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A surrogate model for optimal maintenance workforce cost determination in a process industry

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Abstract

In manufacturing systems, stiff competition in the international markets coupled with the global economic crisis has exerted immense pressure to search for new maintenance approaches. This study focuses on determining the optimal maintenance time and workforce size, as well as a low overall life-cycle cost. Current literature has completely ignored the influence of these measures and the significance of prediction has been downplayed. Consequently, the necessity to develop an approach based on scientific foundations is affirmed. Keeping in view the status of the literature concerning this issue, a surrogate model (an evolutionary algorithm technique and fuzzy inference system (FIS)) for maintenance workforce cost prediction is presented. The key influencing parameters include production volume, routine maintenance time, workforce size and spare parts costs. The surrogate model was tested using process industry data. The result (root mean square error) obtained from the surrogate model was better than those of an artificial neural network (ANN) and FIS. The implication of these results is that the surrogate model could serve as a basis for determining maintenance workforce costs during decision-making processes. The novelty of this study is that it uses a differential evolution algorithm to improve the performance of FIS when dealing with maintenance workforce cost prediction.

Keywords: Artificial neural network, Maintenance workforce cost, Grey relational analysis, Differential evolution, Fuzzy inference system

1. Introduction

In manufacturing systems, stiff competition plays an important role in international markets. Currently, the inability of many organisations to compete is higher than in previous decades. This is because of the current global economic crisis. Apart from impacts of this crisis upon manufacturing activities, the astronomical costs of inputs and corresponding high prices for outputs is characteristic of international markets. Additionally, there is intense pressure to cope with business performance determinants. In response to this pressure, manufacturing organisations look inwards to perfect their operational variables by recruiting employees with the best fit skills and embarking on lean manufacturing programmes to guarantee sustenance.

Today manufacturing activities require proactive measures to improve the performance of the various functions (e.g., production and maintenance) in an organisation. For example, the maintenance function is expected to pursue a zero-breakdown machine policy, while the safety function needs to focus on zero-accident policy. Maintenance activities of today have completely changed from those of the past because of the increased level of automation in manufacturing systems. This has increased the maintenance workforce size as well as maintenance budgets for workers and spare parts. The desire to reduce maintenance budgets has resulted in aggressive deployment of sound management and scientific principles within profit-making orientations.

The cost cutting of inputs for maintenance has resulted in immense pressure on maintenance managers to aggressively search for new, robust and scientific approaches that capture the principles of maintenance progress. Such approaches are meant to achieve a zero-downtime machine policy and optimise the productivity of the maintenance workforce. In the long-run, evaluation of maintenance projects often leads to low overall life-cycle costs.

While the current literature seems to focus on maintenance costs on one side, and maintenance times on the other, there is complete omission of the influence of these measures on workforce-centred measurements. For instance, the significance of prediction in monitoring maintenance progress has been downplayed. A number of studies have shown that performance improvement for maintenance systems is the most effective way of maintaining system continuity [1-5]. A comprehensive analysis of maintenance systems performance evaluation was reported by Parida and Kumar [1]. Studies on maintenance system performance evaluation have taken holistic approaches simultaneously considering the workforce and other maintenance resources.

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More recent studies, including Campbell [6] and Jackson [7], suggest that the employees should be considered. Since the workforce, as attributed by these researchers, is one of the core determinants of progress, efforts are advocated for a new direction of research towards them. Mansour [8] advocated the use of nonlinear programming and genetic algorithms in the computation of maintenance workforce measures. The employment of branch-and-bound procedures and nonlinear programming methods in the optimisation of maintenance workforce costs was done by Ighravwe and Oke [9]. Alfares *et al*. [10] contributed a linear programming procedure that potentially reduces the number of maintenance workers and at the same time ascertaining increased workers' efficiency.

Ighravwe *et al*. [11] suggested that workforce costs are a key determinant of maintenance decisions. To appreciate the influence of maintenance workforce costs on maintenance decisions from a practical perspective, a methodology to predict maintenance workforce costs can be employed. Some researchers have reported it is a common practice that intuition plays a dominant role in maintenance decision making. However, such an approach is not scientific, is somewhat random, prone to errors and may not fully reveal the actual performance of the maintenance workforce in terms of costs.

There is the need for quantitative methods of assessment and understanding of workforce variables. Thus, instead of intuitively determining workforce costs for maintenance systems, predictive approaches to maintenance cost evaluation should be exploited. A number of quantitative studies on workforce costs seek to model the situation using optimisation paradigms. Thus, it was assumed that the uncertainty of requirements in cost issues can be ignored. It may then be advantageous to also inquire into the effects of uncertainties in modelling maintenance costs. This has stimulated the use of a fuzzy inference system (FIS) in the current study. The use of this system is because it has been shown to be highly valid in scientific literature. Many studies have successfully used this methodology.

The existing literature on maintenance shows that researchers and practicing engineers have not considered the use of artificial neural network (ANN) models and FIS for maintenance workforce cost prediction. This knowledge gap motivated this study. The current study examines an approach through which maintenance workforce costs can be optimised. A predictive approach for workforce costs using a surrogate model was used. This area of maintenance research has been surprisingly neglected in the literature until recently, instead focusing on training and time issues.

The principal objective of this study is to investigate the use of surrogate modelling in optimising the parameters in a fuzzy FIS for maintenance workforce cost prediction problems. To the best of our knowledge, the surrogate model has not been used as a predictive model for this purpose. This study uses a differential evolution (DE) algorithm as a means for optimising the FIS parameters because of its ease of implementation as well as its low computation time and high quality results. In the predictive model, production volume, routine maintenance time, workforce size and spare parts costs are considered as input parameters. The performance of the surrogate model is compared with a gradient descent trained ANN model and FIS.

The breakdown of subsequent sections in this study follows. Next is the presentation of methodology for the research. Following this is the application of the model in a process industry as well as a discussion of the results. The conclusions of this study are last.

2. Methodology

A breakdown of the factors that influence maintenance workforce costs revealed that workforce size and total routine maintenance time are major determinants of these costs. The spare parts budget affects their availability, which in turn influences the frequency of routine maintenance. Thus, it is also necessary to consider spare parts costs during maintenance workforce cost determinations. Furthermore, relationships exist between production and routine maintenance time. This study considered production volume to provide a more detailed picture on the level of production activities during the determination of maintenance workforce costs.

Production volume, routine maintenance time, workforce size and spare parts costs are considered input parameters. The output of the predictive model is maintenance workforce costs. The surrogate models, the ANN model and FIS, are considered predictive models for maintenance workforce cost prediction. The surrogate model is a combination of DE ([12]) and FIS (Figure 1).

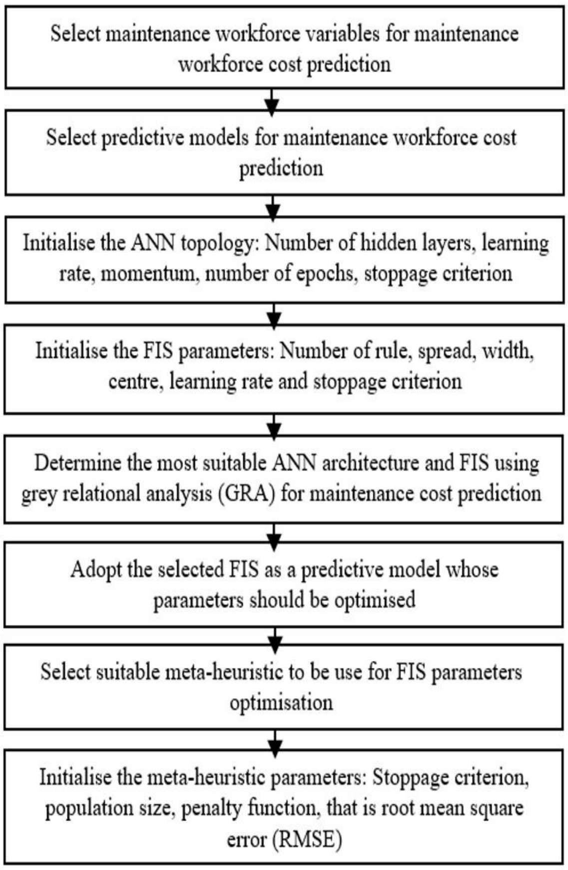

Figure 1 Evolutionary fuzzy inference system flowchart for maintenance workforce cost prediction

2.1 Fuzzy inference system

The FIS considered in this study does not partition input parameters into linguistic terms. The actual values of the input and output parameters are considered. These input and output parameters are used to tune the FIS parameters (Equation 1). The turning process of the FIS parameters ($c_j^{\hat{i}}$, $b_{\hat{i}}$ and $\sigma_j^{\hat{i}}$) is done using learning rates, prediction errors and a learning algorithm [13].

$$f\left(x^{\hat{m}} \middle| \theta\left(\hat{p}=0\right)\right)=\frac{\sum_{\hat{i}=1}^{\hat{R}} b_{\hat{i}}(0) \prod_{\hat{j}=1}^{\hat{n}} \exp\left(-\frac{1}{2}\left[\frac{x_{\hat{j}}^{\hat{m}}-c_{\hat{j}}^{\hat{i}}\left(\hat{k}\right)}{\sigma_{\hat{j}}^{\hat{i}}}\right]^{2}\right)}{\sum_{\hat{i}=1}^{\hat{R}} \prod_{\hat{j}=1}^{\hat{n}} \exp\left(-\frac{1}{2}\left[\frac{x_{\hat{j}}^{\hat{m}}-c_{\hat{j}}^{\hat{i}}\left(\hat{k}\right)}{\sigma_{\hat{j}}^{\hat{i}}}\right]^{2}\right)} \tag{1}$$

where $c_{\hat{j}}^{\hat{\imath}}$ is centre of membership function, *i*, for data j, $b_{\hat{\imath}}$ is width of the membership function, *i*, for data j, and $\sigma_{\hat{j}}^{\hat{\imath}}$ is spread of the membership function, *i*, for data j.

The purpose of turning the FIS parameters is to minimise prediction error. This is achieved by searching for the most suitable number of rules for a prediction problem. Selection of this number of rules for the maintenance workforce cost prediction problem is based on a grey relational analysis (GRA) approach. The performance of the FIS is evaluated using the RMSE (Equation 2).

$$\text{RMSE} = \sqrt{\frac{1}{m}\sum_{\bar{i}=1}^{m}\left(A_{\bar{i}} - f\left(x^{\hat{m}} \middle| \theta\left(\hat{p}=0\right)\right)\right)^{2}} \tag{2}$$

Where $A_{\bar{\imath}}$ is actual output $\bar{\imath}$.

2.2 ANN model

In order to evaluate the performance of the surrogate model, an ANN model is used in this study. The following are the basic steps for ANN implementation [14 - 16]:

Step 1 Data pre-processing: This step involves the selection of variables that affect the value of a dependent variable. The size of training and testing datasets are also considered at this step.

Step 2 Neural network paradigms: This step in an ANN model implementation involves determination of the number of hidden layers and number of hidden neurons. Consideration is also given to type of transfer functions to be used during ANN model training [15].

Step 3 Model evaluation: During the training of ANN models, the performance of models is evaluated based on the type of problem that is being solved. For a prediction problem, statistical means such as RMSE, mean absolute percentage error (MAPE), and the coefficient of correlation are used.

Step 4: Model training: This step entails considerations of the number epoch, learning rate, momentum and learning algorithm for the ANN models [16].

2.3 Grey relational analysis

The RMSE and MAPE results from the FIS and ANN model are used in formulating a multi-attribute performance index. The desired values for RMSE ($x_{\text{gg}}^{o}(1)$) and MAPE ($x_{\text{gg}}^{o}(2)$)are their minimum values. Thus, the normalisation scheme used for RMSE and MAPE is lower-the-better (Equation 3). For statistical measures whose maximum values are desired (co-efficient of correlation), a higher-the-better is applicable (Equation 4).

$$x_{gg}^{*}\left(y\right)=\frac{x_{gg}^{o}\left(y\right)-\min\ x_{gg}^{o}\left(y\right)}{\max\ x_{gg}^{o}\left(y\right)-\min\ x_{gg}^{o}\left(y\right)} \tag{3}$$

$$x_{gg}^{*}\left(y\right)=\frac{\max\ x_{gg}^{o}\left(y\right)-x_{gg}^{o}\left(y\right)}{\max\ x_{gg}^{o}\left(y\right)-\min\ x_{gg}^{o}\left(y\right)} \tag{4}$$

where $x_{\text{gg}}^{*}(y)$ represents the sequence of parameter *y* after data pre-processing, $x_{\text{gg}}^{o}(y)$ represents the original sequence of parameter *y*, max $x_{\text{gg}}^{o}(y)$ represents maximum value of $x_{\text{gg}}^{o}(y)$, and min $x_{\text{gg}}^{o}(y)$ represents minimum value of $x_{\text{gg}}^{o}(y)$.

The results from Equation (3) are used to compute the grey relational coefficient [17] for each of the FIS rules and ANN architectures. The value of the grey relation coefficient is expressed as Equation (5).

$$\zeta_{i}\left(y\right)=\frac{\Delta\min+\zeta\Delta\max}{\Delta_{o,i}\left(y\right)+\zeta\Delta\max} \tag{5}$$

$$\Delta\min = \min_{\forall gg}\min_{\forall y}\left\|x_{o}^{*}\left(y\right)-x_{gg}^{*}\left(y\right)\right\| \tag{6}$$

$$\Delta\max = \max_{\forall gg}\max_{\forall k}\left\|x_{o}^{*}\left(y\right)-x_{gg}^{*}\left(y\right)\right\| \tag{7}$$

where $x_{i}^{*}(y)$ represents the comparative sequence of parameter *y*, $x_{O}^{*}(y)$ represents the reference sequence of parameter *y*, and ζ represents the identification coefficient.

The last stage of GRA involves the computation of the grey relational grade (Equation 8) for each experiment [17].

$$\gamma = \frac{1}{n}\sum_{i=1}^{n}\zeta_{i}\left(y\right) \tag{8}$$

where γ represents the grey relational grade for a FIS rule or ANN architecture, and *n* represents the total number of performance measures.

After the determination of the most suitable number of rules for the maintenance workforce cost prediction problem using GRA, the optimal values for the FIS parameters ($b_{\hat{\imath}}, \sigma_{\hat{j}}^{\hat{\imath}}\ and\ c_{\hat{j}}^{\hat{\imath}}$) are determined using the DE algorithm. By using the DE algorithm to determine the optimal values of the parameters in the FIS, a surrogate model is formed. The objective function of the surrogate model is Equation (2).

2.4 Differential evolution algorithm

This study uses a DE algorithm as a solution method for improving the power of the FIS model. A brief discussion of the DE algorithm is presented as follows.

DE algorithms belong to a group of metaheuristics that are known as evolutionary algorithms. The basic operations of most evolutionary algorithms consist of three steps. The first step involves a mutation operation (Equation 9). Three parents are randomly selected from a population. During the mutation operation, mutant vectors are produced. This is achieved using a mutation probability (*M*).

$$v_{ij} = x_{ij1} + M\left(x_{ij2} - x_{ij3}\right) \tag{9}$$

where $x_{ij} \neq x_{ij1} \neq x_{ij2} \neq x_{ij3}$

The second step is a crossover operation (Equation 10). This operation is used to determine mutant ($v_{ij}(t)$) and target ($x_{ij}(t)$) vectors to find a trial vector ($u_{ij}(t)$). The operation is aided by a crossover probability and a randomly selected integer (I_d). The value of $I_d$is between1 and the total number of decision variables (d).

$$u_{ij}(t) = \begin{cases} v_{ij}(t) & rnd(0,1) \le C \text{ and } I_d \ne d \\ x_{ij}(t) & Otherwise \end{cases} \tag{10}$$

The last step is the selection operation (Equation 11). This operation involves comparison of the newly generated solutions at generation (t + 1) and the previously generated solutions at generation t. The newly generated solution are known as offspring ($f_j^c(x)$), while the previous solution are known as parents ($f_j(x)$).

$$x_{ij}(t+1) = \begin{cases} u_{ij}(t) & f_j^c(x) \le f_j(x) \\ x_{ij}(t) & Otherwise \end{cases} \tag{11}$$

The procedure for standard DE algorithm implementation is given as follows [18-19]:

```
Initialise the population size and decision variables
Evaluate the fitness of each particle
Determine the global best solution
   Do
      For each individual in the population
         Perform mutation operation
         Perform crossover operation
         Evaluate the fitness function of offsprings
         Perform selection operation
      End for
   Until the stoppage criterion is met
```

3. Model application and discussion of results

The proposed surrogate model performance was verified using information obtained from a process industry. The industry operates three production lines and specialises in the production of alcoholic and non-alcoholic drinks that are sold in bottles and cans. The size of the maintenance workforce is between 24 and 36 workers. The company uses the same workers for maintenance activities on the production lines. Thus, information on production volume, routine maintenance time, workforce size and spare parts costs as well as maintenance costs for the three production lines were not separated during the application of the proposed model. The cost of spare parts used for routine maintenance activities on the three production lines per day was between ₦ 219,023.88 and 453,238.32. The total routine maintenance time for the three production lines was between 286.96 and 3492.99 hr. The total production volume was between 3578965 and 4328711 units. These values are per year. The annual maintenance workforce cost was between ₦18,548,286.50 and 25,706,244.50.

Based on the company's maintenance records and Ighravwe's [20] model, 180 datasets were generated. These datasets were for the inputs (production volume, routine maintenance time, workforce size and spare parts cost) and output (maintenance workforce cost) parameters. For maintenance systems where sufficient information is available, there is no need to use existing model to generate datasets for these input and output parameters. The number of training datasets for the surrogate model was 144, while the testing datasets numbered 36.

Information on the parametric settings for the DE algorithm, FIS and ANN model are given as follows:

DE algorithm: The mutation probability for the DE algorithm was 0.3, while its crossover probability was 0.2. The total number of generations for the DE algorithm was 200, while the population size was 30.

FIS: During implementation of the FIS, twenty different FISs were considered. The learning rates for the FIS parameters were the same (one). The selection of a suitable FIS for maintenance workforce cost prediction was based on the RMSE and MAPE.

ANN model: Twelve different ANN architectures were considered as possible models for maintenance workforce cost prediction. The ANN models were trained using a gradient descent algorithm, while their performance was monitored using RMSE. A two-layer hidden ANN model was considered. The learning rate for the ANN models was 0.5.

From the FIS results, none of the rules considered for FIS had a testing MAPE value that was less than its training MAPE value (Table 1). The MAPE values for the training and testing data did not follow a regular pattern. The RMSE values for the training and testing data followed the same pattern. However, the RMSE results for the training data were better than those of the testing data. Based on the GRA results, the 13-rule FIS had the highest grey relational coefficient. Thus, it was deduced that the most suitable model was a 13-rule based FIS (Table 1).

The parameters in the 13-rule FIS were optimised using a standard DE algorithm. The values of RMSE for the maintenance workforce cost prediction decreased as the number of generations of the DE algorithm increased (Figure 2). This implies that the parameters values in the FIS improved from local optimal values to global optimal values. The convergence of the surrogate model started after the 80th generation. For the training dataset, the surrogate model RMSE value for the 200th generation was 1,299,816.4180. The surrogate model RMSE value for the test datasets was 1,440,976.1170.

The results that were obtained from the ANN were not significantly different from one another (Table 2). To determine the most suitable ANN architecture for the case study, GRA was used as a means for empirical evaluation of the ANN results. The GRA results showed that the 4-8-10-1ANN architecture had the highest grey relational value (Table 1). Thus, it is the most suitable model for maintenance cost prediction [21]. The convergence plot for the 4-8-10-1ANN architecture showed that the value of RMSE decreased steadily as the number of epochs increased up to the 78th epoch, after which the RMSE began to rise (Figure 3).

The RMSE results during testing of the various ANN architectures showed that they had lower values when compared with the training data RMSE for the various architectures. The MAPE values during testing of the ANN architectures were less than for the training data (Table 2).

On the basis of the RMSE results were obtained from the 13-rule based FIS and 4-8-10-1 ANN model, it could be deduced that the 4-8-10-1ANN architecture is a more suitable predictive model than the 13-rule based FIS. However, the surrogate model RMSE value was less than that of the ANN model.

Table 1 Comparison of different FIS rules

Rules	Training datasets		Testing datasets		GRG	Ranks
	RMSE	MAPE	RMSE	MAPE		
1	1,514,575.3420	5.6652	2,556,928.2791	10.5303	0.8680	20
2	1,528,122.8518	5.8082	1,736,510.5843	6.9149	0.9409	11
3	1,605,405.3519	6.0958	1,889122.6086	7.6085	0.9127	19
4	1,603,237.8440	5.9416	1,833,813.8630	7.2785	0.9228	12
5	1,612,549.0594	5.9320	1,853,546.3176	7.3326	0.9206	17
6	1,615,396.1059	5.9248	1,840,349.6346	7.2361	0.9224	13
7	1,619,950.8036	5.9477	1,841,155.7672	7.2106	0.9219	14
8	1,623,020.1531	5.9652	1,842,813.9266	7.1981	0.9214	15
9	1,626,768.0931	5.9780	1,854,224.6326	7.2389	0.9198	18
10	1,618,561.7914	5.8794	1,881,560.3458	7.3035	0.9201	16
11	1,536,693.4621	5.4031	1,825,555.6054	6.9374	0.9435	10
12	1,471,293.8664	5.2920	1,614,056.2504	6.1636	0.9732	9
13	1,429,234.0118	5.1576	1,452,518.0965	5.4424	1.0000	1
14	1,436,121.2157	5.1821	1,469,645.0546	5.5109	0.9968	2
15	1,440,359.2390	5.1971	1,500,937.8216	5.6405	0.9922	3
16	1,440,388.3011	5.1972	1,517,587.0219	5.7140	0.9900	8
17	1,438,279.3037	5.1894	1,519,148.9175	5.7134	0.9903	7
18	1,437,408.8801	5.1849	1,517,926.9157	5.6984	0.9908	6
19	1,435,873.6329	5.1806	1,516,414.8472	5.6932	0.9912	4
20	1,438,578.7409	5.1866	1,514,156.4164	5.6868	0.9910	5

Table 2 Performance statistics of different ANN architectures

S/n	Architectures	Training datasets		Testing datasets		No. of epoch	GRG	Ranks
		RMSE	MAPE	RMSE	MAPE			
1	4-8-7-1	1,418,461.8200	5.1497	1,409,575.3084	4.9859	103	0.9746	12
2	4-8-8-1	1,415,059.0289	5.1213	1,415,746.9866	4.9941	69	0.9987	6
3	4-8-9-1	1,414,872.6694	5.1217	1,413,414.2477	4.9858	66	0.9991	3
4	4-8-10-1	1,416,072.9458	5.1300	1,408,490.1241	4.9690	78	0.9997	1
5	4-9-7-1	1,416,109.5438	5.1250	1,414,603.8479	4.9806	103	0.9990	4
6	4-9-8-1	1,416,879.0432	5.1298	1,412,615.7722	4.9840	76	0.9989	5
7	4-9-9-1	1,415,957.4224	5.1263	1,413,205.2078	4.9749	224	0.9992	2
8	4-9-10-1	1,494,199.0059	5.3347	1,435,364.4072	5.1664	249	0.9818	9
9	4-10-7-1	1,493,787.1001	5.3340	1,438,039.6849	5.1567	354	0.9818	10
10	4-10-8-1	1,501,939.2685	5.3632	1,440,111.6016	5.1802	272	0.9798	11
11	4-10-9-1	1,418,296.7661	5.1280	1,416,833.0771	4.9845	228	0.9984	7
12	4-10-10-1	1,487,851.3524	5.3180	1,425,822.9798	5.1186	247	0.9846	8

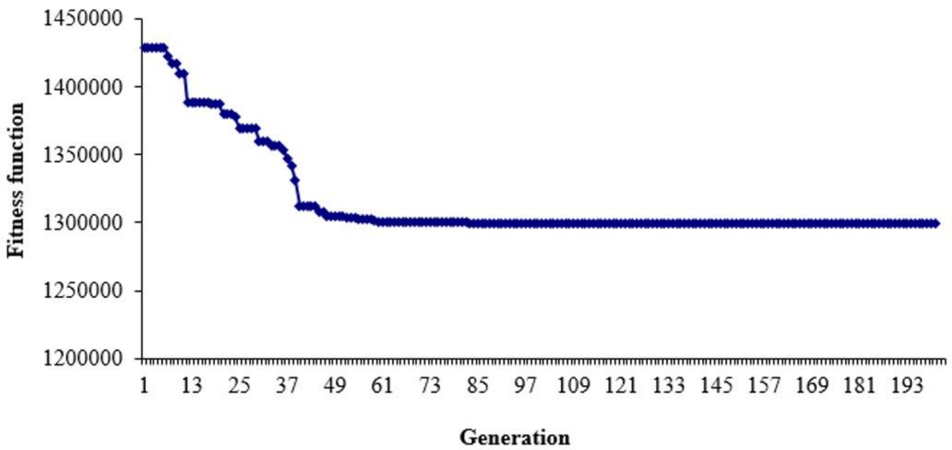

Figure 2 Convergence plot for the surrogate model

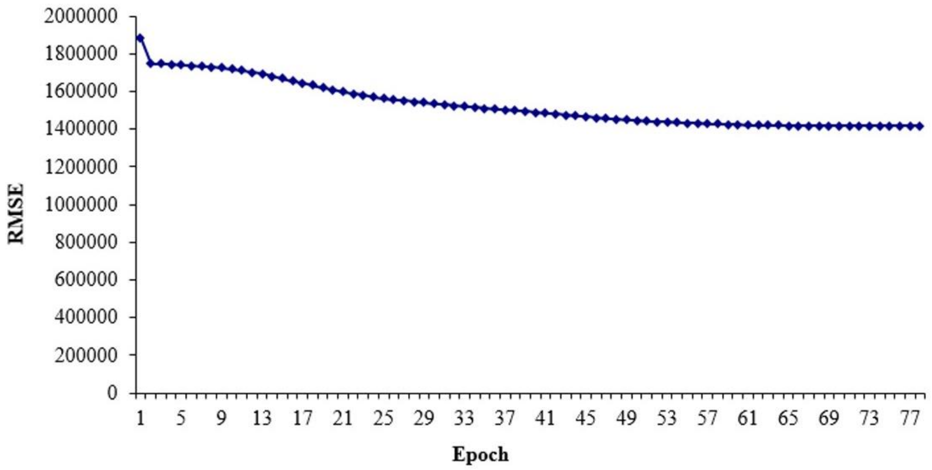

Figure 3 Convergence plot for a 4-8-10-1 ANN architecture

4. Conclusions

In this study, a surrogate model for maintenance workforce cost prediction was proposed. The performance of the surrogate model was compared with that of the FIS and ANN model. The behaviour of different ANN models under various numbers of hidden layer nodes was analysed using GRA. Additionally, GRA was applied in selecting the most suitable number of rules for the maintenance workforce cost FIS. The quality of results that was obtained from the FIS was improved using the surrogate model. The RMSE result obtained from the surrogate model was better than that of the FIS. The training result of the surrogate model was better than that of the ANN model, while the ANN model testing result was better than that of the surrogate model.

A study, which considers the performance of GRA as selector of ANN architecture with those of other multi-attribute approaches (VIKOR and weighted aggregated sum product assessment) could serve the purpose of a further study. Additionally, the DE algorithm in the surrogate model could be replaced with other metaheuristics and the results compared.

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