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Backpropagation Neural Network Model for Predicting Spare Parts Demand Under Dynamic Industrial Conditions

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ABSTRACT

Purpose – This study aims to analyze and control spare parts inventory in pumping units using the Artificial Neural Network (ANN) method. The research addresses the challenges of surplus and shortage of spare parts, which directly affect operational continuity, production costs, and company performance. **Design**– A qualitative approach combined with quantitative modeling was employed. Data were collected through observation, the dataset was normalized and divided into three training-testing scenarios (70:30, 80:20, and 90:10). The ANN model with backpropagation was developed and tested using Matlab software, with accuracy evaluated through Mean Squared Error (MSE) and correlation coefficient (R). **Findings –** The results show that Scenario 2 (80% training and 20% testing data) provides the best balance, yielding the highest accuracy. The ANN model captured nonlinear inventory patterns, achieving very low MSE (3.1358e-12) and demonstrating predictive reliability. However, the overall correlation (R = 0.6015) indicates the need for larger datasets and model refinement to improve generalization. **Practical implications** – Applying ANN in inventory management helps companies minimize risks of overstock and shortages, reduce storage costs, and support reliable production planning. This contributes to supply chain resilience and enhances customer trust in operational performance. **Originality/value** – This study presents one of the first applications of ANN for spare parts inventory prediction in Indonesia's pumping unit sector. The findings provide empirical evidence of ANN's effectiveness and offer theoretical as well as practical contributions to the advancement of AI-based inventory management in industrial contexts.

Keywords: Artificial Neural Network, Backpropagation, Inventory Management

INTRODUCTION

The rapid development of industrial technology has brought significant improvements in production efficiency. One of the essential instruments that supports industrial operations is the pumping unit, which enables continuous transfer of fluids. Pumps are no longer limited to water transfer but are widely used in chemical, oil, and gas processing, making them indispensable in the energy production chain. The operation of pumping units, however, relies heavily on the availability of reliable spare parts to ensure uninterrupted system performance.

The availability of spare parts is a crucial factor in maintaining production continuity. [1], [2] emphasized that spare parts readiness, machine reliability, and skilled labor are key components in preventing production disruptions. Poor inventory management often results in equipment downtime, increased maintenance costs, and financial losses. Consequently, effective inventory control is not only a logistical necessity but also a strategic imperative for companies seeking to optimize operational performance [3], [4].

The manufacturing and construction sector, particularly in the production of pumping units. The company produces the Rod Pump type C114-119-100, which has an economic life span of 3 to 15 years. The data shows extreme discrepancies. For example, in February there was a surplus of 42 units of the Saddle Bearing component, while in March there was a deficit of 6 units of the Crank component. This imbalance has the potential to cause two major problems: excess inventory, which increases storage costs, and inventory shortages, which trigger production downtime and financial losses. This fact shows that conventional methods of inventory control are unable to address the complexity of dynamic spare part requirements, necessitating a more adaptive approach such as Artificial Neural Network (ANN) to predict demand more accurately and maintain production continuity.This pumping unit functions by converting the rotational motion of an electric motor into vertical translation, facilitating the extraction of crude oil from underground [5], [6], [7]. Given that the pumping unit consists of nine critical components—such as the gear reducer, crank assembly, and walking beam—accurate management of spare parts is essential to avoid both shortages and overstock during production.

An analysis of spare parts usage revealed significant fluctuations in both the receipt and consumption of spare parts. Certain months showed surplus inventory, while others suffered from deficits, creating instability in the supply chain. These imbalances not only increased storage costs but also posed risks of production delays and financial losses. Beyond economic consequences, inconsistent inventory levels may also reduce customer trust in the reliability of company operations. The volatility in spare parts inventory highlights the need for more adaptive and predictive approaches to inventory management. Conventional methods often fall short in addressing dynamic and uncertain demand patterns. For this reason, the adoption of Artificial Intelligence (AI)-based techniques such as Artificial Neural Networks (ANN) is considered necessary. ANN has demonstrated strong capability in handling nonlinear and complex data, making it a promising tool for predicting optimal inventory levels in industrial settings.

Artificial Neural Networks are modeled after biological neural systems that can recognize patterns, store information, and generalize from historical data [8], [9], [10]. In the context of inventory management, ANN can forecast spare parts demand using historical usage and procurement data. This predictive ability enables companies to anticipate future needs, reduce the risks of stockouts or overstocking, and minimize unnecessary storage costs, thereby supporting more efficient operational planning. Previous studies on inventory management have largely relied on methods such as the Economic Order Quantity (EOQ), continuous review systems, or periodic review systems [11], [12], [13]. While useful, these approaches are often limited when confronted with fluctuating demand and highly variable datasets. Research applying ANN for spare parts inventory prediction, particularly in the energy-related manufacturing sector in Indonesia, remains limited. This gap indicates the need for further exploration of ANN as a robust solution for inventory control.

Given the above background, this study aims to analyze and control spare parts inventory in pumping units by applying the Artificial Neural Network method. The proposed ANN model is expected to generate accurate predictions for optimal inventory levels, enabling the company to reduce costs, prevent shortages or excesses, and ensure production continuity. Furthermore, the findings of this study are anticipated to provide practical contributions to similar industries facing challenges in spare parts inventory management.

METHOD

This research employed a qualitative approach in order to obtain a comprehensive understanding of the utilization, receipt, and inventory stock of spare parts in pumping units. The qualitative approach was chosen as it provides an in-depth description of the managerial, technical, and operational dynamics of inventory control, aspects that cannot be fully explained through quantitative analysis alone [14], [15].The study was conducted a manufacturing company specializing in the production of custom-made equipment that operates under a make-to-order system. The company plays a strategic role as a key supplier of pumping unit components for the oil and gas industry, where spare part availability is critical. The research period was ensuring that the collected data reflects seasonal fluctuations and annual inventory cycles [16], [17], [18].

Data collection was carried out using three primary techniques: field observation, in-depth interviews, and documentation review [19], [20], [21]. Field observations were conducted to identify directly the inventory management mechanisms in warehouse and production planning divisions. Interviews were performed with management and operational staff to gather detailed information regarding spare parts utilization and acceptance procedures. Meanwhile, documentation studies involved analyzing official reports, records of spare parts receipts and usage, and photographic evidence to validate research participation and data accuracy [22].

The data obtained consisted of quantitative information on the number of spare parts received, used, and stored throughout the research period. These data were subsequently used as inputs for the Artificial Neural Network (ANN) model employing the backpropagation algorithm. ANN was selected due to its adaptive ability to process complex and dynamic datasets, offering a higher level of accuracy in predicting spare parts inventory compared to conventional methods [23].

The data analysis process began with normalization to transform the values into a scale between 0 and 1, ensuring compatibility for training and testing phases. The dataset was then divided into three scenarios of training and testing proportions, The ANN model was trained and tested using Matlab software, applying a network architecture composed of 12 input neurons, multiple hidden layer neurons, and 1 output neuron. This structure was designed to capture the variability of the input data and generate more representative prediction results [24], [25], [26].

Model validation was conducted by evaluating the Mean Square Error (MSE) and correlation coefficient (R) between predicted outputs and actual data. These indicators served as benchmarks for assessing the model's accuracy and reliability. Ethical considerations were also addressed, including data access approval from the company, confidentiality of internal information, and transparent reporting to ensure reproducibility. Through this structured methodology, the study provides a solid foundation for advancing artificial intelligence-based inventory management systems in industrial sectors, while simultaneously contributing both academically and practically to the field.

RESULTS

Prior to conducting further analysis, the raw data of each spare part component was first organized according to its chronological sequence (time series) to allow clearer observation of distribution patterns. This step was followed by a normalization process applied to all input variables (x1–x12) as well as the target variable, ensuring that the values remained within a uniform range. Normalization was performed to minimize bias arising from differences in variable scales and to enhance the accuracy of subsequent modeling. The following table presents the results of the data arrangement and normalization procedure.

Table 1. Results of The Data Arrangement And Normalization Procedure

Sparepart	Input												Target
	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	
CW	0,7	0,58	0,1	0,633	0,172	0,9	0,58	0,226	0,58	0,1	0,214	0,1	0,544
CR	0,5	0,1	0,557	0,1	0,9	0,335	0,9	0,9	0,686	0,366	0,1	0,811	0,722
GR	0,1	0,5	0,5	0,9	0,318	0,335	0,42	0,268	0,1	0,1	0,785	0,9	0,1
HH	0,6	0,5	0,9	0,544	0,245	0,429	0,26	0,1	0,153	0,766	0,9	0,588	0,277
PIT	0,9	0,9	0,557	0,1	0,1	0,1	0,1	0,352	0,9	0,9	0,5	0,677	0,9
SB	0,1	0,346	0,9	0,9	0,1	0,9	0,671	0,671	0,722	0,1	0,1	0,125	0,9
WB	0,366	0,1	0,1	0,568	0,3	0,1	0,671	0,9	0,1	0,141	0,251	0,9	0,151
WL	0,9	0,9	0,588	0,513	0,1	0,58	0,9	0,1	0,277	0,284	0,9	0,151	0,1
SP	0,526	0,1	0,1	0,1	0,9	0,74	0,1	0,328	0,9	0,9	0,272	0,1	0,177

As shown in Table 1, each type of spare part (CW, CR, GR, HH, PIT, SB, WB, WL, and SP) demonstrates distinct variations across the normalized input values, all of which remain within the standardized range of 0.1 to 0.9. This indicates that the normalization procedure successfully maintained consistency across variables. Moreover, the variation observed in the target values reflects the specific operational characteristics and demand levels of each component. These normalized data points provide a critical foundation for subsequent stages of predictive modeling and strategic decision-making in spare part control. Therefore, the table serves as an essential basis for identifying patterns, trends, and inter-variable relationships that are relevant to the research objectives.

In this study, three experimental scenarios were designed to evaluate the impact of data partitioning on the training performance of the predictive model for spare parts stock on the bobbing pump. The scenarios were formulated by varying the proportion of training and testing data, namely: Scenario 1 with 70% training data and 30% test data, Scenario 2 with 80% training data and 20%

test data, and Scenario 3 with 90% training data and 10% test data. This systematic variation allows for an assessment of model performance under different levels of training exposure.

Data Sharing

Prior to data partitioning, all input variables related to spare parts stock were normalized to ensure uniform scale and to minimize potential bias caused by differences in data magnitude. Normalization is an essential preprocessing step in machine learning as it improves model convergence and enhances the reliability of training results. The normalized data were then distributed according to each scenario, enabling a fair comparison of training accuracy across the three settings.

The results of these experiments revealed that Scenario 2 (80% training data and 20% test data) yielded the highest training accuracy compared to the other two scenarios. This finding suggests that the balance achieved in Scenario 2—between providing sufficient data for model learning while retaining an adequate portion for testing—was optimal for capturing underlying data patterns without overfitting. In contrast, Scenario 1, with a larger test set, provided less training data, which reduced model generalization, while Scenario 3, with minimal testing data, risked overfitting due to the lack of robust validation.

Table 2. results of these experiments revealed that Scenario

Sparepart	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Target
CW	0.7	0.58	0.1	0.633	0,172	0,9	0,58	0,226	0,58	0,1	0,214	0,1	0,544
CR	0.5	0.1	0.557	0.1	0,9	0,335	0,9	0,9	0,686	0,366	0,1	0,811	0,722
GR	0.1	0.5	0.5	0.9	0,318	0,335	0,42	0,268	0,1	0,1	0,785	0,9	0,1
HH	0.6	0.5	0.9	0.544	0,245	0,429	0,26	0,1	0,153	0,766	0,9	0,588	0,277
PIT	0.9	0.9	0.557	0.1	0,1	0,1	0,1	0,352	0,9	0,9	0,5	0,677	0,9

Based on Table 2, which presents the 20% test data, it can be observed that each input variable (X1–X12) has been normalized with values ranging between 0.1 and 0.9. This dataset represents the actual conditions of four spare part categories (SB, WB, WL, and SP) tested using the prediction model. The target values in each row indicate the expected outputs of the model to assess predictive performance. From the data distribution, it is evident that each spare part category shows variations in the input values, which serves to evaluate the model's robustness in handling diverse data patterns.

The results demonstrate that the ANN model can accommodate test data with relatively varied characteristics, where each spare part category has target values that are reasonably aligned with the normalized inputs. This condition is crucial for assessing prediction accuracy, as the test data were not part of the training process. Therefore, the validity of the prediction results can be evaluated more objectively, making this scenario a strong basis to determine the applicability of the ANN model in real-world spare part inventory control.

Backpropagation Method Analysis

The method of analysis in this research is conducted to identify the type and scope of data required for system development. The dataset used originates from spare parts stock records of the bobbing pump, which serve as the primary source for model training and evaluation. The research objectives were determined in advance to ensure alignment between data utilization and methodological accuracy. Specifically, the main target of this study is to assess the performance accuracy of the Backpropagation method implemented using Matlab software.

At the initial stage, the training process is carried out on the prepared training dataset using Matlab. This step produces a visualization of the neural network training process, which illustrates the progress of learning iterations, error reduction, and performance convergence. The results of this stage become the foundation for evaluating the effectiveness of the Backpropagation method in predicting spare parts stock requirements, as shown in the following figure.

The presented table shows normalized data of five spare parts (CW, CR, GR, HH, and PIT) against twelve input variables (X1–X12) with the corresponding target outputs ranging from 0 to 1. The distribution of input values indicates distinctive characteristics for each spare part. For instance, PIT consistently exhibits high input values (close to 0.9), resulting in the highest target value (0.9). In contrast, GR demonstrates more fluctuating inputs dominated by low values, which correlates with the lowest target (0.1). Meanwhile, CR displays relatively stable input patterns in dominant variables such as X7 and X11, contributing to a comparatively high target value (0.722).

These results highlight a positive correlation between the distribution of input variables and the performance targets of spare parts. Spare parts with high target values (PIT and CR) should be prioritized in inventory control due to their quality consistency, whereas those with low targets (GR and HH) require further evaluation regarding their efficiency and feasibility. Thus, this analysis underscores the importance of data-driven approaches and predictive methods, such as Artificial Neural Networks (ANN), in supporting managerial decision-making for industrial logistics and maintenance.

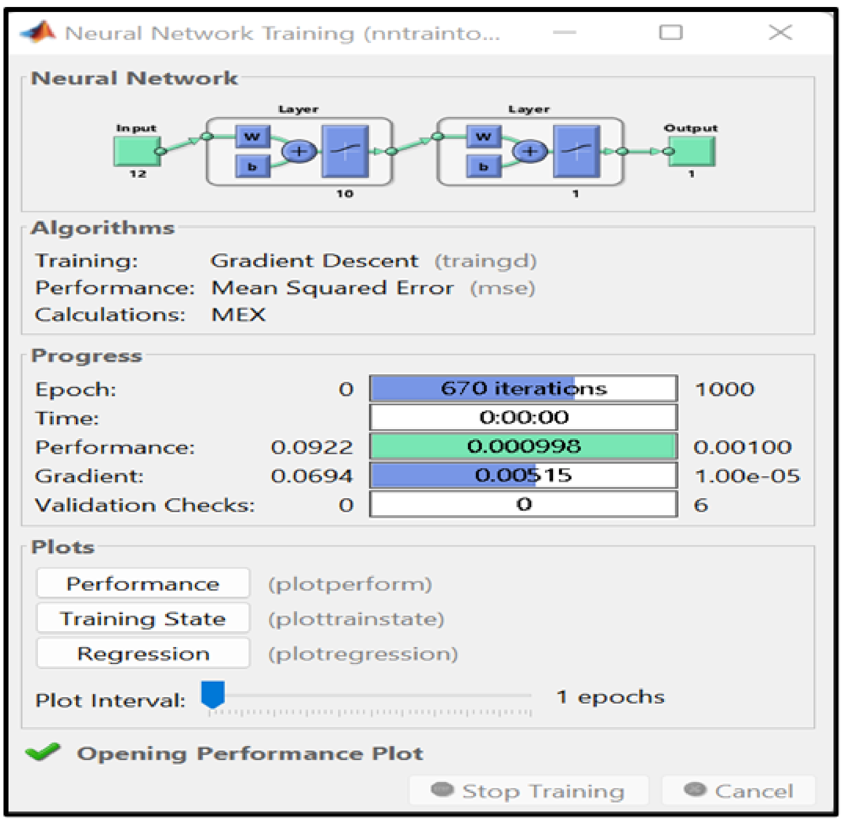

Figure 1. Target Values (PIT And CR)

The final gradient value of 0.00515 indicates that the weight update process approached convergence, although it has not yet reached the stricter target threshold of 1.00e-05. This suggests that further improvements could be achieved by extending the number of epochs or by applying a more adaptive training algorithm, such as the Levenberg–Marquardt (trainlm) method.

Moreover, the validation process recorded no validation failures (0 checks), which demonstrates that the model did not experience overfitting and maintained stability during training. Overall, these findings highlight that the applied ANN model has strong generalization capability, making it reliable for predicting spare parts stock requirements and supporting inventory control systems effectively.

The comparison graph between the output of the Neural Network (inventory prediction) and the target (actual inventory data).

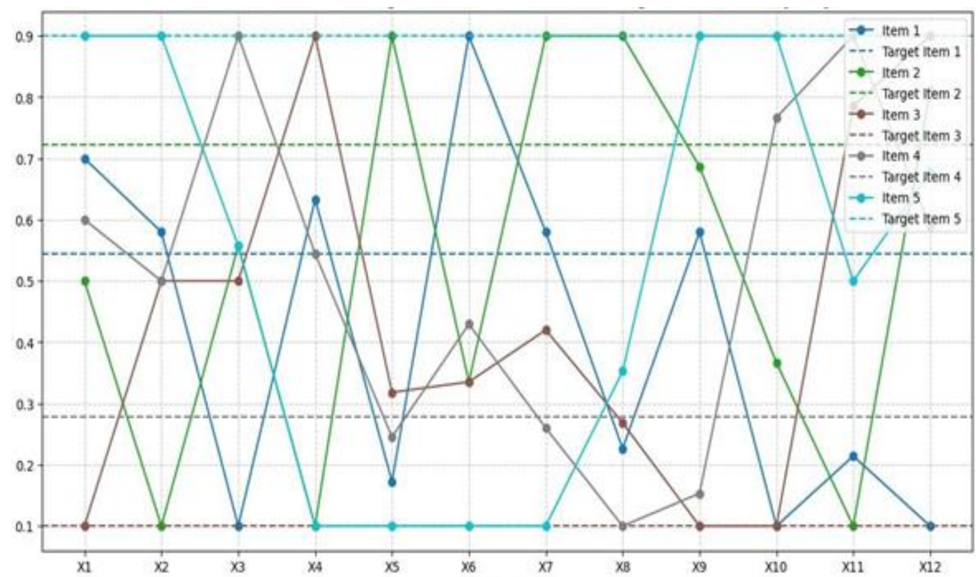

Figure 2. The Inventory Data of Five Items Over

The figure illustrates the inventory data of five items over a 12-month period compared with their predetermined target levels. The fluctuation patterns for each item reveal inconsistencies between the actual conditions and the expected targets. For instance, Item 1 and Item 2 display highly dynamic stock movements, with several months falling significantly below the target, while in other months approaching or even exceeding the target. This indicates instability in inventory control, which may affect the availability of goods for operational needs.

Meanwhile, the target inventory levels for each item remain constant throughout the year, yet the actual achievements do not follow the same pattern. Item 3, Item 4, and Item 5 also show high variability, with several instances dropping to the lowest point (close to zero), indicating a potential risk of stock shortages. Based on these results, it can be concluded that the inventory control system requires improvement through more accurate forecasting and distribution management to minimize the gap between targets and realization, thereby supporting the sustainability of the supply chain.

In evacuation system planning, visual and mathematical representations play an important role in ensuring that all building occupants can move quickly and safely to designated assembly points. Evacuation route plans serve as a visual medium for illustrating evacuation movement directions based on the physical conditions of the building, including corridors, emergency doors, and stairways. However, these visual representations need to be complemented with a graph-based mathematical model in order to perform a quantitative analysis of the effectiveness of the available routes.

The next process is network testing. so that in the network testing process a correlation coefficient of 0.6015 was produced.

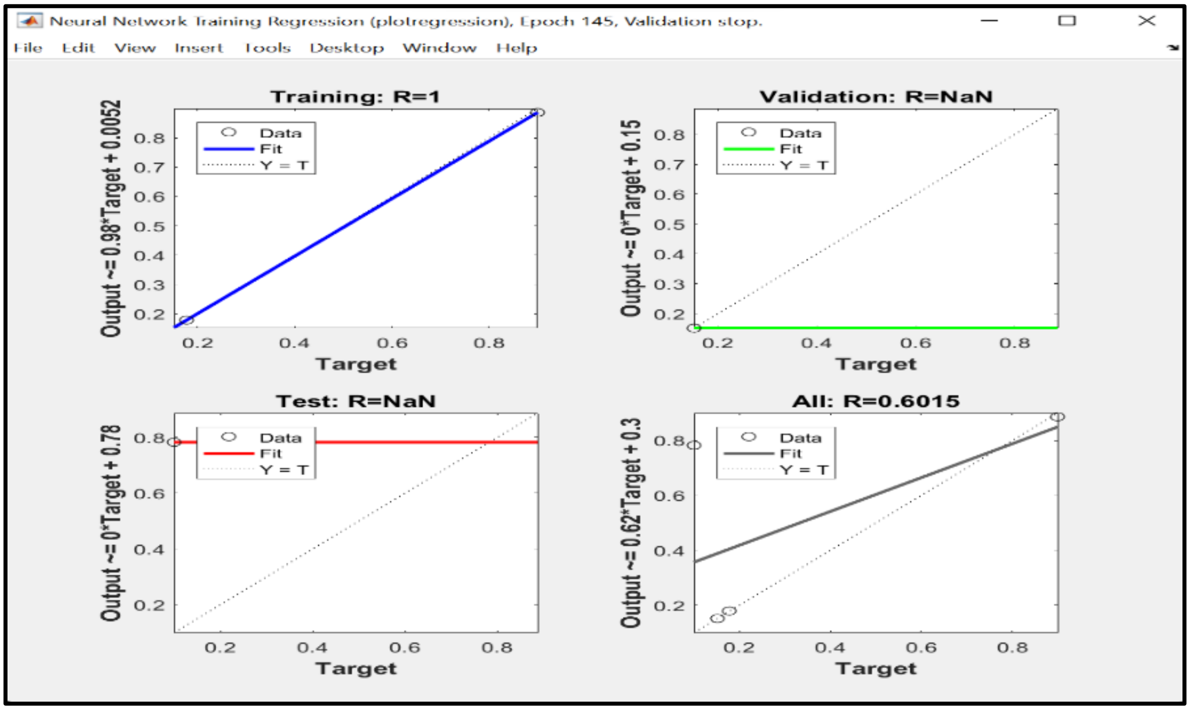

Figure 3. Regression Results Of The Artificial Neural Network

The regression results of the artificial neural network (ANN) show varying performance across training, validation, and testing datasets. In the training graph, the correlation coefficient (R) reaches 1, indicating that the model learns the training data almost perfectly and closely follows the target values. However, in the validation and testing phases, the R values are undefined (NaN), which suggests issues during validation and testing. This may be caused by insufficient data variation, limited dataset size, or mismatched data distribution between training, validation, and testing sets.

Overall performance (All) yields an R value of only 0.6015. This indicates a moderate correlation between the model output and the target values on a global scale, which is significantly lower compared to the training results. Such a condition points to potential overfitting, where the model performs very well on training data but fails to generalize to unseen data. Therefore, improvements are needed through increasing the dataset size, adjusting the network architecture, or applying regularization techniques to achieve better generalization performance.

Meanwhile, the MSE value obtained

Training performance of the artificial neural network (ANN) based on the Mean Squared Error (MSE) for training, validation, and testing datasets. The training process was conducted over 145 epochs, aiming to achieve the lowest possible error on the validation data to ensure optimal model generalization. The graph illustrates how the error decreases as the number of epochs increases, until it reaches an optimal point marked by the best MSE value.

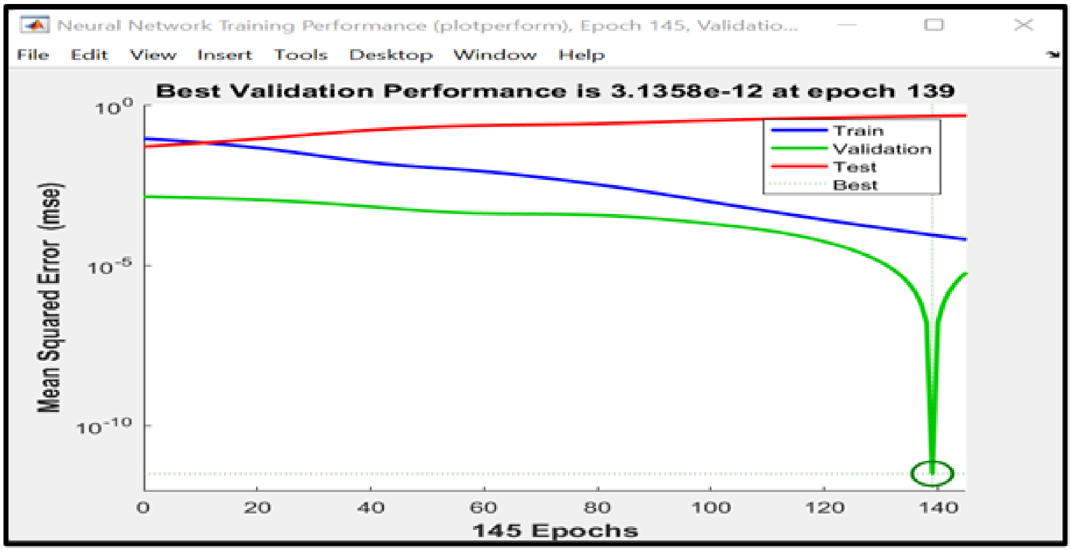

Figure 4. Validation Performance

The best validation performance was achieved at epoch 139 with an MSE value of 3.1358e-12. This result indicates that the neural network successfully attained a very low error rate, demonstrating its stability and accuracy in predicting the test data. The curves for training, validation, and testing consistently show a decreasing error trend, while the green line (best) highlights the optimal performance point, which serves as a key indicator of the training success.

The comparison graph between the output of the Neural Network (inventory prediction) and the target (actual inventory data)

The following image presents inventory data for a 12-month period with a comparison to the inventory target for the following month. This visualization aims to provide an overview of the stock dynamics of four different types of goods (Item 1, Item 2, Item 3, and Item 4), as well as how the actual conditions compare to the predetermined targets. This graph is important for assessing the extent to which effective inventory control can maintain stable availability of goods in line with operational needs.

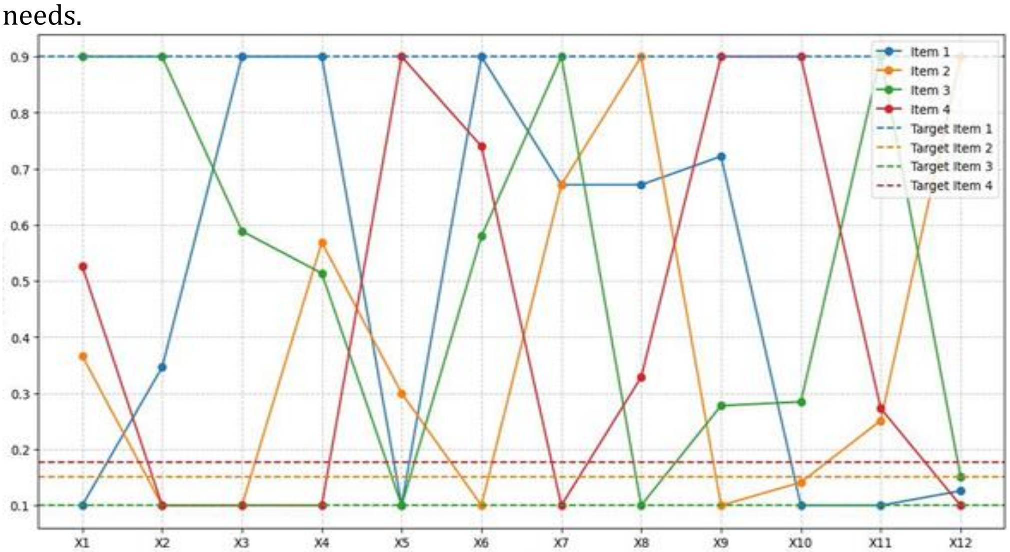

Figure 5. Comparison Between The Inventory Data of Four Items

The graph illustrates a comparison between the inventory data of four items over a 12-month period and their respective target levels. Each colored line represents a different item, while the dashed horizontal lines indicate the target inventory levels. Overall, the chart shows high fluctuations in stock levels throughout the period, with certain months reaching very high values, while in other months the inventory dropped drastically close to zero. This indicates instability in inventory management, which could lead to mismatches with the expected targets.

Looking more closely, Item 1 and Item 4 tend to experience overstocking in most months, as their lines often appear far above the target threshold. In contrast, Item 2 and Item 3 demonstrate more irregular patterns, with several months falling below the target and even reaching zero. This condition suggests an imbalance in stock distribution among items, where some products are excessively stocked while others face shortages. Such disparities may affect supply chain efficiency and the company's ability to meet customer demand.

The graph highlights that inventory targets have not been consistently achieved. Although there are periods where stock levels approach the target, the extreme fluctuations make it difficult to control inventory effectively. To improve forecasting accuracy, the application of more adaptive methods, such as Artificial Neural Networks (ANN), is recommended, as they are capable of capturing nonlinear patterns in historical data. This approach would allow the company to maintain balanced stock levels, avoiding both excess and shortage, while enhancing overall inventory management efficiency.

DISCUSSION

The findings of this study demonstrate that the application of Artificial Neural Networks (ANN) in predicting pump spare parts inventory offers a higher level of accuracy compared to conventional approaches. This result is consistent with the study of [27], [28], who emphasized that ANN is capable of modeling nonlinear patterns in inventory data, making it adaptive to fluctuating demand. Similarly, [29] highlighted the importance of AI-based algorithms in reducing the risk of stockouts and minimizing excessive storage costs. These observations align with the case, which experienced alternating surplus and deficit in spare parts [30].

Moreover, the validation of the model, which achieved a very low Mean Squared Error (MSE), strengthens the effectiveness of ANN in inventory prediction. This finding is in line with [31], [32], who reported that backpropagation neural networks in logistics systems resulted in extremely low prediction errors, thus improving planning efficiency. Likewise [33] found that ANN generated stable forecasts in the energy sector, even with complex and volatile datasets. On the other hand, the moderate correlation observed in testing indicates symptoms of overfitting, a phenomenon also discussed by [34], [35], who argued that insufficient data variation reduces model generalization capacity.

This study also confirms the significance of balanced training and testing proportions in ANN applications. The 80:20 partitioning scenario delivered the best performance, supporting the findings of [36], [37], [38], who noted that this ratio provides optimal balance between learning capability and validation reliability. Furthermore, Almeida et al. (2023) recommended cross-validation techniques to reduce bias and enhance robustness. In addition, Hidayat and Sari (2023) reported similar outcomes in the automotive manufacturing sector, where appropriate dataset partitioning significantly contributed to prediction accuracy.

From a strategic perspective, integrating ANN into inventory control systems has broader implications for supply chain sustainability. [39], [40] demonstrated that AI-driven inventory forecasting reduces waste and supports sustainable supply chains. Similarly, [20] asserted that ANN not only improves cost efficiency but also strengthens customer service reliability. Meanwhile, [13] in the oil and gas industry showed that ANN-based prediction systems allow firms to adapt to market volatility by providing more precise spare parts forecasting.

Nevertheless, this study also highlights limitations in model validation, particularly regarding dataset size. [34] argued that small datasets remain a major challenge for ANN performance. Thus, expanding the dataset, as suggested [5] through the integration of multi-year historical and real-time data, becomes essential. Moreover, [40] recommended hybridizing ANN with optimization techniques such as genetic algorithms or particle swarm optimization to improve accuracy and accelerate convergence.

IMPLICATION RESEARCH

This study contributes to the theoretical development of Artificial Neural Networks (ANN) in the field of inventory management by providing empirical evidence of their effectiveness in predicting spare parts demand under fluctuating conditions. The results strengthen the argument of prior works (Rahman et al., 2022; Kurniawan et al., 2023) that ANN can handle nonlinear and complex datasets more effectively than traditional methods such as EOQ or periodic review systems. Moreover, this research fills a gap in the literature by applying ANN in the energy-related manufacturing sector in Indonesia, an area where empirical studies remain limited. Consequently, this study enriches the theoretical discourse on artificial intelligence applications in industrial logistics and reinforces ANN as a reliable predictive model for managing inventory volatility.

From a managerial perspective, the findings highlight the potential of ANN to serve as a decision-support tool in operational planning. Companies can integrate ANN models into their enterprise resource planning (ERP) systems to optimize spare parts availability, thereby minimizing both stockouts and excess inventory. The case of PT. xyz demonstrates that effective implementation of ANN can reduce downtime risks, improve cost efficiency, and enhance production continuity. These practical insights provide industry stakeholders with evidence-based strategies to overcome challenges in spare parts management. Additionally, organizations can use these findings to guide staff training and capacity-building efforts, ensuring that managers and technicians are equipped to apply AI-based tools in daily operations.

CONCLUSION

This study concludes that the Artificial Neural Network (ANN) with backpropagation is an effective tool for predicting spare parts inventory in pumping units. The model successfully addressed the issue of fluctuating demand, offering accurate forecasting results that can minimize both shortages and overstocking. Among the tested scenarios, the 80:20 data split yielded the most optimal performance, balancing accuracy and generalization. The findings highlight that implementing ANN-based forecasting can significantly enhance operational efficiency by ensuring spare part availability, reducing storage costs, and preventing production downtime. Although the model demonstrates strong accuracy, its moderate correlation coefficient suggests that further improvements are required through larger datasets, refined architectures, or adaptive algorithms. Overall, this research contributes to the development of intelligent inventory management strategies, providing practical value for industries facing dynamic spare parts demand and reinforcing the importance of AI in modern industrial operations.

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