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Research Article

Determining and forecasting OEE based on reliability and maintainability using polynomial regression and neural networks

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Abstract

Production maintenance ensures equipment remains in good working order, enabling the generation of goods complying with specifications. The purpose of this research was to assess and evaluate the machine performance in one of the plastic industries. This research will determine how machine performance is correlated with OEE, MTBF, and MTTR, optimise the OEE variables and forecast the future OEE values. The relationship between OEE, MTBF, and MTTR has been analysed by linear and non-linear regression using polynomial and artificial neural networks (ANN). Meanwhile, the OEE optimization is performed using SciPy optimizer on linear and nonlinear objective functions, whereas the OEE forecasting employs Convolutional Neural Network (CNN) in addition to the ANN and the polynomials. All regression analysis indicate OEE is well explained by MTBF and MTTR as all R-squared values are above 95%. Specifically, those R-squared values are 98.25%, 97.78%, 97.64%, and 95.56%, for ANN, polynomial degree 3, degree 2 and degree 1, respectively. Furthermore, the optimal value of MTBF is found to be at least 3.706 whereas that of MTTR is at most 0.899 hours to achieve an OEE value of at least 0.85. Lastly, the accuracy of OEE predictions using CNN achieves the best performance by having the lowest RMSE of 0.0156, followed by ANN with an RMSE of 0.0166, and the polynomials with RMSEs of around 0.02.

Keywords: OEE; MTBF; MTTR; Regression; Neural network

1. Introduction

Plastics have become an essential component in every technology sector to make human life simple and comfortable (Pathak et al., 2023). Plastic is inexpensive and its properties make it a popular alternative to metals and wood in various applications. It is also advantageous in production due to their ease of softening or melting and their ease of being molded into many shapes (Islam, 2012). The plastics industry has grown due to low production costs and energy-efficient techniques and is one of the main users of non-renewable resources and sustainability aspects that should be considered (Mwanza & Mbohwa, 2017). The plastics sector is a large contributor to the world economy, exceeding both Gross domestic product and energy demand (Pathak et al., 2023).

The manufacturing business establishes production targets to satisfy customer delivery expectations. Sustaining consistent and hygienic machine conditions is essential to maintaining output in proportion to production capacity. Production maintenance ensures that equipment remains in good working order, enabling the generation of good meeting specifications. The dependability of an industry's machinery significantly influences its capacity to compete. More extensive maintenance procedures are undoubtedly required for older, heavily used machinery. When the final products fail to meet expectations, the production machine is not operating optimally. Therefore, to ensure that the production process is efficient and high-quality, it is imperative to enhance the quality of efficient machine maintenance (Nurcahyo, Winanda, et al., 2023). Reliability, operating rate, and maintenance costs are considered while developing maintenance strategies for automated manufacturing lines (Li et al., 2018). The costs of downtime, redundancy, and item reliability characteristics are some of the elements that influence the choice of maintenance method (Stenström et al., 2016) . The time allotted for preventive maintenance is dependent on the critical component reliability values. Preventive maintenance will be performed to obtain and increase the reliability value in the future (Pamungkas et al., 2021).

The mean time between a machine's first failure is known as MBTF. A system component or piece of equipment fails when it can't operate as intended in a given situation. Furthermore, the average time between a failure and a device's ability to function again is called the maintenance time to repair (MTTR) (Ahmadi et al., 2019a). MTBF and MTTR are crucial for production system analysis, sustainable improvement, and design (Alavian et al., 2018). An earlier study proposed a framework for conducting a study on reliability, availability, and maintainability (RAM) to evaluate the performance of power generation machines in office infrastructure (Nurcahyo, Tri Nugroho, et al., 2023). RAM are the three metrics utilized for evaluating maintenance performance and assessing machine performance (Pamungkas et al., 2021).

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Beside that, overall equipment effectiveness (OEE), measures how well the current production and manufacturing process units operate over a given period with their intended capability(Ahmadi et al ., 2019b). The probability that a device or system will function properly at a given time when used under certain ideal conditions is known as availability (Simon et al., 2014). MTBF, MTTR, OEE, and Availability are preliminary analyses used to identify faults and define the machine's condition (Pamungkas et al., 2021; Ribeiro et al., 2019).

Iran Khodro, the leading automotive producer in Iran and the Middle East, has transitioned to using compressed air, derived from contaminated air, as an alternative to energy to optimize its production processes. To achieve this goal, the corporation has created a polluted air department equipped with 50 air compressors, including screw and centrifugal models. Over time, the department has consistently expanded in size. They calculate OEE to find out the effectiveness of the compressors used (Larky & Javidrad, 2019).-Another example in the railway industry, the cost-benefit analysis method is used to conduct cost-based analysis for maintenance performance assessment (Stenström et al., 2016). In the broader logistics context, this approach can be useful to assess the cost-effectiveness of various processes and interventions. However, the assessment scope in earlier research was somewhat constrained, with a primary emphasis on the conventional OEE components. In rather large research aimed at broadening the area of OEE applications, the scope of evaluation has mostly been limited to taking equipment or process utilization, operating speed (performance), and quality into account as part of an overall efficiency evaluation (Garza-Reyes, 2015).

Taking into account the challenges and prevailing trends, this corporate performance study focused on maintenance operations in the plastics industry will be conducted by calculating the OEE, maintainability, and reliability. Hence, this study attempts to determine the OEE based on the MTBF and MTTR values instead of all determinant variables consisting of availability, quality, and performance. The feasibility of our approach will be validated using regression analysis with polynomial functions and Artificial Neural Networks (ANN). The suitability of polynomial functions and ANN for regression has been presented in several literatures (Kim et al., 2020; Krulický & Brabenec, 2020; Lee et al., 2017; Mattas et al., 2021).

Furthermore, it is necessary to undertake numerical analysis because the industry frequently encounters excess stock and product delivery shortages(Haber & Fargnoli, 2022; Hosseini et al., 2024; Sayuti et al, 2019) due to unforeseen equipment breakdowns. OEE provides an overview of a company's performance based on historical data, but it does not optimize or predict future performance, which is useful for anticipating problems(Kechaou et al., 2024).

Optimization of OEE parameters, namely the availability, quality, and performance, has been analyzed through various methods, including Genetic Algorithms (VivekPrabhu et al., 2014) and Response Surface Methodology (Chikwendu et al., 2020; Tonny et al., 2023) Similarly, the optimal values of stock keeping units for OEE has been computed by Linear Programming using LINGO Optimizing Software and Excel Solver (Encarnacion et al., 2022). In this study, the OEE parameters to optimize are the MTBF and MTTR while the method to optimize is the SciPy which can handle both linear and non-linear optimization (Virtanen et al., 2020), as the objective functions of MTBF and MTTR are formed using linear function (Polynomial of degree 1) as well as non-linear functions (Polynomial of degree 2 and 3, and Artificial Neural Networks).

In addition, OEE calculations are often performed by the end of the production cycle, which makes it quite late to provide necessary improvements. Hence, it is necessary to predict the estimate of OEE value in advance to allow managers to examine the inputs of the production process.

Machine learning-based models have been used to predict future OEE values, such as SVM, random forest, gradient boosting, and deep neural networks (El Mazgualdi et al., 2020), a combination of ANN and genetic algorithm (Al-Toubi, 2023) and a combination of moving average and adaptive neuro-fuzzy inference system. Convolutional neural networks (CNN) have produced excellent results for time series domains, according to recent studies (Asesh & Dugar, 2023; Hou et al., 2018; Markova, 2022). Meanwhile, Artificial Neural Network (ANN) has become more popular for fitting statistical models and research aimed at deep learning to forecast, predict, and capture time trends production (Jahn, 2018; Wang, et al, 2023). Hence, this study investigates CNN's and ANN's suitability for OEE forecasting based on MTBF and MTTR values.

Since there has been no previous research discussing machine performance assessment using OEE, MTTR, and MTBR indicators, as well as optimizing and forecasting these OEE, MTTR, and MTBF indicators, this research is conducted. The aim of this research includes:

1. Determining machine performance based on OEE, MTBF, and MTTR by examining the relationship between OEE, MTBF, and MTTR.
2. Optimizing the MTBF and MTTR to achieve the OEE threshold value as an indicator of machine effectiveness.
3. Forecasting the future values of OEE based on the previous values of OEE or the previous values of MTBF and MTTR as a basis for management decision-making.

The contributions of this paper are as follows:

1. Instead of using all variables which determine the OEE, this study stresses on the use of MTBF and MTTR.
2. The use of linear and non-linear functions as the objective functions during the optimization of OEE based on MTBF and MTTR values.
3. Comparing the feasibility of CNN, ANN and polynomial functions to forecast the OEE values.

2. Literature Review

2.1. Machine Performance

The most important and widely used performance metrics in manufacturing are productivity and quality and OEE is a quantitative metric that is increasingly used in the industry not only to control and monitor the productivity of production equipment but also as an indicator and driver of process and performance improvement. OEE is capable of measuring performance, identifying development opportunities, and directing improvement efforts towards areas related to equipment or process utilization (availability) such as MTBF, MTTR, operational level (performance), and quality (Arturo Garza- Reyes et al., 2010)

2.1.1 Overall Effectiveness Equipment (OEE)

Compared with when it was first developed, the OEE application is now more extensive. At the point, OEE is a method for efficient corrective maintenance actions before significant failure occurs and can be used as an indicator in a process to determine whether to conduct process improvement activities (Nurcahyo, et al., 2023). OEE is one of the performance evaluation methods that are most common and popular in the production industries (S. Nayak et al., 2020). Organizations, in this case the industry and other businesses, make these attempts to carry out continual improvements, which ultimately lead to further advances. Each industry is expected to grow and endure into the future while keeping up with the times thanks to growing power and competition (Nurcahyo et al., 2019) To guide remedial action, OEE seeks to identify lost time in the production system (Kechaou et al., 2024). Furthermore, organizations can evaluate their current state and begin to enhance them using OEE (Kifta & Putri, 2021). OEE offers a quantitative matrix to assess the efficiency of machinery and process performance based on availability, performance, and quality (Garza-Reyes, 2015). The OEE calculation is as follows (Nakajima, S., 1988):

$$OEE = AV\ x\ PE\ x\ QR \tag{1}$$

where AV is Availability, PE is Performance Efficiency, QR is Quality Rate.

The relationship between the time available for production and the actual time that production equipment is employed is referred to as availability (Kechaou et al., 2024). According to (Kechaou et al., 2024), scheduled downtime can be acquired through rest, meetings, preventive maintenance, and machine cleaning. The availability calculation is as follows (Nakajima, S., 1988):

$$AV = \frac{Planned\ Production\ Time - Down\ Time}{Planned\ Production\ Time}\ x\ 100\% \tag{2}$$

The link between production time and time available for production is referred to as performance efficiency (Kechaou et al., 2024). To show the relationship between the quantity produced and the production time of the machine, the number of products also influences the Performance Efficiency rating (Nakajima, S., 1988)

$$PE = \frac{Total\ Product\ x\ Ideal\ Rate\ Run}{Planned\ Production\ Time - Down\ Time}\ x\ 100\% \tag{3}$$

The quality factor or quality rate calculates the number of faults. When there is a production failure, defective products impact production. The quality rate was calculated using the following formula (Nakajima, S., 1988):

$$.QR = \frac{Good\ Product}{Total\ Product}\ x\ 100\% \tag{4}$$

2.1.2 Mean Time Between Failure (MTBF)

The reliability of machines takes regular machine failures and planned downtime into account. The equation is used to calculate reliability using the MTBF formula (Dervitsiotis, 1981):

$$MTBF = \frac{Planned\ Production\ Time - Down\ Time}{Breakdown\ Frequency} \tag{5}$$

2.1.3 Maintenance Time To Repair (MTTR)

The maintainability of the machine is influenced by the time and frequency of machine breakdowns. Equation is used to calculate maintainability using the MTTR formula (Dervitsiotis, 1981):

$$MTTR = \frac{Breakdown\ Time}{Breakdown\ Frequency} \tag{6}$$

2.2 Optimizing and forecasting

Calculations for optimizing and forecasting analysis can use, among others, linear regression, polynomial regression, and ANN. However, for forecasting, CNN analysis can be added.

2.2.1 Linier regression

Regression analysis is typically employed in forecasting and prediction, where its use closely parallels the field of machine learning (Jia et al., 2019). Crucially, regression analysis by itself only reveals relationships between a dependent variable and a defined dataset made up of many variables (Maulud & Abdulazeez, 2020). According to (Kumari & Yadav, 2018), linear regression is a type of regression that displays a linear relationship and further determines the correlation between the dependent variable and the independent variable predictor. Simple regression is a form of linear regression that involves using only one predictor variable to determine the target variable (Patil & Patil, 2021). While the independent variables may be categorical or continuous, the target value must be real or continuous (Patil & Patil, 2021). The equation for simple regression is as follows:

$$y = a_0 + a_1 x + \varepsilon \tag{7}$$

Where, a_0 = intercept of line, a_1 = slope of line, e = error/ miscalculation, x, y = predictor and target respectively. Multiple linear regression analysis is conducted when there are multiple predictor values that have a cause-and-effect connection with the target value (Uyanık & Güler, 2013). In the context of simple regression, multicollinearity—the lack of intercorrelation between the values of the predictors—occurs infrequently or never at all. The equation for multiple regressions is as follows:

$$y = b_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + \ldots + b_n x_n \tag{8}$$

Where, y = output/response variable, b0, b1, b2, b3, bn = coefficients of the model, and x1, x2, x3, xn = predictor value.

2.2.2 Polynomial regression

Polynomial regression is a specific form of linear regression that is used when the linear regression model has low accuracy or efficiency because of numerous errors or miscalculations (Patil & Patil, 2021). To obtain the highest accuracy while minimizing the effects of over-fitting or under-fitting, we often fit the regression line using a polynomial equation that fits the data in the best curvilinear form. Since linear regressions do not perform well in this situation, the dataset that was run through the model was primarily nonlinear (Patil & Patil, 2021). The equation for multiple regressions is as follows:

$$y = b_0 + b_1 x^1 + b_2 x^2 + b_3 x^3 + \ldots + b_n x^n \tag{9}$$

Where, y = output/response variable, b0, b1, b2, b3, bn = coefficients of the model, and x1, x2, x3, xn = predictor value.

2.2.3 Artificial Neural Networks (ANN)

ANN, which has been used successfully in both classification and regression problems *(Jacob Hallman, 2019; Jahn, 2018)* typically consists of multiple layers of nodes with an input layer that receives data having various features and an output layer for the final output. Fig 1 illustrates a fully connected neural network with one input layer, two hidden layers, and an output layer. The general function of an ANN, as stated in *(Crone & Kourentzes, 2009)*, can be written as follows:

$$f(X, w) = \beta_0 + \sum_{h=1}^{H} \beta_h g(\gamma_0 + \sum_{i=0}^{I} \gamma_{hi} x_i) \tag{10}$$

Where x = [x0, x1, ..., xn] is the vector of input data having n features and w = (β, γ) are the weights. Where I and H are the number of input and hidden units in the network, respectively, and g is a nonlinear transfer function. During the experiment, the transfer functions used in hidden nodes are the Rectified Linear Unit (ReLU), which produces 0 as an output when $x < 0$ and produces a linear with a slope of 1 when $x > 0$, as stated in (Agarap, 2018). A multilayer neural network with only one hidden layer is capable of approximating a continuous function of n real variables arbitrary well (Csáji, 2001; Hsu et al., 2021)

2.2.4 Convolutional neural networks (CNN)

CNNs are a analysis technique that may be applied to environmental and climate change data to identify, categorize, and predict patterns (Haidar & Verma, 2018; Shu et al., 2021). In addition, the CNN module is employed to detect the local trend of the load data pattern (Rafi et al., 2021). CNN are network topologies commonly utilized in machine vision and classification applications (Haidar & Verma, 2018). As a result, several activation functions have been n used to map the input features into a set of categories. A CNN comprises of three layers: convolutional, pooling, and fully connected. A 2-dimensional CNN is usually used for image classification while 1-dimensional CNN can be employed for time series forecasting. (Haidar & Verma, 2018; Asesh & Dugar, 2023).

3. Methods

The purpose of this study was to assess machine performance in the plastic industry. The steps to assess such performance include collecting and analyzing data related to OEE from the plastic industry that supplies straws for the packaged beverage industry. The next step is to determine the relationship between the independent variables (MTBF and MTTR), and its dependent variables (OEE). The optimum values of the dependent variables are then determined by the optimization function. Finally, the future values of OEE are forecasted based on either the dependent variables or the previous value of OEE itself. The afore mentioned steps are illustrated in Fig 1.

One production line uses the following four machines: an extruder machine, a flexible machine, a wrapping machine, and a packing machine. Considered factors for evaluating performance include total machine efficiency, maintenance capability, and machine reliability. MTBF is used to measure the ability and reliability of a machine, MTTR for machine maintenance, and OEE to measure the overall effectiveness of the machine.

Data collection was taken from the industrial maintenance division data for a period of 1 year, January-December 2023. The data used are the planned production time, down time, ideal run time, breakdown time, breakdown frequency, total product, and Good Product. To make changes increase performance, the first step is to identify issues in order to determine the reason for poor engine performance. Finding the most recent study based on issues that emerge is how literature reviews are completed. To identify the machines that required ongoing improvement, data processing was performed on four of the machines before the study was conducted.

Fig 2 shows the relationship among the parameters availability, performance efficiency, quality rate, reliability, and maintainability.

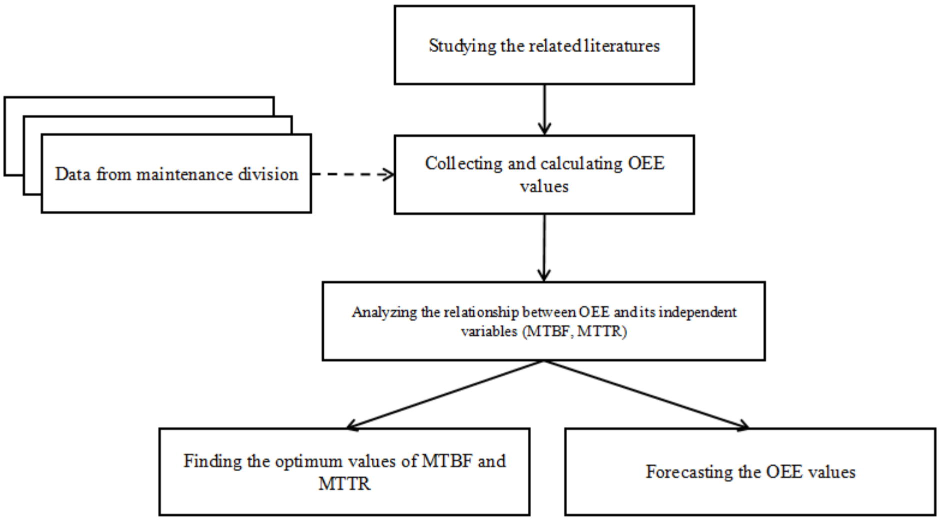


Fig 1. Study stages

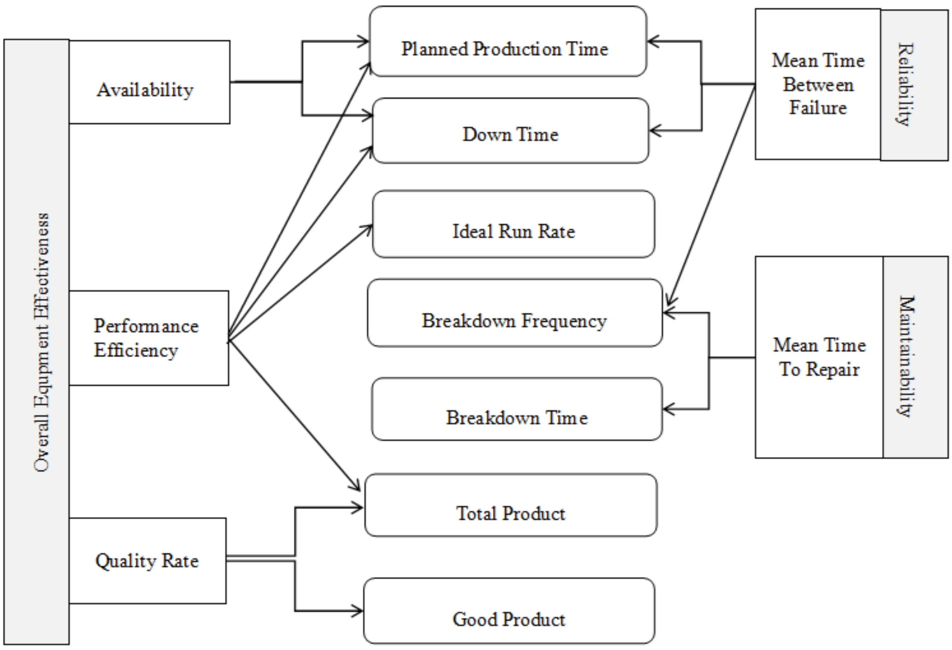


Fig 2. Production maintenance data correlation

The computation of machine performance involves the interdependence of OEE, reliability, and maintainability. The OEE calculation includes an important element known as availability, which is strongly tied to reliability and is dependent on reliability and maintainability (Schiraldi, 2013). The OEE calculation measures asset management effectiveness based on reliability, availability, and maintainability indicators (Arturo Garza- Reyes et al., 2010; Gibbons & Burgess, 2010). The OEE availability equation emphasizes on maintenance, which is classified as MTTR, whereas OEE availability focuses on the total time between failures, classified as MTBF (Gibbons & Burgess, 2010)

Table 1
Calculation of OEE criteria

Month	Mc. Extruder			
	Av	PE	QR	OEE
January	95,29%	85,40%	99,60%	81,05%
February	95,36%,	80,26%	99,20%,	75,92%
March	95,44%,	80,53%	98,40%,	75,63%
April	95,42%,	90,13%	98,90%,	85,05%
May	95,29%	92,75%	98,80%,	87,32%
June	95,42%,	89,32%	99,00%,	84,37%
July	95,29%	84,32%	99,11%,	79,64%
August	95,29%	83,65%	98,80%,	78,76%
September	95,42%,	77,14%	99,00%,	72,86%
October	95,29%	79,34%	98,10%,	74,16%
November	95,56%	84,71%	98,70%	79,90%
December	95,44%,	84,70%	98,00%	79,22%
Average	**95,38%**	**84,35%**	**98,80%,**	**79,49%**
	Mc. Flexible			
January	**Av**	**PE**	**QR**	**OEE**
February	95,29%	85,06%	98,99%	80,23%
March	95,36%,	79,61%	98,91%	75,09%
April	95,13%	84,98%	98,85%	79,91%
May	95,42%,	89,14%	98,98%	84,19%
June	95,29%	91,63%	98,99%	86,44%
July	95,42%,	88,42%	98,82%	83,38%
August	95,29%	83,57%	98,21%	78,21%
September	95,29%	82,65%	98,86%	77,86%
October	95,42%,	76,36%	98,90%,	72,06%
November	95,44%,	75,20%	98,91%	70,99%
December	95,42%,	86,53%	97,92%	80,85%
Average	**95,44%,**	**83,00%**	**98,90%,**	**78,35%**
	Mc. Wrapping			
January	94,35%	102,05%	98,30%	94,64%
February	95,36%,	78,74%	98,90%,	74,26%
March	95,13%	84,01%	98,10%,	78,40%
April	95,42%,	88,23%	98,80%,	83,18%
May	95,29%	90,71%	98,40%,	85,05%
June	95,42%,	87,38%	98,44%	82,08%
July	95,29%	82,08%	98,44%	76,99%
August	95,29%	81,71%	98,91%	77,01%
September	95,42%,	75,53%	99,22%	71,50%
October	95,44%,	74,38%	97,70%	69,36%
November	95,42%,	84,73%	97,90%	79,15%
December	95,44%,	82,09%	98,21%	76,95%
Average	**95,27%**	**84,30%**	**98,44%**	**79,05%**
	Mc. Packing			
January	95,29%	82,77%	98,60%,	77,77%
February	95,67%	72,45%	98,09%	67,99%
March	95,29%	79,53%	98,99%	75,02%
April	95,09%	93,72%	98,80%,	88,05%
May	95,29%	89,26%	98,93%	84,14%
June	95,42%,	86,02%	98,92%	81,19%
July	95,29%	80,80%	99,10%	76,30%
August	95,29%	80,82%	99,01%	76,25%
September	95,42%,	74,94%	98,90%,	70,72%,
October	95,29%	75,21%	98,91%	70,89%
November	95,42%,	82,95%	98,77%	78,18%
December	95,29%	83,44%	98,10%,	78,00%
Average	**95,34%**	**81,82%**	**98,76%**	**77,04%**

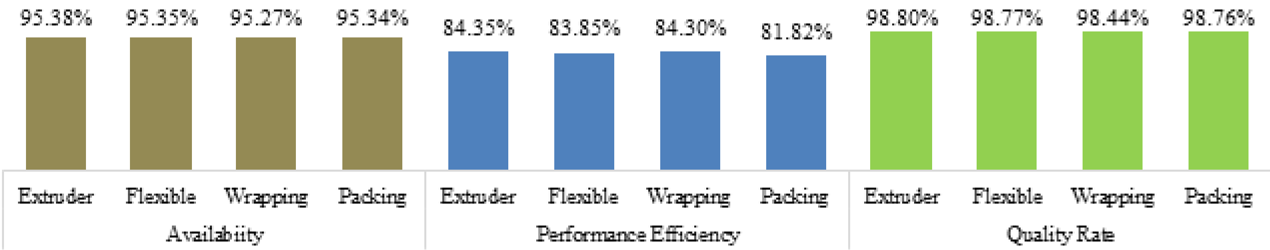


Fig. 3. Calculation of the OEE values

4. Results and Discussion

4.1. OEE calculation

The information gathered was derived from production and maintenance log sheet data and interviews with maintenance professionals. Calculation of OEE criteria is shown Table 1. The average OEE of every machine for each criterion, if shown as a graph, is described in Fig 3. Out of all OEE variables and the three supporting sub-variables, the extruder machine has the highest value in availability (95,38%), performance efficiency (84,35%) and quality rate (98,80%) and shows that out of the four machines, the extruder machine is the best condition, can produce the most items as planned and fewest rejected products. The lowest OEE (77,04%), including the performance efficiency sub-variable, packing machine requires greater attention. Packing machine has the lowest anticipated production time because they are the most likely to breakdown. One of the machines has the highest repair time (4 h 42 min and 36 s) and the highest breakdown frequency (32 times a year).
and improved quality control procedures are required to increase operational efficiency. A business needs a quality improvement plan if the OEE value is below the value (Kifta & Putri, 2021).

Table 2
Ideal OEE versus calculated OEE

Criteria	Ideal Value	Calculation results			
		Extruder	Flexible	Wrapping	Packing
Availability	>90%	95,38%	95,35%	95,27%	95,34%
Performance Efficiency	>95%	84,35%	83,85%	84,30%	81,82%
Quality Rate	>99%	98,80%,	98,77%	98,44%	98,76%
OEE	**>85%**	**79,49%**	**78,96%**	**79,05%**	**77,04%**

Table 2 shows the comparison of ideal values calculation of OEE. In contrast to the ideal OEE value is 85% (Nakajima, S., 1988), four machines in the plastic industry satisfy the availability criteria with an ideal value of >90% but none satisfy it; none of them satisfy the performance efficiency criteria with an ideal value of >95%; and also none of them satisfy the quality rate criteria with an ideal value of >99%. In conclusion, none of the equipment used in the plastic industry satisfies the optimal OEE value. This demonstrates that even though there is hardly any downtime for machines, output quality and operational efficiency are still top priorities. The lack of tools that provide the optimal OEE value indicates that availability, performance efficiency, and quality level are not balanced. Machine performance audits, improved maintenance, increased operational training,
Because it entails judgments about corporate policy that must be developed, top management approval is required. Availability of machines to produce products as planned. From the planned time, almost all machines can be used and operated within the planned production time. The performance efficiency of the machines in the plastic industry is below the ideal value because to determine the ideal run rate value, more analysis must be done in accordance with production capacity and available resources, which will make the ideal run rate value more representative.
The quality rate is still within the adequate limits even though it is below the ideal value because the plastic industry management policy provides a maximum product rejection target of 2%.
The OEE results from the plastic industry are below ideal values; therefore, companies need to increase machine capacity, train operators, and develop preventive maintenance to ensure the best machine performance (Kifta & Putri, 2021). The next step is to determine a strategy to increase the OEE value because
not all machines have the same maintenance strategy depending on the type of machine, operating conditions, and the time value of the machine (García & Salgado, 2022).
Table 3 shows the calculations of OEE, MTBF and MTTR over the course of a year by looking at the details per month. The OEE in 2023 is 0.786 (78.6%). The value is still below the ideal OEE so that requires evaluation and improvement measures for the performance of the next machine by continuous improvement in their products, processes, production facility and identify the important components in the system (D. M. Nayak, 2013; Sayuti et al, 2019; Simon et al., 2014)

Table 3
OEE values per months

Month	Av	PE	QR	OEE (Av x PE x QR)
January	0,951	0,888	0,988	0,834
February	0,954	0,778	0,988	0,733
March	0,952	0,823	0,986	0,772
April	0,953	0,903	0,989	0,851
May	0,953	0,911	0,988	0,857
June	0,954	0,878	0,988	0,828
July	0,953	0,827	0,987	0,778
August	0,953	0,822	0,989	0,775
September	0,954	0,760	0,990	0,718
October	0,954	0,760	0,984	0,714
November	0,955	0,847	0,983	0,795
December	0,954	0,833	0,983	0,781
Average	**0,953**	**0,836**	**0,987**	**0,786**

Table 4
Comparison MTBF, MTTR, and OEE

Month	**Mc. Extruder**			**Mc.Flexible**			**Mc.Wrapping**			**Mc. Packing**		
	MTBF	MTTR	OEE	MTBF	MTTR	OEE	MTBF	MTTR	OEE	MTBF	MTTR	OEE
January	4,765	0,180	0,811	0,000	0,000	0,802	0,000	0,000	0,946	2,382	0,180	0,778
February	2,967	1,070	0,759	0,742	0,857	0,751	1,483	0,853	0,743	4,783	1,740	0,680
March	0,000	0,000	0,756	0,000	0,000	0,799	0,000	0,000	0,784	2,382	0,060	0,750
April	4,771	0,066	0,851	0,000	0,000	0,842	2,385	0,102	0,832	0,000	0,000	0,880
May	3,176	0,030	0,873	0,000	0,000	0,864	4,765	0,059	0,851	3,176	0,475	0,841
June	4,771	0,161	0,844	0,000	0,000	0,834	0,000	0,000	0,821	1,908	0,195	0,812
July	3,176	0,137	0,796	0,000	0,000	0,782	3,176	0,027	0,770	2,382	0,319	0,763
August	0,000	0,000	0,788	2,382	0,258	0,779	0,000	0,000	0,770	0,000	0,000	0,763
September	0,000	0,000	0,729	0,000	0,000	0,721	1,590	1,023	0,715	3,181	1,658	0,707
October	3,176	1,533	0,742	0,000	0,000	0,710	1,409	0,543	0,694	0,000	0,000	0,709
November	4,938	0,380	0,799	0,000	0,000	0,808	3,181	0,045	0,792	1,363	0,082	0,782
December	0,000	0,000	0,792	0,000	0,000	0,784	3,288	1,261	0,769	0,000	0,000	0,780
Average	3,967	0,445	**0,7949**	0,2603	0,558	**0,7896**	2,660	0,489	**0,7905**	2,695	0,589	**0,770**

4.2. Relationship between OEE, MTBF, MTTR,

The average values of the OEE MTBF, and MTTR of the four machines collected from the industrial maintenance division over a one-year period are shown in Table 4.
The machine with the highest MTBF is the most reliable because the distance between each failure and other damage is the furthest, namely, on the extruder machine. The extruder machine also has a high availability value compared with the other three machines, however, based on the frequency of machine failure, which are rare, flexible machines have the best MTBF because breakdowns occur only in February and August.
MTTR with the value is the one with the smallest value. The extruder machine has the smallest MTTR value, indicating the fastest repair process. The highest OEE value is owned by the extruder machine, indicating that the extruder machine can be considered the most effective compared to other machines. Therefore, based on the results of the extruder machine, it can be concluded that the OEE value is directly proportional to the MTBF and inversely proportional to the MTTR.

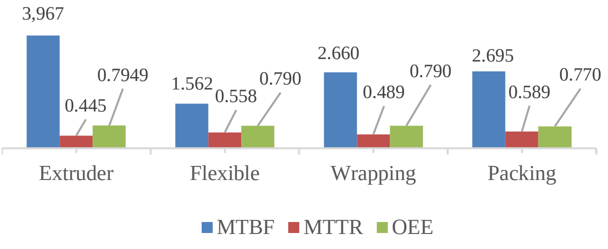


Fig. 4. Relationship between the MTBF, MTTR, and OEE values

Fig 4 shows a graph of the relationship between the MTBF, MTTR, and OEE values for each machine in the plastic industry, and no corrective action has been
taken for problems related to machine failure. The MTBF values appear to be more fluctuating in the four machines when compared with the values of MTTR and OEE.

4.3. Multiple linear regression for OEE,MTBF, TTR

In addition to the calculation and observation of OEE results, validation of the relationship between OEE, MTBF, and MTTR is necessary. The SPSS (Statistical Package for the Social Sciences) software is the instrument used for testing. Based on the SPSS output, the Entered/Removed Variables column indicates the variables used in this study, and the Entered Variables column shows the independent variables used. It can be seen that the independent variables are MTTR and MTBF. It can be explained that R-Square is the proportion of variance in the independent variables that can be explained by the dependent variable. There was a 96.6% variation in MTTR and MTBF, as explained by the OEE value

Table 5.
SPSS results of the coefficients

Model	**Unstandardized Coefficients**		**Standardized Coefficients**	**t**	**Sig.**
	B	**Std. Error**	**Beta**		
(Constant)	.614	.024		26.067	.000
MTBF	.065	.007	.722	8.986	.000
MTTR	-.039	.008	-.413	-5.145	.001

a. Dependent Variable: OEE

Table 5 demonstrates that the significance level (sig,) <0.05, indicating that the variable has a high influence on the dependent variable. MTBF has a considerable positive effect (8.986) on OEE, however MTTR has a significant negative impact (-5.145).

Based on the results of multiple linear regression analysis calculations using SPSS, the following equation is obtained:

$$y = 0{,}065x1 - 0{,}039x2 + 0.614 \qquad (11)$$

where y is the OEE value, $x1$ represents the MTBF, and $x2$ represents the MTTR.

4.4. Polynomial and Neural Network Regression for Fitting OEE, MTBF, and MTTR values

To complement the SPSS validation result on multivariate linear regression, this study also attempts to determine the nonlinear relationship between OEE as a dependent variable and MTBF and MTTR as independent variables. This nonlinear relationship is simulated using polynomials of degrees 2, 3, and the ANN. The polynomial of degree 1 was also computed for comparison with the previous calculation. The values of MTBF, MTTR, and OEE were first averaged before data processing with Python, as indicated in Table 6.

From these average values, multivariate polynomial regression computations with a degree of three are then performed in Python, yielding the following equation:

$$Order\ 1: u = ax + by + c \tag{12}$$

$$Order\ 2: u = ax + by + cx^2 + dxy + ey^2 \cdot \tag{13}$$

$$Order\ 3: u = ax + by + cx^2 + dxy + ey^2 \cdot + gx^2 + hxy^2 + iy^3 + j \tag{14}$$

Table 7 displays the constant coefficient values that were discovered throughout the data processing. Subsequently, the multivariate polynomial regression equation is adjusted to include their constant coefficients. For illustration, the third-order polynomial regression equation takes the following form after the constant coefficient values are substituted:

$$u = -3{,}21064\,(MTBF) + 0{,}01508\,(MTTF) + 1{,}04639\,(MTBF)^2 - 0{,}02208\,(MTBF)(MTTR) - 0{,}01416\,(MTTR)^2 - 0{,}10968\,(MTBF)^3 + 0{,}00839\,(MTBF)^2\,(MTTR) - 0{,}01886\,(MTBF)\,(MTTR)^2 - 0{,}00284\,(MTTR)^3 + 3{,}96221 \tag{15}$$

Equation 15 is an optimization equation using the third-order multivariate polynomial regression method, where the coefficient values are based on calculations in Table 7. Meanwhile, for the Neural Networks, the number of inputs is 2, which represents MTBF and MTTR, while the number of nodes in both hidden layers is set to 32, as suggested by the experiments in (Thomas et al., 2015). The output layer requires only one node for the regression problem. Data standardization was performed by eliminating the mean and scaling to unit variance. The standard score of a sample x is determined as z = (x - u) / s, where u is the mean of the training samples and s is the standard deviation. The scaled regression result is later converted back to its original scale. The monthly predicted values of OEE based on the MTBF and MTTR values from the polynomials and ANN are shown in Table 8. For in-sample accuracy, where the testing and training are the same monthly data, the best R2 is produced by Polynomial 3, followed closely by ANN and then Polynomials 2 and 1. For out-of-sample accuracy, where the testing data are set aside from the training data, daily data, which is interpolated from the monthly data, is used because the monthly data are insufficient for further splitting into training and testing. Setting 20% of the data as testing, the best regression accuracy is given by ANN, followed by Polynomial 3, Polynomial 2, and Polynomial 1.

The study uses spline smoothing to fill the time series gaps and obtain the interpolated daily data, as shown in Fig 5. As suggested by (Wang, 2013), spline interpolation, which uses several formulas of a low degree polynomial to pass through all the data points, is preferred over polynomial interpolation because the interpolation error can be minimized. The interpolated daily data of MTBF, MTTR, and OEE are superimposed in two aligned subgraphs in Fig 5 to see the relationship among those variables. As emphasised by the correlation graph in Fig 6, MTBF and OEE are positively correlated whereas MTTR and OEE are negatively correlated.

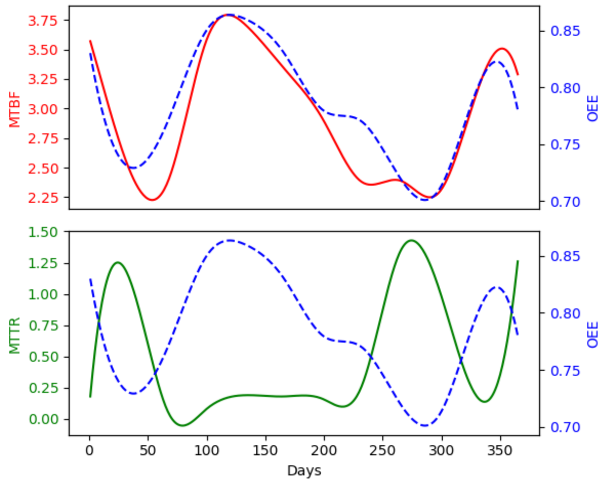


Fig 5. The trends of MTBF, MTTR, and OEE

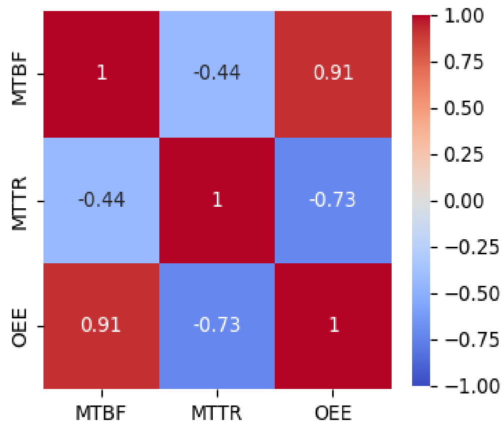


Fig. 6. Correlation coefficients between MTBF, MTTR, and OEE

4.5. Optimizing OEE

The optimal values of MTBF, MTTR, and OEE are determined by setting a minimal OEE value of at least 85%, while MTBF should be as high as possible and MTTR as low as possible. During the experiment, Python's SciPy function, which provides optimization functions for minimizing (or maximizing) objective functions, possibly subject to constraints, is used to determine the optimal values of x variables with the following specification:

Objective function: $y = f(x)$

Constraint: $0{,}85 \leq y \leq 1$

$min\ (MTBF\ values) \leq x1 \leq 1000$

$0 \leq x2 \leq max\ of\ (MTTR\ values)$

Where *f* is either a polynomial function or a neural network for regression. The initial values of MTBF and MTTR can be set to arbitrary numbers and start with the maximum value of MTBF and MTTR. The COBYLA (Constrained Optimization BY Linear Approximation) optimization method is used because it takes the inequality constraints and a scalar value for the objective function. The optimal MTBF, MTTR, and OEE values determined by the SciPy function are shown in Table 9.

The optimal OEE values, which are obtained by applying Polynomials 1, 2, and 3 as well as ANN, are representation of the optimal values for MTBF, MTTR, all 0,85 or 85%, as shown in Table 8. Fig 7 shows the possible paths of MTBF and MTTR to get an optimal OEE value. The area above the optimal point of MTBF and MTTR in these figures indicates the possibility of OEE improvement by increasing the MTBF values beyond that optimal point or by decreasing the MTTR values below that optimal point.

Table 6
Average values of MTBF, MTTR, and OEE

Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
MTBF	3,57	2,49	2,38	3,58	3,71	3,34	2,91	2,38	2,39	2,29	3,16	3,29
MTTR	0,18	1,13	0,06	0,08	0,19	0,18	0,16	0,26	1,34	1,04	0,17	1,26
OEE	0,83	0,73	0,77	0,85	0,86	0,83	0,78	0,77	0,72	0,71	0,8	0,78

Table 7
Coefficient values of the multivariate polynomial regression

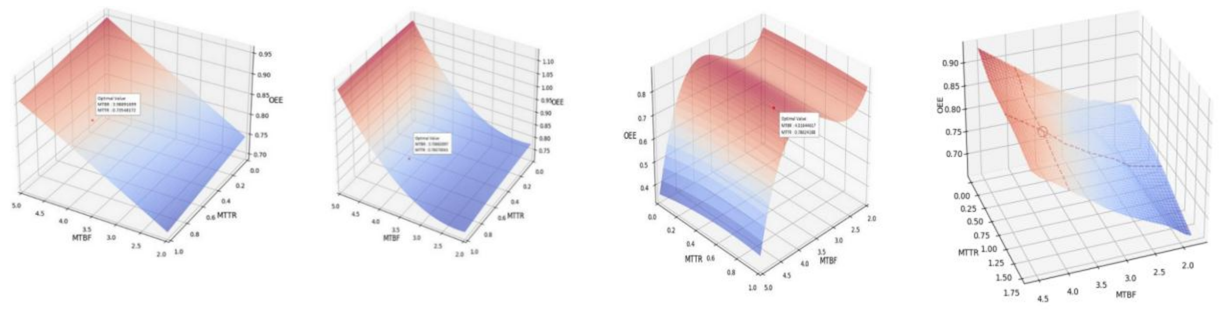
Constant	A	B	C	D	E	F	G	H	I	J
Polynomial order coefficients 1	0,06776	-0,0403	0,60937	-	-	-	-	-	-	-
Polynomial order coefficients 2	0,21357	0,04185	0,04668	0,00888	0,01476	1,01636	-	-	-	-
Polynomial order coefficients 3	3,21064	0,01508	1,04639	0,02208	0,01416	0,10968	0,00839	0,01886	0,00284	3,96221

Table 8
Predicted value of OEE

Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	In-Sample Accuracy (R^2)	Out-of-Sample Accuracy (R^2)
Polynomial 1	0,84	0,73	0,76	0,84	0,85	0,82	0,8	0,76	0,71	0,72	0,81	0,78	**95.29%**	**95.56%**
Polynomial 2	0,84	0,72	0,77	0,85	0,86	0,82	0,79	0,76	0,72	0,72	0,8	0,78	**97.58%**	**97.64%**
Polynomial 3	0,84	0,73	0,77	0,85	0,85	0,82	0,78	0,77	0,72	0,71	0,8	0,78	**99.03%**	**97.78%**
ANN	0,84	0,73	0,77	0,85	0,86	0,82	0,78	0,77	0,72	0,72	0,8	0,78	**98.56%**	**98.25%**

Table 9
Optimal of MTBF, MTTR, and OEE

Methods	Optimal Value of MTBF	Optimal Value of MTTR	Optimal Value of OEE
Polynomial 1	3,98891699	0,73548172	0,850
Polynomial 2	3,70602097	0,78170041	0,850
Polynomial 3	4,01644617	0,78624188	0,850
ANN	3,91003168	0,89954117	0,850



a) Polynomial degree 1 (b) Polynomial degree 2 (c) Polynomial degree 3 (d) ANN

Fig 7. Representation of the optimal values of OEE. MTBF, MTTR

4.6. Forecasting OEE

The main steps to perform forecasting consist of: (1) prepare the dataset, (2) run the predictors, and (3) evaluate the results. The OEE data, which are related to the values of MTBF and MTTR, were collected during a one-year period and aggregated every month. Hence, there are 12 data points available for each variable. To perform multipoint forecasting and properly evaluate the predictor's performances, the number of points needs to be increased, such that it can represent daily data collection. Previously, several authors have suggested the use of interpolation methods to increase the number of time series data, such as in (Lepot et al., 2017; Musial et al., 2011). In addition, during the experiment, the fluctuation of time series is simulated by adding random noise as much as 1% of its standard deviation. In time series forecasting, the prediction of its future values can be calculated based on its own previous values or based on the past values of the others (Daniel Pen˜ a & Ismael Sa´ nchez, 2006; William W. S. Wei, 2006) and explores both the use of univariate time series of the OEE dataset and multivariate dataset of the OEE and its corresponding MTBF and MTTR datasets. As shown in Fig 8, in the case of a univariate time series, its dataset is composed of a certain number of steps or lags (often denoted as x variable) to predict the outcome (denoted as y variable). These collections of (x, y) pairs are further selected as a subset of the training and testing datasets. Similarly, a multivariate time series is also partitioned into several (x, y) pairs; however, the x part is composed of several steps of MTBF and MTTR data, while the y part is that of OEE data. Lastly, the last x data is used to forecast the unknown future OEE values.

In addition to multiple forecasting outcomes, there is another alternative to forecasting just one future point (Marcellino et al., 2006; Taieb & Hyndman, 2012). Hence, to forecast several points, as much as n for example, n number of x data is needed and examines the feasibility of both options of direct multiple forecasting and iterative single forecasting. The neural networks used as forecasting methods have as many input nodes as the number of steps in the univariate time series and as many prediction points as the number of output nodes.

On the other hand, in CNN for multivariate time series, each sample of sequence steps of given variables, such as MTBF and MTTR, is converted into feature maps by convolutional operation with the length of kernel size (Chandra et al., 2021; Hou et al., 2018; Pérez-Enciso & Zingaretti, 2019) . After the pooling and flattening operation, the one-dimensional feature map is fed into a dense ANN. Likewise, CNN can also be applied to univariate time series by substituting the two variables of MTBF and MTTR with a variable of OEE containing the previous values. Fig 9 illustrates the steps in the one-dimensional CNN to forecast the OEE values based on the previous values of MTBF and MTTR of a certain sequence length.

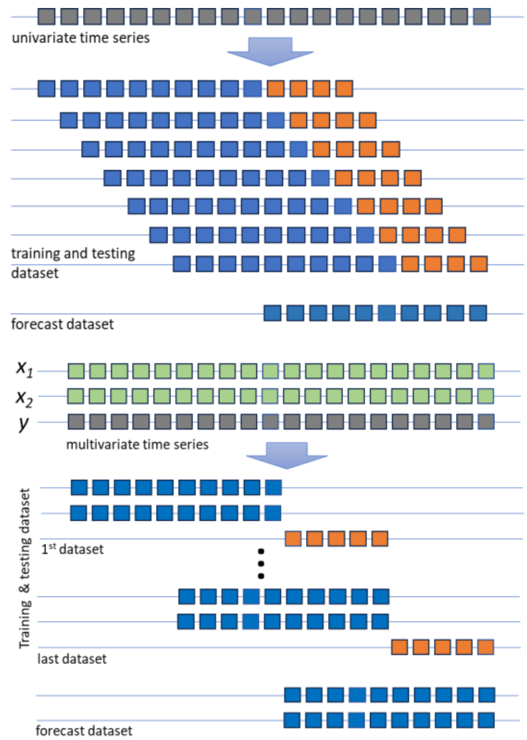


Fig 8. Sequences of training and testing datasets derived from univariate versus multivariate time series

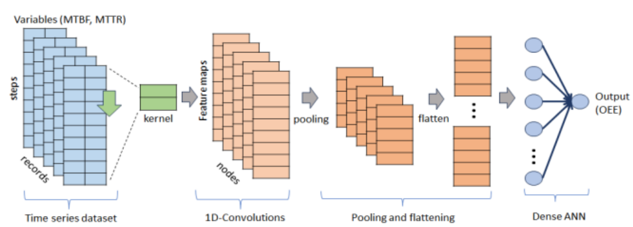


Fig. 9. Architecture of a 1-D CNN

The experiment was implemented using Python code, as described in (Jason Brownlee, 2020). The percentage of samples designated as training is 90%, whereas those designated for testing are 10%. To evaluate the performance of the forecasting methods, several measures are employed, namely the RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), and SMAPE (Symmetric Mean Absolute Percentage Error). The smaller the value of the error, the better the performance of the predictor.

The optimal lengths of the sequence steps of the time series for all predictors were calculated using cross validation of several possible values, such as from 5 to 200 with a multiple of 5, on the training dataset. The optimal value is 150, as shown in Fig 10, as their RMSEs begin to taper off downward. Other settings use the default values as stated in

(Jason Brownlee, 2020). For example, the number of hidden nodes or filters in convolution layers is 64 and that in the dense layer is 50. These numbers are in accordance with the experimental result in (Thomas et al., 2015). In addition, the kernel size and max pooling size are both set to a minimal value of 2 to capture the data locality, as suggested in (Nagi et al., 2014; Sabyasachi Sahoo, 2018).

Table 10 shows the performance of each forecasting method according to these measures. Multiple Input in that table means that the independent variables, namely the MTBF and MTTR, are used as the input, while Multi-Step Output means that the specified number of predictions are directly calculated for each sample. Meanwhile, Univariate Input means that the input is the previous OEE values, and the Iterative single-step output refers to the one-point output of each sample that is repeated iteratively to obtain the specified number of predictions.

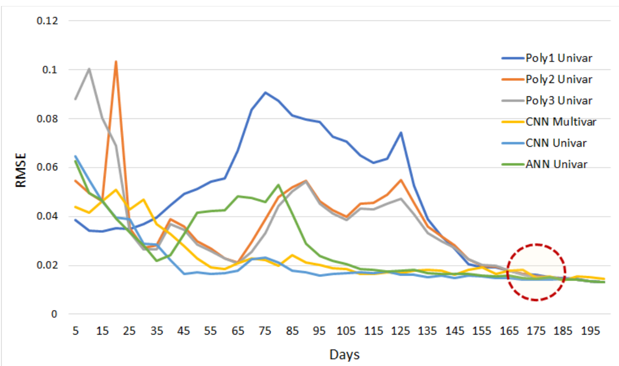


Fig. 10. Optimal length of the time series sequence

The experimental result indicates that CNN using univariate input and multi-step output yields the best result with an RMSE value of 0.0156. All other performance measures, such as SMAPE, MAE, and MAPE, also show the lowest number of errors for this method. Likewise, CNN using multivariate input and multi-step output and ANN using univariate input and multi-step output have very close RMSE results of 0.0157 and 0.0166, respectively. In addition, Polynomials of order 1, 2, and 3 also yield fairly good with RMSE values of 0.0206, 0.0226, 0.0224, respectively.

Table 10
Performance measures among the forecast methods

No	Forecast Methods	RMSE	SMAPE	MAE	MAPE
1	ANN univariate input	0.0166	0.0177	0.0138	0.0182
2	CNN univariate input	**0.0156**	**0.0168**	**0.0130**	**0.0172**
3	CNN multivariate input	0.0157	0.0173	0.0133	0.0177
4	Polynomial order 1	0.0206	0.0217	0.0169	0.0225
5	Polynomial order 2	0.0226	0.0248	0.0186	0.0246
6	Polynomial order 3	0.0224	0.0248	0.0184	0.0244

The results of the prediction on the last data testing and the forecast of future OEE values are shown in Fig 11. To perform the 100-day forecast, it needs the last dataset with a certain length, based on the previously calculated optimum sequence which can be referred in Fig 10. Given a 365 point dataset, for the predictor with multivariate input, it is converted into matrix X with the size of (116, 150, 2) and vector y with the size of (116, 100), where 116 is the number of samples, 150 is the in-steps (or sequence) size, 2 is the number of variables, and 100 is the out-steps (or number of prediction) size. Likewise, for the predictor with univariate input, the matrix X will have the size of (116, 150) and the same size of vector y.

The forecast pattern in Fig 11 indicates that the OEE values for the next 100 days fluctuate according to the future trends predicted by each predictor. Based on these trends, the policy makers in the organisation need to halt or even reverse, the possible downward trend of OEE by maintaining MTBF and MTTR at their optimum values.

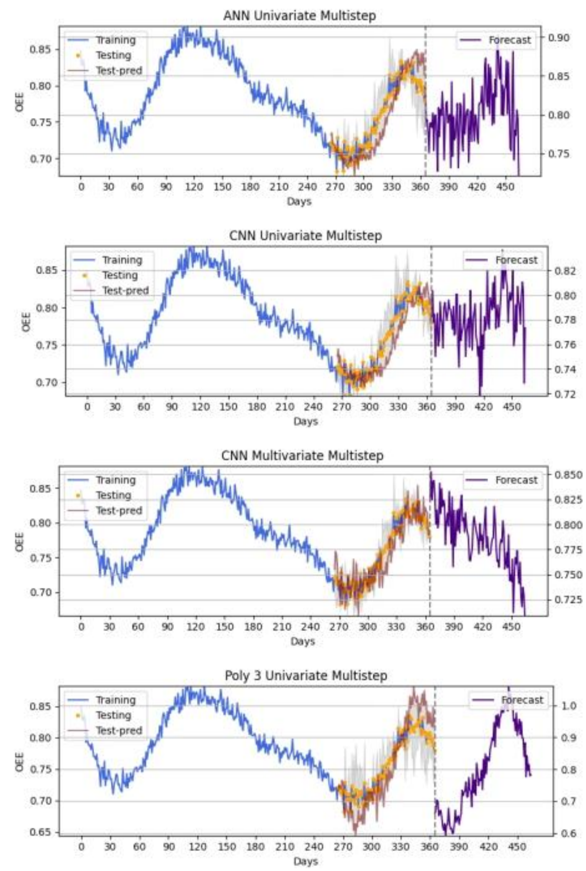


Fig 11. Results of prediction on data testing and future forecasts

5. Conclusion

This study evaluates the reliability, maintainability, availability, performance efficiency, and quality rate of machines in the plastic industry. Four machines were measured: extruder machines, flexible machines, wrapping machines, and packing machines.

Based on the calculation results, the extruder machine shows the best performance and the highest value for availability of OEE, performance efficiency of OEE, and reliability of MTBF. The extruder machines have the highest quality rate OEE and show that the number of good products produced by extruder machines has the smallest rejection rate and it also has the smallest value of maintainability MTTR compared to all other machines. Therefore, it is necessary to prioritize improvements and further analysis of the other machines, namely wrapping machine, packing machine, and flexible machine.

Meanwhile, the relationship between OEE and its independent variables, namely MTBF and MTTR, was analysed by linear and nonlinear regression using polynomial and artificial neural networks (ANN). Using testing data, which is set aside from the training data, the regression accuracies in R-Square are 98.25%, 97.78%, 97.64%, and 95.56% for ANN, polynomial degree 3, degree 2, and degree 1, respectively. Furthermore, by using the SciPy optimization function, which takes a scalar objective function and inequality constraints, the optimal value of MTBF is found to be at least 3.706, whereas that of MTTR is at most 0.899 to achieve an OEE value of at least 0.85.

Furthermore, the accuracy of OEE predictions using CNN achieves the best performance by having the lowest RMSE value of 0.0156, followed closely by ANN which also yields good results by having an RMSE value of 0.0166. The polynomials of degree 1, 2, and 3 also produce decent results as having the RMSE value of about 0.02. The values of the next 100 days' forecast are then calculated based on the last testing dataset.

This research findings can provide direction in the implementation of managerial tasks. By understanding future OEE patterns, management may optimize resource allocation, enhance productivity, and diminish operational expenses. Possible actions encompass maintenance planning, production optimization, problem detection, strategic decision-making, evaluation of improvement efforts' efficacy, and modification of performance targets. The study's findings indicate that machine efficiency management should prioritize machines exhibiting suboptimal performance. Management must perform additional analysis to ascertain the sources of inefficiency and implement suitable corrective actions, including minimizing downtime and enhancing machine reliability. Furthermore, the firm can employ the most suitable machine learning techniques with a high degree of precision for preventative maintenance planning and OEE monitoring. Hence, a data-driven methodology utilizing predictive models and enhanced maintenance can assist management in optimizing operational performance and maximizing productivity within the plastics manufacturing industry.

For future study, a more comprehensive dataset and more diverse type of industries would validate the result even better. In addition, the use of the state-of-the-art of machine learning methods in forecasting would enhance the prediction accuracy.

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