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Prediction of Equipment Effectiveness using Hybrid Moving Average-Adaptive Neuro Fuzzy Inference System (MA-ANFIS) for decision support in Bus Body Building Industry

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Abstract: Managers are driven to accomplish significantly higher levels of operational performance due to the difficulty of today's dynamic production environment. Typically, the precision of production facilities and the efficiency of manufacturing systems are significant variables in productivity. Thus, predicting machine performance has become an inevitable challenge for production managers. However, the question of how managers can reliably assess the effectiveness of equipments for resource allocation remains unaddressed properly. This issue has received little attention in previous research, but it is important in today's manufacturing environment. This study introduces a hybrid moving average - adaptive neuro-fuzzy inference system (MA-ANFIS) to predict the possible effectiveness of equipment. Three real-world problems are considered when developing and evaluating three distinct equipment effectiveness prediction models. The evaluation confirms that the hybrid MA-ANFIS model based on Gaussian membership function outperforms other developed models. This comprehensive solution is packaged as a decision support system. This aids production managers in evaluating the equipment effectiveness, and effectively improving equipment's performance to reduce time and cost of bus body building.

Key words: adaptive neuro-fuzzy inference system (ANFIS), moving average (MA) model, hybrid extremal-micro genetic algorithm (Ex-µGA), predictive analysis, equipment effectiveness.

1 - INTRODUCTION

The competitive industrial environment forces industries to maintain consistent productivity. Therefore, maintenance activities are becoming increasingly important to enhance equipment performance and ensure consistent production. Total Productive Maintenance (TPM), Just In Time Manufacturing (JITM) and Business Process Reengineering (BPR) are just a few technological examples of machine performance improvement in the industrial sector (Ljungberg 1998, Nikolopoulos et al. 2003, Chou et al. 2005). The TPM is widely considered as the most promising strategic technology for assisting industries in achieving competitiveness (Nakajima 1988). In practice, TPM is an integrated approach based on American and Japanese maintenance principles for maintaining equipment performance and reducing machine failures. This also includes employee participation in self-maintenance (Ahuja & Khamba 2008). The quantitative metric assessment of the TPM process named as Overall Equipment Effectiveness (OEE) (Anvari et al. 2011). The OEE is an issue that draws the attention of production managers for the purpose of enhancing productivity. In this regard, continuous OEE monitoring is carried out in order to assess equipment efficiency and propose appropriate measures for its management. Benchmarking analysis is commonly used to determine the best management techniques for increasing manufacturing plant efficiency and the effective rate of OEE (Fattah et al. 2017). In particular, the OEE is quantified by combining three distinct variables into a single one. The variables are equipment availability (A), equipment performance (P), and quality (Q) of production (Sharma 2019).

There have been significant progresses in assessing OEE, since then Wang & Lee (2001) formulated time constant regression model. In that study, expected OEE is used to compare the maintenance performance of TPM implementations that have been implemented in two different industries from Taiwan and Japan. The findings imply that both industries perform similarly in terms of maintenance, and that expected OEE may be easily determined by tracking maintenance progress. However, the equipment uncertainties are not taken into account in the study's input parameters. Ma et al. (2012) used exponential smoothing technique to measure the OEE for a welding workshop. The results confirmed that the smoothing time series observation has the best effect while considering loss functions of A, P, and Q. Relkar & Nandurkar (2012) developed a regression equation for predicting OEE using Design of experiments (DoE). The study found that focusing on equipment performance would improve OEE. Likewise, Yuniawan et al. (2014) integrated the Arena simulation model with DoE technique. The capability of the suggested anticipated model enables decision makers to benefit. Regrettably, the two inquiries do not provide a systematic approach for defining the input parameters. In addition, Kurscheidt Netto et al. (2017) used a statistical process control tool to link cycle time and equipment stoppage trends. This finding demonstrates that equipment breakdowns are putting a strain on the equipment's performance, resulting in an inaccurate prediction of OEE. Nonetheless, this study has focused solely on the performance loss function. In a another research Prasetyo & Veroya (2020) investigated continuous improvement tools to identify bottlenecks in the semiconductor sector in the Philippines in order to improve OEE. The results show a 30 percentage increase in OEE and recommend employing the DMAIC method to improve OEE in the long term. The main problem with these models is that there is no systematic method for determining the membership function parameters, which must be determined by expert knowledge of the represented system.

Furthermore, substantial progress has been made in analyzing OEE using machine learning. In the context of machine learning, Ok & Sinha (2006) developed a Neural Network model for predicting construction equipment performance. In this study, seven different factors were taken into account. The results were compared to the results of a multiple regression model. The Neural Network (NN) model outperforms the others with a minimal mean square error of 0.0014. Likewise, Kuo & Lin (2010) developed four different Neural Network models for equipment performance forecasting in a washing machine manufacturing company. According to the comparison analysis, the combination of NN and decision tree model is the most likely to reproduce reality, with an average test data error of 8.73 %. The NN is a set of algorithms meant to recognize patterns that are similar to those seen in the human brain. These can ability to learn from a set of input and output data in real time. The adaptive neuro-fuzzy inference system (ANFIS) is gaining significance in dealing with inadequately and unexpected domains such as OEE forecasts as a result of these insights. In a research Bekar et al. (2015)

used the concept of ANFIS for prediction of OEE in production system. However, triangular membership function was solely used for determining of the membership degrees for each input parameter. Other membership function was not taking in account for finding membership degrees. In addition, Hassani et al. (2019) proposed five different machine learning (ML) algorithms for forecasting expected OEE values. According to the findings, deep neural networks perform much better, with a mean absolute error of 6.27 and a mean absolute percentage error of 11.76%. However, this prediction model is only a test case. A combination of genetic algorithm optimization must be incorporated to build a prediction model for real-time case validation. Likewise, Engelmann et al. (2020) proposed a machine learning model and evaluated it using the MATLAB classification learner to forecast OEE based on machine availability. Based on the results, the fine tree decision algorithm provided the greatest fit, with an overall accuracy of 92.8%. The RUS boosted tree, on the other hand, outperforms the fine tree by 0.93 to 0.92. As a result, the RUS boosted tree technique was found to be superior in classifying the changeover process. The model provided here solely considers machine availability losses. These findings indicate that when developing OEE prediction models, a more thorough assessment of input parameter selection is required. However, the approach is determined by the type and volume of available input data.

According to the literature, ANFIS has been recognized an improved prediction tool than other methods. The learning abilities of NN were combined with the reasoning abilities of fuzzy logic to build a working platform. ANFIS provides specialized knowledge in the form of fuzzy "if-then" rules based on a membership function approximation from specified determinants and response data sets. The fuzzy set theory handles the uncertainties associated with network computation, while the NN provides model adaptability. The membership function parameters linguistic rules can adjust directly from NN training capabilities concerning refining model performance. The development of a hybrid supervised learning system that can predict the relationship between predictor and responder variables using artificial neural abilities based on evidence-based intelligence. Therefore, the hybrid ANFIS approach is selected to propose an OEE prediction model.

The computation of OEE allows managers to keep track of their processes and pinpoint the major losses that limit machine effectiveness using substitution of latest technology like IoT. However, this estimate is posses huge cost. The goal of this work is to develop a hybrid ANFIS model that can forecast the estimated OEE value, allowing managers to assess the equipment's effectiveness with low cost. In this study, 3 input parameters (production losses) are selected to develop prediction model from the bus body building industry. The moving average smoothing technique is used to smooth the input data based on the findings of Ma et al. (2012) and Lotfi et al. (2020). Further, according to Hassani et al. (2019) hybrid Extremal-Micro genetic algorithm (Ex-μGA) used to tune the input parameters. Finally, three hybrid moving average-ANFIS (MA-ANFIS) models have been developed to validate the performance of proposed model. This will be used as a decision support tool to assist production managers in preventing various types of losses and then respond appropriately to the circumstance in order to maximize productivity. Figure 1 depicts the proposed system's architecture, namely the Equipment Effectiveness Prediction System (EEPS).

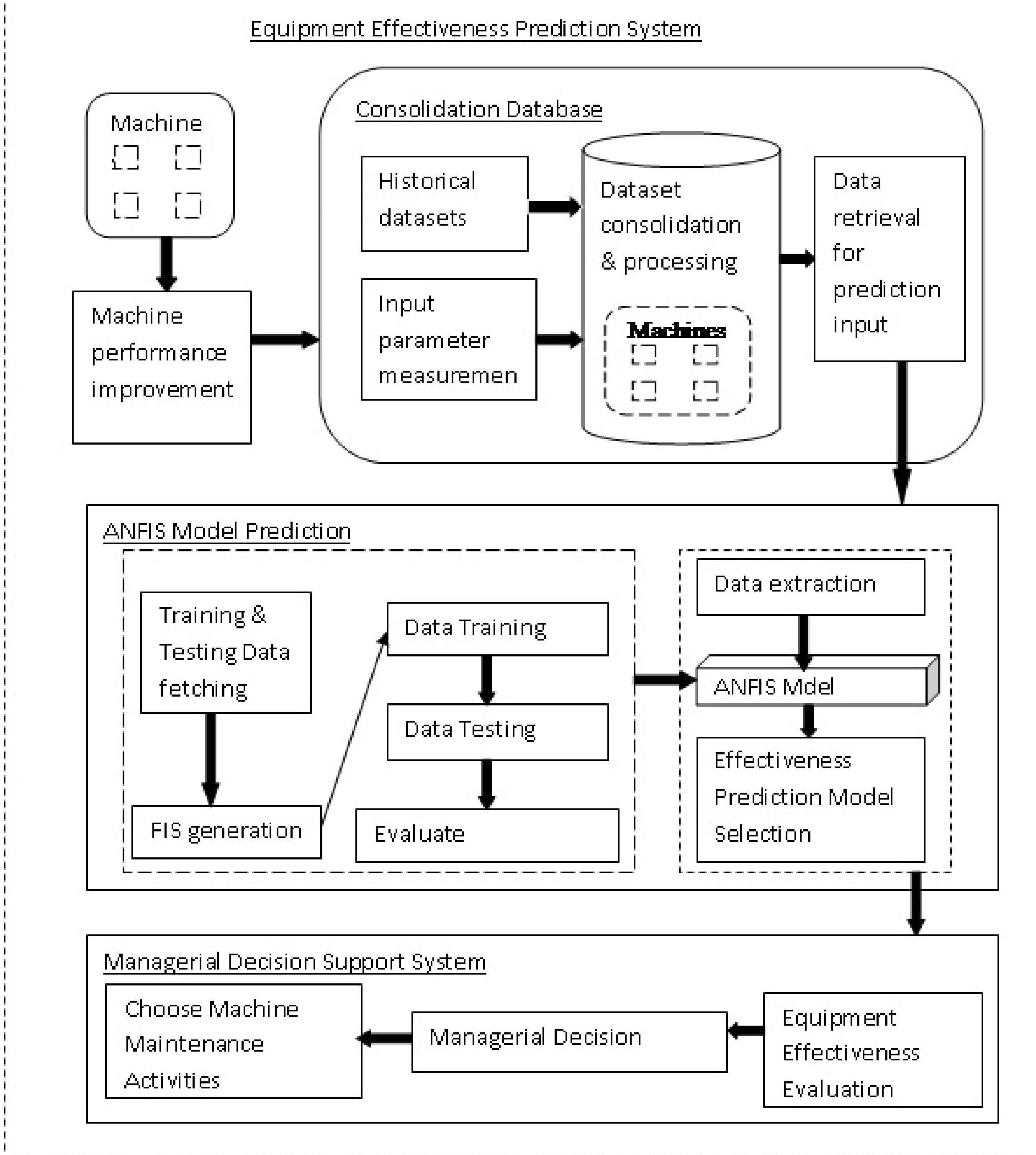

Figure 1. Equipment effectiveness prediction system model.

2 - ARCHITECTURE OF ANFIS MODEL DEVELOPMENT

ANFIS is exposed to be the best function approximator with fast convergence when compared to other hybrid neuro-fuzzy models (Akcayol 2004, Karaboga & Kaya 2019, Tiruneh et al. 2020). Mamdani's fuzzy inference method is commonly used in developing prediction models in the Fuzzy inference system (FIS) analysis. However, when compared to Mamdani's fuzzy inference method, Takagi-Sugeno (TS) model fuzzy inference achieves better results in model output interpretation (Wang & Chen 2008). Thus, TS fuzzy inference is used for model development in this study. The general architecture of the TS-based ANFIS model has been presented here for better comprehension. More details regarding ANFIS model can be found in many studies such as Chang (2008), Nguyen & Choi (2015), Azimi et al. (2017). ANFIS' architecture is comprised of 5 fixed layers, each of which has a number of nodes specified as node function. This system is considered to have two inputs of 'x' , 'y' and an output of 'f' to simplify the discussion. The two fuzzy if-then rules for a first order two rule TS type FIS can be computed as illustrated in equation 1-2.

$$\text{If x is } A_1 \text{ and y is } B_1 \text{ then } f_1 = a_1x + b_1y + c_1 = \omega_1 \tag{1}$$

$$\text{If x is } A_2 \text{ and y is } B_2 \text{ then } f_2 = a_2x + b_2y + c_2 = \omega_2 \tag{2}$$

In these, fuzzy sets are described as A_1, A_2, ..., A_n. The output is described as 'y_i' and output parameters mentioned as a,b,c. Furthermore, following are the FIS activities that are specified under the 5-layer architecture:

Layer 1: The first layer is referred to as the input layer. Each 'i' node in this layer is a square node. Equation 3 represents the node function. The membership function of 'A_i' is 'O_{1i}' and it describes how much the provided 'x' satisfies the quantifier 'A_i'.

$$O_{1i} = \mu_{\mathrm{Ai}}(x) = \frac{1}{1 + \left(\frac{x - c_i}{a_i}\right)^{2b_i}} \text{ for } i = 1, 2 \tag{3}$$

In this equation the output of i^{th} node is represented as 'O_{1i}'. The inputs of i^{th} node and membership function are represented as 'x', $\mu_{\mathrm{Ai}}(x)$ respectively. Likewise, the premise parameters are represented as 'a_i, b_i, c_i'.

Layer 2: This second layer consists of circular node and multiplication of input signals deliverers output, represented by ω_i. The relation is expressed in equation 4.

$$O_{2i} = \omega_i = \mu_{\mathrm{Ai}}(x)\mu_{\mathrm{Bi}}(y) \text{ for } i = 1, 2 \tag{4}$$

Where, ω_i – firing strength

Layer 3: This third layer is also comprised of circular nodes and is denoted by the symbol $\overline{\omega}$.

The ratio of the firing strength is calculated by the i^{th} node using equations 5-6. This layer's output is normalized firing strengths.

$$(\overline{\omega}) = (\Sigma \text{ ith node firing strength})/(\Sigma \text{ all rules firing strength }) \tag{5}$$

$$O_{3i} = \overline{\omega_i} = \frac{\omega_1}{\omega_1 + \omega_2} \text{ for } i = 1, 2 \tag{6}$$

Layer 4: In this layer, each interactive node is a square node that calculates the contributions of the i^{th} node to overall output; the relationship is stated in equation 7.

$$O_{4i} = \overline{\omega_i}\ f_i = \overline{\omega_i}\ (a_i x\ +\ b_i y\ + c_i)\ for\ i = 1, 2 \tag{7}$$

Layer 5: This layer's only fixed node is a circular node indicated by notation 'Σ'. This calculates the network's overall output by adding all of the rules' contributions together. Equation 8 expresses the relationship.

$$O_{5i} = \Sigma\overline{\omega}_i f_i = f = overall\ output \qquad \text{for } i = 1, 2 \tag{8}$$

The total output function defined as the linear combination of the consequent parameters in equation 9 with the values of the premise parameters constant.

$$f = (\omega_1 f_1\ +\ \omega_2 f_2\ )/(\omega_1 + \omega_2) = \overline{\omega}f_1 + \overline{\omega}f_2 \tag{9}$$

3 - CONSTRUCTING AND VALIDATING OF HYBRID MA-ANFIS MODEL

The complete approach for the proposed model is presented in this section. The network models are developed and configured using the MATLAB 2018b ANFIS editor. After a trial and error method, the most appropriate network type is selected based on the features of the situation. The most appropriate training function for the problem is chosen as a result of a review of several training functions. ANFIS parameters have been optimized after numerous trials. Furthermore, the testing data has been utilized to evaluate the performance of prediction model, while training data is being used to train the network model. Finally, the proposed hybrid MA-ANFIS models are compared to determine which is the most effective.

3.1 - Case selection

Human mobility is greatly influenced by the automobile industry. On-road and off-road vehicles are used to meet human transportation needs. In particular, buses are mostly used by the public sector for daily transportation. Bus body building is an essential milestone in the bus manufacturing process. The bus chassis is supplied by automobile manufacturers, while the body is built by vehicle bodybuilders. Medium-scale bus bodybuilding industries are back-born of the vehicle fabrication industry and this sector is strengthening by the massive number of labour forces. The Karur medium-scale bus bodybuilders play a vital role in bus bodybuilding sector of Tamil Nadu, India. A leading industry with three different cases was chosen to examine the feasibility of proposed research methodology. The selected medium-scale industry is specializing in fabricating, repairing, strip work, exterior and interior designing for bus manufacturing.

3.1.1 - Case 1

The case-1 is used to the analysis of a real-world case involving of school buses body building. This first industrial case contributed a year's worth of data, which was collected weekly from January to December 2019. There are total of 11 activities were observed to build the school bus. The fabrication of school bus included with more additional safety features. The initial measurement is done with actual equipment effectiveness. The initial measurement of mean OEE is 29 %, mean production loss due to stoppages (L_{st}) is 89 units, mean production loss due to reduced production speed (L_{sp}) is 564 units and mean quality loss (L_q) is 17 units. The losses are computed using equation 10-12.

$$Lst = T_{\mathrm{LRS}} \times S_r \tag{10}$$

$$L_{\mathrm{SP}} = \frac{(T_{\mathrm{oaq}})}{(S_r \times T_o)} - \frac{(T_{\mathrm{oaq}})}{(S_p \times T_o)} \tag{11}$$

$$L_q = T_{\mathrm{ow}} - T_{\mathrm{oaq}} \tag{12}$$

Where T_{LRS} represents realized stoppage duration, S_r represents realized production speed, T_{oaq} represents total acceptable quantity of work units, T_o represents total operating time, S_p represents planned production speed and T_{ow} represents total quantity of unit produced. In addition, total fabrication duration (D_F) measured as 46 days, total fabrication cost (FC) is measured as Rs. 182029 and these are computed using equation 13-14.

$$D_F = Q * P \;\; / \; DMH \tag{13}$$

Where

$$FC = \sum_{x=1}^{n} \left[DLC_x^{L_u D_F} \right] \tag{14}$$

Where, ‘Q’ is quantity of work to be done, ‘DMH’ is daily man hours multiplied by daily straight hours (default: 8 hours), and ‘P’ is labour productivity. Likewise, ‘x’ represents activities carried out to complete fabrication, ‘n’ is number of activities, ‘DLC’ is direct labour cost, ‘Lu’ is labour usage.

3.1.2 - Case 2

In the second case, the analysis of a real-world case involving of tour bus body building from the same industry selected in case-1. This industrial case also contributed a year’s worth of data, which was collected weekly with the same duration case-1. The same case-1 computation method was used to measure input values. The initial measurement is done with actual equipment effectiveness. The initial measurement of mean ‘OEE’ is 29 %, mean ‘L_{st}’ is 89 units, ‘L_{sp}’ is 564 units and ‘L_q’ is 17 units. Likewise, ‘D_F’ is measured as 44 days, and ‘FC’ is measured as Rs. 179443.

3.1.3 - Case 3

In the third case, the same industry as in case-1 was chosen. This case seems pertinent to the scenario of city bus body building. This industrial case also contributed weekly interval data and computation methods also follow same as mentioned in ‘case-1’. The initial measurement is done with actual equipment effectiveness. The initial measurement of mean ‘OEE’ is 44 %, mean ‘L_{st}’ is 89 units, ‘L_{sp}’ is 564 units and ‘L_q’ is 17 units. Likewise, ‘D_F’ is measured as 41 days, and ‘FC’ is measured as Rs. 143780.

3.2 - Input parameter selection

In most cases, standard production speed is taken into account while calculating OEE. This has the potential to conceal the true capability of the process. Similarly, this raises the OEE score artificially while concealing losses and limiting improvement. Furthermore, excessive data collecting by labours while performing task may result in work disruption. This could cause work to be slowed and productivity to be lost. On the other hand, using cutting-edge technologies such as IoT, for data collection while manufacturing, can help to solve these issues. This substitution technology is more expensive and suited to automated discrete manufacturing systems. However, this technology substitution is inapplicable when considering a manually operated or partially automated discrete manufacturing system of labour intensive medium scale bus body building works. Because technology substitution and labour management training require significant investment and raise direct labour costs. Alternatively, these complexities in OEE score improvement can be resolved by performing a critical analysis of production losses with respect to varying production speed in a real-world problem. This interesting combination occurs in the context of OEE, which has received little attention in the literature. Hence, the volatility of equipment effectiveness prediction using different loss functions is addressed in this study. Kuo & Lin (2010) predicted equipment effectiveness using only the loss function of equipment performance as a quantitative measure. Similarly, Engelmann et al. (2020) used the loss function of equipment availability to predict equipment effectiveness. Hence, this critical analysis for selecting input parameter considers loss functions of availability, performance and quality with respect to varying production speed. Totally six input parameters that influence equipment effectiveness has been found as a result of these critical analyses. Machine availability (A), losses due to stoppages (Lst), machine performance (P), losses due to production speed (Lsp), machine quality (Q), and quality losses (Lq) were found in the literatures Kuo & Lin (2010), Ma et al. (2012) and Engelmann et al. (2020). Determining the probability (p-value) of obtaining a test statistic is essential for verifying the association between each input and output variable. The p-values are in the range of 0 to 1. The test statistic p-value must be at least as extreme as the computed value if the null hypothesis is true. In this study, the relationship between each input and output variable was verified using Pearson correlation analysis. This assessment has been based on the case-1 data sets. A commonly used alpha level of 0.01 was chosen for this study. The Pearson correlation matrix and p-values are illustrated in Table I. The results show that 'Lst', 'A', 'P,' and 'Q' are all positively related to 'OEE.' Similarly, the input parameters 'Lsp' and 'Lq' have an inverse relationship with the output parameter 'OEE'. Correspondingly, the p-values of 'Lst', 'Lsp', and 'Lq' are 0, 0, 0 respectively. This confirms that the test statistic's p-values are less than the chosen alpha level of 0.01. As a result, the null hypothesis is rejected. On the other hand, the p-values of 'A', 'P', and 'Q' have 0.382, 0.060, and 0.407, respectively. This statistic demonstrates that the p-values are greater than the alpha level of 0.01, implying that the null hypothesis is accepted. The results of the Pearson correlation analysis confirm the linear relationship between the input and output parameters. Furthermore, these results show that 'Lst', 'Lsp', and 'Lq' have low p-values. This indicates that the loss function variables 'Lst', 'Lsp', and 'Lq' are the best input parameters for OEE prediction.

Furthermore, the complexity of defining membership function also addressed in this research. The volatility of systematic method for defining the membership function is an important signal

Table I. Pearson correlation matrix with p-values.

Parameters	A	Lst	P	Lsp	Q	Lq	OEE
A	1	-0.62547	0.02314	-0.35303	-0.21356	0.25058	0.12390
Lst	-0.62547	1	0.61454	-0.09730	0.43240	-0.22009	0.55048
P	0.02314	0.61454	1	-0.80432	0.31466	-0.05463	0.98969
Lsp	-0.35303	-0.09730	-0.80432	1	-0.11669	0.00981	-0.82161
Q	-0.21356	0.43240	0.31466	-0.11669	1	-0.92069	0.37855
Lq	0.25058	-0.22009	-0.05463	0.00981	-0.92069	1	-0.11752
OEE	0.12390	0.550480	0.98969	-0.82161	0.37855	-0.11752	1
p-value	0.38200	0.00000	0.06000	0.00000	0.40700	0.00000	---

for predicting equipment effectiveness. Bekar et al. (2015), used the triangle membership function to calculate membership degrees and developed an OEE prediction model. However, this solely considers triangle membership function. Hence, in this work, the triangle membership function, as well as two other membership functions from Gbell and Gauss, is used to compute membership degrees. In this study, three hybrid MA-ANFIS models have been developed to predict equipment effectiveness. Each model is made up of three independent input variables that lead to deterioration in equipment performance. The Case-1 model employs three loss functions and a triangle membership function to determine membership degrees. Case-2 uses the identical loss functions as case-1 and a Gbell-shaped membership function to calculate membership degrees. All given loss functions, as well as the Gauss membership function, are taken into account in the Case-3 model. Evaluation and error analysis are used to determine the optimal prediction model. As a result, various constraints for selecting maintenance operations have been proposed for assessing the decision-making of production managers.

3.3 - Data sets selection

The designed system is initially assumed to perform OEE predictions on a weekly basis. The input variable is explained in full below. Recorded OEE in past 'n' periods, which including period t, t-1, t-2,… t-n, have been recognized as an important prediction signals for predicting equipment effectiveness in the next period t+1. The trend analysis is appropriate since the component deterioration trend is reported in a time serious form (Maurya et al. 2010). In addition, Ma et al. (2012) also confirms that the data smoothing is a very useful technique to enhance data quality. Therefore, one of the realistic trend analysis models of moving average smoothing technique is used to smooth the input data. The moving average model uses an equation 15 for estimating the value.

$$y_t = c + \varepsilon t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \ldots + \theta_q\varepsilon_{t-q} \tag{15}$$

Where, εt is noise, y_t is weighted moving average forecast errors. The data has been further tuned to enhance the data quality. According to Hassani et al. (2019), the optimization model of genetic algorithm used in this study. However, simple genetic algorithm probably produces an optimized data tuning, but, this will happen at a relatively slow rate. Hence, this is ineffective in real-world problem solving because it requires rapid convergence. Structure of the Micro Genetic Algorithm (μGA) is identical to that of simple GA, and it is used to work with small populations. Hence, it necessitates lesser function evaluations than traditional GA (Anderson et al. 2015). The crossover operation is carried out in μGA. However, the mutation isn't required, because sufficient variance had been maintained during micro population convergence. On the other hand, the self-organized critical idea is at the heart of the extremal optimization technique. The most unfavorable variables in a suboptimal response are gradually replaced by newly produced random variables in this method. The physical instinct to streamline also can serve as a source of inspiration for extremal optimization. This path is commonly followed by its forerunners, such as simulated annealing and GA (Majumdar et al. 2021). In this study, the μGA is combined with the extremal optimization technique. The chromosome symbolizes the improving strategy, and the gene symbolizes the decision variable in this process. Therefore, the input parameter has been tuned using hybrid Extremal-micro genetic algorithm (Ex-μGA) to enhance the data quality. The Table II describes the data sets used for developing prediction models.

Table II. Descriptive data sets.

Cases	N	Input variables	Min	Max	Mean	STDEV
Case 1	52	L_{st}	61	260	89	28
		L_{sp}	320	828	564	131
		L_q	8	25	17	5
Case 2	52	L_{st}	77	204	126	36
		L_{sp}	197	582	341	81
		L_q	4	13	9	3
Case 3	52	L_{st}	70	260	116	41
		L_{sp}	114	797	419	172
		L_q	5	25	14	7

3.4 - Training of fuzzy inference system parameters

The major purpose of creating this prediction model is to determine the effectiveness of equipment from the perspective of bus body builders. It's worth noting that the impact of variables on forecasting isn't always clear. The obtained data set, which consists of 52, 52, 52 data pairs, is being used to validate the neural system. The entire data set is split into two sections: training and testing. The training data sets represent approximately 80% of the data in the study, with the rest being utilized to test and improve the adaptive network, as evidenced in various studies (Hasanipanah et al. 2016, Mojtahedi et al. 2019). The testing data set, on the other hand, is used to determine whether the model has been over fit during training. One of the most beneficial TS inference systems is utilized to achieve better results and model output. When compared to Mamdani's fuzzy inference, it has proven to be more accurate and easier to interpret (Wang & Chen 2008, Ebtehaj & Bonakdari 2014). The structure of Case-3 TS model is presented in Figure 2 as instance.

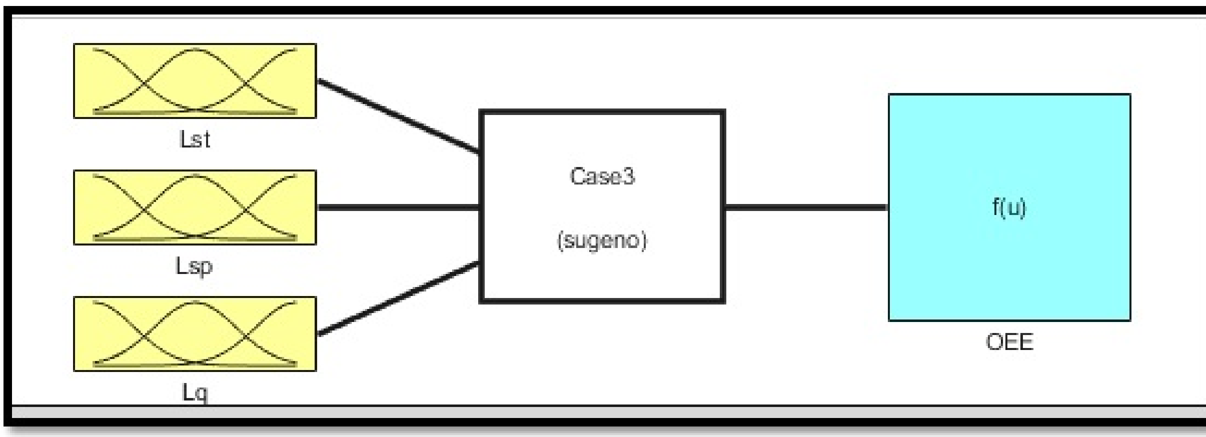

Figure 2. Structure of Takagi-Sugeno model.

Generally, subtractive clustering (SC), grid partitioning (GP) and fuzzy c-means (FCM) techniques are used to generate FIS structure. The 'SC' is fast as well as one-pass method of estimating the clusters in a set of data. This is useful when it's unclear how many clusters should present for a given set of data (Chiu 1994). The GP divides the input space into various rectangle subspaces using a number of small fuzzy regions. The fuzzy rules, on the other hand, grow exponentially as the input variables increases (Moradi et al. 2019). Furthermore, in FCM techniques, each data set is connected to a cluster to a degree specified by a membership grade. It demonstrates how to divide data points in a multidimensional space into 12 separate clusters (Bezdek 1981, Safari et al. 2019, Lotfi et al. 2020). Therefore, this study used one of the most effective and appropriate grid partitioning techniques to generate membership functions.

Then, learning approach is one of the most important characteristics of neural networks. The hybrid learning function uses neural networks for training and learning to find fuzzy parameters. The fuzzy rules and membership functions (MF) can be fine-tuned through learning. The hybrid learning strategy for a neural fuzzy system consists of two phases: data-driven rule creation and back-propagation (BP) learning-based rule adjustment. Further, the back propagation and basic learning algorithm is combined with Least Square Estimates (LSE) to speed up the process. Back propagation is currently combined with the LSE in adaptive inference systems to update the parameters of membership functions. The hybrid learning methodology comprises a forward and backward run in each epoch. In the forward pass, the input data functions are used to compute each node response. The function will continue to run till the error value is computed. The error rates travelled from the output terminal to the input terminal during the backward pass, and the parameters were adjusted accordingly. The gradient descent methodology is now integrated with the BP-LSE technique to report the parameters of MFs. The input data functional procedure continues in the forward pass until the error measure evaluates each node output. In the backward pass, the error rates propagate and are updated using the gradient technique (Loganathan & Girija 2014). Hence, this study used LSE and BP gradient descent method.

In general, various membership function (MF) available in ANFIS editor, such as, trapezoidal, triangular, generalized bell, Gaussian curve, etc. Among this, three membership functions have been selected to develop proposed prediction model. The triangular membership function (Trimf) used to develop Case-1 model. This is the most primitive because of the triangular curve shapes. Three factors are used to identify three points: 'a' , 'c' for the feet, and 'b' for the tip of the curve (Raharja et al. 2021). The generalized bell membership function (Gbellmf) used to develop case-2 model. The Gbellmf is a symmetrical shape that resembles a bell. This function has three parameters: 'a' specifies the breadth of the bell-shaped curve, 'b' is a positive integer, and 'c' determines the curve's centre in the universe of discourse (Babanezhad et al. 2021). The Gaussian membership function (Gaussmf) used to develop Case-3 model. This has been the most widely used MF for characterizing fuzzy systems due to its simple notation and smoothness. This does have its own set of benefits, including the fact that it is non-zero, smooth, and is defined by only two parameters that are optimized during the training process (Gholami et al. 2018, Yaseen et al. 2017). Table III depicts an overview of the training parameters for three selected cases.

Table III. Training parameters for ANFIS modeling.

S.No	Performance index	Case 1	Case 2	Case 3
1	Number of input variables	3	3	3
2	Number of output variables	1	1	1
3	Number of layers	5	5	5
4	Size of samples	52	52	52
5	Training data pairs	126 observations (42*3)	126 observations (42*3)	126 observations (42*3)
6	Testing data pairs	30 observations (10*3)	30 observations (10*3)	30 observations (10*3)
7	Initial FIS generation	Grid partitioning	Grid partitioning	Grid partitioning
8	MF type	Triangular	generalized Bell	Gaussian
9	Training algorithm	LSE-BP gradient descent method	LSE-BP gradient descent method	LSE-BP gradient descent method
10	Error tolerance	0	0	0
11	Number of epochs	100	100	100

4 - RESULTS AND DISCUSSION

In the present work, three hybrid MA-ANFIS has been proposed to predict effectiveness of equipment. This is based on three independent losses and three type of (Tri, Gbell, and Gauss) membership function. Likewise, three statistical indices (RMSE, R^2 and MAPE) are used to evaluate precisions of the predictive models.

4.1 - Results of ANFIS parameters in relation to the proposed prediction models

4.1.1 - Case 1

This proposed prediction model has been developed using triangular membership function. The initial FIS generated using Grid partitioning. The estimated value of each variable is used to define the discourse universe of each variable, which is then divided using Grid partitioning. The initial input membership function is [2 3 3] which generates 18 number of fuzzy rules. Then, triangular shape activation function computes fuzzy membership values and the function are characterized as equation 16.

$$y = f(x; a, b, c) \ = \max\left(\min\left(\frac{x-a}{b-a},\ \frac{c-x}{c-b}\right), 0\right) \tag{16}$$

Where, ‘y’ is membership value, ‘x’ is input values for which to compute membership values. The ‘a, b, c’ are membership function parameter. In this ‘a, c’ define the feet and ‘b’ defines its peak of triangular membership function. These parameters can be set and updated by the hybrid learning algorithm during the training procedure. The quantity of membership functions for each input as well as the types of output membership functions followed constant functions. The proposed overall performance model’s ANFIS characteristics have 48 nodes under the best structure. Furthermore, there are a total of 39 pairs of parameters, with 18 linear parameters and 21 nonlinear parameters. In addition, 42 and 10 data samples have been used for training and testing, respectively. This proves that the network’s total number of data pairs is less than the number of training data pairs. The run time is 72 seconds. The ANFIS characteristic of the proposed model is presented in Table IV.

4.1.2 - Case 2

This proposed prediction model has been developed using generalized bell membership function. The number and initial positions of cluster centers are estimated using Grid partitioning. The estimated value of each variable is used to define each variable’s discourse universe, which is then divided via Grid partitioning. The initial input membership function is [2 3 2] which generates 12 number of fuzzy rules. Then, bell shaped activation function is used to develop the ANFIS model in this study, and the function is characterized as equation 17.

$$y \ = f\ (x; r,\ s,\ t) = \frac{1}{1 + \left|\frac{x-t}{r}\right|^{2s}} \tag{17}$$

Where ‘y’ is membership value, ‘x’ is input values for which to compute membership values. The ‘r, s, t’ are the parameters that respectively control the slope, centre and width of the bell-shaped function. These parameters can be set and updated by the same as case 1. This learning methodology combines the LSM and the BP, followed by the gradient descent learning method. Initial bell shaped functions with specific parameters are assigned to each fuzzification neuron at the beginning. The neuronal function centre associated to input ‘x_i’. Thus, domain of ‘x_i’ is uniformly segregated. Further, the function widths and slopes are also chosen to allow enough overlap between the respective functions. The quantity of membership functions for each input as well as the types of output membership functions followed constant functions. The proposed overall performance model's ANFIS characteristics have 44 nodes under the best structure, and 12 fuzzy rules have been constructed. Furthermore, there are a total of 33 pairs of parameters, with 12 linear parameters and 21 nonlinear parameters. This proves that the network's total number of data pairs is less than the number of training data pairs. The run time is 76 seconds. The ANFIS characteristic of the proposed model is presented in Table IV.

4.1.3 - Case 3

This proposed prediction model has been developed using Gaussian membership function. The number and initial positions of cluster centers are estimated using Grid partitioning. The minimum and maximum values of each variable are utilized to define each variable's discourse universe, which is then divided via Grid partitioning. The initial input membership function is [2 2 3] which generates 12 number of fuzzy rules. Then, Gaussian function is used to develop the ANFIS model in this study, and the function is characterized as equation 18.

$$y = f\,(x;\sigma,\ c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{18}$$

Where 'y' is membership value, 'x' is input values for which to compute membership values. The 'σ' is standard deviation, 'c' is mean. These parameters can be set and updated by the same as case 1 learning methodology. The quantity of membership functions for each input as well as the types of output membership functions followed constant functions. The proposed overall performance model's ANFIS characteristics have 44 nodes under the best structure, and 12 fuzzy rules have been constructed. Furthermore, there are a total of 26 pairs of parameters, with 12 linear parameters and 14 nonlinear parameters. This proves that the network's total number of data pairs is less than the number of training data pairs. The run time is 70 seconds. The ANFIS characteristic of the proposed model is presented in Table IV.

4.2 - Discussion of proposed MA-ANFIS prediction models evaluation

The trained fuzzy inference system then concern to testing data with various parameter combinations to evaluate the neural system's generalization capabilities and avoid over fitting the training data set. Based on the testing error of each combination of parameters, the optimum configuration for the chosen cases is determined. The variables of proposed model are assumed as constant function for several past 'p' measured observations, 'q' prediction observation and 'n' number of samples. The performances among these ANFIS models are statistically assessed by root mean squared error (RMSE), the coefficient of determination (R^2) and mean absolute percentage error (MAPE). The relation is represented in equation 19-21.

$$\text{Root mean squared error} = \sqrt{\frac{\sum_{i=1}^{n}(p_i - q_i)^2}{n}} \tag{19}$$

$$R\text{ squared } = 1 - \frac{\sum_{i=1}^{n}\ (p_i - \overline{q_i})^2}{\sum_{i=1}^{n}\ (p_i - \overline{p_i})^2} \tag{20}$$

Table IV. Characteristics of best structure model and corresponding ANFIS information.

ANFIS Information	Case 1	Case 2	Case 3
MFs for each input	2,3,3	2,3,2	2,2,3
Types of input MFs	Triangular	generalized Bell	Gaussian
output function	Constant	Constant	Constant
Nodes	48	44	44
Linear parameters	18	12	12
Nonlinear parameters	21	21	14
Total parameters	39	33	26
Training data pairs	42	42	42
Testing data pairs	10	10	10
Fuzzy rules	18	12	12
Run time (Seconds)	72	76	70

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{p_i - q_i}{p_i} * 100\right| \tag{21}$$

The OEE $_{measured}$ and OEE $_{predicted}$ values are statically evaluated by means of error analysis. This is worth noting that a prediction with an RMSE of 0; R^2 of 1; and MAPE of 0 is a perfect model. Table V shows the error analysis for the selected three cases predictive models using training and testing datasets. Based on error analysis the case 3 model possess minimal RMSE of 0.87, high predictive accuracy of 98.9 percent and minimal MAPE of 1.5 percent. Thus, the case 3 predictive model (Gaussianmf based model) has the best performance for the OEE estimation. Further, the Figure 3 a-c, shows the values of OEE $_{measured}$ versus OEE $_{predicted}$ by the predictive models.

Table V. Error analysis comparison.

Error measures	Case 1		Case 2		Case 3	
	Training	Test	Training	Test	Training	Test
RMSE	1.2816	6.6678	1.62	0.98	1.1626	0.87224
R^2	0.883	0.868	0.960	0.956	0.991	0.989
MAPE (%)	3.79	5.90	1.96	2.76	1.36	1.50

As shown in these figures the prediction through hybrid MA-ANFIS model case 3 are very accurate and closer to measured values. The high R^2 values shown by case 3 developed models as compared to other models indicate better prediction capability. The optimal values of the preceding and subsequent parameters for the Case-3 model are shown in Table VI.

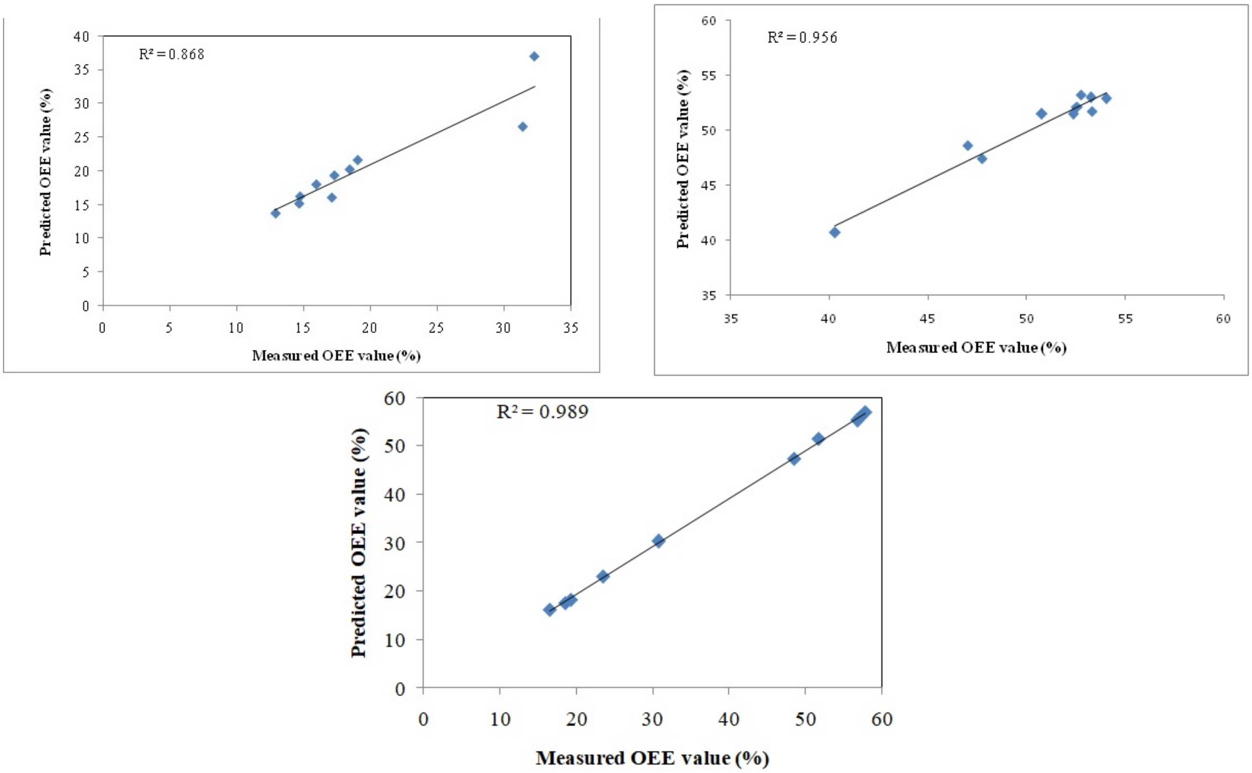

Figure 3. Testing data- Measured versus predicted R^2 accuracy comparison.

Table VI. Optimal parameters of Gaussian membership functions.

Parameter	MF(x)	Parameters	
		σ	c
Input parameter 1 (Lst)	1	80.69	70.05
	2	80.54	260.1
Input parameter 2 (Lsp)	1	289.9	114.9
	2	290	795
Input parameter 3 (Lq)	1	6.5	5.54
	2	6.6	14.26
	3	6.65	24.27

4.2.1 - Comparison with other existing work

The performances of proposed models are compared with existing prediction models to validate the prediction ability. Three previous models were chosen to compare the current proposed models. Existing models simply employed one statistical index to validate results. However, the findings of this investigation have been validated using three statistical indices. The Table VII shows the comparison of proposed and existing models test results with respect to RMSE, R^2 and MAPE. These findings of error measures confirms that the accuracy of Case-3 proposed model is outperform than other models in predicting OEE. In combination with existing prediction research, this study demonstrates that the Gaussian membership function based hybrid MA-ANFIS model is capable of handling production losses for accurate equipment effectiveness prediction.

Table VII. Comparison with other existing work.

Reference	Modeling technique	RMSE	R^2 (in %)	MAPE (in %)
Kuo & Lin (2010)	Neural Network	--	91.3	--
Hassani et al. (2019)	Deep Neural Network	--	--	11.8
Engelmann et al. (2020)	Machine Learning Algorithm	--	92.8	--
Proposed case 1 model	Hybrid MA-ANFIS	6.67	86.8	5.9
Proposed case 2 model	Hybrid MA-ANFIS	0.98	95.6	2.8
Proposed case 3 model	Hybrid MA-ANFIS	0.87	98.9	1.5

4.2.2 - Statistical hypothesis test

This statistical test provides a mechanism for making quantitative decisions about the prediction process. The superiority case-3 prediction model results are selected for doing statistical hypothesis test. The intent is to determine whether there is enough evidence to accept a hypothesis about the prediction process. The paired t-test is selected for conducting hypothesis test, because the mean difference between $OEE_{measured}$ and $OEE_{predicted}$ are paired observations. The paired t-test computes the difference between each before and after pair of measurements. This calculates the mean of these OEE changes, and reports whether this mean of the difference is statistically significant. The test uses the 95 % confidence interval (CI) and following hypothesis:

H0: $\mu\ (OEE_{measured}) = \mu\ (OEE_{predicted})$ (OEE prediction value is closer to measured value)

H1: $\mu\ (OEE_{measured}) \neq \mu\ (OEE_{predicted})$ (OEE prediction value is not closer to measured value)

The Table VIII demonstrates the paired T-test results. The calculated probability of obtaining the observed sample data is 0.960. This confirms that accept the null hypothesis, which means the measured and predicted OEE values are closer. This determined quantitative statistical evidence provides decisions to accept the hypothesis of the prediction process.

Table VIII. Paired T-test results.

	N	Mean	STDEV	SE mean	Mean difference for 95 CI	T-value	P-value
$OEE_{measured}$	52	34.44	17.34	2.40			
$OEE_{predicted}$	52	34.43	17.03	2.36	(-0.417, 0.439)	0.05	0.960
Difference	52	0.011	1.537	0.213			

4.3 - Practical implication of this research

The greatest analysis of prediction model is to extracting valuable knowledge from raw data and assists production managers to determine the cut-off percentage of equipment effectiveness for selecting appropriate maintenance technique. The average equipment effectiveness value predicted by the superior Gaussianmf based hybrid MA-ANFIS model (case-3) is 34 percentages. However, this $OEE_{predicted}$ value is lower than the fair (65%) and world class (85%) OEE values ($OEE_{predicted} < OEE_{fair} < OEE_{world\ class}$) and this is required of further improvement. Hence, this work initiates failure analysis as well as countermeasures to reduce production losses and to enhance OEE values. The subsystem's failure patterns aid production managers in understanding failure behavior and designing preventative maintenance programs. Finally this work proposes cut-off values of OEE for selecting appropriate maintenance technique. This is also provides higher accuracy in the evaluation of losses and prediction of effectiveness in a complex environment. Initially, losses due to failures and causes of machine centers have been investigated from a human, electrical, and mechanical perspective. The Table IX showcases the investigation statistics.

Table IX. Failure and repair statistics.

S.No	Failure causes	MTBF in hours	MTTR in hours	No of failures
1	Human failures	1.60	0.18	11
2	Electrical failures	1.13	0.11	16
3	Mechanical failures	3.00	0.35	6

According to data, human failures contribute to the high number of failures in the machine centre. This kind of failures is caused by commission flaws such as a lack of attention, inadequate tool and material arrangements, and so on. Human failures have a mean time to repair (MTTR) of 0.18 hour and a mean time between failures (MTBF) of 1.6 hours. Next to human failure, the mechanical failures have been analyzed. Mechanical failures accounted for 18 percent of all failures, with one occurring every three hours on average and a 0.35-hour average repair time. Ultimately, mechanical failures are linked to failures of electrode holders, circuits, wires, liners, hoses, regulators, and inside guns, resulting in a stoppage. Electrical failures have also been studied, in addition to mechanical failures. Electrical problems accounted for 48 percent of all failures. Electrical failure had the second-shortest MTBF, with one failure per 1.13 hours and the shortest repair time of 0.11 hours. These evaluations are essential to analyze the current situation in order to enforce the appropriate counter measures. The first line of counter measure is self-maintenance procedures like cleaning, rod storage, and equipment management. This means maintaining the right equipment by following the principles of the Japanese 5'S. To regularly update the machine, preventive maintenance (PM) has been encouraged. The electrical maintenance countermeasures include weekly power source monitoring by blowing air into the unit, which reduces overheating and intermittent arc output. Problems such as excessive circuit resistance would also be caused by the cable and electrode holder, so the connections, circuits, wires, liners, hoses, regulators and inside guns should be regularly inspected. Direct replacement ones with instant excess wear. Of course, with blended coolant from the manufacturer, the coolant level is regulated to solve the problem related to sludge build-up. Concentrate primarily on generator welding engines such as oil change, filter, air cleaner and filter for fuel. Lastly, conduct the load test to ensure that the welding output is precise. A failure monitoring template has been developed with a view to supporting maintenance activities. The model consists of a critical complete record of often missing details related to relevant specifics, such as machine number, the period of failure detection, mean repair time and the mean time between repair failures. This lower buffer inventories result in low production losses and shorter lead times because tasks do not have to wait as long in lines. So, the company's performance and adaptability have improved, making it more competitive. Increases in quality entail reduced scrap and rework, resulting in a higher quality rate. In addition, the countermeasures have been estimated for each selected parameters and OEE values are estimated using proposed prediction model. Likewise, the cut-off value of OEE is proposed as follows,

OEE cut-off value		Equipment status	Proposed maintenance strategy
$85 \leq OEE_{predicted}$	$\longrightarrow$	Excellent	Follow same PM technique
$65 \leq OEE_{predicted} \leq 85$	$\longrightarrow$	Good	Follow same PM technique
$55 \leq OEE_{predicted} \leq 65$	$\longrightarrow$	Normal	Implement proposed PM technique
$OEE_{predicted} \leq 55$	$\longrightarrow$	Fail	Rigorous implementation of proposed PM method

The OEE prediction using proposed model are described in Figure 4. The predicted average OEE value is 66 percentages. As a result, the OEE has risen from 34 to 66 percent. Thus, the equipment effectiveness reached fair OEE of 65%. Now the OEE value is higher than fair value and lower than world class value ($OEE_{fair} < OEE_{predicted} < OEE_{world\ class}$). In order to reach world-class performance of 85 % OEE, the production managers must continue these countermeasures effectively. This prediction can assist production managers to choose appropriate maintenance strategy especially for manual and semi automated production environment scenario.

Lst	Lsp	Lq	OEE	Equipment status
260	461	8	31	Fail
121	359	8	37	Fail
130	326	7	41	Fail
138	292	7	45	Fail
		↓	After countermeasures	
128	198	4	61	Normal
120	158	8	66	Good
117	140	10	69	Good
139	119	7	70	Good

Figure 4. OEE prediction using proposed model.

4.4 - Cost effectiveness of proposed study

The superior proposed model (case-3) is used to analyze a real world case which is fabrication of city buses. The production manager could be able to enhance labour productivity by using the integrated improvement method. The results show that when improvement factor (E_{EI}) performs the maximum output valued at average of 86 percentages. Due to the improvement factor the average optimal L_{TTC}^{*} is reduced from 0.56 to 0.46 (man hours required to complete unit quantity of work). The optimal labour productivity (L_P^{*}) increased to 2.84 from 1.95 units per man hour. The total fabrication duration (D_F) could be reduced from 41 days to 27 days. The improvement cost of this work is calculated as 19,000 rupees. The optimal direct labour cost associated with reduced duration is 120486. The methods surveyed are compared in terms of OEE, productivity, time, and cost effectiveness in Figure 5a-d.

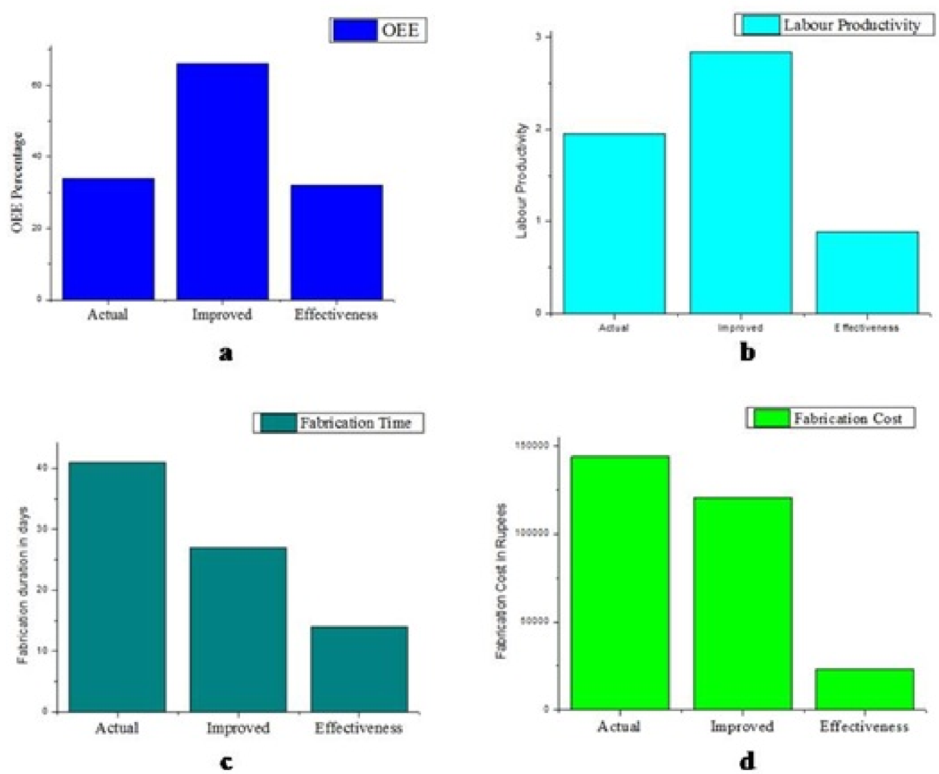

Figure 5. Effectiveness of the proposed methods surveyed.

5 - CONCLUSION

There are enormous challenges in today's volatile industrial environment to improve operational efficiency in order to boost competitiveness and overall business success. In the dynamic environment, medium-scale bus body builders are struggling to retain existing customers and gain new customers. Bus body builders who produce high-quality vehicles will be able to thrive in core manufacturing. These builders work hard to increase their competitive advantages by focusing on the efficiency of their equipment. On the other hand, Precision OEE prediction is critical in these kinds of extremely difficult manufacturing environments. This study combines a moving average (MA) model and hybrid Extremal- micro genetic algorithm (Ex-μGA) model with an adaptive neural fuzzy inference system (ANFIS) to develop three different prediction models for equipment effectiveness prediction. Various stages of evaluation were carried out in order to determine the best ANFIS parameters and validate the ability of the hybrid MA-ANFIS model. The empirical results clearly show that the performance of the Gaussianmf-based hybrid MA-ANFIS model (case-3) outperforms other developed models. The proposed system assists production managers by providing decision support for quantifying and predicting OEE performance. The proposed equipment effectiveness prediction can aid in the effective implementation of maintenance management programs in the manufacturing environment. The results of implementing the superiority model in a bus body building firm show significant improvements in labour productivity, machine performance, fabrication time, and fabrication cost. According to the real-world analysis, bus body building production managers must track failures on a regular basis. Otherwise, failures will have increased significantly in comparison to the projected output.

5.1 - Limitation and future direction of proposed study

This section discusses the limitations of the current study as well as an attractive future direction. The present hybrid MA-ANFIS superiority model based on Gaussianmf has the ability to immediately improve task performance. However, it has only used grid partitioning clustering and the Ex-μGA as input parameter tuning technique. Hence, few other clustering techniques and input parameter tuning methods can be given more strength in OEE prediction. In addition, the production managers have to predict some other flexible preventive maintenance technique to accelerate equipment performance within the budgeted range.

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