Probabilistic Life Cycle Cost Model for Repairable System

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Abstract. Traditionally, Life cycle cost (LCC) has been predicted in a deterministic approach, however; this method is not capable to consider the uncertainties in the input variables. In this paper, a probabilistic approach using Adaptive network-based fuzzy inference system (ANFIS) is proposed to estimate the LCC of repairable systems. The developed model could handle the uncertainties of input variables in the estimation of LCC. The numerical analysis shows that the acquisition and downtime cost could have a high effect towards the LCC compared to repair cost. The developed model could also provide more precise quantitative information for decision making process.

1. Introduction

LCC has been used widely as a decision making tool in various industries as the industries have experienced high maintenance cost, limitation of budgets, high cost of products and higher cost of ownership [1]. Generally, LCC can be estimated using two approaches, namely deterministic and probabilistic approaches [2]. The deterministic LCC analysis uses fixed and distinct input variables. Korpi and Alarisku [3] found that manufacturers prefer deterministic method compared to probabilistic which 83% of the manufacturer uses the deterministic approach while 13% of them uses the probabilistic method of LCC. Although this method has been practiced by various industries, it is unable to consider the uncertainties of the input variables. In other words, estimation of LCC using deterministic method may not reflect the actual phenomena of the system [4]. In fact, probabilistic LCC analysis is capable to handle the uncertainties of input variables such as maintenance cost, downtime and failure rate [5], however; the application of probabilistic method is very limited. Thus, it is required to develop the probabilistic LCC model to improve the estimation of LCC.

Probabilistic method of LCC can be estimated using soft computing technology. This technology is able to compromise the imprecise, uncertainty and vague data. There are three common soft computing techniques such as genetic algorithm (GA), artificial neural network (ANN) and fuzzy logic system (FL). In order to handle uncertainties, hybrid approaches are recommended [4]. In this study, adaptive network-based fuzzy inference system (ANFIS) is proposed to evaluate LCC which

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The developed ANFIS LCC model can be integrated with reliability, availability and maintainability (RAM) to manage the uncertainty which can be caused by maintenance. Integrating RAM analysis in LCC model, it can mitigate the uncertainties due to maintenance [7]. As a result, the accuracy of LCC estimation could be increased. Furthermore, when reliability and availability of the system are increased, failure rate and downtime are minimized so that LCC can be reduced [8]. Hence, by integrating RAM analysis with LCC model, the accuracy of the model could be improved. Therefore, in this paper, the probabilistic LCC model is proposed to evaluate the overall cost of the repairable system.

2. Methodology

2.1. LCC Model
LCC model has played an important role in the decision making process and to evaluate the effectiveness of the repairable system. The governing equation for LCC model can be defined as (1):

$$LCC = C_{aq} + C_m + C_{op} + C_d \tag{1}$$

where, C_{aq} = acquisition cost; C_m = maintenance cost; C_{op} = operation cost; and C_d = downtime cost.

2.2. Acquisition Cost
Acquisition cost is consists of fixed (C_{FA}) and replacement cost. Fixed cost is the initial cost of equipment while replacement cost (C_{RA}) is the purchased cost of sub components when the equipment is failed. The acquisition cost can be defined using Equation (2):

$$C_{aq} = C_{FA} + C_{RA} \tag{2}$$

2.3. Maintenance Cost
Maintenance can run anytime when there is a failure occurs. The present value of maintenance cost can be estimated as [9]:

$$C_m = \int_0^t C_r \frac{\beta}{\alpha^\beta} t^{\beta-1} \exp\left[-\left(\frac{t}{\alpha}\right)^\beta - \theta t\right] dt \tag{3}$$

where, C_r = cost of repair per failure; t = number of years; θ = continuous discount rate; α = scale parameter; and β = shape parameter.

2.4. Operation Cost
Operation cost is the related cost to the operation and it can be referred to the cost to operate a certain equipment or device. Operation cost can be estimated using (4).

$$C_{op} = C_{fo} + C_v \tag{4}$$

where, c_{fo} = fixed operating cost; and c_v = variable operating cost.

The present value of operating cost can be expressed using (5):

$$C_{op} = [C_{fo} + C_v] \cdot \left[\frac{(1+i)^n - 1}{i(1+i)^n} \right] \tag{5}$$

2.5. Downtime Cost

When the system is down, the production is either reduced or totally zero, this causes huge financial consequence. Since the system failure is stochastic in nature, the downtime cost is a random variable and it can be expressed:

$$C_D = D_t \cdot Q \cdot C \tag{6}$$

where, D_t = cumulative downtime due to failure; Q = production per hour; and C = production lost per unit. The cumulative downtime can be expressed as:

$$D_t = [1 - A(t)] \cdot T \tag{7}$$

where, $A(t)$ = availability of the system and T = total operating time for the system.

The availability of the system can be determined by using the mean time between failure (MTBF) and mean time to repair (MTTR) [10].

$$A(t) = \left[\frac{MTBF}{MTTR + MTBF} \right] \tag{8}$$

Thus, the present value of downtime cost for the system can be expressed as:

$$C_D = \left[1 - \frac{MTBF}{MTTR + MTBF} \right] \cdot T \cdot Q \cdot C \cdot e^{-\theta t} \tag{9}$$

Hence, the probabilistic LCC model for repairable system is expressed as:

$$LCC = \left[C_F + C_{RA} \cdot \frac{1}{(1+i)^n} \right] + \int_0^t C_r \frac{\beta}{\alpha^\beta} t^{\beta-1} \exp\left[-\left(\frac{t}{\alpha} \right)^\beta - rt \right] dt + \left[C_{fo} + C_v \right] \cdot \left[\frac{(1+i)^n - 1}{i(1+i)^n} \right]$$
$$+ \left[1 - \frac{MTBF}{MTTR + MTBF} \right] \cdot T \cdot Q \cdot C \cdot e^{-\theta t} \tag{10}$$

2.6. ANFIS LCC Model

ANFIS is used to simulate the LCC of the repairable system for 20 years. It is able to solve data sets by using hybrid learning rules and it is capable to learn the training data [6]. Four numerical data sets are used to train the ANFIS as shown in Table 1. Each data set is used to calculate the cumulative LCC for the next 20 years with a discount rate of 10%.

Table 1: Train and test data set for ANFIS

No.	Fixed C_{aq}, $ (10^6)	Annual C_{aq}, $ (10^6)	Annual C_m, $ (10^6)	Annual C_{op}, $ ((10^6)	Annual C_d, $ (10^6)
1	21.0	2.0	0.6	3.1	4.5
2	13.0	1.5	0.4	2.0	2.8
3	31	3	1.2	4.9	6.0
4	20	1.8	0.5	2.9	4.2

Based on 20 years life span, 21 data sets are produced for each data set in Table 2. Data set 1 to 3 are used as training data and data set 4 is for testing data. Testing data is important in generating

ANFIS as it can prevent overfitting when it is training the data [11]. Thus, ANFIS LCC model has five inputs and layers which contributes to estimate LCC as indicated Fig 1.
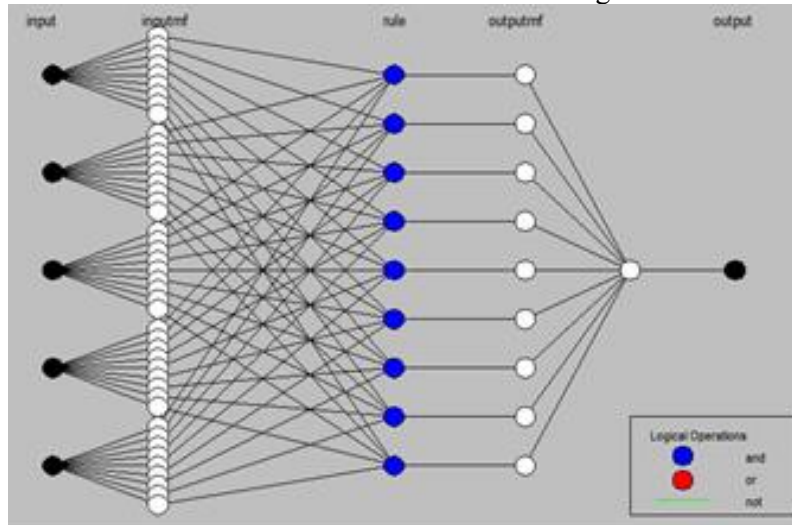

Figure 1: ANFIS LCC Model Structure

- Layer 0 is the input parameters for ANFIS which are acquisition cost, maintenance cost, operation cost, downtime cost and year.
- Layer 1 consists of the input membership function of the five input parameters. Each input parameter is subjected to five Gaussian membership functions. The Sub-clustering method is used to generate the membership function for all the input parameters.
- Layer 2 consists of nine rules. In this layer, the input parameters multiplied by their own member-ship functions and the output of this multiplication could firing strength of the rules.
- Layer 3, the nodes are used to calculate the ratio of rule's firing strength to the total sum of rule's firing strength. The output of this layer is known as normalized firing strength of rules.
- Layers 4, the nodes in this layer are known as adaptive node and it is the output membership function. In this stage, the input parameters with its own membership function and normalized firing strength of rules will be further integrated with the IF-THEN fuzzy rules.
- In Layer 5, there is only one node which is the final output (LCC) of the ANFIS.

Once the ANFIS-LCC model developed, the input data train is conducted to minimize the error of the model. In this study, the model has been trained for 100 epochs with a targeted error tolerance of 0 values. As a result, the training error has decreased linearly when the epoch is increasing. After 100 epochs, the training error has reached 0.24 as shown in Fig 2. This is a very small error which it shows that the accuracy of the model has been greatly increased.
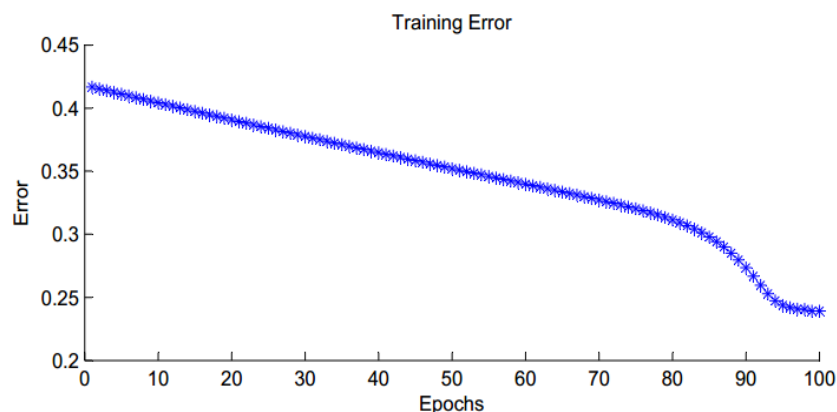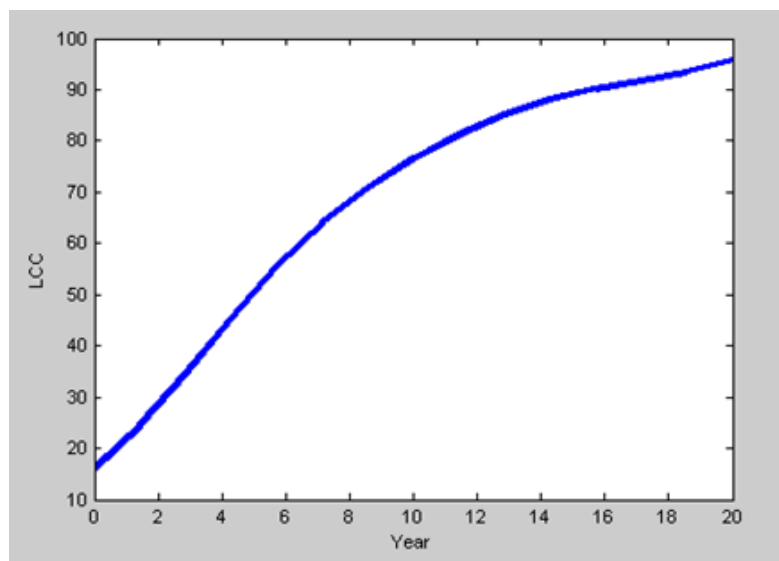
Figure 2: Training Error of ANFIS Model

3. Result and discussion

To illustrate the model, the numerical data used in this paper are indicated in Table 2. The numerical data for each cost value are calculated by using the Equation (2), (3), (5) and (9). Using Table 3, the estimated LCC of a repairable system for 20 years is shown in Fig 3. Based on Fig 3, LCC of the system is increasing linearly for the first 10 year. This is due to the high acquisition cost effect at the beginning of operation. After year 10, LCC of the system increases in a lower gradient compared to a previous 10 years. In year 20, the cumulative LCC of the repairable system is estimated to be $95.8 million.

Table 2. Numerical Data for LCC Prediction

Cost elements	Value
Fixed C_{aq}, \$(million)	21.0
Annual C_{aq}, \$(million)	2.5
Annual C_m, \$(million)	0.6
Annual C_{op}, \$(million)	2.45
Annual C_d, \$(million)	3
Discount Rate, %	10

Figure 3: Training Estimation of LCC

The relationships between the input parameters with the LCC are indicated in Fig. 4 and Fig. 5 for 20 year life span of time. Fig. 4 shows the relationship between acquisition cost and maintenance cost with LCC prediction. Fig. 4 shows increasing in acquisition cost can produce a significant increasing of LCC while the maintenance cost only produces a minor effect.
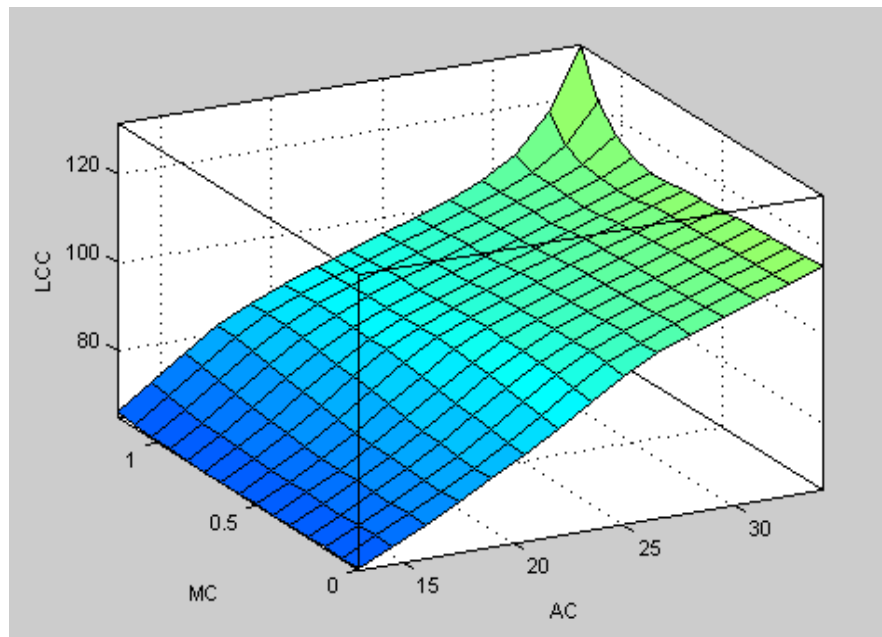
Figure 4: Effect of Acquisition Cost and Maintenance Cost with LCC

Fig. 5 shows the relationship between the operation cost and downtime cost with LCC of the repairable system. The result indicates that downtime cost will have a significant effect on LCC. As the downtime cost is increased, LCC is increased drastically. The LCC is decreased drastically when the operating cost is increased from $ 3 million to $ 5 million. Decreases in LCC will increase the financial benefit of the system as they use lesser cost to sustain the system.
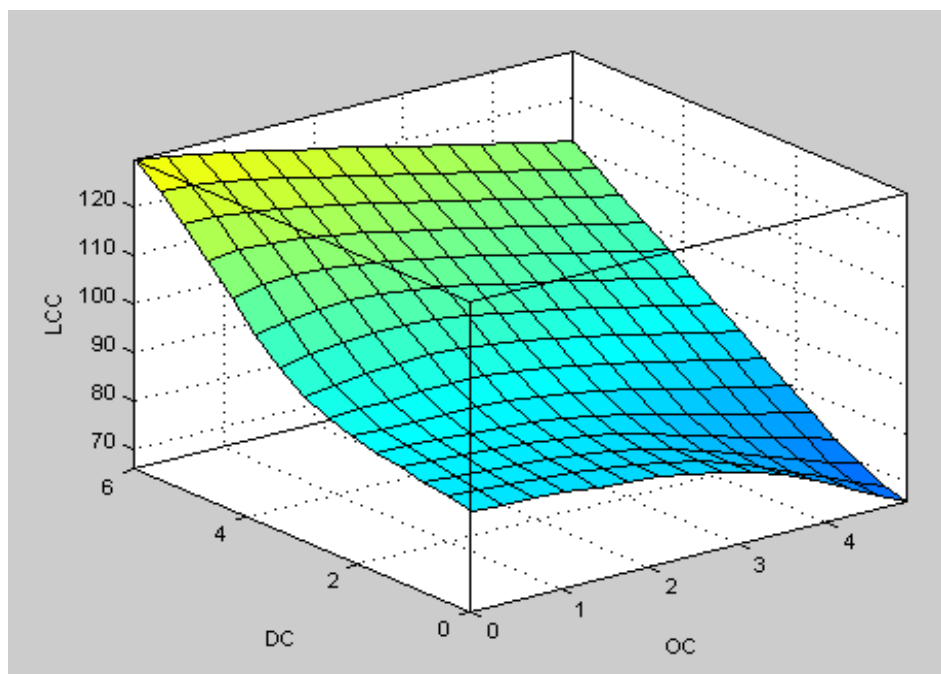

Figure 5: Effect of Acquisition Cost and Maintenance Cost with LCC

3.1. Model Validation

In order to validate the hypothesis, a Monte Carlo (MC) method proposed by Barringer [8] was employed to estimate the LCC. This estimated LCC value compared with developed ANFIS-LCC Model. LCC has been estimated for 20 years by using the same numerical value and the result is compared with the ANFIS prediction. Figure 6 shows the percentage of difference between the prediction of MC and ANFIS. Year 0, 1 and 2 showed high variation which is more than 20% and when the time goes on, the percentage of difference is decreasing. After year 4, the percentage of difference is less than 10% which is acceptable. The comparison indicates that ANFIS model could be used in LCC prediction for the repairable system as an alternative.
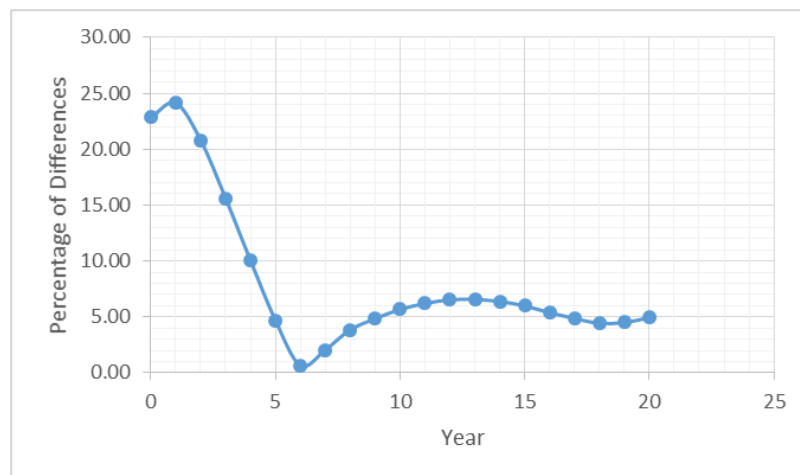

Figure 6: Differences between Prediction of Excel and ANFIS

4. Conclusion

This study developed the probabilistic LCC model using ANFIS to estimate the overall LCC of the repairable system. The developed model also enables easily to incorporate the uncertainties of the input variables. The findings show that repair cost has a minor effect towards the LCC while acquisition cost and downtime cost have a greater effect on LCC. The ANFIS model is validated by comparing Monte carlo approach. The validation shows that the percentage of difference between ANFIS and MC is less than 10%. Hence, ANFIS could be used to predict the LCC as alternatives.

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