Evaluating and Predicting Overall Equipment Effectiveness for Deep Water Disposal Pump using ANN-GA Analysis Approach

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ABSTRACT

This study proposes the Artificial Neural Network with a Genetic Algorithm analysis approach to investigate the Overall Equipment Effectiveness of the deep-water disposal pump system. The ANN-GA model was developed based on six big losses over eighteen successive months of the operating period to evaluate the current and future performance of the DWD system. 70% of the data was used for training and 15% for each data validation and testing. The DWD system faces frequent failure issues, significantly impacting its performance, so it is important to reveal the main causes of these failures to manage them properly. ANN-GA is applied to make a linear trend prediction and assesses the confidence and accuracy of the results obtained. Analysis of ANOVA (variance) was adopted as an additional decision tool for detecting the variation of process parameters. ANN-GA results showed that the current OEE value ranges between 29% to 54%, whereas the predicted future system performance average is approximately 49%, which reflects the poor performance of the DWD pump system in the future compared to the world-class target (85%). ANN-GA analysis results indicated were very close and matched with the actual values. The model framework and analysis presented are used to develop a decision support tool for managers for early intervention to minimize system deterioration, reduce maintenance costs and increase productivity. Furthermore, it allows early identifying the potential area of

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improvement to support continuous improvement (CI) objectives by identifying and eliminating unnecessary maintenance activities. The proposed model framework uses the ANN approach to identify the current state and predict the future of the system performance to ensure confidence in the results. The contribution of the paper will be helpful for experts like managers, reliability engineers, and maintenance engineers to identify the state of the system's performance in advance.

Keywords: *Overall Equipment Effectiveness; Genetic algorithm; Artificial Neural Network; Performance; Six Big Losses*

Introduction

Deep Water Disposal (DWD) pumps are widely used in the Oil and Gas industries. Their primary function is to dispose of contaminated water associated with oil and gas production. The DWD is vital to the smooth operation, representing a significant segment of the entire operation. High reliability of these pumps is envisaged to reduce the maintenance cost (failure cost), and thus reduce the process disruption and ensure continuous plant productivity, which reflects positively on the revenue generated. The current state of the pump system performance is decreasing based on the number of failures during the specified operating period. Identification and prognosis of the cause of the main failures will help to set a clear maintenance strategy to reduce these deficiencies and maintain system performance and effectiveness. The rated capacity of each DWD pump was approximately 20,000 m^3/day. The pump is supplied by Sulzer (HPCP 200-330, 5 stages) and connected to the electric motor by coupling through a gearbox. The electric motor from ABB 11 KV/4.50 MW brush type is used in all the pumps. Moreover, 11 KV motor switching fed through the circuit breaker make Alstom GEC rated from the step-down transformer 33/11 KV, rated current 1250 Amps with closing and opening voltage of 50 V DC. The gearbox (fluid coupling) is situated between the motor and driven machine (pump), and it’s made by Voith type R 17K2, which provides variable speed (discharge pressure) depending on the well’s reservoir condition.

The concept of lean manufacturing is widely adopted by engineering organizations to maintain their position in the competitive business arena. This has prompted organizations to evaluate their challenges continuously and use appropriate techniques to improve their efficiency” [1]. Overall Equipment Effectiveness (OEE) is a critical measurement that has evolved over the years and its relevance was discussed extensively by Seiichi Nakajima in 1988 [2]. The OEE measurement is becoming increasingly popular, and the TPM concept is used as a standalone powerful benchmark key performance indicator (KPI) tool for productivity improvement [3]. Nakajima defined OEE as a metric to evaluate the equipment's effectiveness [4]. OEE quantifies how well a machine performs relative to its designed capacity during the scheduled periods. It is a well-known notion in maintenance and is a way of measuring the machine effectiveness and assess how effectively an equipment is utilized to its full potential. Initially, the OEE metrics consisted of six big losses: breakdowns, setup and adjustment, idling and minor stoppage, reduced speed, defects in the process, start-up losses, and reduced yield. On the other hand, it identifies and measures losses of essential aspects of equipment, focusing on three analyzing tools based on availability, performance, and quality rate directly related to six big equipment losses [5]. OEE provides a systematic process to readily identify and eliminate the six big loss sources and support continuous improvement to achieve zero breakdowns and defects related to equipment [6]. OEE is a global best practice measure to monitor and improve the effectiveness of manufacturing processes.

Over recent years, management has focused on the wastes generated due to failure or breakdown of machines that incurred a significant organization investment through loss in production and time. One of the significant challenges faced in the industrial environment is the appropriate and efficient use of the available resources for operation and workforce to sustain productivity. According to Dal et al. [7], the OEE role could go beyond just monitoring and controlling of process improvement initiatives, it provides a systematic method to achieve the production target and combines practical management techniques and tools to realize operational excellence and optimize the whole process individually. The optimal utilization of the machine during its productive life with minimum investment is the crucial goal of any organization. Therefore, the OEE philosophy acts as one of the tools used for continuous improvement. The Overall Equipment Effectiveness model is shown in Figure 1 [8].

The Artificial Neural Network (ANN) is inspired from the human brain neuron network. It has a motivating design that effectively models highly complicated problems and nonlinear systems [9]-[11]. Evolutionary feed forward single layer configuration using Levenberg Marquardt backpropagation algorithm has been employed in this study. The architecture of ANN consists of two input layers, ten hidden layers and one output layer, and each layer has some nodes representing artificial neurons. These neurons are usually assembled in layers [12]. Each layer has some nodes or neurons that interact through weighted connections [13]. Training of the network is carried out by refinement of the weight of the neurons, so the error condition is minimized and achieves the desired result, and this method is called backpropagation. Training patterns are formed of a set of matching input and output vectors, and a learning algorithm (LM) uses these vectors to train the network. It measures the difference between the desired output vector and actual output and modifies the weight's connection to decrease the propagated error. This process will continue until the error reaches the desired level [9].

ANN and GA are two of the most promising natural computation techniques and have applications in several studies for parameter optimization. These two techniques are considered adequate in process optimization, and their use has recently increased [14]. Thereby, integration of ANN with GA is implemented in this paper to model and optimize the OEE data analysis of the DWD pump system.

This research paper aims to assess the current overall effectiveness of the deep-water disposal pump system and categorize the major losses that lead to poor performance according to their weight, which allows managers to evaluate the equipment's effectiveness. Therefore, investigate inputs to the production process and eliminate the relative losses. Also, it will form a decision support tool for managers to prevent loss and then act and react to maximize and improve production effectiveness. Eighteen-month values were collected of the six big losses: total operating time, downtime, actual production, design capacity, proposed amount, and defect amount. Thereby find out the availability, performance efficiency, and quality rate, then take an average of the given period to estimate the OEE.

The remainder of this paper is organized as follows: literature review is discussed in Section 2. While Section 3 presents the research methodology in detail. Section 4 introduce the results and discussion of the research. Finally, the conclusion is offered in Section 5.

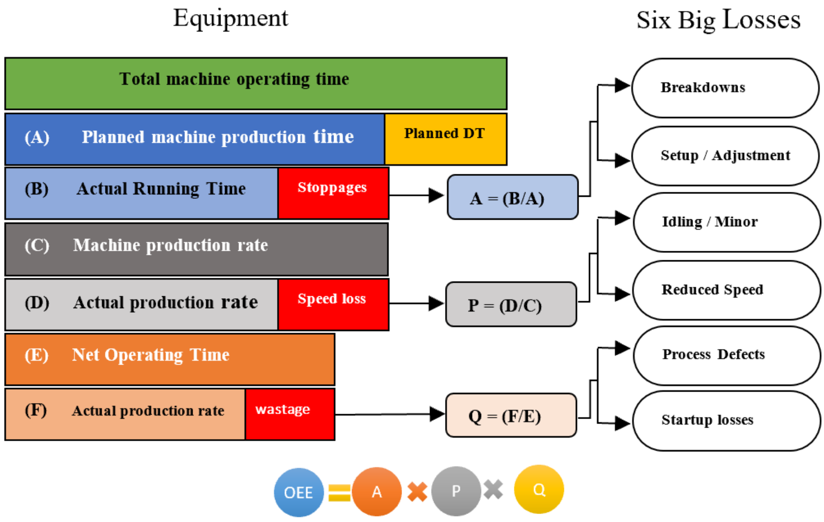

Figure 1: Overall equipment effectiveness model [2]

Literature Review

Overall equipment effectiveness is frequently used as a key metric in Total Productive Maintenance (TPM) and lean manufacturing programs to deliver operational excellence. It gives the industrials a consistent way to measure the effectiveness of the TPM and other initiatives (5S and world-class manufacturing) by providing an overall framework for measuring production efficiency. It considers three factors quality, speed, and downtime. It is merely the ratio of fully productive time to planned production time. In other words, it represents the percentage of production time spent making a reasonable production rate (no quality loss), as fast as possible (no speed loss), without interruption (no downtime loss). The Implementation of TPM has shown considerable results in Japanese enterprises. It has been unusual to increase the level of overall utilization from 60% to 90% according to [15], and Schaffer et al. [16] have observed that most companies implementing continuous improvement (CI) failed to achieve results. Its mission is to focus on results rather than on activities. If the magnitude and reasons for losses are unknown, the activities will be unallocated toward optimally solving the major losses. If the measurable results are not provided within a short period, the management and operator can lose reliance on TPM. If the success tastes unexperienced soon enough, the driving force of change will eventually vanish. Ahuja et al. [17] said that "TPM is a production-driven improvement methodology designed to optimize equipment reliability and efficiently manage plant assets through employee evolvement linking manufacturing, maintenance, and engineering".

Ng Corrales et al. [18] worked in their research on reviewing and analyzing OEE, presenting modifications made over the original model, and identifying future development areas. They are establishing procedures and criteria to present a structured and transparent methodical literature review. They obtained 862 articles, and after implementing duplicates and applying certain inclusion and exclusion criteria, 186 articles were used in this review. The research outcomes are summarized in three principles: (1) the academic interests increased in the last five years and the keywords being developed from maintenance and production to lean manufacturing and optimization; (2) creating a list of authors who have developed models based on OEE; (3) OEE is an emerging topic in areas like services and logistics. The research serves as a basis for future relevant studies. Williamson [19] defined OEE as a measure of total equipment performance which is the degree to which the equipment is doing what it is supposed to do. OEE broke down into three availability, performance, and quality analysis tools. These metrics help to gauge the machine's effectiveness and categories the big six productivity losses to improve asset performance and reliability. According to Jonsson and Lesshammar [20], the losses occur due to process interruptions that are either chronic or sporadic. Chronic disturbances are small and hidden and result from several concurrent causes. In contrast, sporadic disturbances are more apparent since they happen faster and significantly exceed the normal state. Nakajima [21] stated that it is a bottom-up approach where an integrated workforce strives to achieve overall equipment effectiveness by eliminating six significant losses. Blanchard [22] has reported that the OEE world-class figures are widely argued to be around 85%. Parida et al. [23] argue that the most massive problem that exists in the industry today is low OEE being 15%-25% below the target level. Several studies showed that 30% of energy consumption in industry is wasted on machines in repair, idle, and standby states, which negatively impacts ecological sustainability [24].

The essence of lean is removing waste and identifying anything that does not add value. Domingo and Aguado [25] stated that OEE is associated with lean and green manufacturing, considered OEE for environmental issues, and gave the term Overall Environmental Equipment Effectiveness (OEEE). They carry out OEE calculations for various manufacturing industry lines, and the effect of factors associated with OEE is examined. Castro and Araujo [26] identified how to reduce waste and assure compliance production process as a key variable in the beverage industry. They applied OEE in the plant production line, filling beverages in bottles. Gibbons et al. [5] introduced enhancement to OEE, which is very useful for the OEE measurement framework by providing a benchmark. Enhanced OEE framework as an indicator of lean six sigma capability is introduced.

Artificial neural networks are the most popular in machine learning (ML) algorithms. The first invention of these neural networks was in 1943 and then developed by Frank Rosenblatt in 1958, based on McCulloch and Pitts model. It gained massive popularity over the years due to its computation power [27]. Artificial neural networks are sophisticated nonlinear computational tools capable of modelling extremely complex functions. ANN operates the nonlinear statistical mapping between an input set and a corresponding output set (target) to discover a new pattern [28]. Marini et al. [29] implemented deep learning in their study to measure production performance on fresh product packing. The goal is to predict future values of the key performance of machines' overall equipment effectiveness (OEE) and Machine Mechanical Efficiency (MME). Thus, avoiding sudden machine breakdowns by levering historical data. Sari et al. [30] conducted a study to evaluate metrics of production of OEE and overall line effectiveness (OLE) using intelligence techniques aiming to improve the calculative methods. Mamdani fuzzy interface system (FIS) and Sugeno were used to evaluate OEE, whereas FIS and Artificial neural networks (ANNs) were employed for OLE metrics evaluation. This study will allow the operator to share his knowledge and intervene in these measurements. Moreover, this method was tested in different scenarios. Bekar et al. [31] conducted a study to predict the overall equipment effectiveness (OEE) using simulation software aiming to identify the optimal level of the OEE to increase the time between failures and reduce the mean repair time. OEE process optimization used various methods like Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Interface System (ANFIS), and Response Surface Methodology (RSM). It used Sequential Quadratic Programming (SQP) algorithm to determine the input values. The study outcomes influence avoiding frequent failures in the production process.

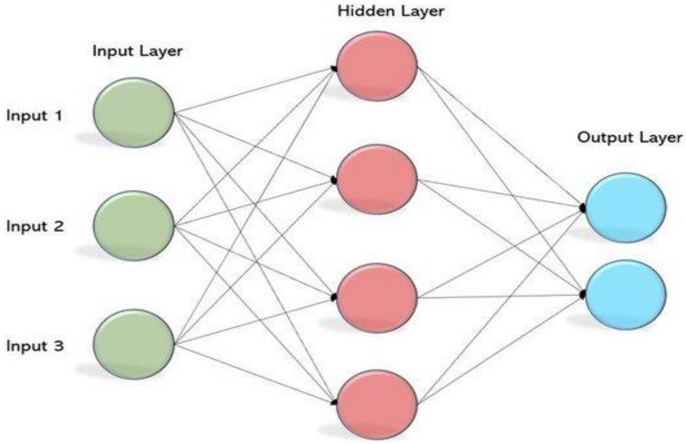

Figure 2: Artificial neural network structure [32]

A genetic algorithm (GA) is a search algorithm inspired by Charles Darwin's theory of natural evolution is based on survival of fitness; that is, some parents with stronger fitness ability to the environment will be chosen. The genes of these parents will be exchanged with each other to produce offspring. In this way, some offspring are expected to have higher fitness than their parents since the good genes would be preserved, and the chromosome could become even better after the crossover operation. With the processes of crossover, reproduction, and selection, the best chromosome with the strongest fitness ability to the environment will eventually evolve [33]. These algorithms maintain and manipulate a population of solutions and perform their search for the best solutions. This algorithm can treat linear and non-linear problems by selecting the fittest individuals from a population through crossover, selection, and mutation operations. Genetic algorithm uses involve determining six essential problems: genetic operator making up the reproduction function, selection function, chromosome representation, the creation of the initial population, termination criteria, and the evaluation [9], [34]. The methodology of combining ANN with GA is illustrates in Figure 3.

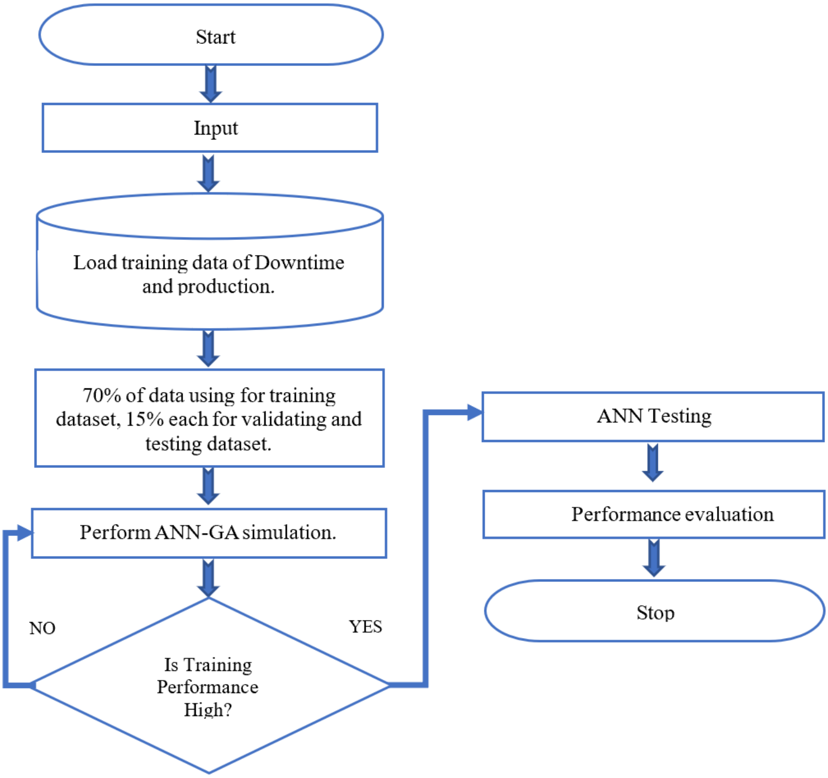

Figure 3: Flow diagram of ANN with GA

Methodology

The deep-water disposal (DWD) pump system data for eighteen successive months period is presented in this paper based on six big losses. The data information is used for computing OEE metrics (availability, performance, and quality) and therefore estimating the OEE value. The collected data were classified as total operating time, total downtime, actual produce amount, design capacity amount, proposed amount, and defect amount (Figure 1 shows the six big losses and OEE metrics).

$$OEE = Availability\ x\ Performance\ x\ Quality \quad (1)$$

Equation 1 is used to calculate the OEE metrics as follows:

- Availability: represents the percentage of scheduled time that the equipment is available to operate. 100% availability means the process has been running without any stops machine. The availability formula can be expressed as [35]:

$$Availability = \frac{(\text{Total time} - \text{Total down time})}{\text{Total time}} x\ 100 \tag{2}$$

  Availability considers "Downtime losses" from
  Pumps failures (pump is breakdown >15 min)
  Setup and adjustments (pump breakdown >15 min)

- Performance: represents the percentage of the total actual amount of water produced on the pump machine to the machine's production rate (actual vs designed capacity). 100% performance means the process has been consistently running at its theoretical maximum speed. The formula to calculate the performance rate can be expressed as [35]:

$$Perfomance\ rate = \frac{\left(Actual\ amount\ of \frac{produced}{Total} operating\ time\right)}{Design\ capacity\ of\ produced} x\ 100 \tag{3}$$

  Performance considers "Speed Losses" from
  Idling and minor stoppages (pump is stop < 15 min)
  Reduced speed operation (actual vs. design cycle time)

- Quality: represents the percentage of good amounts produced out of the proposed amounts produced on the pumping machine. 100% quality means there has been no defect amount. The quality rate can be expressed in a formula as follows [35]:

$$Quality\ rate = \frac{(Proposed\ amount - Defect\ amount)}{Proposed\ amount} x\ 100 \tag{4}$$

  where, defect amount = proposed amount – actual amount of contaminated water supply.
  Quality considers "Defect Losses" from
  Start-up losses (pump required warm-up time)
  Production losses (no production according to specification)

The Artificial Neural Network (ANN) models developed for Downtime (DT) and Actual Produced amount (AP) data where employed optimization procedures using Genetic Algorithm (GA) using MATLAB (version-2019b) software. These two data sets are variables and will be employed as input for the ANN-GA model, whereas the rest are independent (identical values for all months) and will ignore in the model. Consequently, these two parameter values' changes will reflect on the OEE value and consider different losses weight. Integrated ANN with GA as an effective tool to study the current performance status of the DWD system and identify the main losses influencing the system performance and use its full design capacity.

After that, estimated future Downtime (DT) and actual production (AP) values based on eighteen months gained data to predict the DWD system performance in the coming thirty-six months. To provide a status report about DWD system behavior patterns and their effectiveness to give management adequate time and allow them for an early intervention to minimize system deterioration, reduce maintenance costs, and increase productivity.

Analysis of variance (ANOVA) was adopted as an additional decision tool for detecting the variation of process parameters. It is a statistical method to determine the optimal level of factors that impact independent variables have on the dependent variable in a regression study [36]. In this study, ANOVA of the 36-month data will be carried out the variable 1 (downtime) and variable 2 (actual produced amount) directly related to OEE. Linear regression analysis using two variables provides a basis for estimating the OEE. The predicted OEE of the developed model through ANOVA techniques is more realistic and reliable. The ANOVA equation has been presented below (Equation 5) [37].

$$F = \frac{MST}{MSE} \tag{5}$$

where F is the ANOVA coefficient, MST is the mean sum of squares due to treatment, and MSE is the mean sum of squares due to error.

$$\mathrm{r} = \frac{\sum(\mathrm{x_i} - \bar{\mathrm{x}})(\mathrm{y_i} - \bar{\mathrm{y}})}{\sqrt{\sum(\mathrm{x_i} - \bar{\mathrm{x}})^2 \sum(\mathrm{y_i} - \bar{\mathrm{y}})^2}} \tag{6}$$

where r is the correlation coefficient x_i are values of X-variable, $\bar{x}$ is the mean of the values of the x-variable, y_i is values of y-variable, and $\bar{y}$ is the mean of the values of the y-variable.

$$y = \beta_0 + \beta_1 X_1 + \ldots + \beta_n X_n + \in \tag{7}$$

where y is the predicted value of the dependent variable (OEE value in our study), β_0 is the y-intercept (y value when all parameters are set to 0), $\beta_1 X_1$is the regression coefficient (β_1) of the first independent variable (X_1), $\beta_n X_n$ is the regression coefficient of the last independent variable, and e is the model error (known as residuals).

Data Analysis and Results

ANN-GA analysis modelling of OEE evaluation

The Deep-Water Disposal (DWD) pump system is vital to smooth operation, and they represent a significant segment of the entire operation. The high reliability of these pumps is envisaged to reduce the maintenance cost (failure cost), thus reducing the process disruption, and ensuring continuous plant productivity, which reflects positively on the revenue generated. These pumps have to operate 24 hours a day / seven days a week. The current state of the pump system performance observed is decreasing based on the number of failures during the specified operating period. Obtained data for eighteen operated months was trained using ANN-GA analysis modelling to evaluate the present DWD pump system OEE performance. Figure 4 shows the mean square error (MSE) versus the iteration plot of ANN for training, validation, and test performance of the Overall Equipment Effectiveness (OEE) evaluation. The sample data used can be referred to the appendix A. The most popular algorithm is backpropagation because it is a capable and efficient simulation. Also, used Levenberg–Marquardt algorithm (LM) because it has more successive performance predictions for complicated relationships between input variables. The LM algorithm, a trust-region model, contains three primary steps: data enters the input and crosses the network layers, then the mean square error ((MSE) (Equation 8) of the output computed by the net is propagated and lessened to the training target; finally, the connection weights are adjusted and updated [38].

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (t_i - y_i)^2 \tag{8}$$

where y_i denoted the network's output, t_i denoted the desired goal and n is the number of inputs.

During training, errors are propagated back through the neurons, thereby adjusting the neurons' weights. Each cycle of error propagation during the network training is an epoch, and the number of epochs indicates how long the ANN simulation lasts. This performance plot shows unnoticeable problems, and the validation and test curves do not indicate overfitting. This training process undergoes till it gets saturated. Thereby, once the network's performance reaches the best fit, it will undergo training for the other six epochs, stop the training process, and avoid overfitting the network. The green ring circle indicates the best-fit point of the performance parameter neural network achieved with Mean Square Error (MSE) is 0.0003388 at epoch 9, which is very small and close to zero. In other words, the MSE mean (average) the magnitude of the error square estimates that the distance between the test value and the actual test value is close to each other. Moreover, the training and validation datasets gap is minimal and referred to as the "generalization gap". At epoch 15, the generalization stops improving, and the training is halted.

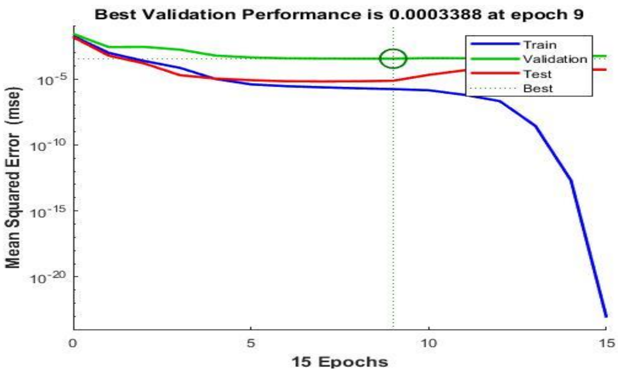

Figure 4: Plot of validation performance of the network

The correlation coefficient R regression plot is a valuable measurement of how well the ANN-GA network fits the data. The correlation coefficient is used to measure the strength of the relationship between two variables (Equation 6). The regression plot illustrates the correlation between the actual network output and the respective targets of the present OEE evaluation experiment. A correlation coefficient R-value of 1 means the output precisely matches the targets. In training, 70% of the provided data sets are used for training, 15% are used to validate the network, and 15% are used to test the network. In the case of a small number of learning data, like in our case, the training data should be subtracted sparingly; therefore, we have chosen 70 % for training data. There are no hard rules for data division. It depends on the complexity of the problem and the amount and nature of the learning data (much or less noise). However, there not a clear connection between the data division and the network performance. But 70% for training, 15% for validation, and 15% for testing data are recommended in certain literature [39]-[42].

Multiple linear regression (Equation 7) predicts the outcome variable based on two or more variables, also called multiple regression. This technique enables the determination of the model variation and the relative contribution of each independent variable in the total variance. Generally, the regression plot has four curves showing output for training, validation, test, and combination, as shown in Figure 5. It observes a higher value of regression R and indicates greater than 99% for both training and validation sets. For all data sets, the fit value is exceptional. The regression plot for this experimental network illustrates that all data sets are appropriately fitted to the line and indicate that the neural network structure is accurate and coherent.

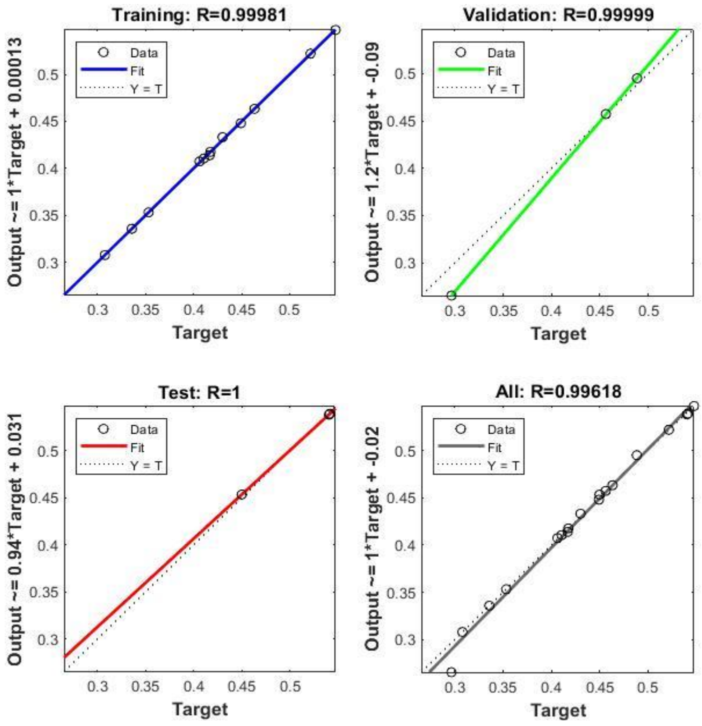

Figure 5: Regression Plot results for the current DWD system performance

Figure 6 shows the topology of the ANN model with two input neurons and output neurons (OEE) along with the optimum number of ten hidden layer neurons. The learning rate was adjusted to 0.01, the maximum number of epochs set to 1000, and the performance set to 0.0. During analyzing datasets, 70% were used to train the network and 15% each for the validation and the test. The network used in this study is a single-layer perceptron feed forward learning algorithm (Levenberg Marquardt backpropagation). This study will frame the input variables as machine downtime and actual production in the network, and the output/ target variables are considered to evaluate and maximize overall equipment effectiveness, improve efficiency, and recognize the main losses of the Deep-Water Disposal (DWD) pump system. The input/output variables data sets are loaded in the neural network structure to train the network using the Trainlm function. This function type updates the weight and bias values according to the Levenberg Marquardt optimization method. Gradient descent with momentum weight and bias learning function (Learngdm) is used for adoption. Input neurons use the Logsig function to generate the output signal, and the transfer function used for the hidden layer is the Tansig function.

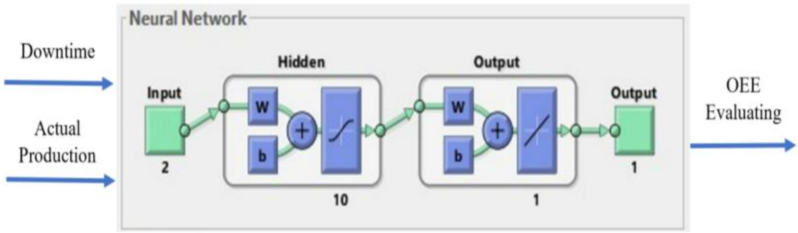

Figure 6: Neural network structure of OEE evaluation

In Figure 6, 'w' denotes the weight, whereases 'b' denote the bias, and the network randomly assigned their values. The associated transfer function Tansig showed a curve in the hidden layer and the output layer associated transfer function is Purelin and shown as a straight line. The number of hidden neurons was adjusted to 10 found optimum to increase the training performance and decrease the mean square error (MSE). The Levenberg-Marquardt training algorithm requires the least number of epochs for training the network. The MSE represents the average square difference between the output and the target. In other words, the lower values of the MSE are the better. The artificial neuron gets several input data as a vector x= $(x_1, x_2, \ldots\ldots, x_n)$ where n is the number of the input. It weights each input x_i with a pre-determined weight w_i and sums up all the weighted input. A bias b is added to the sum and the result is provided to an activation found λ which is nonlinear. The output of the artificial neurons can be written as follows [42]. The Levenberg-Marquardt algorithm needs more memory but less time.

$$Output\ from\ neurons = \lambda(\sum_{i=1}^{n} w_i\, x_i + b) \tag{9}$$

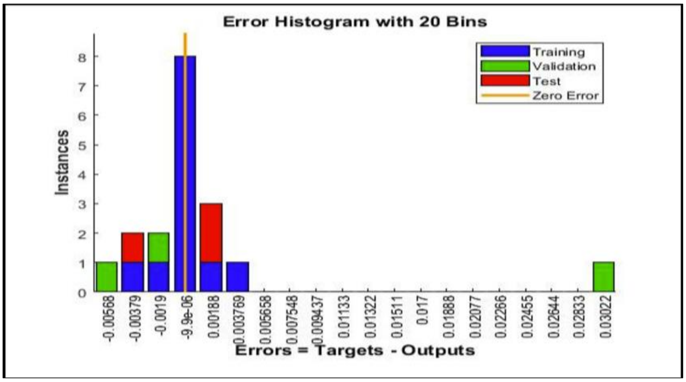

Figure 7: Error histogram network with 20 bins of the ANN-GA

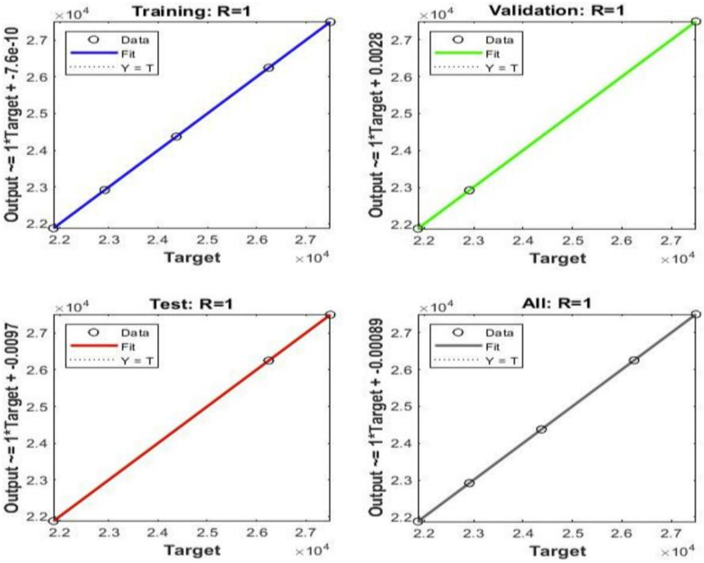

Figure 8: Regression plot results for the predicted DWD system performance

Error histogram values were calculated as demonstrated in Figure 7 through mean square error (MSE) by measuring the distance of the observed y values from the predicted y values at each value of x, then squaring each distance, followed by taking the mean of each square distance. It shows that the residual coverage between targets and the network output = [-0.00568 _ 0.03022]. Moreover, this histogram illustrates the target and predicts values errors with 20 bins after training the feedforward neural network for training, validation, and testing. Y-axes represent the number of dataset samples. A bin corresponds to the error shown at mid-plot, and the height of the bin for the training dataset lies around eight instances. Zero error point falls under the bin with the center -9.9e-06. The data from eighteen months was collected for two variables, downtime, and actual production amount, for forecasting the effectiveness of the deep-water disposal pump system in the coming thirty-six months. 70% of provided data sets are used for training, 15% of data sets are used for testing the prediction, and the rest 15% of data sets are used for validating the network. Figure 8 shows the performance regression plot result of the prediction of the two parameters. It is observed that the correlation coefficient (R) value of 1 for training, test, validation, and all datasets implies a perfect fit of outputs precisely equal to the target. Error histogram can help assess the quality of the trained network because it demonstrates the residuals between targets and network output and indicates outliers.

Figure 9 illustrates the error histogram and shows that most errors lie at -0.05, which is within the acceptable limit. Hence, the quality of learning data is exceptionally close to a value of 1 and without any outliers.

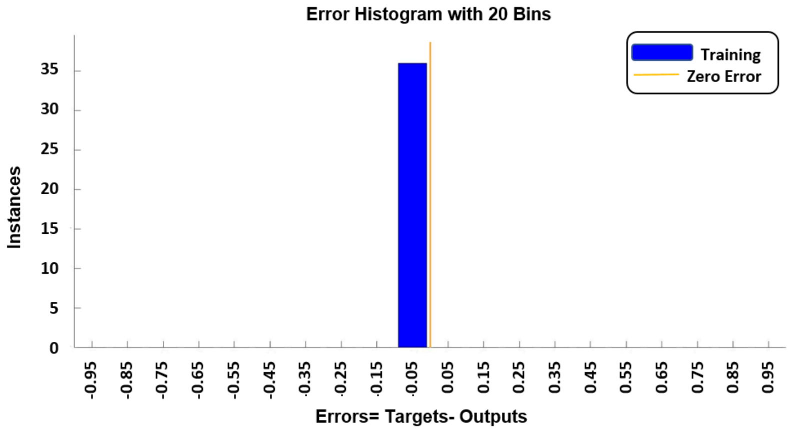

Figure 9: Error histogram network with 20 bins of the ANN-GA predicted dataset

The error has been calculated as shown in Equation 10 [42].

$$Errors = Targets - ANN\ outputs \tag{10}$$

The error histogram figure shows that the fitting data errors are distributed within a reasonably good range around zero, denoted as the orange vertical line for the training (blue) validation (green) and test (red) data. The number of bins of 20 represents the vertical bars observed in the error histogram ranging from -0.95 (leftmost bin) to 0.95 (rightmost bin). This error range is then divided into 20 smaller bins, so each bin has a width of 0.095, by

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The vertical bar represents the number of samples from the datasets which lie in a particular bin and their corresponding error. As can be seen, the higher the number of datasets plugged in ANN, the lower the error associated. As the number of instances (dataset combinations) decreases, the associated error increases (positive and negative errors), directly affecting the ANN prediction performance.

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ANOVA or variance analysis is a statistical procedure that separates variance data into different components for additional tests and measures the dependent variable from an independent variable. Moreover, it is used to model the

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relationship strength between two variables where a dependent variable is predicted based on one or more independent variables. This study used thirty-six months of data on downtime (hrs) and actual produced amount (m^3/hrs) to perform the ANOVA.

Table 1: The test evaluation of the multiple regression statistics

Regression statistics	
Multiple R	0.99862195
R square	0.9972458
Adjusted R square	0.99707888
Standard error	0.00481302
Observations	36

Table 1 shows that the value of the multiple R is 0.998; close to 1 means having a positive and robust linear relationship. Whereas the R square value indicates the points that fall in the regression line is 0.997, which is very good. 97%, close to 1, and the regression line fits the data. The standard error of 0.0048 illustrates that regression analysis is precise and that the average distance of the data point falls from the regression line is very small.

Table 2: The ANOVA analysis statistics

ANOVA					
	df	SS	MS	F	Significance F
Regression	2	0.276793992	0.1384	5974.36	5.7533E-43
Residual	33	0.000764451	2.3E-05		
Total	35	0.277558443			

	Coefficients	Standard error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	-0.4483	0.0104	-43.058	1.4E-30	-0.4695	-0.4272
*DT	-0.0006	2.3582E-05	-27.556	2.4E-24	-0.0007	-0.0006
*AP	3.9241E-05	4.0551E-07	96.770	4.4E-42	3.8416E-05	4.0066E-05

* AP: Actual produced amount (M^3/hrs.) * DT: Downtime

In the ANOVA analysis (Table 2), F statistics (ratio of mean squares) is equal to 0.138396996 /2.31652x10-5 = 5974.355. The distribution is F (2, 33), and the probability of observing significance F (P-value) is very low, 5.75334E-43; this means 5.75x10-43. The convention is that the relationship is highly statistical significance because the P-value is very small (P< 0.001).

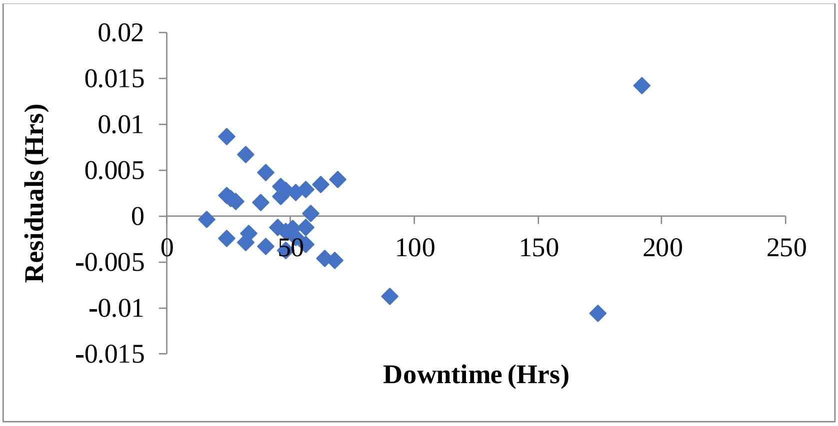
Also, strong evidence that the slope of the regression line is not equal to zero. The squared multiple correlations (regression SS) R^2 = SSM / SST= 0.276794 / 0.277558 = 0.997, indicating that 99.7% of the variability in the "ratings" variables is explained by downtime and actual production amount variables. The lower and upper 95% confidence interval for downtime is -0.0007 and -0.0006, whereas 0.000038 and 0.00004 for the actual produced amount and the boundaries prove that does not contain zero and 95% confidence the significant linear relationship between downtime scores and actual production amount and the chance of acceptance. Where DF denoted the degree of freedom, SS denoted the sum of squares, and MS denoted the mean square.

A residual plot is a graph that shows residual values on the vertical axis and the independent variable on the horizontal axis. The vertical distance is called residual, which means when the data point is above the line, the residual is positive, and the residual is negative for the data point below the line. The closer the data point residual is to 0, the better the fit. The residual output shows that the difference between the actual value and the predicted value of the regression model is minimal and very close to each other refer to appendix B. Both residual downtime and actual produced amount plots in Figure 10 show a reasonably random pattern and indicate that a linear model fits the data well. There is a strong correlation between model prediction and the actual result for both residual plots. It is observed that both plots have a high density of points close to the origin and low-density points away from the origin.

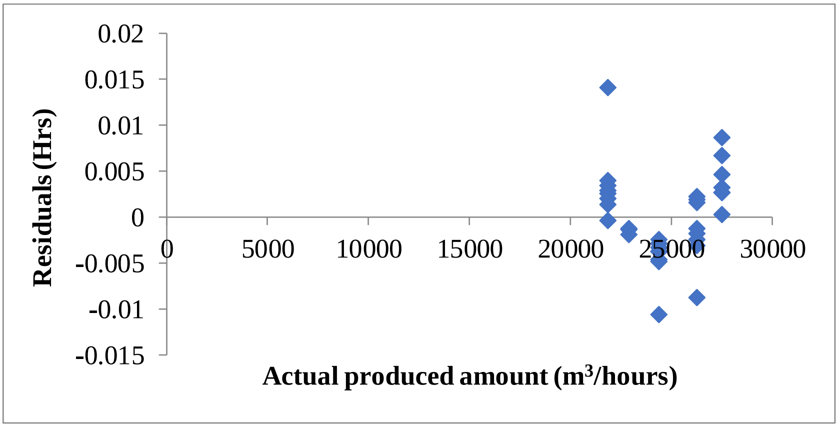
The regression analysis can be used to predict the OEE for any future combination of variables 1 (downtime in hours) and variable 2 (actual production m^3/hr. This means the data obtained in ANN prediction modelling of variables 1 and 2 meet the actual data (refer to Appendix B). Analysis showed a linear relationship with the OEE, and selected variables and Equation 11 can be used to predict the OEE with 99.7% accuracy.

$$Predicted\ OEE\ = -0.000649834\ x\ Down\ time\ (hours) +\ 3.9241E - 05\ x\ Actual\ produced\ amount\ \left(\frac{m^3}{hrs}\right) + (-0.448339865) \tag{11}$$

Figure 11 shows the plot of actual residual OEE and predicted OEE for 36 observations used for the study. The regression model developed shows very low residuals indicating that the predicted model closely matches the actual one. Thus, this OEE prediction model is satisfactory and can be used to set a target for improving the OEE value of DWD pumps. To achieve the desirable higher OEE level at the DWD pump system, Equation 11 can be used in two ways. For the desired OEE, field operators can target actual production for a month in m^3/hr for a maximum allowable monthly downtime (hours) to meet the desired OEE. Conversely, for the desired OEE, maintenance departments can work towards the maximum allowable downtime per month (hours) for targeted actual production m^3/hr to meet the desired OEE. For instance, if desired OEE of 70%, the maintenance team has to maintain frequent failures (downtime) not exceeding 30 hours per month; and ask the production team to produce an output within 30000 m^3/hr.



(a)



(b)

Figure 10: (a) Downtime; and (b) actual produced amount of residual prediction plots

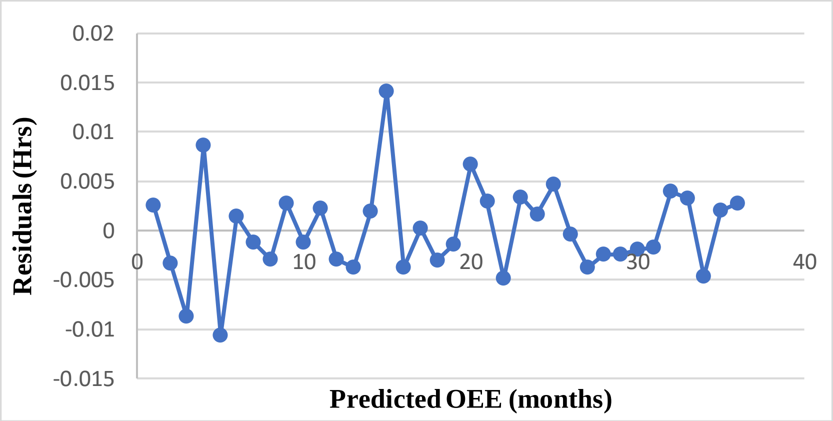


Figure 11: The residual plot of actual OEE and predicted OEE for 36 observations

Conclusion

This paper presents the overall equipment effectiveness (OEE) current performance evaluation of the deep-water disposal (DWD) pump system using an ANN-GA modelling analysis approach by MATLAB software based on eighteen months of historical data collected. The results show that the system OEE currently performed between 29% and 54%, with an average of around 43.5%, far from the world-class target (85%). Also noticed is that the availability factor has a stronger impact on the OEE formula than the performance and quality factors, which means it has a higher weight. Accordingly, concentrating on and improving the DWD system availability will make a difference in the system's effectiveness without sacrificing performance and quality factors. To achieve that, minimize the frequent failures (breakdown) of the DWD system and align all system setup and adjustments activities according to the operator's weekly schedule plan. Integration of ANN-GA analysis was used to predict the DWD pump system's overall equipment effectiveness future for the coming thirty-six months and was developed and validated. The results showed that the predicted future system performance average is approximately 49%, which reflects the poor performance of the DWD pump system in the future compared to the world-class target. In addition, the prediction data observed matched the actual data, proving that the data quality used in the analysis was reasonable. Also, the ANN-GA analysis result confidence was very close and matched the actual values. In an analysis of variance (ANOVA) of the 36-month data, it is observed that variable 1 (DT) and variable 2 (AP) are directly related to OEE.

Linear regression analysis using two variables provides a basis for estimating the OEE with 99.7% confidence with a standard error of 0.0048. This demonstrates that regression analysis is precise and that the average distance of the data point falls from the regression line very small. The lower and upper, 95% confidence, is the significant linear relationship between downtime scores, actual production amount, and the chance of acceptance. The linear regression equation developed in this study helps determine the combined impact of variables 1 and 2 on OEE. The residuals of predicted OEE were significantly lower; it is observed that both plots have a high density of points close to the origin and low-density points away from the origin, and thus the model developed through ANOVA techniques is more realistic and reliable. This study analysis can help maximize the OEE target level from a poor level to an acceptable level and support management with a clear vision report of DWD system performance behaviour in the current and future. Furthermore, it provides a base for identifying the potential area of early improvement and supports continuous improvement (CI) objectives by identifying and eliminating associated maintenance waste.

Contributions of Authors

Soud Al-Toubi conducted all research sections and wrote the original draft manuscript as part of his Ph.D. project. Babakalli Alkali, David Harrison, and Sudhir C.V.: supervision, reviewing, and guidance. All authors reviewed and approved the final version of this work.

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Conflict of Interests

All authors declare that they have no conflicts of interest

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Appendix A

The table below shows the current OEE values results in actual and ANN-GA analysis output where both values match each other.

Months	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**July**	**Aug**	**Sept**	***Oct**	**Nov**	**Dec**	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**June**
T/ Time	720	720	720	720	720	720	720	720	720	600	720	720	720	720	720	720	720	720
DT	97	138	82	203	116	211	254	218	243	114	109	175	117	109	128	143	177	197
(A)	86.53%	80.83%	88.61%	71.81%	83.89%	70.69%	64.72%	69.72%	66.25%	81.00%	84.86%	75.69%	83.75%	84.86%	82.22%	80.1%	75.4%	72.64%
Actual	21875	27500	24375	27500	27500	27500	27500	27500	24375	20313	27500	27500	27500	24375	24375	24375	21875	21875
Design Cap	37500	37500	37500	37500	37500	37500	37500	37500	37500	31250	37500	37500	37500	37500	37500	37500	37500	37500
(P)	58.33%	73.33%	65.00%	73.33%	73.33%	73.33%	73.33%	73.33%	65.00%	65.00%	73.33%	73.33%	73.33%	65.00%	65.00%	65.0%	58.3%	58.33%
Proposed	31250	31250	31250	31250	31250	31250	31250	31250	31250	26042	31250	31250	31250	31250	31250	31250	31250	31250
Defect	9375	3750	6875	3750	3750	3750	3750	3750	6875	5729	3750	3750	3750	6875	6875	6875	9375	9375
(Q)	70%	88%	78%	88%	88%	88%	88%	88%	78%	78%	88%	88%	88%	78%	78%	78%	70%	70%
Actual OEE	35.33%	52.16%	44.93%	46.34%	54.14%	45.62%	41.77%	44.99%	33.59%	41.07%	54.76%	48.85%	54.05%	43.02%	41.69%	40.63%	30.80 %	29.66%
ANN-GA	0.3533	0.522	0.4481	0.4633	0.5393	0.4573	0.4177	0.4534	0.3359	0.4106	0.5472	0.4951	0.5382	0.4332	0.414	0.4074	0.308	0.2654

DT: Downtime
Cap: Capacity
A: Availability
T/Time: Total Time in hours
P: Performance
Defect: The loosed amount of production.
Q: Quality
Proposed: The amount target set by the operation team.
***All** production amounts are measured in cubic meters per day

Appendix B

The below table shows the predicted future OEE values results for the 36 months. It observed that the OEE actual values were matched with ANN-GA analysis output.

S/N	T/ Time Hrs	DT	A %	APA M^3/hrs.	DPA m^3/hrs.	P %	PPA M^3/hrs.	DA m^3/hrs.	Q %	OEE %	ANN-GA %
1	720	52	92.78	21875	37500	58.33	31250	9375	70	37.88	38
2	720	40	94.44	24375	37500	65.00	31250	6875	78	47.88	48
3	720	90	87.50	26250	37500	70.00	31250	5000	84	51.45	52
4	720	24	96.67	27500	37500	73.33	31250	3750	88	62.38	62
5	720	174	75.83	24375	37500	65.00	31250	6875	78	38.45	40
6	720	38	94.72	21875	37500	58.33	31250	9375	70	38.68	39
7	720	45	93.75	26250	37500	70.00	31250	5000	84	55.13	55
8	720	32	95.56	24375	37500	65.00	31250	6875	78	48.45	49
9	720	48	93.33	27500	37500	73.33	31250	3750	88	60.23	60
10	720	56	92.22	22917	37500	61.11	31250	8333	73	41.33	41
11	720	24	96.67	26250	37500	70.00	31250	5000	84	56.84	57
12	720	32	95.56	24375	37500	65.00	31250	6875	78	48.45	49
13	720	48	93.33	24375	37500	65.00	31250	6875	78	47.32	48
14	720	26	96.39	26250	37500	70.00	31250	5000	84	56.68	56
15	720	192	73.33	21875	37500	58.33	31250	9375	70	29.94	29
16	720	48	93.33	24375	37500	65.00	31250	6875	78	47.32	48
17	720	58	91.94	27500	37500	73.33	31250	3750	88	59.33	59
18	720	56	92.22	26250	37500	70.00	31250	5000	84	54.23	55
19	720	51	92.92	22917	37500	61.11	31250	8333	73	41.64	42
20	720	32	95.56	27500	37500	73.33	31250	3750	88	61.67	61
21	720	56	92.22	21875	37500	58.33	31250	9375	70	37.66	37
22	720	68	90.56	24375	37500	65.00	31250	6875	78	45.91	46
23	720	62	91.39	21875	37500	58.33	31250	9375	70	37.32	37
24	720	28	96.11	26250	37500	70.00	31250	5000	84	56.51	56
25	720	40	94.44	27500	37500	73.33	31250	3750	88	60.95	60
26	720	16	97.78	21875	37500	58.33	31250	9375	70	39.93	40
27	720	48	93.33	24375	37500	65.00	31250	6875	78	47.32	48
28	720	52	92.78	26250	37500	70.00	31250	5000	84	54.55	55
29	720	24	96.67	24375	37500	65.00	31250	6875	78	49.01	49
30	720	33	95.42	22917	37500	61.11	31250	8333	73	42.76	43
31	720	48	93.33	26250	37500	70.00	31250	5000	84	54.88	55
32	720	69	90.42	21875	37500	58.33	31250	9375	70	36.92	37
33	720	46	93.61	27500	37500	73.33	31250	3750	88	60.41	60
34	720	64	91.11	24375	37500	65.00	31250	6875	78	46.19	47
35	720	46	93.61	21875	37500	58.33	31250	9375	70	38.22	38
36	720	48	93.33	27500	37500	73.33	31250	3750	88	60.23	60

DT: Downtime **A:** Availability **P:** Performance **Q:** Quality
DPA: Defect Produced amount. **APA:** Actual Produced Amount.
PPA: Proposed Produced Amount **T/Time**: Total Time.