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# Prediction of maintenance workforce efficiency using neural networks, fuzzy inference system and autoregressive fractionally integrated moving average for a process industry

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***Abstract:***

**This study establishes the efficiency of the maintenance workforce in a process plant, utilising combined models, including artificial neural networks (ANN)-weighted aggregated sum product assessment (WASPAS) and ANN-fuzzy inference system (FIS)-WASPAS. ANN models with 12 architectures and a maximum epochs ranging from 64 to 173 were the limits of the analysis. Real-life data were used to train, test and rank the different architectures. WASPAS was superimposed on the ANN model for selection and ranking purposes, while FIS rules were introduced to the ANN results to uncover the uncertainty and imprecision in the model. These results were compared with those of the autoregressive fractionally integrated moving average (ARFIMA) method. At different λ values, the 4-8-10-1 ANN architecture and the FIS with 18 rules were the fittest for the ANN-WASPAS and the ANN-FIS-WASPAS methods, respectively. The ARFIMA method revealed a coefficient of maintenance workforce efficiency of -1.8636x10$^{-2}$. The constant parameter in the ARFIMA model and the root mean square error (RMSE) for the training and testing datasets are 0.9267, 0.0162, and 0.0150, respectively. In conclusion, the 4-8-10-1 ANN architecture more suitably predicts maintenance workforce efficiency than the 18-rule and ARFIMA models. This study predicts maintenance workforce efficiency, providing significant insights into the application of ANN, FIS, WASPAS, and ARFIMA models in a process industry.**

***Keywords:*** **artificial neural network, autoregressive fractionally integrated moving average, fuzzy inference system, weighted aggregated sum product assessment, workforce efficiency.**

***Classification numbers:*** **1.3, 2.3**

## 1. Introduction

Workforce planning is pivotal in the control of labour used in executing the available tasks in a system, with cost improvement as the goal. In controlling labour, the actual issue is the ability to design, develop and implement effective workforce-efficient schedules. Here, the maintenance teams' effort is controlled at a required level necessary to deliver the anticipated performance level for the plant. From this viewpoint, maintenance workforce efficiency is an important pillar of progress in manufacturing systems.

The efficiency of the maintenance workforce is typically known to rely on several factors, including preventive maintenance plans, inspections, operator training (in-house and off-the-job), calibration, maintenance technique, the choice of hardware used in the system (i.e., cables and components), and cleanliness and hygiene. It also has interrelationships with the consideration of workers' availability, the quality of work done and mean time to repair. When considering the quality of work done, the amount of workload and the type of maintenance activity are factors that need to be estimated. Since maintenance workers work as a team, the size of a maintenance team also influences the quality of work done. Thus, it is obvious that, among others, information on workforce size, availability, quality of work done and amount of workload is required to determine maintenance workforce efficiency. Bearing in mind the interrelationships among these factors, the maintenance workforce efficiency and the workforce size, a model framework to predict the efficiency of the maintenance workforce and the determination of the workforce size for a manufacturing system has been proposed in this work. To date, this linkage and predictive attempt for this beverage process-industry dataset and the combined ANN-FIS-WASPAS comparison have been ignored in the literature. Notwithstanding, this work acknowledges its limitations, including synthetic data usage, a single case company and a single-industry treatment in the present study. Since the above conceptualisation is complex and challenging

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in modelling, a literature foundation was relied on to develop the novel approach proposed in this work.

To justify the approach followed in this work, consider the foundational study by A. Parida, et al. (2009) [1]. From a maintenance system perspective, A. Parida, et al. (2009) [1] defined worker efficiency as the ratio of actual maintenance time to planned maintenance time (total expected workload in hours). Thus, the total maintenance workforce efficiency computation required workforce size consideration. In this study, we assumed that maintenance workers are qualified workers. A qualified maintenance worker is a worker who possesses the required skill sets for timely defect identification and repair of faulty equipment, as well as machine monitoring and inspections. A qualified maintenance worker's attributes are not limited to the above-mentioned skill sets. These skill sets may be acquired through periodic training programmes and collaborative knowledge sharing. The existence of collaborative knowledge sharing when dealing with qualified workers affects the quality of maintenance work done and workers' efficiency.

Furthermore, the generation of maintenance workforce information is important for the scheduling of workers who will manage an organisation's maintenance activity. In manufacturing systems, workforce planning has a strong influence on machine bottlenecks and availability, as well as production time. Maintenance workforce planning is among the most difficult workforce planning operations in manufacturing systems. This is because the nature of maintenance activities does not always follow a deterministic pattern. For example, maintenance time, workforce size and maintenance cost are often considered stochastic variables during maintenance planning [2].

Although several studies have been reported on maintenance workforce size planning for different systems, the problem of maintenance workforce efficiency prediction is sparsely considered in the literature. Recent studies on maintenance workforce planning have explored the use of mathematical models and artificial intelligence. D.E. Ighravwe, et al. (2014) [3] utilised non-linear programming to evaluate the workforce size in a production system. D.E. Ighravwe, et al. (2016a) [4] presented a non-linear model for maintenance workforce sizing using a genetic algorithm as a solution method. The use of simulated annealing for machine scheduling and maintenance planning was considered by N. Safaei, et al. (2008) [5].

Maintenance policy implementation has also benefited from the use of artificial intelligence (meta-heuristics). For instance, the particle swarm optimisation algorithm was used to implement a reliability-based centred maintenance for a transmission system [6]. Apart from the above-mentioned artificial intelligence tools whose applications have benefited manufacturing systems, an artificial neural network (ANN) is another artificial intelligence tool that has generated useful results for improving manufacturing activities.

Different predictive models have been proposed for manufacturing systems' parameters. Some examples of ANN as predictive models are in the areas of wear prediction [7, 8], control chart design [9], equipment performance evaluation [10, 11] and fault detection [12, 13]. Also, ANN models have been used for classification [14, 15] and selection [16] problems. Currently, the problems of maintenance parameters classification, selection and prediction have not been adequately addressed using ANN models. The scope of this study covers only the application of ANN as a predictive model for maintenance workforce efficiency.

The design of a workforce prediction model is a challenging task [17]. This problem is more complex when dealing with the maintenance workforce for manufacturing systems. This complexity makes the use of a regression model less suitable for maintenance parameter prediction. This study selects ANN as a predictive model for maintenance workforce efficiency prediction because of its unique feature of not considering the assumption of the distribution of workforce parameters [18]. A multi-layer perceptron (MLP) ANN model is considered because of its capacity to generate accurate predictions [19]. Recently, M. Hadi, et al. (2025) [20] examined the role of artificial intelligence in microgrid maintenance. The idea from that work could strengthen the ANN-WASPAS method presented in this study by enhancing the flexibility and precision of the neural network parts through consideration of enhanced data. It could also offer data-oriented weight creation, which is aided by the weighted aggregated sum product assessment (WASPAS) method. Furthermore, Y. Zeng, et al. (2025) [21] analysed neural networks by considering uncertainty reduction using fuzzy logic. The application was drawn from a hydropower scheme. The idea from that work could strengthen the ANN-WASPAS method proposed in this study by improving the capability of the proposed method to account for imprecision in data and use historical data to learn the criteria weights for the method. The method could enhance interpretability by considering fuzzy rules. It could also improve robustness, where noise is reduced from the system.

This study uses maintenance workers' availability, quality of work done, workload and size parameters, which are contributing factors to workforce efficiency. On the basis of these parameters, maintenance workforce efficiency is predicted using an ANN model. The performance of the ANN model is compared with a fuzzy inference system (FIS) and autoregressive fractionally integrated moving average (ARFIMA) on the basis of root mean square error (RMSE). This study aims to select an ANN model for maintenance workforce efficiency prediction using the weighted aggregated sum product assessment (WASPAS) approach based on RMSE and mean absolute percentage error (MAPE).

The remaining sections of this study are organised as follows: in Section 2, the research methodology is presented, while Section 3 contains the selected predictive models, application, and discussion of results. The conclusions of this study are in Section 4.

## 2. Methodology

This section presents the different predictive models that are used for maintenance workforce efficiency prediction. In addition, a brief discussion on WASPAS is presented.

### 2.1. Artificial neural network

Data input selection, number of hidden layers, training algorithm selection, and evaluation criteria are the main factors that determine the accuracy of an ANN model when used as a predictive model. The features of an ANN model are characterised by interconnecting weights (Fig. 1). The input parameters into the ANN model are normalised. The normalisation of input parameters helps to reduce the influence of large input parameter values on prediction results. The mean and standard deviation values for each parameter can be used to normalise parameters (Equations 1a and 1b). The same normalisation scheme is used in normalising the ANN output (maintenance workforce efficiency).

Normalisation (z-score):

$$nor_{ij} = \left(x_{ij} - \mu_i\right) / \sigma_i \tag{1a}$$

For a min-max scaling to [0,1]:

$$x_{ij}^{'} = \frac{\left(x_{ij} - \min_i x_i\right)}{\left(\max_i x_i - \min_i x_i\right)} \tag{1b}$$

where $nor_{ij}$ is the normalised value of input *i*, which belongs to tuple *j*, $x_{ij}$ is the original value of input *i* belonging to tuple *j*, $\sigma_i$ is the standard deviation of input *i*, and $\mu_i$ is the mean value of input *i*.

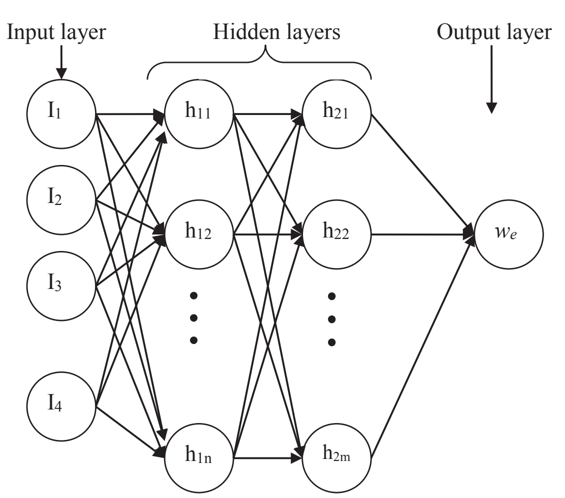


**Fig. 1. A two-layer hidden ANN model structure.**

To obtain a desired result from ANN models, the connecting weights are adjusted during the change of epoch. In this study, the output (workforce efficiency) from the ANN model is estimated using a sigmoid transfer function (Equation 2). This transfer function is selected because the value of maintenance workforce efficiency is between 0 and 1.

$$f_{AN} = \frac{1}{1 + e^{-(net_m - \theta_m)}} \tag{2}$$

where $f_{AN}$ is the workforce efficiency (output), represented as a sigmoid function, $net_m$ is the weighted sum of the inputs to a neuron plus bias, and $\theta_m$ is the maintenance system workforce characteristics.

During the training of the different ANN models, RMSE is used to evaluate the quality of the solution obtained from a particular ANN architecture (Equation 3). The termination criterion for the ANN architecture occurs when the difference between the current epoch's RMSE value and the previous epoch's RMSE value is greater than zero.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(p_j - o_j\right)^2} \tag{3}$$

where *n* is the total number of training data, $p_j$ is the predicted value for output *j*, and $o_j$ is the actual value of output *j*.

The error generated from the ANN model is used in adjusting the values of the connecting weights. In addition, momentum and learning rate are used to further reduce the network error and convergence time of ANN models. Optimal values for the connecting weights are generated using a training algorithm. This study uses the gradient descent algorithm as its training algorithm, with batch gradient descent chosen as the specific optimiser. The attraction to this optimiser is its uniquely stable convergence property for the medium-scale training dataset, such as the 144 entries used in the present study. In achieving this goal, it deploys the whole dataset to calculate the sole but accurate update, the gradient of the cost function. Basically, the three main steps taken for the gradient descent optimiser are, first, to evaluate the gradient, second, to update parameters, and third, to repeat the above steps, awaiting convergence of the cost function to the lowest value. The expression for updated weights is given as Equations 4a and 4b, which use standard gradient descent with momentum.

$$\Delta w_{ij}(t) = \eta \frac{\partial E}{\partial w_j(t)} + \alpha \Delta w_j(t-1) \tag{4a}$$

$$w_{ij}(t+1) = w_j(t) + \Delta w_j(t) \tag{4b}$$

where $w_{ij}(t)$ is the connecting weight between neurons $i$ and $j$ at epoch $t$, $\eta$ is the learning rate, $\alpha$ is the momentum value.

### *2.2. Fuzzy inference system*

A basic FIS consists of five steps. These are random initialisation of parameters (spread, width, and centre), calculation of predicted values, estimation of prediction error, updating of parameters and changing the number of rules. A basic FIS algorithm is summarised as follows [22]:

```
Initialise the maximum number of rules
  Repeat
    While p ≤ P
      Compute prediction values for each tuple
      Calculate predictive errors
      Update spread, width, and centre using dataset p
    End while
  Increase the number of rules
Until stopping criteria are met
```

The initialisation of the spread, width, and centre contained in a FIS is required at the start of a FIS implementation. The next stage involves the calculation of the outputs in a training dataset. Each output is calculated based on its corresponding input parameters. At this stage, the values of the FIS spread, width, and centre are the same for all the training datasets. The estimation of the difference between the actual and predicted values of the training datasets is used to evaluate the performance of several rules for a FIS. When a satisfactory error value for the training datasets is not obtained, the values of the spread, centre, and width of a FIS are updated using the prediction errors of the current data size, which has not been used previously for spread, centre, and width updating. The updating process is enhanced using different or the same learning rate values for spread, centre, and width. When a particular number of rules does not generate satisfactory results, the current number of rules is increased by one. This process continues until a stopping criterion is met. Stopping criteria for a FIS could be the maximum number of rules, convergence of the FIS solution or a maximum error limit. The maximum error limit for a FIS could be statistical measures such as RMSE and MAPE [22]. The phrase "increase number of rules" in the basic FIS algorithm shown earlier suggests an ad hoc search. The process consists of initialisation, an update algorithm and learning rates for spread/centre/width. Moreover, the process is described as ad hoc since it adds rules when necessary. This is opposed to generating a fixed rule base in advance.

### *2.3. Autoregressive fractional integrated moving average model*

The ARFIMA model [23] has enjoyed considerable success in different fields of human endeavour [24]. The basic expression for an ARFIMA model is given in Equation 5.

$$\varphi(B)(1-B)^d X_t = \theta(B)e_t \tag{5}$$

where $\theta$ and $\varphi$ are polynomials (Equations 6 and 7), $e_t$ represents a white noise process with zero mean and variance, $B$ represents the back-shift operator, and $d$ represents the fractional differencing parameter.

$$\varphi(B) = \left(1-\varphi_1 B - \cdots - \varphi_p B^p\right) \tag{6}$$

$$\theta(B) = \left(1-\theta_1 B - \cdots - \theta_q B^q\right) \tag{7}$$

The parameter $p$ in Equation 6 represents the autoregressive order, while $q$ in Equation 7 stands for the moving average. The value of $d$ affects the quality of the solution from an ARFIMA model. For a stationary process, the value of $d$ is between -½ and ½, while for a long-memory behaviour process, the value of $d$ is between 0 and ½. Several studies have reported methods for $d$ estimation in the literature. Some of the methods for $d$ estimation are the Whittle estimator [25], periodogram estimator [26], maximum likelihood estimators [27], smoothed periodogram estimator [28] and Robinson estimator [29]. In this study, the maximum likelihood estimates method in the Stata package version 12 is used to determine the value of $d$.

### *2.4. Weighted aggregated sum product assessment*

The performance of predictive models is evaluated using different statistical measures. A selected measure for a predictive model is often dependent on the choice of the modeller. To present a single-attribute measure using different statistical measures, this study applied the WASPAS approach. The steps involved in WASPAS implementation as applied to ANN architecture selection are as follows:

*Step 1: Formulation of the initial performance matrix*

The initialisation of the performance matrix for different statistical measures represents the first step during the implementation of the WASPAS approach.

*Step 2: Data normalisation*

This step entails the conversion of the actual statistical measure values into normalised values. The expression for normalising a statistical measure whose maximum is desired is expressed in Equation 8, while Equation 9 is used to determine a normalised value for a statistical measure whose minimum value is desired.

For beneficial criteria:

$$x'_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \tag{8}$$

For cost criteria:

$$x'_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \tag{9}$$

where $x_{ij}$ is the assessment value of the $i$-th ANN architecture with respect to the $j$-th statistical measure and $x'_{ij}$ is the normalised value of the variable.

*Step 3: Determination of the relative importance of ANN architecture*

The weighted sum method (Equation 10) and the weighted product method (Equation 11) are used to determine the relative importance of the ANN architecture.

$$Q_i^{(1)} = \sum_{j=1}^{n} w_j x'_{ij} \qquad \text{(weighted sum)} \tag{10}$$

$$Q_i^{(2)} = \prod_{j=1}^{n} x'^{\,w_j}_{ij} \qquad \text{(weighted product)} \tag{11}$$

where $w_j$ is the weight for statistical measure $j$ and $\bar{x}_{ij}$ is the normalised value of the statistical measure whose minimum value is desired.

*Step 4: Ranking of ANN architecture*

The ranks for each ANN architecture are determined by combining the weight sum method and weighted product method outputs additively using a constant parameter (Equation 12).

$$Q_i = \lambda\, Q_i^{(1)} + (1\text{-}\ \lambda\, Q_i^{(2)}) \qquad \text{(final score)} \tag{12}$$

where $\lambda$ is a parameter that lies within 0 and 1.

Moreover, the schematic representing the maintenance data splitting process is shown in Fig. 2.

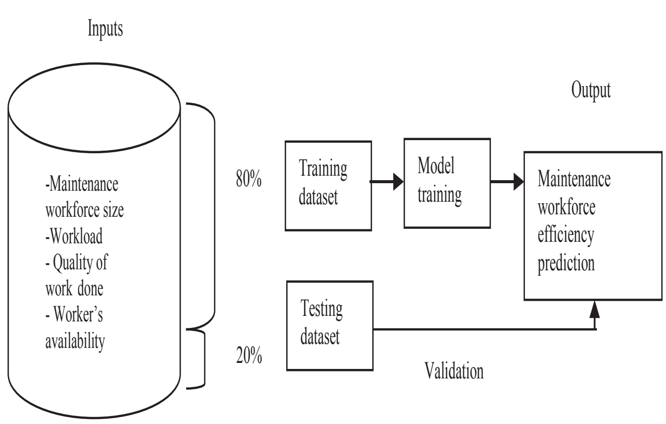


**Fig. 2. Schematic showing maintenance data splitting (random).**

## 3. Model application and discussion of results

### *3.1. Model application*

During the application of the predictive models, datasets were obtained from a process industry that specialises in the production of alcoholic and non-alcoholic drinks. The company has three production lines. Two of the production lines are used for bottled drinks production, and the last production line is used for canned drinks production. Currently, the company's maintenance workforce size varies between 29 and 34 workers. The maintenance workers' availability was between 79.94 and 92.43%, while their efficiency was between 85.20 and 94.93%. The range of the annual maintenance workload was between 51,329.59 and 88,374.70 hours, while the quality of work done by the maintenance workers was between 70.69 and 90.11%.

The values for maintenance workers' availability, efficiency, and size, as well as quality of work done and total maintenance workload, were obtained during the implementation of an optimisation model [2]. It should be noted that for a system where there is sufficient data, the use of an optimisation model for data generation is not required. The values for maintenance workforce efficiency from the optimisation model were taken as the actual values during the computation of prediction errors.

A basic understanding of the type of data used to test the proposed ANN-WASPAS model for the maintenance workforce sizing problem is extremely important. Its disclosure will aid in understanding the limitations of the proposed approach and the extent to which future efforts should be invested to make this foundational method robust and widely used. It is declared that the optimisation data in an earlier work are used, which makes them synthetic. It is a case from a beverage plant. Although this does not diminish the credibility of the model, it shows that future efforts should be directed at obtaining real-world data. The synthetic data generated by the optimisation routine reflect the assumptions of optimisation, which may show some biased results. The ANN and FIS will learn the generator assumptions. Synthetic data are used in this work as they may represent the real process since they are created by schemes that are amenable to learning. They show potential to replicate patterns, statistical characteristics and associations among the parameters of the original data. Moreover, they attain a high level of representativeness when such representative data are used to capture the complexity of the process. Furthermore, since bias is known to be present in synthetic data, it is mitigated through the balance of the data representation. The observed flaws in the causal association are corrected to help mitigate bias.

The reason for generating information using the optimisation model is that the ANN model requires a sufficient amount of training datasets. The training datasets numbered 144, while the testing datasets numbered 36. In performing the training and testing of the data, a monthly time resolution was used, and the sample span is 1 year. Moreover, it is assumed that throughout the analysis, seasonality or policy changes do not occur. This is an assumption that guides the development of the model.

The ANN model and FIS were coded using the VB.NET programming language on a Windows 8 computer with 3.9 GB RAM and a 64-bit operating system. The ANN model termination criterion was guided by standard earlystopping with a validation set and a patience parameter (e.g., stop after p consecutive non-improving epochs). During the evaluation of the different ANN architectures and FIS rules, the weights for RMSE and MAPE of the training and testing datasets were the same (0.25). This was also applicable to the selection of the most suitable number of rules for the FIS. To explain the assignment of 0.25 equal weights to RMSE and MAPE, it should be noted that researchers guard against bias in weight assignment. As the sum of the weights is assigned 1, the effect of all criteria on the eventual outcome will be unity, where high values are not disproportionately assigned to any of the criteria.

The ARFIMA model was implemented using Stata 12 software. The maintenance workforce availability was $-6.7473 \times 10^{-2}$, while a value of $-1.8636 \times 10^{-2}$ was obtained as the coefficient for the maintenance workforce efficiency. Although availability cannot be negative in absolute terms, the negative values displayed are coefficients that provide useful information about the availability. The same idea presented for availability applies to maintenance workforce efficiency. The quality of work done coefficient was $1.2620 \times 10^{-3}$, while the maintenance workforce size coefficient was $1.1800 \times 10^{-7}$. The constant parameter in the ARFIMA model was 0.9267. The RMSE for the training datasets was 0.0162, while RMSE for the testing datasets was 0.0150. In this work, a sample size of 180 (144 for training and 36 for testing) is used for ARFIMA parameter estimation reliability. Although functional models require care and usually larger samples for stable estimates, the limited data have constrained this research to a small amount of data. However, this study established the feasibility of using the ARFIMA model for the prediction process, and future studies could provide more data for reliability. With an expanded dataset, the risk of small sample size bias will be avoided.

### 3.2. Discussion

Based on the results obtained from the ANN model, the values of RMSE and MAPE for all the ANN architectures that were considered showed that the testing results were better than the training results (Table 1). The "ranks" column in Table 1 shows the ranks of the ANN architectures using the WASPAS method, guided by Equation 12. In terms of MAPE, all the ANN architectures generated highly accurate predictions [30]. When λ=0.1, the WASPAS for the ANN showed that a 4-9-8-1 architecture and a 4-8-10-1 architecture had the same grade (Table 2). To break the ties, the architecture with the lowest total number of epochs was selected as the most suitable ANN architecture. For the different values of λ, the 4-8-10-1 ANN architecture was ranked first (Table 2). Since the 4-8-10-1 ANN architecture had the highest WASPAS values for the different λ values, it is the most suitable ANN architecture for the case study [31, 32]. The convergence of the 4-8-10-1 architecture showed a steady decreasing plot after an initial steady drop in RMSE value (Fig. 3).

**Table 1. Performance statistics of different ANN architectures.**

| S/n | Architectures | Training data | | Testing data | | Max* epoch | Ranks |
|---|---|---|---|---|---|---|---|
| | | *RMSE* | *MAPE%* | *RMSE* | *MAPE%* | | |
| 1 | 4-8-7-1 | 0.0184 | 1.6480 | 0.0146 | 1.3209 | 105 | 9 |
| 2 | 4-8-8-1 | 0.0183 | 1.6363 | 0.0145 | 1.3194 | 71 | 5 |
| 3 | 4-8-9-1 | 0.0183 | 1.6354 | 0.0145 | 1.3189 | 64 | 4 |
| 4 | 4-8-10-1 | 0.0183 | 1.6372 | 0.0145 | 1.3149 | 76 | 1 |
| 5 | 4-9-7-1 | 0.0183 | 1.6350 | 0.0146 | 1.3178 | 111 | 7 |
| 6 | 4-9-8-1 | 0.0183 | 1.6353 | 0.0145 | 1.3159 | 86 | 1 |
| 7 | 4-9-9-1 | 0.0183 | 1.6355 | 0.0146 | 1.3166 | 117 | 3 |
| 8 | 4-9-10-1 | 0.0184 | 1.6587 | 0.0146 | 1.3340 | 117 | 12 |
| 9 | 4-10-7-1 | 0.0186 | 1.6367 | 0.0145 | 1.3185 | 173 | 8 |
| 10 | 4-10-8-1 | 0.0184 | 1.6568 | 0.0146 | 1.3315 | 106 | 10 |
| 11 | 4-10-9-1 | 0.0183 | 1.6372 | 0.0145 | 1.3191 | 111 | 5 |
| 12 | 4-10-10-1 | 0.0184 | 1.6581 | 0.0146 | 1.3317 | 99 | 11 |

*: Max epoch - maximum number of epochs allowed until termination.

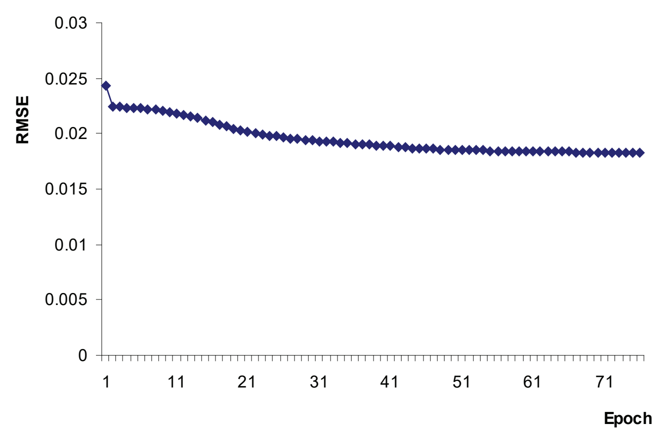


**Fig. 3. Convergence plot for a 4-8-10-1 ANN architecture.**

**Table 2. WASPAS results for ANN architecture selection.**

| S/n | Architectures | $Q_1$ | $Q_2$ | λ = 0.1 | λ = 0.2 | λ = 0.3 | λ = 0.4 | λ = 0.5 | λ = 0.6 | λ = 0.7 | λ = 0.8 | λ = 0.9 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4-8-7-1 | 1.0099 | 1.0068 | 1.0071 | 1.0074 | 1.0077 | 1.0073 | 1.0084 | 1.0087 | 1.0090 | 1.0093 | 1.0096 |
| 2 | 4-8-8-1 | 1.0111 | 1.0120 | 1.0119 | 1.0118 | 1.0117 | 1.0119 | 1.0115 | 1.0114 | 1.0113 | 1.0113 | 1.0112 |
| 3 | 4-8-9-1 | 1.0114 | 1.0122 | 1.0122 | 1.0121 | 1.0120 | 1.0121 | 1.0118 | 1.0118 | 1.0117 | 1.0116 | 1.0115 |
| 4 | 4-8-10-1 | **1.0145** | 1.0127 | 1.0129* | **1.0131** | **1.0133** | **1.0130** | **1.0136** | **1.0138** | **1.0140** | **1.0142** | **1.0143** |
| 5 | 4-9-7-1 | 1.0123 | 1.0108 | 1.0109 | 1.0111 | 1.0112 | 1.0110 | 1.0115 | 1.0117 | 1.0118 | 1.0120 | 1.0121 |
| 6 | 4-9-8-1 | 1.0138 | **1.0128** | **1.0129*** | 1.0130 | 1.0131 | 1.0130 | 1.0133 | 1.0134 | 1.0135 | 1.0136 | 1.0137 |
| 7 | 4-9-9-1 | 1.0132 | 1.0109 | 1.0112 | 1.0114 | 1.0116 | 1.0113 | 1.0121 | 1.0123 | 1.0125 | 1.0128 | 1.0130 |
| 8 | 4-9-10-1 | 1.0000 | 1.0027 | 1.0024 | 1.0022 | 1.0019 | 1.0023 | 1.0014 | 1.0011 | 1.0008 | 1.0005 | 1.0003 |
| 9 | 4-10-7-1 | 1.0118 | 1.0080 | 1.0084 | 1.0088 | 1.0091 | 1.0086 | 1.0099 | 1.0103 | 1.0106 | 1.0110 | 1.0114 |
| 10 | 4-10-8-1 | 1.0019 | 1.0035 | 1.0033 | 1.0031 | 1.0030 | 1.0032 | 1.0027 | 1.0025 | 1.0024 | 1.0022 | 1.0020 |
| 11 | 4-10-9-1 | 1.0113 | 1.0119 | 1.0119 | 1.0118 | 1.0117 | 1.0118 | 1.0116 | 1.0115 | 1.0115 | 1.0114 | 1.0114 |
| 12 | 4-10-10-1 | 1.0017 | 1.0032 | 1.0031 | 1.0029 | 1.0028 | 1.0030 | 1.0025 | 1.0023 | 1.0022 | 1.0020 | 1.0019 |

*: Equal maximum WASPAS value, Q1 is weighted sum output, Q2 is weighted product output, λ sweep, i.e. λ=0.1 to 0.9 in steps of 0.1, is a scheme showing how sensitive the varied values of the combined parameter λ from 0 to 1 influence the ranks of options.

**Table 3. Comparison of different FIS rules.**

| Rules | Training data | | Testing data | |
|---|---|---|---|---|
| | *RMSE* | *MAPE%* | *RMSE* | *MAPE%* |
| 1 | 0.0277 | 2.5252 | 0.0145 | 1.3237 |
| 2 | 0.0279 | 2.5862 | 0.0148 | 1.3285 |
| 3 | 0.0270 | 2.4516 | 0.0161 | 1.3763 |
| 4 | 0.0243 | 2.1594 | 0.0167 | 1.4833 |
| 5 | 0.0229 | 2.0062 | 0.0168 | 1.5027 |
| 6 | 0.0214 | 1.8560 | 0.0163 | 1.4436 |
| 7 | 0.0213 | 1.8566 | 0.0162 | 1.4270 |
| 8 | 0.0210 | 1.8320 | 0.0160 | 1.4019 |
| 9 | 0.0209 | 1.8266 | 0.0159 | 1.3907 |
| 10 | 0.0208 | 1.8236 | 0.0158 | 1.3775 |
| 11 | 0.0207 | 1.8154 | 0.0157 | 1.3632 |
| 12 | 0.0205 | 1.8026 | 0.0155 | 1.3493 |
| 13 | 0.0203 | 1.7830 | 0.0154 | 1.3399 |
| 14 | 0.0200 | 1.7590 | 0.0153 | 1.3345 |
| 15 | 0.0198 | 1.7423 | 0.0151 | 1.3292 |
| 16 | 0.0196 | 1.7347 | 0.0151 | 1.3246 |
| 17 | 0.0196 | 1.7339 | 0.0150 | 1.3188 |
| 18 | 0.0196 | 1.7382 | 0.0150 | 1.3118 |
| 19 | 0.0197 | 1.7452 | 0.0150 | 1.3064 |
| 20 | 0.0198 | 1.7525 | 0.0150 | 1.3025 |

The FIS results for the training and testing data (Table 3) showed that all the FIS rules had the capacity to predict workforce efficiency with high accuracy [30]. The most suitable number of rules for the FIS was 18 rules. This decision is based on the fact that, for the different values of λ, the 18 rules had the highest WASPAS values (Table 4). After the 5-rule FIS, the RMSE and MAPE during testing followed a decreasing pattern. However, the RMSE during training for the different rules decreased after the 5 rules, while the MAPE during training started decreasing after 2 rules, up to the 18 rules (Table 4). Apart from the 18-rule FIS MAPE results during testing, which were better than those of the 4-8-10-1 ANN architecture, the 4-8-10-1 ANN architecture generated better results than the 18-rule FIS MAPE (Tables 1 and 3). Thus, it can be deduced that the 4-8-10-1 ANN architecture is a more suitable predictive model for maintenance workforce efficiency than the 18-rule FIS and the ARFIMA model.

Furthermore, to depart from previous research, which predominantly employed optimisation methods to enhance overall operational efficiency, reduce downtime and improve human and non-human resources in manufacturing industries, the proposed maintenance workforce efficiency model offers effective maintenance management policy decision tools. For instance, many prior research demonstrate optimisation of maintenance workload, reduction of accidents and absenteeism [4, 33-36], and improvement in the reliability of technicians [2]. However, unlike these traditional methods, which are not competent to discern imprecision in complex data such as those from the process industry, the proposed approach incorporates a fuzzy inference system to handle imprecise and uncertain data, involving human beings in reasoning and offering understanding. This marks a significant departure from previous deterministic methods, enhancing flexibility. This method removes potential oversimplification in dealing with maintenance data and therefore addresses long-standing challenges in achieving reliable maintenance analytical results and interpretations.

**Table 4. WASPAS results for FIS rule selection.**

| Rules | $Q_1$ | $Q_2$ | λ=0.1 | λ=0.2 | λ=0.3 | λ=0.4 | λ=0.5 | λ=0.6 | λ=0.7 | λ=0.8 | λ=0.9 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.0813 | 1.0793 | 1.0795 | 1.0797 | 1.0799 | 1.0796 | 1.0803 | 1.0805 | 1.0807 | 1.0809 | 1.0811 |
| 2 | 1.0666 | 1.0645 | 1.0647 | 1.0649 | 1.0651 | 1.0648 | 1.0655 | 1.0657 | 1.0659 | 1.0661 | 1.0664 |
| 3 | 1.0559 | 1.0557 | 1.0557 | 1.0557 | 1.0557 | 1.0557 | 1.0558 | 1.0558 | 1.0558 | 1.0558 | 1.0559 |
| 4 | 1.0912 | 1.0880 | 1.0883 | 1.0887 | 1.0890 | 1.0885 | 1.0896 | 1.0899 | 1.0903 | 1.0906 | 1.0909 |
| 5 | 1.1269 | 1.1195 | 1.1202 | 1.1210 | 1.1217 | 1.1207 | 1.1232 | 1.1239 | 1.1246 | 1.1254 | 1.1261 |
| 6 | 1.1922 | 1.1816 | 1.1826 | 1.1837 | 1.1847 | 1.1833 | 1.1869 | 1.1879 | 1.1890 | 1.1901 | 1.1911 |
| 7 | 1.1982 | 1.1881 | 1.1891 | 1.1901 | 1.1911 | 1.1897 | 1.1932 | 1.1942 | 1.1952 | 1.1962 | 1.1972 |
| 8 | 1.2155 | 1.2054 | 1.2064 | 1.2074 | 1.2084 | 1.2070 | 1.2104 | 1.2115 | 1.2125 | 1.2135 | 1.2145 |
| 9 | 1.2220 | 1.2120 | 1.2130 | 1.2140 | 1.2150 | 1.2136 | 1.2170 | 1.2180 | 1.2190 | 1.2200 | 1.2210 |
| 10 | 1.2284 | 1.2188 | 1.2197 | 1.2207 | 1.2217 | 1.2203 | 1.2236 | 1.2246 | 1.2255 | 1.2265 | 1.2275 |
| 11 | 1.2362 | 1.2268 | 1.2277 | 1.2287 | 1.2296 | 1.2283 | 1.2315 | 1.2324 | 1.2334 | 1.2343 | 1.2353 |
| 12 | 1.2483 | 1.2390 | 1.2400 | 1.2409 | 1.2418 | 1.2405 | 1.2437 | 1.2446 | 1.2455 | 1.2465 | 1.2474 |
| 13 | 1.2593 | 1.2497 | 1.2507 | 1.2516 | 1.2526 | 1.2512 | 1.2545 | 1.2555 | 1.2564 | 1.2574 | 1.2584 |
| 14 | 1.2723 | 1.2619 | 1.2630 | 1.2640 | 1.2651 | 1.2636 | 1.2671 | 1.2682 | 1.2692 | 1.2703 | 1.2713 |
| 15 | 1.2841 | 1.2736 | 1.2746 | 1.2757 | 1.2767 | 1.2753 | 1.2789 | 1.2799 | 1.2810 | 1.2820 | 1.2831 |
| 16 | 1.2903 | 1.2793 | 1.2804 | 1.2815 | 1.2826 | 1.2811 | 1.2848 | 1.2859 | 1.2870 | 1.2881 | 1.2892 |
| 17 | 1.2936 | 1.2830 | 1.2841 | 1.2851 | 1.2862 | 1.2847 | 1.2883 | 1.2894 | 1.2904 | 1.2915 | 1.2926 |
| 18 | 1.2942 | 1.2839 | **1.2849** | **1.2860** | **1.2870** | **1.2856** | **1.2891** | **1.2901** | **1.2911** | **1.2922** | **1.2932** |
| 19 | 1.2921 | 1.2823 | 1.2833 | 1.2843 | 1.2852 | 1.2839 | 1.2872 | 1.2882 | 1.2892 | 1.2901 | 1.2911 |
| 20 | 1.2896 | 1.2803 | 1.2812 | 1.2822 | 1.2831 | 1.2818 | 1.2850 | 1.2859 | 1.2868 | 1.2878 | 1.2887 |

*: $Q_1$ is weighted sum output, $Q_2$ is weighted product output, λ sweep, i.e. λ=0.1 to 0.9 in steps of 0.1, is a scheme showing how sensitive the varied values of the combined parameter λ from 0 to 1 influence the ranks of options.

The proposed method also introduces effectiveness in handling maintenance data with time-series characteristics, making it capable of holding memory of data and exercising fractional differencing. This sets the proposed method apart from existing literature. While previous work provides an analysis of data that easily loses memory during processing, the application of the proposed method is novel. Moreover, in the proposed method, the unique ability to learn associations from the variables of the model, despite being complex and non-linearly presented, offers the advantage to the model in handling datasets, which is characteristic of the process data used to validate the proposed method. The advancement proposed in these preceding paragraphs contrasts with earlier studies that lacked such vital benefits, situating the proposed method as forming a new knowledge structure to be applied in similar process industries such as pharmaceutical, oil and gas, and mining industries.

The contribution of this work lies in its complete combination of these developments, connecting the literature by introducing joint approaches. Unlike previous methods, the priority of this paper includes effective maintenance management policy practices through the introduction of uncertainty capturing, learning from complex associations and handling time-series data. Explicitly stated, the contributions of this paper are as follows: (1) comparison of ANN, FIS, and ARFIMA on workforce-efficiency prediction; (2) use of WASPAS to select ANN architecture; and (3) demonstration on a beverage factory dataset.

Evidence validating the WASPAS-oriented ANN method with practical implications

The argument made in this work is that the use of WASPAS for ANN architecture selection in the framework of maintenance workforce efficiency prediction is novel and contributes to the maintenance literature. However, to enhance this contribution, additional evidence of its improvement using the literature is provided. Previously, hybridising the neural network framework with WASPAS in the context of regression analysis was reported to show satisfactory results by R. Zende, et al. (2025) [37]. It excels in performance with 1.67 and 5.62% improvement over WASPAS and regression analysis, respectively. This highlights the utility of combining ANN and WASPAS in the context of enhancing certainty and reducing imprecision when utilised in hole drilling. Based on this success, it is argued that the knowledge is transferable to the maintenance area. Moreover, this contribution has implications for practice in the industry when the computational cost of experiments with neural networks and the accuracy of the results are considered. In such a situation, a trade-off among these conflicting criteria is introduced. Furthermore, the diverse architectural configurations are considered as options in a problem formulated with a multicriteria perspective using WASPAS. Practically, the proposed method could be useful in several industrial contexts. These include manufacturing logistics/supply chain and precision agriculture.

## 4. Conclusions

The problem of maintenance workforce efficiency prediction has been addressed in this study using an ANN model and the WASPAS approach. The ANN model uses maintenance workforce size, workload, quality of work done and workers' availability as input parameters. A back-propagation algorithm was considered during the ANN implementation in a process industry. The RMSE result of the ANN model was compared with those of the FIS and ARFIMA model. Based on the results obtained, it can be concluded that the ANN model results compete favourably with those of ARFIMA. Thus, the ANN model can be used for maintenance workforce efficiency prediction in the process industry. Furthermore, the predicted workforce efficiency could be integrated into maintenance scheduling using a threshold via artificial intelligence coupled with machine learning schemes. These tools examine maintenance data to activate maintenance assignments when particular efficiency is nearby. The plant manager can avoid expending resources in maintenance over- or under-staffing by making use of the correct prediction values.

In this study, a ranking tool (WASPAS), which is currently gaining acceptance among researchers and industrial practitioners, was used to select the most suitable ANN architecture for maintenance workforce efficiency prediction. Previous work on ANN architecture selection has not considered the use of WASPAS. Thus, this serves as one of the contributions of the current study. Another contribution is the use of an ANN model for maintenance workforce efficiency prediction. Some benefits of the proposed framework are as follows: (i) the framework may complement optimisation models when a sufficient amount of information is available for workforce efficiency evaluation because the prediction error of the framework was small; and (ii) simulation of different maintenance workforce efficiency values using the proposed framework is easier than the use of optimisation models, which require expert judgement.

The future scope of the proposed integrated neural networks-fuzzy inference system-ARFIMA method lies in its deployment for predictive maintenance, where the model could be integrated with the Internet of Things and sensor technology. It is hoped that this will stimulate more efficient measures, minimise downtime, enhance asset management and reduce maintenance costs. Moreover, expanding research into multimodal learning and improving the proposed method to incorporate the competence to learn from unlabelled data could unlock new functionalities. This will enable the proposed model to map input data to outputs in a learning process. Furthermore, the selection of the number of rules for the neuro-fuzzy model could be determined using VIKOR and COPRAS techniques. This is an area of future research. Also, a study in this direction could consider computation time and the quality of the solution from a neuro-fuzzy model.

In developing the proposed model, one of the key limitations observed is that we were unable to check for multicollinearity among inputs, which might bias interpretation. However, between the inputs named availability and workload, there is a possibility that they are highly correlated with each other. This is a situation that largely influences the precision of the coefficients of the regression. Thus, this could be considered a limitation of the study that may be overcome in future studies. Moreover, a possible future extension of the present framework is consideration of the digital twin and advanced fuzzy techniques in the ANN-WASPAS integration. This means transforming the ANN-WASPAS method to account for dynamic yet complex and uncertain maintenance workforce problems. The results are expected to provide real-time solutions with rich data for a complex maintenance system. The digital twin method could leverage comprehensive frameworks coupled with changing values of real-world simulations. Moreover, a digital twin may be employed to overcome the paucity of data in maintenance through the creation of quality synthetic data together with an enrichment of a delimited real-life dataset. Furthermore, type-2 fuzzy synthesis could be preferable to a type-1 fuzzy inference system on the condition that high-order uncertainty exists and there is the presence of measurement noise.

## CRediT author statement

Sunday Ayoola Oke: Conceptualisation and Methodology, Writing - Original and Final draft preparations, Revision; Desmond Eseoghene Ighravwe: Conceptualisation and Methodology, Writing - Original draft preparation.

## COMPETING INTERESTS

The authors declare that there is no conflict of interest regarding the publication of this article.

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