EASR

Engineering and Applied Science Research

https://www.tci-thaijo.org/index.php/easr/index

Published by the Faculty of Engineering, KhonKaen University, Thailand

Selection of an optimal neural network architecture for maintenance workforce size prediction using grey relational analysis

Desmond Eseoghene Ighravwe[1, 2], Sunday Ayoola Oke*[1] and Kazeem Adekunle Adebiyi[2]

[1]Department of Mechanical Engineering, Faculty of Engineering, University of Lagos, Lagos, Nigeria
[2]Department of Mechanical Engineering, Faculty of Engineering and Technology, Ladoke Akintola University of Technology, Ogbomoso, Nigeria

Received 21 April 2016
Accepted 7 July 2016

Abstract

Prediction is necessary in industrial practices according to the norms of modern scientific development. Recognising maintenance problems before they occur potentially helps to improve workforce performance as effective preventive maintenance actions are developed. A large number of industrial systems worldwide owe their gains to predictive analysis. Furthermore, precise predictions can aid maintenance policy makers in making decisions as well as promoting the quality of decision making in maintenance, particularly on maintenance workforce issues. This study reports the use of grey relational analysis cum artificial neural networks (ANN) for maintenance workforce size prediction through the selection of an optimal neural network architecture. Workforce cost, workload, productivity and effectiveness represent the input parameters utilised in the ANN framework. The method competitively determines the most suitable ANN architecture for maintenance workforce size. Comparison of the ANN model results reveal that its performance is better than a fuzzy inference system. Conclusively, the application of the framework advanced in this work was found useful with practical data obtained from a process industry that operates as a brewery. The efficiency of the proposed approach was documented.

Keywords: Maintenance workforce size, Artificial neural network, Grey relational analysis, Fuzzy inference system

1. Introduction

The determination of maintenance workforce size is a significant issue for managers in the maintenance function, particularly for large-scale production systems with wide-ranging equipment maintenance schedules [1]. The workforce provides the necessary support for implementing programmes of preventive, corrective and overall maintenance of operations. Based on the level of activities in the maintenance function, the requirements for service fulfilments are made, known as the service demand of the maintenance workforce [2]. In response to this, the total available workforce may not meet requirements, referred to as the supply. Thus, the demand-supply aspect of workforce planning is a critical issue and may change in a significant manner depending on a number of factors, including the wages paid to current and potential employees, the working conditions and potentials for skill development and training.

A critical and difficult maintenance management function is the determination of workforce size for the diverse skill levels in maintenance [1]. A precise determination of workforce size in planning for the projected periods aids proper allocation and implementation of budgets. It also assists in the allocation of resources as well as decisions about equipment repairs, plant overhaul and decisions on replacements [3]. Thus, the significance of workforce size determination must not be downplayed. It is a crucial determining factor for plant survival, productivity and effectiveness. If a plant trivialises workforce size determination, it is certain that it is on its way to doom. As such, workforce size determination must be given the best attention with the utmost care and skill that it deserves. Proper planning of workforce size can reveal problem areas long before they emerge, as well as the strengths and weaknesses of the maintenance function and the engineering organisation as a whole. Unfortunately, workforce size determination is not taken very seriously by many organisations.

The current practice uses intuition in the determination of workforce size. This is faulty because failures of equipment are random in nature. Intuition is ineffective and prone to errors, so these practices must be stopped. They must be replaced with scientific, merit-driven approaches that permit easy and precise determination of workforce sizes. Traditionally, maintenance managers evaluate workforce sizes of diverse production systems solely on previous experience. Intuition is unreliable as it cannot predict frequent machine breakdowns and leads to waste of maintenance resources. Severe disagreements arise between labour unions and the management of enterprises on compensation issues, claiming that the workforce is being overloaded without due compensation. This is a strong

*Corresponding author.
Email address: sa_oke@yahoo.com
doi: 10.14456/easr.2018.8

support for the abandonment of intuitive practices in maintenance. Consequently, it can be pivotal to solving labour problems.

Previous studies often utilised the workload and competency of a set of workers [2], trend analysis and regression [4], multi-objective mixed-integer non-linear model [5], workforce balancing concept [6] and optimisation [7]. Others were models for workforce size determination in a nut and bolts manufacturing plant [8], Taguchi-fuzzy approach [1] and a reliability method [9]. The stochastic limitation on workforce activities was identified by De Bruecker [10]. Furthermore, Masmoudi et al. [11] integrated the idea of stochastic modelling and uncertainties in workload plans with practical application to shipyard maintenance. The focus of Antonovsky et al. [12] was on the perception of the team on system reliability. Van den Bergh et al. [13] conducted studies on maintenance personnel.

From the foregoing literature review, it is clear that previous studies have been limited as there has been no study identified that employed the powerful attributes of historical data for predictive purposes for required workforce size. It is surprising to observe that many of the approaches still being used in literature are cumbersome and offer little assistance to the practicing maintenance manager who requires simple yet useful approaches for the determination of workforce size. The determination of workforce size, using predictive models, is a scientific management approach. When applied by the maintenance management, it will minimise uncertainties of maintenance actions in the future [14]. The principal intent of prediction in maintenance is to reduce the uncertainty of future actions as well as to present the maintenance administration with relevant information and data for accurate decision making. Recognising maintenance problems before they occur can potentially help to improve workforce performance. Workforce cost, workload, productivity and workforce effectiveness are among maintenance workforce parameters that introduce uncertainty to workforce analysis.

It is therefore important to predict and use an artificial neural network (ANN) in a non-linear prediction of maintenance workforce size that is relevant and fundamental. ANN is outstanding and largely well-positioned to learn highly-complex associations among datasets. This has led to its wide appeal and success in medicine, stock markets, geology and engineering [15-16]. Despite its success, which ANN modelled gained over the years, their applications in maintenance have been downplayed. Their specific applications to maintenance workforce size prediction have not yet been proven. Since ANNs have been established as powerful predictive models [17-18], there is a need to investigate their applications to maintenance workforce size determination. Furthermore, since there is no general understanding and agreement of a scientific approach to the determination of workforce size, modelling of this phenomenon using artificial neural networks aided by grey-relational analysis presents a better and unique quantitative method to determine this parameter. Its uniqueness is its capability of determining the maintenance workforce size in situations of sparse or incomplete data when aided by the powerful structure of grey relational analysis.

When determining the performance of different ANN architectures, various performance measures are often considered, including root mean square error (RMSE) and mean absolute percentage error (MAPE). The justification of an architecture for ANN modelling using two or more performance measures is that it is more realistic than using a single performance measure. To the best of our knowledge, an approach that combines two or more performance measures for ANN architecture has not been documented in the literature. This study selects grey relational analysis (GRA) that combines RMSE and MAPE values as a basis for optimal ANN architecture determination. Thus, the objective of this study is to select the most suitable ANN architecture for maintenance workforce prediction using a grey relational analysis (GRA) approach.

In Section 2, the ANN model, fuzzy inference system (FIS) and the GRA framework are discussed, while Section 3 contains model application and a discussion of results. The current study's conclusions are presented in Section 4.

2. Methodology

This section describes the predictive models and the ranking techniques for a suitable number of FIS rules and ANN architecture selection.

2.1 Artificial neural network (ANN)

ANN models are artificial intelligence models that are developed to mimic the neurons in human brains [19]. The structure of a neuron is shown in Figure (1), while Figure (2) shows an ANN node [19-20]. Synapses in natural neurons are represented as connecting weights in ANN models.The signals sent into a node in hidden and output layers is a function of incoming signals, connecting weights and bias [19]. Summation and product operators are employed in combining incoming signals and connecting weights in obtaining a net value($Net_{\bar{m}}$). The value, Net_m, is combined

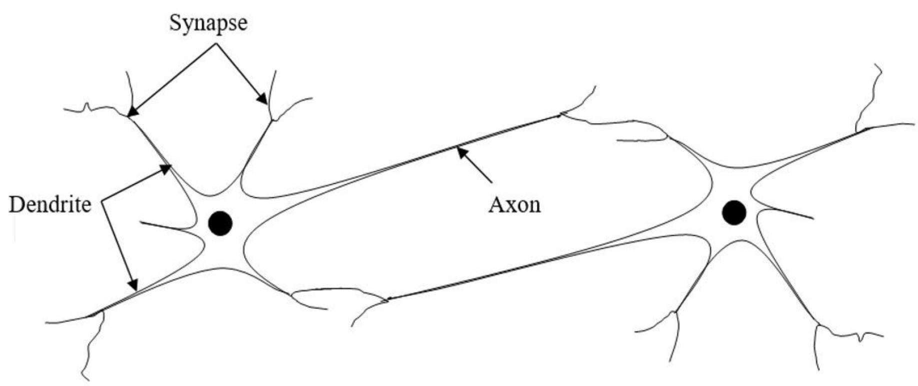

Figure 1 A biological neuron (Adapted from [19-20])

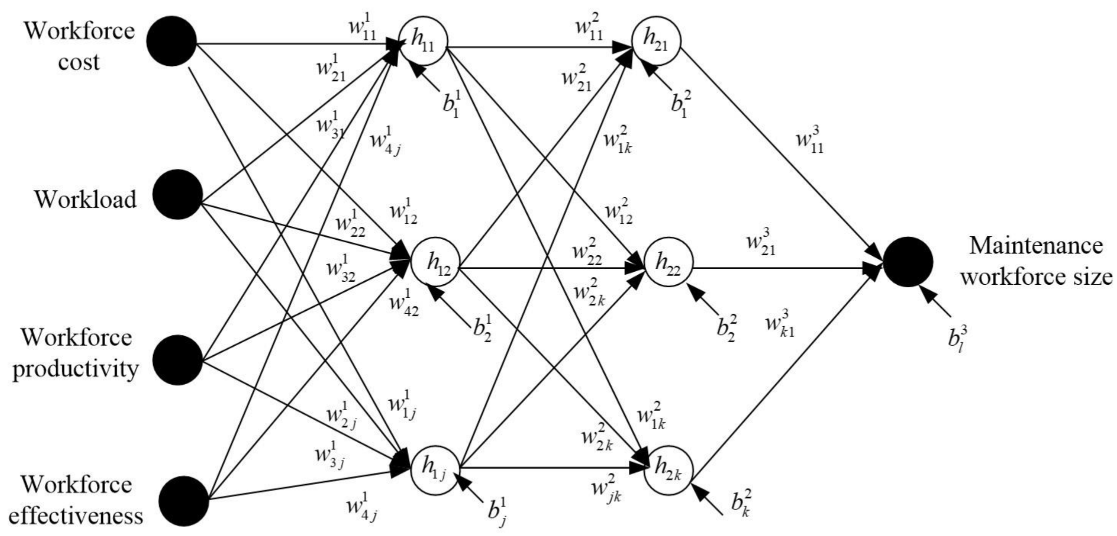

Figure 2 A 4-layer artificial neural network model

with a bias to determine the signal value of a node using an activation function.

In Figure 2, w_{1j}^{1} is the value of the connecting weight between input 1 and node *j* in the first hidden layer, while w_{2j}^{1} is the value of the connecting weight between input 2 and node *j* in the first hidden layer. The value of the connecting weight between input 3 and node *j* in the first hidden layer is represented as w_{3j}^{1}, while w_{4j}^{1} represents the value of the connecting weight between input 4 and node *j* in the first hidden layer. The value of the connecting weight between the nodes *j* and *k* is represented as w_{jk}^{2}, while the value of the connecting weight between nodes *k* and *l* is represented as w_{kl}^{3}. The bias for node *j* in the first hidden layer is represented as b_j^1, while b_k^2 represents node *k'*s bias in the second hidden layer. The value of bias for node *l* in the output layer is represented as b_l^3. The value of node *j* in the first hidden layer is represented as h_{1j}, while h_{2k} represents the value of node *k* in the second hidden layer.

The common activation functions in the literature are linear, sigmoid (Equation 1), Gaussian (Equation 2) and exponential functions. ANN models that combine different activation functions using product and summation operators are known as higher order ANN models [19, 21].

$$f_{AN} = \frac{1}{1+e^{-(net_{\bar{m}}-\theta_{\bar{m}})}} \tag{1}$$

$$f_{AN} = e^{-(net_{\bar{m}}-\theta_{\bar{m}})^2/\sigma_{\bar{m}}{}^2} \tag{2}$$

$$Net_{\bar{m}} = \sum_{v=1}^{mm} \dot{x}_v \dot{w}_{v\bar{m}} \tag{3}$$

where *mm* represents the total number of signals entering a node, $\dot{w}_{v\bar{m}}$ represents the connecting weight between layers *v* and $\bar{m}$ (e.g., input and hidden layers (w_{4j}^{1})), $\dot{x}_v$ represents the value of node *v* (e.g., h_{1j}), f_{AN} represents the signal value entering a node, $\theta_{\bar{m}}$ represents the bias for the node $\bar{m}$ (e.g., b_l^3) , and $\sigma_{\bar{m}}$ represents the spread of a function.

Training of ANN models is achieved using training algorithms. In the literature, a back-propagation algorithm has gained wide acceptance because of its ability to produce promising results for different types of problems. These problems cut across different fields of human endeavour, among which are agriculture, transportation, finance, manufacturing and telecommunication [21]. The application of a back-propagation algorithm for supervised learning problems is predominant in the literature [22-23]. During the training of an ANN model, new weights ($w_{v\bar{m}}^{tt}$) are generated (Equation 4). The value of new weights is dependent on a network error. The values of network errors to be used in generating a new weight are directly related to the layers between a connecting weight. The network error of a hidden layer is expressed as Equation (4).

$$w_{v\bar{m}}^{tt} = w_{v\bar{m}}^{tt-1} + \bar{\eta} E_{\bar{m}}^{tt-1} x_{v\bar{m}}^{tt-1} \tag{4}$$

$$E_{\bar{m}}^{tt} = O_{\bar{n}}(1-O_{\bar{n}}) \sum_{j=1}^{N} w_{v\bar{m}} E_{\bar{m}-1}^{tt} \tag{5}$$

where *tt* represents the iterative step or generation, $w_{v\bar{m}}^{tt}$ represents the connecting weight, $E_{\bar{m}}^{tt}$ represents the error generated from a node in the hidden layer $\bar{m}$ in an ANN model at the iteration *tt*. The symbol $\bar{\eta}$ represents the learning rate, $x_{v\bar{m}}^{tt}$ represents the value of a signal for a node between layers *v* and $\bar{m}$ at iteration *tt*, and $O_{\bar{n}}$ represents the error values for node $\bar{n}$ in an ANN model.

According to Kaastra and Boyd [18], design of an ANN model requires the following steps. First, two variables are selected followed by data collection. This is followed by data pre-processing (including training, testing as well as validation). The fourth step is development of the neural network framework (including the number of hidden-layers, hidden-neurons and outputs as well as the transfer function). The last two steps are the evaluation criteria and neural network training (including epoch number, the learning rate and momentum).

2.2 Fuzzy inference system (FIS)

This study considered the FIS since it has the capacity to predict workforce size [1]. The principle of logic and set theory was used in the design of the FIS based on the concepts of human reasoning systems [22]. FIS makes use of membership functions (μ_i) in determining the level to which an element belongs to a set. The value of μ_i lies between 0 and 1 [22]. FIS has wide applications because of its ability to deal with imprecision, noise and vagueness in practical datasets [22]. This is achieved with "IF-THEN" rules. The "IF" section of the rule is known as the premise, while the "THEN" section is called the consequence [24].

FIS is built on the concept of "IF-THEN" statements, so the relationships among input parameters are used in adjusting the values of the membership functions for each input to properly model a system [22]. This is achieved with the use of fuzzy rules. The number of rules in a FIS can be determined using a gradient method [22]. The output from a FIS model is expressed as shown in Equation (6).

$$f\left(x^{\hat{m}} \middle| \theta(\hat{p}=0)\right) = \frac{\sum_{\hat{i}=1}^{\hat{R}} b_{\hat{i}}(0) \prod_{\hat{j}=1}^{\hat{n}} \exp\left(-\frac{1}{2}\left[\frac{x_{\hat{j}}^{\hat{m}} - c_{\hat{j}}^{\hat{i}}(\hat{k})}{\sigma_{\hat{j}}^{\hat{i}}}\right]^2\right)}{\sum_{\hat{i}=1}^{\hat{R}} \prod_{\hat{j}=1}^{\hat{n}} \exp\left(-\frac{1}{2}\left[\frac{x_{\hat{j}}^{\hat{m}} - c_{\hat{j}}^{\hat{i}}(\hat{k})}{\sigma_{\hat{j}}^{\hat{i}}}\right]^2\right)} \tag{6}$$

The parameters ($b_{\hat{i}}$, $c_{\hat{j}}^{\hat{i}}$and $\sigma_{\hat{j}}^{\hat{i}}$) in Equation (6) are updated at the termination of every iterative step. When a gradient descent is employed as a training procedure for FIS, the expression for computing a new value for $b_{\hat{i}}$is expressed as Equation (7), while a new value for $c_{\hat{j}}^{\hat{i}}$ is expressed as in Equation (8). A new value for $\sigma_{\hat{j}}^{\hat{i}}$ is expressed as Equation (9).

$$b_{\hat{i}}(\hat{p}) = b_{\hat{i}}(\hat{p}-1) - \eta_1\left(\in_{\hat{p}}(\hat{p}-1)\right)\frac{\mu_{\hat{i}}(x^{\hat{p}}, \hat{p}-1)}{\sum_{\hat{i}=1}^{\hat{M}} \mu_{\hat{i}}(x^{\hat{p}}, \hat{p}-1)} \tag{7}$$

$$c_{\hat{j}}^{\hat{i}}(\hat{p}) = c_{\hat{j}}^{\hat{i}}(\hat{p}-1) - \eta_2\left(\in_{\hat{p}}(\hat{p}-1)\right)\frac{b_{\hat{i}}(\hat{p}-1) - f\left(x^{\hat{p}} \middle| \theta(\hat{p}-1)\right)}{\sum_{\hat{i}=1}^{\hat{M}} \mu_{\hat{i}}(x^{\hat{p}}, \hat{p}-1)} \tag{8}$$

$$\sigma_{\hat{j}}^{\hat{i}}(\hat{p}) = \sigma_{\hat{j}}^{\hat{i}}(\hat{p}-1) - \eta_3\left(\in_{\hat{p}}(\hat{p}-1)\right)\frac{b_{\hat{i}}(\hat{p}-1) - f\left(x^{\hat{p}} \middle| \theta(\hat{p}-1)\right)}{\sum_{\hat{i}=1}^{\hat{M}} \hat{\mu}_{\hat{i}}(x^{\hat{p}}, \hat{p}-1)} \tag{9}$$

Where $\hat{p}$ represents pattern, $x^{\hat{p}}$ represents the input pattern$\hat{p}$,$\mu_{\hat{i}}$ represents the membership function input $\hat{\imath}$,$f(x^{\hat{p}}\theta(\hat{p}-1))$ represents the predicted output for pattern $\hat{p}$, and $\in_{\hat{p}}$ represents the prediction error associated with pattern $\hat{p}$. Furthermore, $c_{\hat{j}}^{\hat{i}}$, $b_{\hat{i}}$and $\sigma_{\hat{j}}^{\hat{i}}$represent the centre, represents the spread and width, respectively, of a membership function for input.η_1, $\eta_2$and$\eta_3$represents the learning rate for the spread, represents the learning rate for centre, and represents the learning rate for width, respectively [25].

2.3 Grey relational analysis (GRA)

To combine the outputs from the ANN and FIS frameworks, the classic structural model GRA [26] was used in formulating a single multi-attribute performance index. For a maintenance system, there exists two possible outcomes. The first outcome is higher-the-better (Equation 10) for performance indices such as workforce productivity, earned-value, reliability and planning factor. The second outcome is the lower-the-better (Equation 11) for performance indices such as maintenance costs, incidents of accidents and delays in machine release times. The values that obtained from Equations (10) and (11) will assist in addressing the problems of complex interrelationships among the maintenance workforce objective functions in the developed optimisation models. The maximisation and minimisation objectives are considered as higher-the-better (Equation 10) and the lower-the-better (Equation 11)[26].

$$x_{gg}^{*}(y) = \frac{\max\ x_{gg}^{o}(y) - x_{gg}^{o}(y)}{\max\ x_{gg}^{o}(y) - \min\ x_{gg}^{o}(y)} \tag{10}$$

$$x_{gg}^{*}(y) = \frac{x_{gg}^{o}(y) - \min\ x_{gg}^{o}(y)}{\max\ x_{gg}^{o}(y) - \min\ x_{gg}^{o}(y)} \tag{11}$$

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

Equations (10) and (11) generate normalised data that will be used in defining the grey relational coefficients [26] for each of the maintenance workforce objectives. The expression for computing the grey relational coefficients for each of the maintenance workforce objectives is expressed as Equation (12). This represents the second stage in the application of GRA.

$$\zeta_i(y) = \frac{\Delta\min + \zeta\Delta\max}{\Delta_{o,i}(y) + \zeta\Delta\max} \tag{12}$$

$$\Delta\min = \min_{\forall gg}\min_{\forall y}\left\|x_o^{*}(y) - x_{gg}^{*}(y)\right\| \tag{13}$$

$$\Delta\max = \max_{\forall gg}\max_{\forall y}\left\|x_o^{*}(y) - x_{gg}^{*}(y)\right\| \tag{14}$$

where$x_o^*(y)$ is the reference sequence of parameter y,$x_o^*(y)$ is the comparative sequence of parameter y, andζ is the identification coefficient with a value that lies between 0 and 1.

The last stage of GRA involves computation of the grey relational grade (Equation 15) for each experiment [26].

$$\gamma_z = \frac{1}{n}\sum_{i=1}^{n}\zeta_i(y) \tag{15}$$

where γ_z is grey relational grade for experiment z.

3. Model application and discussions of results

The proposed framework for maintenance workforce size prediction was tested with data obtained from a process industry in Nigeria. The process industry manufactures bottled and can drinks and currently operates three production lines. The maintenance crews are centralised, i.e., the same maintenance staff are responsible for the maintenance of all three production lines. Information from the company's accounting and maintenance records was used to determine maintenance workforce costs and size as well as its productivity and effectiveness.

The ANN models were trained using 144 datasets to predict the maintenance workforce size. The learning algorithm employed was a two hidden layer feed-forward neural network. The learning rate of the ANN model was 0.3, while momentum was zero. A zero momentum was considered because the ANN models exhibited a fast convergence. The training algorithm for the ANN model was a gradient descent algorithm. A sigmoid transfer function was used in this study. This transfer function was chosen for its ability to generate reliable results for the back-propagation ANN algorithm [10]. The performance of the predictive model was assessed using two statistical metrics (RMSE and MAPE).

The ANN algorithm and FIS were coded using VB.Net on a 64 bit personal computer (PC) with 4.00 GB of RAM and a 1.80 GHz CPU. The computational times in Tables 1 and 2 are dependent on the configuration of the PC used to implement the ANN model. Additionally, experience in coding ANN algorithms influences their efficiency.

The MAPE results obtained during the training and testing of the various ANN architectures showed highly accurate predictions. Also, the MAPE values for the testing data were all less than those of the training data. Furthermore, the RMSE values for the testing data were better than those of the training data (Table 1). Based on the grey relational grade (GRG) results, the most suitable ANN architecture for the maintenance workforce prediction was a 4-10-7-1 configuration. This result is consistent with the observation that a 4-10-7-1 ANN architecture had the lowest values for MAPE and RMSE during training and testing of the ANN (Table 1). The computational times for the ANN models did not follow a pattern (Table 1).

When using the MAPE of the FIS to evaluate the prediction accuracy of the different fuzzy rules, it was observed that all the fuzzy rules generated highly accurate predictive results [27]. Apart from the 12-rule FIS, the data used for testing using MAPE was more than the data used for training using MAPE. The other testing data used for MAPE were less than the data of the training for the other rules (Table 2). After an initial convex pattern in the MAPE values for the first five rules during FIS training, there was a steady decrease in the training data MAPE values as the number of rules increased for FIS. The only time in which there was an increase in RMSE values between two consecutive rules during the training of FIS was between the 3-rule and 4-rule instances (Table 2). The testing data MAPE and RMSE values did not follow a regular pattern. Based on the GRA results for the FIS, the most suitable number of rules for this case study was a 20-rule structure (Table 2). The computational time of the FIS increased as the number of rules increased. The authors observed a linear relationship between the number of rules and computational time (Table 2).

The selected ANN architectural (4-10-7-1) results (RMSE and MAPE) were better than those of the selected FIS rules (20-rules) [24, 28-31]. Based on the MAPE results for the 20-rule FIS and 4-10-7-1 ANN architecture, it can be inferred that they both yielded highly accurate predictions [27]. Comparison of the RMSE and MAPE values showed that the 4-10-7-1 ANN architecture is a more suitable predictive model for maintenance workforce size prediction than the 20-rule FIS. The 4-10-7-1 ANN architecture only showed a sharp decrease in its RMSE values between the first and second epochs, after which it maintained a steady decrease and converged at 34 epochs (Figure 3). This implies that the computation time of the 4-10-7-1 ANN architecture was smaller. The reason advanced for the superiority of ANN models and FIS during testing is that these are supervised learning models. A supervised learning model has input and output parameters, which enables the model to learn from examples [19].

Table 1 Performance of ANN architectures for the training and testing datasets

S/n	Architectures	Training		Testing		Epoch	Computational time (sec)	GRG	Ranks
		RMSE	MAPE	RMSE	MAPE				
1	4-8-7-1	2.3315	6.1380	1.7829	4.5808	22	68.4310	0.9927	3
2	4-8-8-1	2.3388	6.1449	1.7928	4.5922	29	94.6785	0.9912	4
3	4-8-9-1	2.3742	6.2510	1.8285	4.7114	22	80.5610	0.9818	7
4	4-8-10-1	2.4668	6.4816	1.8362	4.6947	21	83.2407	0.9728	12
5	4-9-7-1	2.2965	6.0431	1.8001	4.6219	30	96.7729	0.9941	2
6	4-9-8-1	2.4594	6.4629	1.8178	4.6305	16	56.8069	0.9764	10
7	4-9-9-1	2.4709	6.5026	1.8253	4.6665	18	69.5718	0.9737	11
8	4-9-10-1	2.4027	6.3145	1.8134	4.6375	27	109.4460	0.9821	6
9	4-10-7-1	2.2641	5.9674	1.7809	4.5716	34	117.1561	1.0000	1
10	4-10-8-1	2.3762	6.2486	1.7892	4.5809	31	115.4491	0.9879	5
11	4-10-9-1	2.4304	6.4051	1.8185	4.6739	29	119.3186	0.9777	9

12	4-10-10-1	2.4033	6.3269	1.8216	4.6828	32	152.9069	0.9801	8

Table 2 Performance of various FIS rules for the training and testing datasets

Rules	Training		Testing		Computational time (sec)	GRG	Ranks
	RMSE	MAPE	RMSE	MAPE			
1	3.2532	9.4315	1.7717	4.4176	1.5240	0.9297	4
2	2.8087	7.6480	2.0138	6.1080	1.9323	0.9238	5
3	2.7386	7.5846	2.1538	6.4167	2.3936	0.9157	6
4	2.8807	7.9579	2.1538	6.4167	2.8929	0.9051	11
5	2.8553	8.0015	2.3274	6.9243	3.4553	0.8900	13
6	2.8699	8.0163	2.3570	7.0201	4.1838	0.8865	15
7	2.8614	7.9922	2.3629	7.1097	4.3236	0.8857	16
8	2.7976	7.8695	2.4777	7.2697	4.8132	0.8826	18
9	2.7751	7.7305	2.5927	7.3428	5.2725	0.8796	20
10	2.7588	7.6595	2.5550	7.2555	5.7789	0.8839	17
11	2.7080	7.5126	2.6141	7.5248	6.3142	0.8819	19
12	2.6431	7.3184	2.5981	7.6011	6.9506	0.8869	14
13	2.5954	7.1752	2.4438	6.6317	7.4630	0.9108	9
14	2.5793	7.1266	2.5276	7.1318	7.6581	0.9015	12
15	2.5658	7.0390	2.5386	6.8793	8.4426	0.9064	10
16	2.5509	6.9701	2.5000	6.5849	9.9166	0.9140	8
17	2.5249	6.8091	2.5276	6.6529	10.6351	0.9153	7
18	2.4650	6.5919	2.3452	6.3107	11.3476	0.9343	3
19	2.4424	6.4895	2.3452	6.3107	12.5133	0.9369	2
20	2.4395	6.4820	2.3333	6.3107	12.9116	0.9376	1

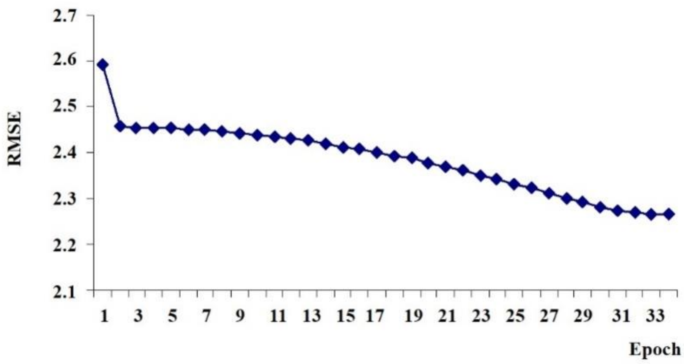

Figure 3 Convergence plot for a 4-10-7-1 ANN architecture

4. Conclusions

This study presented a neural network-based technique for maintenance workforce size determination in a process industry using input parameters (cost,workload, productivity and effectiveness). Additionally, the determination of a suitable ANN architecture when predicting the maintenance workforce size using the GRA (see also [32]) was reported in this study. Data from a brewery plant was used to select a suitable ANN architecture for a case study based on RMSE and MAPE as performance measures. The results obtained from the GRA identified the 4-10-7-1 architecture as the most suitable ANN model for this case study. The results obtained from ANN model were compared with those of FIS. It was observed the performance of the ANN model surpassed that of the FIS. A further study that considers other maintenance workforce requirements, such as efficiency and costs, can be modelled using ANN and FIS.

5.References

[1] Ighravwe DE, Oke SA. Application of Taguchi-fuzzy approach to prediction of maintenance-production workforce parameters for manufacturing systems. KKU Eng J 2016;43(2):69-77.

[2] CPS Human Resource Services. Workforce planning kit: Supply/demand analysis and gap analysis. Washington DC: Human Resource Services; 2007.

[3] Yip HI, Fan H, Chiang YH. Predicting the maintenance cost of construction equipment: comparison between general regression neural network and Box-Jenkins time series models. Autom Construct. 2014;38:30-8.

[4] Aref M, Sabah M. Manpower planning for demand forecasting of faculty members using trend analysis and regression. Int J Acad Res Bus Soc Sci. 2015;5(2): 11-23.

[5] Ighravwe DE, Oke SA. A non-zero integer nonlinear programming model for maintenance workforce sizing. Int J Prod Econ. 2014;150:204-14.

[6] Belmokaddem M, Mekidiche A, Sahed, A. Application of a fuzzy goal programming approach with different

importance and priorities to aggregate production planning. J Appl Quant Methods. 2009;4(3):317-31.
[7] Alfares HK. Aircraft maintenance workforce scheduling: A case study. J Qual Mainten Eng. 1999; 5(2):78-88.
[8] Adebiyi KA, Mudeshiru LO, Ajayeoba AO. Development of model for determination of crew-size requirements for a bolt and nut manufacturing industry. J Eng Appl Sci. 2007;2(12):1782-5.
[9] Ighravwe DE, Oke SA, Adebiyi KA. A reliability-based maintenance technicians' workload optimization model with stochastic considerations. J Ind Eng Int. 2016;12(2):171-83.
[10] De Bruecker P, van den Bergh J, Belien J, Demeulemeester E. A model enhancement heuristic for building robust aircraft maintenance personnel rosters with stochastic constraints. Eur J Oper Res. 2015;246:661-73.
[11] Masmoudi M, Hans E, Leus R, Hait A. Stochastic and fuzzy workload plans in project tactical planning under uncertainty. In: Borangiu T, Dolgui A, Dumitrache I, Filip F, editors. Proceedings of the 14th IFAC Symposium on Information Control Problems in Manufacturing; 2012 May 23-25; Bucharest, Romania. USA: Elsevier Ltd; 2012. p. 616-23.
[12] Antonovsky A, Pollock C, Straker L. System reliability as perceived by maintenance personnel on petroleum production facilities. Reliab Eng Syst Saf. 2016;152: 58-65.
[13] van den Bergh, De Bruecker P, Belien J, De Boeck L, Demeulemeester E. A three-stage approach for aircraft line maintenance personnel roistering using MIP, discrete event simulation and DEA. Expert Syst Appl. 2013;40:2659-68.
[14] Wu WY, Chen SP. A prediction method using grey method GMC (1,n) combined with grey relational analysis: a case study on internet access population forecast. Appl Math Comput.2005;169:198-217.
[15] Hu MY, Tsoukalas C. Combining conditional volatility forecasts using neural networks: an application to the EMS exchange rates. J Int Financ Market Inst Money. 1999;9(4):407-22.
[16] Furness PN, Levesley J, Luo Z, Taub N, Kazi, JI, Bates WD, Nicholson ML. A neural network approach to biopsy diagnosis of early acute renal transplant rejection. Histopathology. 1999;35:461-7.
[17] Zouari R, Sieg-Zieba S, Sidahmed M. Fault detection system for centrifugal pumps using neural networks and neuro-fuzzy techniques. Surveillance 5 CETIM; 2004 Oct 11-13; Senlis, France. 2004. p.1-9.
[18] Kaastra I, Boyd M. Designing a neural network for forecasting financial and economic time series. Neurocomputing. 2006;10:215-36.
[19] Engelbrencht AP. Artificial intelligence: an introduction. England: John Wiley and Sons Limited; 2007.
[20] Krenker A, Bester J, Kos A. Introduction to the Artificial Neural Networks. In: Suzuki K, Editor. Artificial neural networks: methodological advances and biomedical applications. Croatia: InTech; 2011. p. 3-18.
[21] Kamruzzaman J, Begg RK, Sarker RA. Artificial neural networks in finance and manufacturing. London: Idea group publishing; 2006.
[22] Ross TJ. Fuzzy logic with engineering applications. 3rd ed. England: John Wiley and Sons Ltd; 2010.
[23] Zouari R, Sieg-Zieba S, Sidahmed M. Fault detection system for centrifugal pumps using neural networks and neuro-fuzzy techniques. Surveillance 5 CETIM; 2004 Oct 11-13; Senlis, France. 2004. p. 1-9.
[24] Firat M, Denizli T. Sugeno fuzzy inference system for river flow estimation. International Congress on River Basin Management; 2007 Mar 22-24; Antalya, Turkey. Turkey: General Directorate of State Hydraulic Works; 2007. p. 1-16.
[25] Jang J, Sun C, Mizutani E. Neuro-fuzzy and Soft Computing. USA: Prentice Hall; 1997.
[26] Hasani H, Tabatabaei SA, Amiri G. Grey relational analysis to determine the optimum process parameters for open-end spinning yarns. J Eng Fiber Fabr. 2012;7(2):81-6.
[27] Tu JV. Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes. J Clin Epidemiol. 1996;49(11):1225-31.
[28] Ofori T, Ackah B, Ephraim L. Statistical models for forecasting road accident injuries in Ghana. Int J Res Environ Sci Tech. 2012;2(4):143-9.
[29] Vamsidhar E, Varma KVSRP, Rao P, Satapati, R. Prediction of rainfall using backpropagation neural network model. Int J Comput Sci Eng. 2010;2(4): 1119-21.
[30] Iwasokun GB, Egwuche OS, Gabriel JA. Neural network-bases health personnel monitoring system. Afr J Comput Ict. 2015;8(1):79-87.
[31] Patterson P, Draper S. A neural net representation of experienced and non-experienced users during manual wheelchair propulsion. J Rehabil Res Dev. 1998;35: 43-51.
[32] Lu HC, Yeh MF. Robot path planning based on modified grey analysis. Cybern Syst. 2002;33(2):129-59.