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FORECASTING THE EQUIPMENT EFFECTIVENESS IN TOTAL PRODUCTIVE MAINTENANCE USING AN INTELLIGENT HYBRID CONCEPTUAL MODEL

Summary

Production managers are forced to achieve higher levels of operating performance due to the complexity of today's production environment. The accuracy of manufacturing facilities usually has an impact on productivity. Thus, forecasting machine performance has become an inevitable responsibility of production managers. However, the question of how managers may effectively evaluate the effectiveness of equipment remains unresolved. Although this topic has not been given much consideration in earlier studies, the production environment of today makes it significant. In order to predict the equipment effectiveness, this study proposes two different prediction models. The models are Adaptive Neuro Fuzzy Inference System (ANFIS) and hybrid firefly algorithm-adaptive neuro fuzzy inference system (FA-ANFIS). The equipment effectiveness prediction model has been developed and evaluated using a real-world case from a textile processing industry. As a result, the proposed hybrid FA-ANFIS model outperforms with a high accuracy of 99.1 percent and a low root-mean-square error (RMSE) of 0.090766. Moreover, this proposed model helps production managers in evaluating the equipment effectiveness.

Key words: *decision support, equipment effectiveness, predictive analysis, firefly algorithm, ANFIS*

1. Introduction

The most important phase in fabric production is textile fabric processing [1]. In particular, grey and calendar fabric production require a lot of money and resources [2]. On the other hand, Total Productive Maintenance (TPM) is a principle that strives to improve resources by improving industrial system's overall equipment effectiveness (OEE) [3, 4]. According to Jasiulewicz et al. [5], OEE is clearly a strategy including best practices for monitoring and improving equipment effectiveness. Furthermore, OEE has a capability of combining multiple independent functions into a single controllable variable. This was used to generate an integrated production performance indicator that was superior to other performance indicators [6]. Some of the independent functions are equipment availability (A), equipment performance (P), and manufacturing process quality (Q) [7].

There has been a considerable progress in OEE assessment. OEE was utilised by Jain et al. [8] to examine the effects of mobile maintenance as a component of the TPM programme in Indian businesses ranging in size from small to large. This mobile maintenance method can improve equipment quality and OEE while lowering catastrophic failure rates. Ylipää et al. [9] quantified the criteria of availability, utilisation, speed, dependability, and scheduled stop time. According to the above studies, operational efficiency losses have the greatest impact on OEE, followed by availability losses. Prime prospects and long-term maintenance patterns were suggested by the researchers. However, OEE forecasting was not included in these studies.

Mitsel et al. [10] streamlined the production process by computing the probability density value of OEE using the parameters A, P, and Q as random variables. The fundamental shortcoming of the random variable collection for these systems was the lack of a systematic mechanism for defining network parameters. Further, Zammori et al. [11] assessed OEE using the probability density function and the central limit theorem. The investigation revealed that the reported average OEE accuracy was less than 90% and that the loss variability appeared to be quite large. In addition, Ma et al. [12] developed an exponential smoothing model for forecasting OEE for a welding shop. The findings revealed that the loss functions A, P, and Q had the biggest influence on the OEE prediction. Wang & Lee [13] developed a time constant regression model for computing OEE and demonstrated that expected OEE can be predicted by monitoring the maintenance progress. However, equipment's uncertainties were not taken into account as input parameters. Decision making becomes more complex as the level of uncertainty rises. Thus, greater progress was needed in investigating OEE utilising machine learning methodologies.

Maintenance assessment process has progressed significantly in the context of machine learning approaches. Milković et al. [14] developed regression and linear programming models to assist in waggon repair scheduling. These mathematical models were developed using information on maintenance costs and the average time between failures. However, they were difficult for production managers to comprehend. Lin and Zhang [15] investigated challenges in the production and maintenance planning of capacitated lot sizes. Regression models were proposed as a way of optimising preventative maintenance schedules through an integrated modelling framework. Similarly, Noman et al. [16] developed exponentially weighted moving average forecasting models to improve the performance of a manufacturing system by reducing equipment and process failures. In order to do this, corrective and preventative maintenance practices were implemented. However, these models were imprecise. In addition, Frumusanu et al. [17] proposed a causal data-driven modelling technique for managing production system maintenance. Ok & Sinha [18] proposed a neural network (NN) design for forecasting the performance of equipment. The results revealed that NN outperforms regression models with a minimal error. NN is a series of algorithms designed to recognise patterns that mimic the human brain closely. The method consists of a network of neurons that work together to solve a problem. Kuo and Lin [19] also proposed various NN models for predicting equipment performance and discovered that a combination of NNs and decision trees was the most likely to reflect reality. Similarly, Sivakumar et al. [20] implemented a back propagation NN model in production facility priorities in a pandemic scenario and found that the NN model outperformed with high accuracy. However, the NN technique faced difficulties in defining the membership function. Thus, it has been preferable to employ more extensive tools for forecasting, such as the theory of fuzzy sets [21].

The most significant contribution of fuzzy sets is their ability to provide precise data. The method of changing values of input variables into linguistic variables that correspond to them is known as fuzzification. Data collection can be a member in the crisp logic. But in the fuzzy logic, the degree of a member can be chosen from a set of fuzzy integers known as the fuzzy membership function. The membership function would be a curve that depicts how the value of a fuzzy variable was mapped to a degree of membership between 0 and 1 [22]. On the other hand, fuzzy rules were established during the training process. The Adaptive Neuro Fuzzy Inference System (ANFIS) was used to enhance these processes. The ANFIS creates a fuzzy inference system (FIS) using training data to determine the parameters of the membership functions [23].

The ANFIS technique has been described as professional insight into the structure of fuzzy "if-then" guidelines that include membership functions (MF). Bekar et al. [24] proposed an ANFIS model to forecast the OEE parameters. However, the triangular MF was utilized to develop this forecast model. Besides, Gaussian outperforms other MFs in the ANFIS model since its parameters are just two, whereas the triangle-shaped MF has three parameters. Meanwhile, the most efficient methods for finding the best near optimal solution were robust search algorithm, hybrid learning algorithm, and evaluation of qualitative data [25]. Moghadam et al. [26] proposed a hybrid ANFIS-Firefly Algorithm (ANFIS-FA) for forecasting the discharge coefficient with a Gaussian MF. To confirm and select the best model from the results of the six suggested models, a Monte Carlo sensitivity analysis was also performed. The results show that the superiority model outperforms with an accuracy of 85%. However, the number of input variables was nine. Given the size of the input variable, it was necessary to perform a sensitivity analysis to determine which input would lead to a model with fewer inputs and the lowest overall impact. The ANFIS model performed better when the input variables were selected effectively. Furthermore, Hassani et al. [27] suggested various machine learning techniques for forecasting the projected OEE values, and found that deep neural networks performed significantly better, with a mean absolute percentage error of only 12%. Further, Engelmann et al. [28] presented a machine learning model for predicting OEE based on machine availability, and found that the fine tree decision method gave the best fit, with a 93% overall accuracy. However, these prediction models only evaluate one loss function and seem to be a test case.

The findings suggest that a more thorough evaluation of the input parameter selection is essential for creating OEE prediction models. However, the type and quantity of available input data influence the prediction technique. The estimation of OEE allows managers to keep their processes running smoothly and identify significant losses. Unfortunately, the OEE can only provide a static portrayal of a process because it is a deterministic metric. As a result, it fails to capture the true variation in production performance. Thus, the OEE's stochastic nature was taken into account when developing the prediction model presented in this study. Thus, this study proposes a hybrid ANFIS model for forecasting OEE based on Moghadam et al. [26] and using the A, P, and Q input parameters similar to Ma et al. [12]. The proposed approach employs ANFIS along with the firefly algorithm. A renowned textile fabric processing industry was used as a case study to validate the predictions.

2. Research methodology

2.1 ANFIS architecture

The ANFIS paradigm is used in real-time control systems to characterize nonlinear structures and nonlinear modules [29]. ANFIS is used in a variety of engineering fields. It created a hybrid supervised learning system that can anticipate the association between predictor factors and evidence-based intelligence response variables [30]. The approach is defined as professional expertise incorporated into the construction of fuzzy "if-then" guidelines that include a membership function. The benefits of the approaches include qualitative data evaluation, a hybrid learning algorithm, a robust search algorithm, and an effective way to find the best near optimal solution. Nodes 'x' and 'y' were the input attributes in the two-input, one-output fuzzy system, whereas node 'z' was the output attribute. The architecture of fuzzy if-then rules for the Gaussian membership function (MF) can be described as follows [31]:

L-1: This layer's nodes are adaptive. This layer's variables are preceding variables. Equation 1 estimates the output of this layer.

$$O_{1i} = \mu_{Ai}(x) = \frac{e(-(x_i - c_i))^2}{2\sigma_i^2} \text{ for } i = 1,2 \tag{1}$$

Here, 'x' is the linguistic variable 'A_i' and '$O_{1,i}$' are the input and output variables, respectively. The width of the Gaussian MF is 'σ_i' and the centre is 'c_i'.

L-2: The circular node and multiplication of input signals delivering output, represented by ω_i, makes up the second layer. Equation 2 expresses the relationship.

$$O_{2i} = \omega_i = \mu_{Ai}(x)\mu_{Bi}(x) \text{ for } i = 1,2 \tag{2}$$

where ω_i is the firing strength.

L-3: Every node decides that it is fixed, and the following Equation 3 is used to determine the firing length of each rule in relation to the firing strength among all rules:

$$O_{3i} = \overline{\omega_1} = \frac{\omega_1}{\omega_1 + \omega_2} \text{ for } i = 1,2 \tag{3}$$

L-4: Each active node appears to be a square and adjustable node that determines the i^{th} node to the total output, as indicated in Equation 4.

$$O_{4i} = \overline{\omega_1} f_i = \overline{\omega_1}(a_i x + b_i y + c_i) \text{ for } i = 1,2 \tag{4}$$

L-5: This layer's one node is a fixed node that displays the final value of the output parameter. Equation 5 describes the layer's output.

$$O_{5i} = \Sigma \overline{\omega}_i f_i \text{ for } i = 1,2 \tag{5}$$

2.2 Firefly algorithm topology

The firefly algorithm (FA) looks to be a nature-inspired technique that, by simulating the social behaviour of fireflies, may produce optimal solutions for complex nonlinear problems with fast convergence speed [32]. Every time a firefly flies, it creates a distinct pattern of light. This light is used to attract a partner as well as to track down another firefly. The firefly's attraction is proportional to the brightness of the light. Each firefly's behaviour is characterized as an optimization problem, with the brightness of each firefly serving as the objective function. The goal function might be proportional to the maximum brightness of a firefly in certain places 'x'. The density of light drops as the distance between the source and the viewer increases. As a result, attractiveness should change in proportion to absorption [33]. The light intensity, attractiveness, and locations of fireflies are calculated using Equations 6-8 [34].

$$I_{ij}(r_{ij}) = I_i e^{-\gamma r_{ij}^2} \tag{6}$$

$$\beta_{ij}(r_{ij}) = \beta_0 e^{-\gamma r_{ij}^2} \tag{7}$$

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{8}$$

In these equations 'I_0', 'γ', 'β' and 'r' represent the initial density of light, the absorption coefficient of light, the firefly attractiveness and distance, respectively. The optimal conditions of the firefly parameters 'γ' are characterized in the range of [0 ∞], whereas 'α' and 'β', are characterized within the range of [0 1].

3. Case selection

The entire research was carried out in a medium-scale Indian textile fabric processing plant in Erode, Tamil Nadu. The company employs around 150 people, with 120 working on the shop floor. In the processing plant, grey textiles are converted into calendar goods. Multiple sequential processes are carried out in the production of excellent fabrics, such as fabric planning, resizing, scouring, bleaching, dying, and calendaring. According to the customer's specifications, these activities are utilised in fabric preparation at the dye house. A jigger machine is used to obtain the grey cloth with a required dye. The grey cloth is scooped up by another roller after passing through a dye bath from the roller. The dye bath contains chemical dye, water, acid, and other essential elements. As the textiles are packed from one roller to another, the entire cycle is repeated.

In this study, a jigger machine was employed for the OEE measurement and the building of a prediction model. The data were gathered via a web-based application. Machine sensors were used to gather data through processing a group of information that sensors have collected and delivered to the MySQL database. The data were collected weekly for 52 weeks, in two shifts of eight hours each day. The data compiled in the database MySQL were aligned based on the simulation input, such as planned production time, planned production speed, planned fabrics amount, total operating time, total fabrics, total good fabrics, realized stoppage duration, realized production speed. A simulation was used to simulate the production system to estimate the performance of the manufacturing system in real operation, i.e., on the production line. The estimation of the parameters follows Equations 9-12.

$$Availability\ (A) = \frac{(\text{planned production time} - \text{realized stoppage duration})}{\text{planned production time}} \tag{9}$$

$$Performance(P) = \text{realized production speed/planned production speed} \tag{10}$$

$$\text{Quality (Q)} = \text{total good fabrics / total fabrics} \tag{11}$$

$$OEE = A \times P \times Q \tag{12}$$

Table 1 shows the range of the measured values of the A, P, Q, and OEE parameters employed in this investigation. Identifying the uncertainty of the equipment performance was crucial in the production-related operations. Throughout this investigation, OEE was treated as equipment efficiency metric.

Table 1 Parameters used for OEE prediction

Parameters	Mean	Standard deviation	Minimum	Median	Maximum
A in %	81	0.65	79	81	81
P in %	83	2.05	80	84	88
Q in %	98	0.69	97	98	99
OEE in %	66	2.14	62	66	69

4. Proposed hybrid FA-ANFIS model

The proposed intelligence technique, which had been built in the firefly algorithm and the Adaptive Neuro Fuzzy Inference System (FA-ANFIS), was thoroughly discussed to obtain the best accuracy results. The FA-ANFIS was used for the OEE prediction and written in Matlab@2018b. The datasets were divided into two groups, with 80% of the data utilized for training and 20% for validation [35]. The training sample, which comprises 84 observations, and the remaining data were used to confirm the accuracy of prediction of the proposed hybrid model. In this model, the input fuzzy sets follow the Gaussian membership function. Furthermore, the number of iterations considered for learning the network is equal to 1,000 epochs. Moreover, the output fuzzy set follows the constant function. To increase the outcomes and the model output, the most useful Takagi-Sugeno (TS) inference system was applied. This was shown to be more accurate and easier to understand than Mamdani's fuzzy inference [36]. The structure of the TS model is depicted in Figure 1.

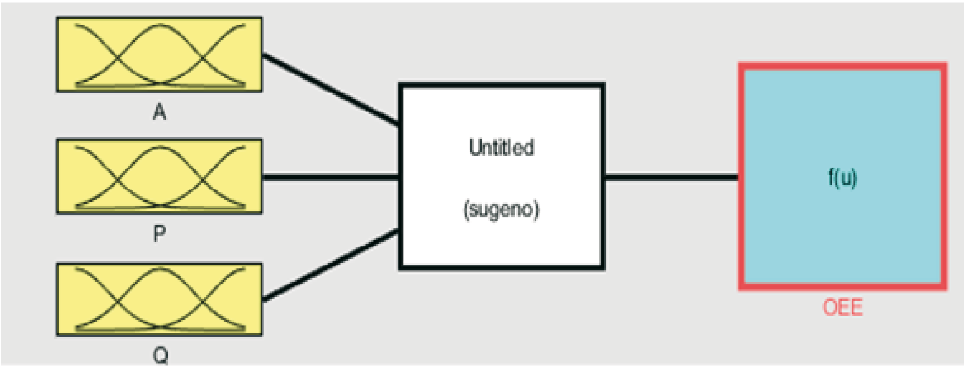


Fig. 1 Structure of Takagi-Sugeno model

In addition, one of the most effective and acceptable grid partitioning (GP) approaches was applied in this study to generate membership functions. By delivering the training sample in a more exact format, the efficiency of ANFIS networks may be increased. Thus, GP [37] was used to divide 84 observations into 8 clusters depending on the number of trails and the fitness function value. The structure of the ANFIS model is given in Figure 2.

The variables to be optimized in the challenge environment should be explored first. The fitness functions were specified by employing the firefly algorithm to create the ANFIS model. To begin, the training data was utilized to build an initial ANFIS network for this study's data. The FA-ANFIS framework was learnt and could be used to anticipate OEE when the optimum parameters for these sections were determined. An optimization method was used to find the best values for antecedents and consequences. Each GP cluster was used to build if-then rules for the ANFIS network. Once a firefly colony was established, the beginning light intensity of the present population was determined. Light attraction coefficients were set to 0.1 and 4 based on the trial-and-error method to get improved performance. After that, the attraction of each firefly was evaluated, and the fireflies were transported to the fireflies with the maximum light intensity. When an original firefly was generated, the beginning light intensity in the existing population was determined. Each firefly's attraction was then determined, and the fireflies were driven toward the fireflies with the highest light intensity. As a consequence, the firefly algorithm looked at different premise values and the selected parameters. The RMSE was utilized to assess the fitness levels of each firefly throughout each contact. The light intensity and position of the firefly were then updated and compared in order to find the best location. The maximum number of iterations was utilized as a stopping condition. The validation of FA-ANFIS as a forecasting model is a critical component of the investigation in order to present a realistic and scientifically meaningful model. In this study, this FA-ANFIS model was created to forecast the OEE based on A, P, and Q of machine manufacturing.

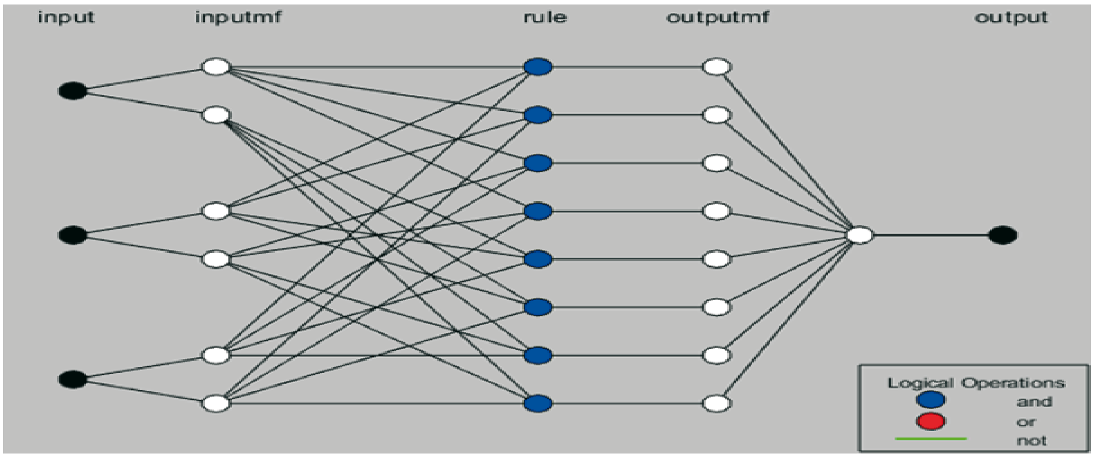


Fig. 2 ANFIS model structure

5. Result and discussion

The GP is used to calculate the number of cluster centres and initial placements. The measured values of each variable are used to define its discourse universe, which is then partitioned using the GP. The initial membership function is [2 2 2], and it produces 8 fuzzy rules. In this study, the ANFIS model is developed using a Gaussian function, which is specified as Equation 13.

$$y = f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{13}$$

where ‘y’ is the membership value, ‘x’ represents the input values for which membership values are to be computed. ‘σ’ is standard deviation, ‘c’ is mean. The amount of MF for each input, as well as the types of the output MF, were determined by a constant function. The ANFIS features of the proposed model contain 34 nodes under the optimal structure, and eight fuzzy rules were established. Furthermore, there was a total of 20 parameter pairs, with eight linear and 12 nonlinear parameters. This demonstrates that the total number of data pairs in the network is smaller than the number of the training data pairs. The total time of the run was 51 seconds. Table 2 shows the ANFIS characteristics of the suggested model. The learnt fuzzy set is then applied to the test data in various control settings in order to assess the neural system's flexibility and avoid over fitting of the training data set. Based on the test error of each parameter combination, an ideal configuration for the defined circumstances was established.

Table 2 Characteristics of the model with the best structure and corresponding ANFIS information

ANFIS Information	
MFs for each input	2,2,2
Types of input MFs	Gaussian
Output function	constant
Nodes	34
Linear parameters	8
Nonlinear parameters	12
Total parameters	20
Training data pairs	84
Testing data pairs	20
Fuzzy rules	8
Run time (seconds)	51

Furthermore, one more ANFIS model was developed to compare the proposed FA-ANFIS model performance. The same dataset was used in the comparative ANFIS model. The input fuzzy sets of this proposed comparative model follow the Gaussian membership function. Furthermore, the GP was used in this study to divide clusters depending on the number of trails and the fitness function value. In addition, the number of iterations considered for learning the network was equal to 1,000 epochs. The output fuzzy set followed the constant function too. To increase the outcomes and the model output, the most useful TS inference system was applied. An optimization method was used to find the best values for antecedents and consequences. The hybrid back-propagation and least square combination were used to tune the data sets to find the best values for antecedents and consequences. The effectiveness of the proposed ANFIS model was statistically assessed using the root mean squared error (RMSE) and the coefficient of determination (R^2). The correlation is depicted in Equations 14-15.

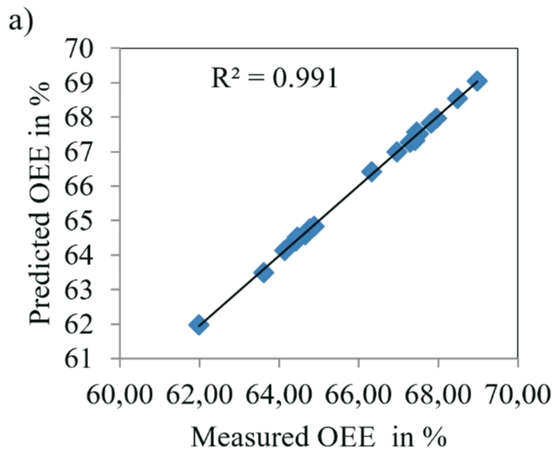
$$\mathrm{RMSE} = \sqrt{\frac{1}{n}} \times \sum_{i=1}^{n}\left[\left(\mathrm{OEE_{measured}} - \mathrm{OEE_{predicted}}\right)^2\right] \tag{14}$$

$$\mathrm{R}^2 = \frac{\left[\sum_{i=1}^{n}(\mathrm{OEE_{measured}}-\mathrm{OEE_{mean}})^2\right]-\left[\sum_{i=1}^{n}\left(\mathrm{OEE_{measured}}-\mathrm{OEE_{predicted}}\right)^2\right]}{\left[\sum_{i=1}^{n}(\mathrm{OEE_{measured}}-\mathrm{OEE_{mean}})^2\right]} \tag{15}$$

The performances of the proposed models were compared to validate the prediction ability. The comparative error analysis for the chosen case prediction model utilizing the training and testing datasets is shown in Table 3. Based on the error analysis, a low RMSE of 0.090766 was noted. The comparative prediction accuracy of the proposed model is demonstrated in Figures 3a-b. As seen in these figures, a high predicted accuracy of 99.1% was observed. Thus, the prediction using the hybrid FA-ANFIS model is highly accurate and close to the measured values. Furthermore, the best values of the antecedent and consequence parameters of the outperformed FA-ANFIS model can be seen in Table 4.

Table 3 Error analysis comparison of the proposed models

Proposed model	Error measures	Training	Test
FA-ANFIS	RMSE	0.098893	0.090766
	R^2	0.999	0.991
ANFIS	RMSE	1.23	2.6
	R^2	0.925	0.868



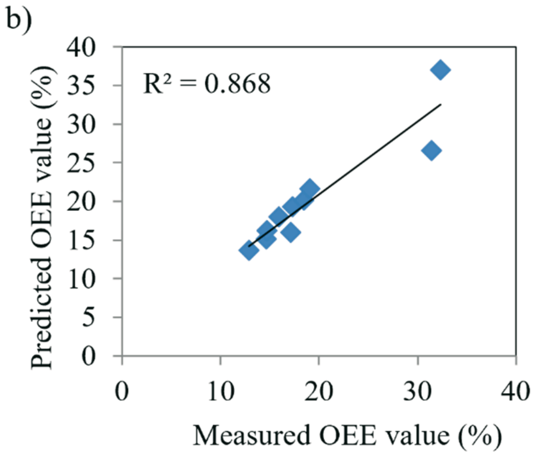


Fig. 3 Performance accuracy of testing data prediction

Table 4 Optimal parameters of Gaussian membership functions

Input variables	MF	Parameters	
		σ	c
A	1	1.169	79.25
	2	1.142	81.06
P	1	4.259	80.87
	2	4.342	87.17
Q	1	1.257	96.66
	2	1.182	98.56

6. Conclusion

Textile processing companies compete to retain old and get new clients in today's competitive market. They strive hard to improve their competitiveness by focusing on equipment efficiency. On the other hand, predicting OEE precociously is crucial in these exceedingly tough industrial circumstances. In this study, two different prediction models (ANFIS and FA-ANFIS) were developed for predicting OEE. In developing the ANFIS model, hybrid back-propagation and least square combination were used to tune the data sets. On the other hand, the FA was used to tune the data sets in FA-ANFIS to find the best values of antecedents and consequences. Further, in this proposed model the input fuzzy sets follow the Gaussian membership function. Furthermore, GP was used to divide the input observations into clusters. The output fuzzy set follows the constant function. To improve the outcomes and model output, the most useful TS inference system was applied. As a result, the hybrid FA-ANFIS model is capable of predicting OEE with 99.1% accuracy and a minimal RMSE of 0.090766. The present hybrid FA-ANFIS model has the capacity to increase task performance quickly. However, it only employed the GP clustering and the FA as input parameter adjustment tools. As a result, a few more clustering methodologies and input parameter tweaking strategies can aid in the OEE prediction.

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