling for Health Monitoring Systems

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Abstract. Condition-monitoring plays an increasingly important role for technical processes in order to improve reliability, availability, maintenance and lifetime of equipment. With increasing demands for efficiency and product quality, plus progress in the integration of automatic control systems in high-cost mechatronic and critical safety processes, the field of health monitoring is gaining interest. A similar research field is concerned with an estimation of the remaining useful life. A central question in these fields is the modelling of degradation; degradation is a process of a gradual and irreversible accumulation of damage which will finally result in a failure of the system. This paper is based on a current research project and explores various degradation modelling techniques. These results are explained on the basis of an industrial product – a system for the generation of health status information for pump systems. The result of this fuzzy-logic based system is a single number indicating the current health of a pump system.

1. Introduction, background and overview

Several research activities referring to “health monitoring”, “remaining useful life estimation” and “degradation modelling” focus on the behavior of a system during its lifetime. The results of these research activities are required for condition-based maintenance, which carries the potential to increase the safety, quality, and reliability, and to reduce the operating costs of a process. One aspect shows the enormous importance of these research activities: systems are very often a part of a superordinate system; if a system ceases operation because of degradation, this might lead to a shutdown of the whole superordinate system causing high costs for the operating company. One strategy to avoid such situations are regularly scheduled changes or upgrades of important systems. A lack of information of the condition of the system often leads to waste – fully functional units are replaced and destroyed. The methodologies for the given field can be divided into model-based and data-driven approaches [1].

In the model-based approach, a mathematical model of the system can be used to calculate an estimation of the outputs based on the current inputs. By comparing the model output and the real measurements a residual can be created from which information about degradation can be derived. With a good knowledge of underlying physics or the degradation structure, a very high level of accuracy of the model can be attained. However, it is often difficult to build good models for large scale systems, especially if the knowledge of underlying physics is limited. Alternatively, using data-driven methods, the information about degradation can be extracted from current and historical data through measurements. Currently, a huge amount of measurement data is collected and thus available from modern process control systems enabling such approaches. One key element of a system’s "health monitoring" or "remaining useful life estimation" is degradation modelling, which is the main content of this paper.

2. Analytical approach

Most failures of engineering systems result from a gradual and irreversible accumulation of damage that occurs during a system's life cycle. This process is known as degradation [2]. In many applications, it can be very difficult to assess and observe physical degradation, especially when real-time observations are required [3]. Degradation modelling attempts to characterize the evolution of degradation signals. There are a significant number of research works that have focused on degradation models; a summary can be found in Zhou et al. [3]. In contrast to many publications which focus on the stochastic nature of damage, this paper focuses on the explanation of certain degradation phenomena, creating additional possibilities to model degradation. These models are usually easy to understand for product development engineers and thus ease implementation of such in an industrial context. In order to explain the degradation mechanism, a typical complex product – a car engine – is used (Figure 1).

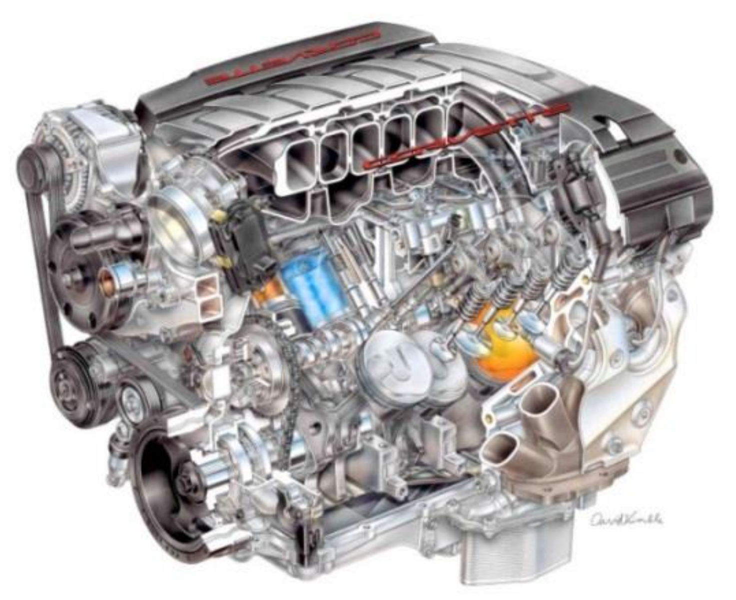

Figure 1. Car engine – example for explaining degradation phenomena (Source: Chevrolet: D. Kimble)

For a detailed discussion of a complicated system, such as a car engine, a technique called "black-box" is frequently used in product development. In this technique only the inputs and outputs to a system are depicted. Figure 2 shows one possible black-box diagram for the engine, which is used to structure to following discussion.

2.1. Performance oriented degradation detection

One of the main indicators of degradation of a product is the performance of the respective system, which means the quantitative fulfillment of the central functions of the system. For an engine the performance is primarily shown by the speed and the torque of the output shaft (which can be multiplied to the power delivered by the engine); secondary indicators could be the ability of the engine to increase the speed within a time frame under a certain load and with certain connected moments of inertia.

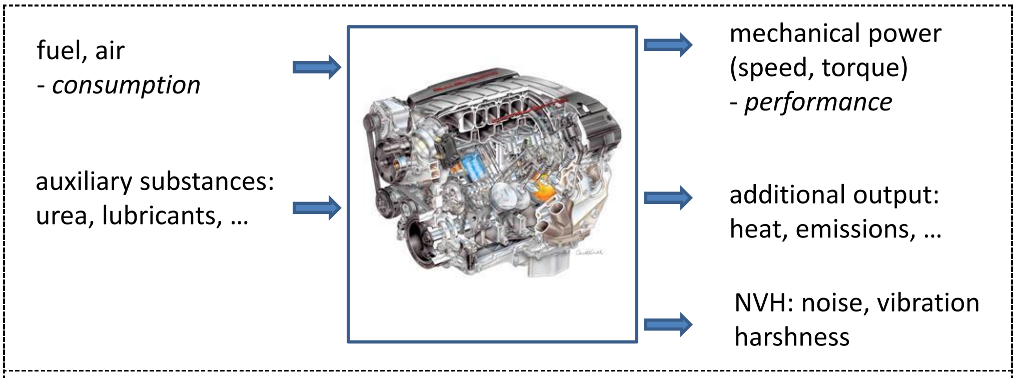

Figure 2. Black-Box diagram car engine.

In general it is sensible to define a dimensionless degradation indicator in relation to the initial performance:

$$DI_{Po} = \frac{\text{current performance}}{\text{initial performance}} \quad (1)$$

Here, DI_{Po} represents the degradation indicator which is performance oriented. For the engine this might be:

$$DI_{Po} = \frac{\text{current output power}\left[\text{kW}\right]}{\text{initial output power}\left[\text{kW}\right]} \quad (2)$$

It is important to note that many systems do not exhibit linear performance degradation. Figure 3 shows typical examples of performance degradation.

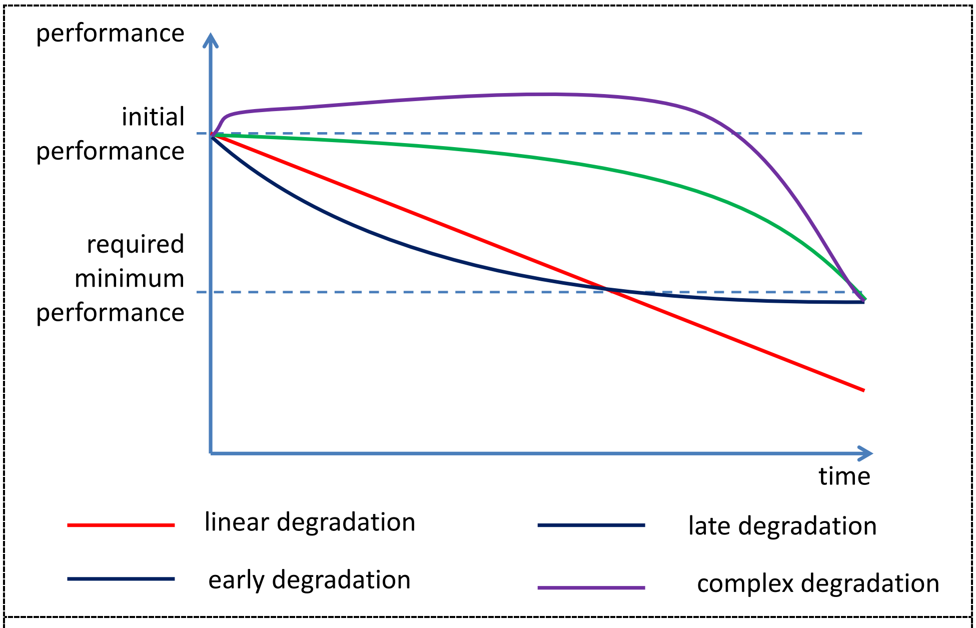

Figure 3. Typical performance degradation

The required minimum performance is usually within the range of 60% to 90% of the initial performance. Linear performance degradation would ease mathematical modelling, but is usually not realistic because damage is usually accumulated stochastically. Additionally, in real systems, the initial operation hours may lead to better friction behavior and reduced impedances (burn-in – see curve complex degradation). In later stages, certain layers of substance (for instance, friction-reducing layers) are partially eroded, leading to higher friction and lower performance. Through combinations of these effects, other performance degradation may occur (compare Figure 3). The complex degradation, in particular, will require intelligent treatment. Simple threshold mechanisms may allow a detection of the required minimum performance but will not allow foresight of the moment in time when the system will reach this threshold. A possible solution is polynomial degradation models based on empirical results together with specified margins. Figure 4 shows one example: a fourth degree polynomial degradation model.

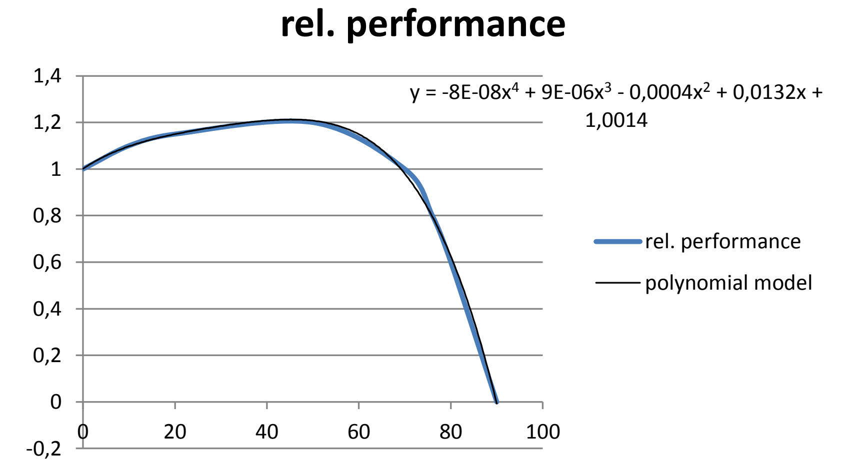

Figure 4. Polynomial degradation model

It is important to note that the performance very often cannot be directly measured. For engines today, the speed is usually measured by appropriate sensors, but torque sensors are still too costly to be implemented. The motor control systems usually contain some knowledge of the torque, but this "knowledge" results from mathematical models and other input signals, such as the amount of fuel injected. Because of this, virtual sensor techniques are often applied to allow performance oriented degradation detection.

2.2. Additional output oriented degradation detection

As visible in Figure 2, systems very often produce several outputs other than the desired outputs which are actually needed for the function of the product. For a car engine, these outputs are heat and emissions. Prime examples for degradation in an engine are worn piston rings. Worn piston rings result in lubricants in the combustion chamber. The burning of these lubricants leads to additional substances in the exhaust gases, which are sometimes even visible and can be easily measured. Similarly, a damaged cylinder head gasket may allow cooling fluid into the combustions chamber, also leading to additional unwanted substances in the exhaust gases. A dimensionless degradation indicator can be defined as:

$$DI_{AOo} = \frac{\text{initial additional output}}{\text{curent additional output}} \quad (3)$$

Here, DI_{AOo} represents the degradation indicator, which is additional output oriented.

2.3. Consumption oriented degradation detection

One important characteristic of degraded systems is decreased efficiency. For the engine example certain effects such as a reduced compression ration leads to inferior engine combustion and higher

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losses. Such effects are visible in a higher consumption; for the engine in a higher fuel consumption. A dimensionless degradation indicator can be defined as:

$$\mathrm{DI}_{\mathrm{Co}} = \frac{\text{initial consumption}}{\text{current consumption}} \quad (4)$$

Here, $\mathrm{DI}_{\mathrm{Co}}$ represents the degradation indicator, which is consumption oriented. It is strongly connected to efficiency.

Therefore, another dimensionless degradation indicator can be defined as:

$$\mathrm{DI}_{\mathrm{Eo}} = \frac{\text{current efficiency}}{\text{initial efficiency}} \quad (5)$$

Here, $\mathrm{DI}_{\mathrm{Eo}}$ represents the degradation indicator, which is efficiency oriented.

2.4. Auxiliary substance oriented degradation detection

Typical auxiliary substances found in car engines are lubricants. The condition of lubricant is usually a very good degradation indicator. A high amount of water in the lubricant is usually an indicator of issues with the cylinder head gasket. Particles in the lubricant may indicate wear of certain parts. Also, the color of a lubricant changes over time. This kind of degradation detection usually relies on a variety factors including the viscosity, light transmissibility and particle content of the lubricant. A dimensionless degradation indicator can be defined as:

$$\mathrm{DI}_{\mathrm{ASo}} = \frac{\left(\sum_{i}^{n} \frac{\text{current substance characteristic}_i}{\text{initial substance characteristic}_i} \right)}{n} \quad (6)$$

Here, $\mathrm{DI}_{\mathrm{ASo}}$ represents the degradation indicator, which is auxiliary substances oriented. A substance characteristic can be a measurement of a property such as viscosity, and n is the number of such characteristics used to characterize the degradation behavior.

2.5. Noise/vibration/harshness oriented degradation detection

The concept of "noise, vibration, and harshness" (NVH), refers to research concerning the noise and vibration characteristics of systems, such as vehicles. A dimensionless degradation indicator can be defined as:

$$\mathrm{DI}_{\mathrm{NVHo}} = \frac{\begin{array}{c}\text{initial noise / vibration /}\\ \text{harshness indicator}\end{array}}{\begin{array}{c}\text{current noise / vibration /}\\ \text{harshness indicator}\end{array}} \quad (7)$$

Here, $\mathrm{DI}_{\mathrm{NVHo}}$ represents the degradation indicator which, is noise/vibration/harshness oriented. The noise / vibration / harshness indicator can be a measurement of a vibration sensor.

It is important to note that it is sometimes it is possible to measure NVH even without specific sensors. Rad et al. [4] report that research concerning an online tool wear estimation algorithm has been developed for milling operations. The algorithm uses the AC current signal of the spindle for the detection process (due to its applicability and low acquisition cost in the industry) and applies a time-frequency analysis, gathering the effects of NVH on the main spindle.

2.6. Life-time oriented degradation detection

One of the most straightforward approaches is to observe the operation time of a system. Here, it is very often sensible to include the load of the system. For an engine, it might also make sense to calculate the delivered power multiplied by the operation time.

A dimensionless degradation indicator can be defined as:

$$DI_{LTo} = 1 - \frac{\int_{0}^{\text{current time}} \text{power}(t) \cdot dt}{\text{expected power} \cdot \text{operation time}} \qquad (8)$$

Here, DI_{LTo} represents the degradation indicator which is life-time oriented.

2.7. Geometry oriented degradation detection

A typical example of a geometry degradation indicator would be worn pistons, which increase the size of the bore hole due to gradual removing of material during operation. A dimensionless degradation indicator can be defined as:

$$DI_{Go} = \frac{\text{current dimension}}{\text{initial dimension}} \qquad (9)$$

Here, DI_{Go} represents the degradation indicator, which is geometry oriented. It is strongly connected to efficiency.

2.8. Selection of degradation indicators

In the previous sections, multiple methods of deriving degradation indicators were explained. It is a major challenge to choose the proper degradation indicators. Quite often, experienced engineers can make a sensible choice. An elaborate methodology is described by Lamoureux et al. [5]. Here, a complete methodology for the selection and validation of health indicators (similar to degradation indicators) in health monitoring systems design is introduced. This methodology, called integrated prognostics and health management, is based on the use of numerical modeling and uncertainties propagation to generate data in sufficient amount to validate health indicators. In order to simulate the distribution of health indicators, a well-known surrogate model called Kriging is utilized. Lamoureux et al. [5] have also defined some numerical key performance indicators as criterion for performing the validation of health indicators. A combination of the product oriented possibilities to find degradation indicators presented in this paper and the methodology of Lamoureux et al. [5] to validate them suggests an interesting possibility for the design of future health monitoring systems.

3. Health Monitoring System for Pumps

The industrial product example for this research is a three spindle screw pump [6]. A three spindle screw pump is a positive displacement pump that uses one or several screws to move fluids or solids along the screw(s) axis (Figure 5).

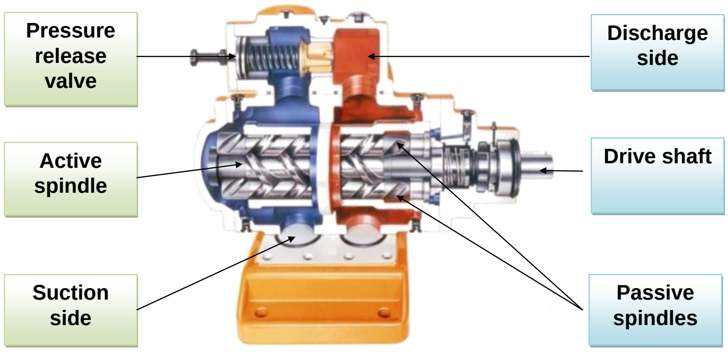

Figure 5. Three spindle screw pump.

Three-Spindle screw pumps are used for transport of viscous fluids with lubricating properties. They are suited for a variety of applications such as fuel-injection, oil burners, boosting, hydraulics,

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fuel, lubrication, circulating and feed and so on. The fuzzy system, which aims to generate a health status information (compare [7], [8]) is based on several inputs which may either come directly from sensors, from information from the frequency converter, which is supplying the motor driving the pump, from an online model of the pump system (compare [9] and **Fehler! Verweisquelle konnte nicht gefunden werden.**) or from a life counter. The inputs and their sources are summarized in Table 1.

Table 1. Inputs and their sources

Inputs	Source
Output pressure	Sensor reading (direct)
Pressure Pulsation	Sensor reading (indirect)
Torque	Frequency Converter
Speed	Frequency Converter
Fluid Temperature	Sensor reading (direct)
Life count	Life counter
Q_V – Leakage Loss	Online model
P_r – Friction Loss	Online model

This information is fuzzified, the rules are applied, and the defuzzification takes places. These steps result in crisp values for certain failure modes (Table 2).

Table 2. *Failure modes*

Failure Modes	Explanation/Example
Vibration	
Line blockage	e.g. clogged filter
Frequency converter failure	e.g. overspeed
Housing failure	e.g. cracks due to ageing
Pump overheat	
Worn spindles	abrasion on spindles
Worn bearings	increased friction

These crisp values are then concentrated to one single health status number by means of an unique algorithm, which is described in detail in Section 5 of this paper. An overview of the process is given in Figure 6.

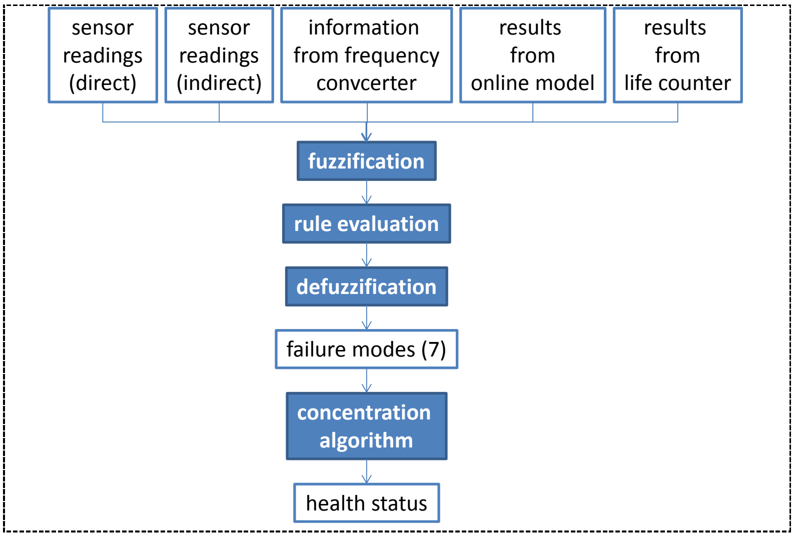

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Figure 6. Process for determining the health status.

Pressure Pulsations (see Table 1) are the fluctuations in the basic pressure/head being developed by the pump. These pulsations can sometimes be very severe and cause damage to the piping or other components in a hydraulic system (Figure 7).

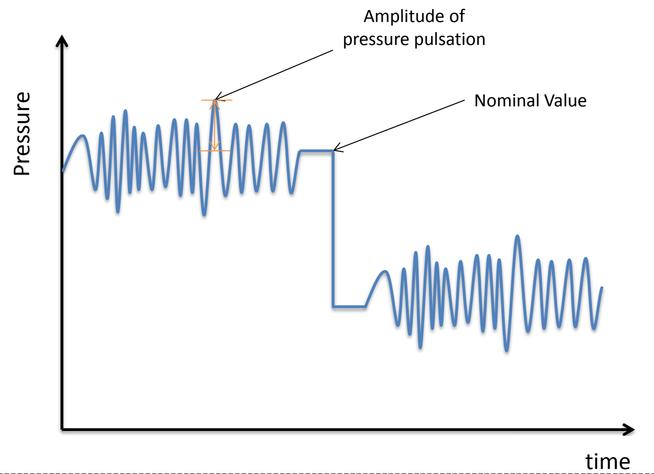

Figure 7. Pressure pulsation.

This indicator uses a special kind of noise/vibration/harshness oriented degradation detection (compare section 2.5). The amplitude of the pressure pulsation is a consequence of the vibrations within the pump.

P_r – the Frictional Power Loss Coefficient is the loss of energy or "head" that occurs in pipe flow due to the viscous effects generated by the surface of the pipe. The friction power of a pump, which is considered as power loss, can be described as in Equation 10:

$$P_{r2} = P_{r1} \cdot \sqrt{\frac{vis_2}{vis_1}} \cdot \left(\frac{n_2}{n_1}\right)^{1,5} \quad (10)$$

The Leakage Loss Coefficient Q_v can be described as in Equation 11:

$$Q_v = Q_{v10} \cdot \left(\frac{\Delta P}{10}\right)^{x} \sqrt{\frac{vis_1}{vis_2}} \quad (11)$$

Q_{v10} and vis_1 are coefficients or reference values proposed by leading pump manufacturers. Both indicators show the efficiency of the pump; so consumption oriented degradation detection is applied (compare section 2.3).

4. Degradation Indicators

One important input to the system which serves as an indicator for degradation, is the Pressure Pulsation (compare section 3). For this indicator the following graph gives a clear idea of the range of pressure pulsation and speed for the three states "New", "Trend" and "Worn" pump. If the pressure pulsation ranges from 2 % -10 % with speed ranges from 2900 rpm-1000 rpm, respectively, then the condition of the pump is new. If the pressure pulsation at 1000 rpm is raised nearly 15%, this indicates the "Trend" condition (indicating the beginning degradation of the pump and thus serving as a pre-warning) pump condition. For "Worn" pump, Pressure pulsation will be approximately 20% at the speed of 1000 rpm (Figure 8).

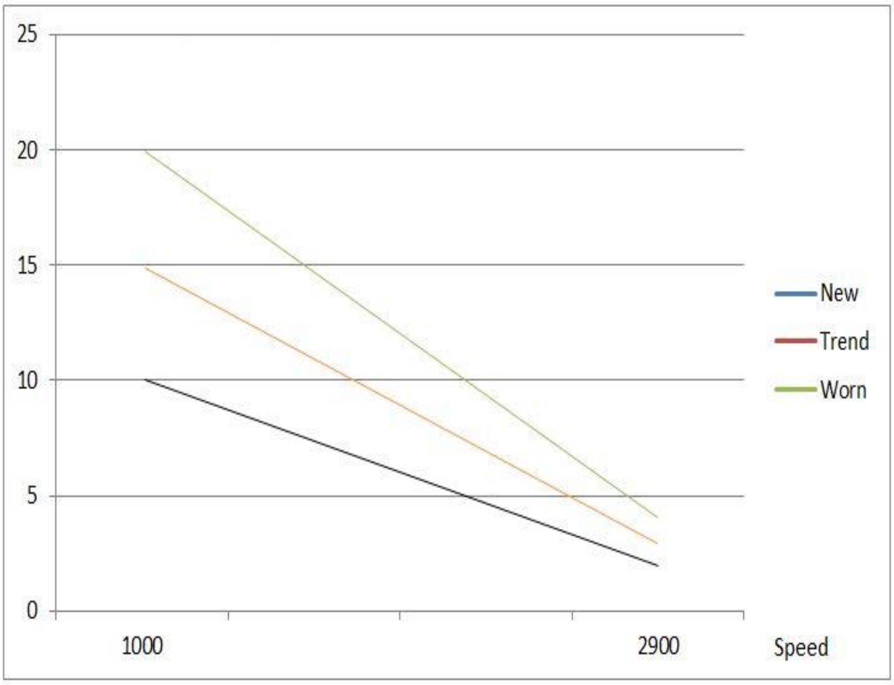

Figure 8. Degradation indicator pressure pulsation.

A second powerful indicator is the Frictional Power Loss Coefficient (compare Section 3). Increased frictional power loss is frequently caused by overloading and insufficient lubrication. New, conditioned pumps have a theoretical frictional power loss coefficient, P_{rth}. A recalculation of P_r after some time that shows friction being 75% higher than the originally calculated value of P_{rth} indicates a "Trend" state. If the friction is 150% higher than the initial value of P_{rth}, then the pump is said to be in the "Worn" state (Figure 9).

As a third indicator, the Leakage Loss Coefficient can be used (compare Section 4). Increased leakage losses may be a result of abrasive flow causing wear of spindles in the pump. New pumps have a theoretically calculated leakage loss coefficient, Q_{vth}. If the leakage loss is 30 % higher than the calculated theoretical value of Q_{vth}, then the condition of the pump is "Trend".

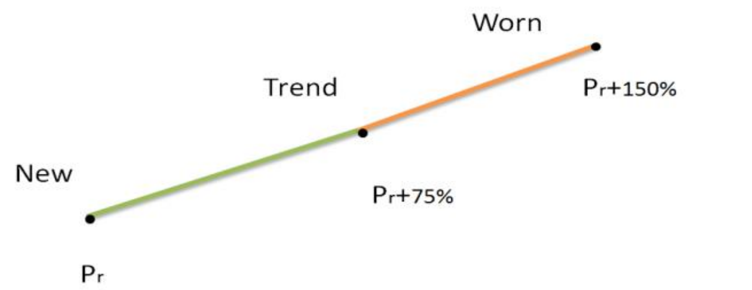

Figure 9. Degradation indicator friction power.

For "Worn" pumps, the leakage loss can be 100% higher than the calculated value of Q_{vth} (Figure 10).

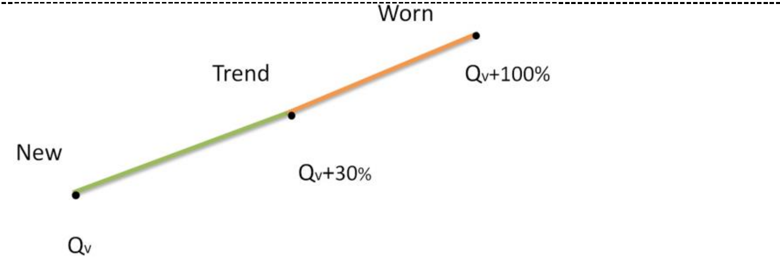

Figure 10. Degradation indicator leakage loss.

Figure 11 gives an overview of the degradation of a pump.

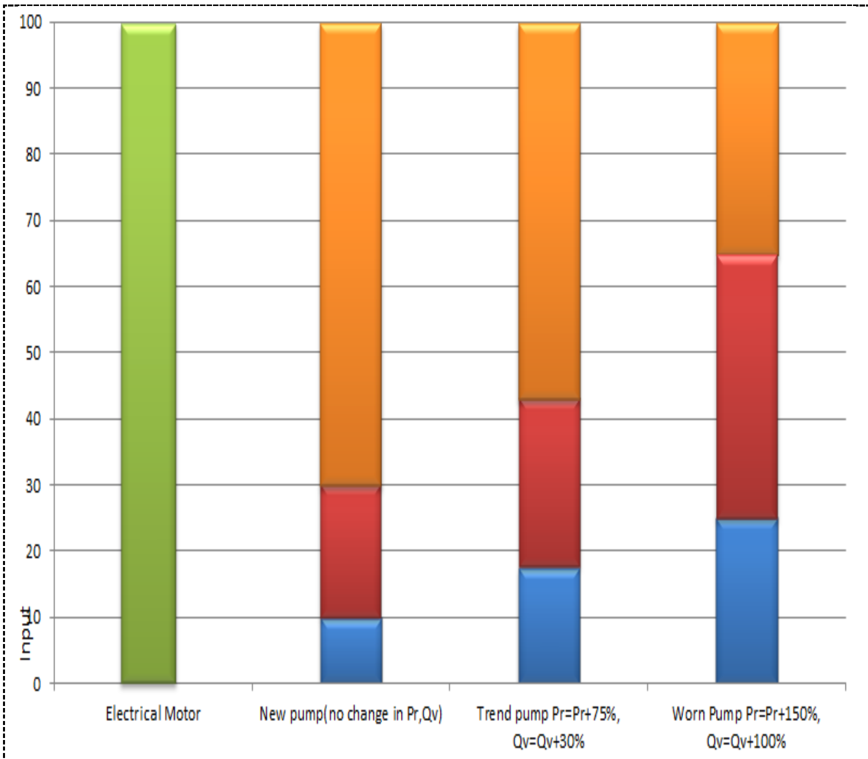

Figure 11. Overview of degradation indicators.

5. Calculation of the Health Status Number

A useful health status number can be calculated through an analogous process to FMEA [7], [8]. The severity of a failure mode plays an important role in the sensible health status, as not all failure modes have the same effects, and, therefore, the same severity. Here, a variable "importance" can be used. The occurrence can be understood, in this case, as the single failure mode output from the fuzzy model - the variable can, for instance, be named "fuzzy output". The third parameter "compensatability" is optional: analogous to "detection", some failure modes can be compensated by means of a control system. Equation 12 explains how the pump health status is calculated based on the fuzzy outputs obtained.

$$\text{Health status }(\text{HS}) = 1000 \cdot n - \sum_{i=1}^{n} \text{importance(I)}_n \times \text{fuzzy output(FO)}_n \times \text{compensatability(C)}_n \qquad (12)$$

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Here, n is the number of failure modes. The sources of this equation are described in detail in [7]. The health status calculation includes a threshold setting to amplify bigger failures and attenuate smaller failures [11]. This will avoid exaggeration of the effect of failure modes. Figure 12 shows a flow chart describing the algorithm for this threshold.

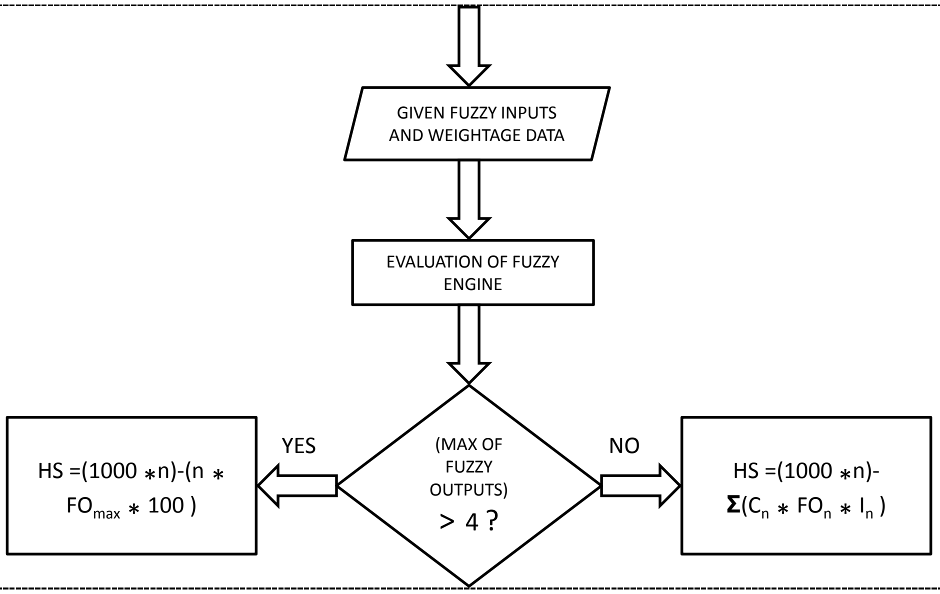

Figure 12. Threshold algorithm.

6. Validation

An intuitive set of test cases with 15 contrasting operating modes was formed to test behavior of the model. The results are shown in the Figure 13.

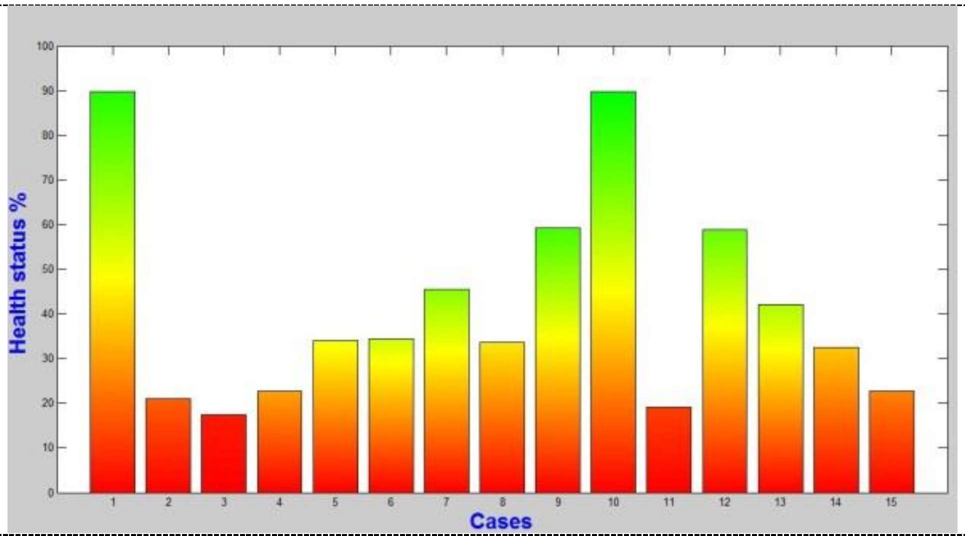

Figure 13. Health status results for certain test cases.

In Figure 14, the 3rd and the 11th case show a very low health status number due to the failure mode “frequency converter failure” and “highly worn bearings”. Cases 1 and 10 have a good health status because of their normal operating conditions. Cases 9 and 12 show medium health. Case 8 is for highly worn spindles. High speed and torque failure mode are depicted in Case 15. It is evident from Figure 13 that fuzzy mapping gives a meaningful representation of the health status of the pump in the form of a unique number or as percentage.

7. Summary

The main goal of this project, which is the basis the research described in this paper, is the development of a prognosis of future control and diagnosis technologies for pumps and intelligence in pumps. Experts in the field agree that in future health status analyses, information about the components is desirable in order to reduce shut-down times, plan availability and service, and extend the lifetime of systems. In this paper, the main focus was on the modelling of degradation. Several degradation mechanisms were explained and initial indicators were defined. Three different degradation indicators were explained with an application example. Further work will investigate additional degradation indicators and expand the mathematical modelling possibilities.

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