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Research Article

The application of artificial neural network (ANN) with backpropagation algorithm to predict supply chain demand

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Abstract

Supply chain management (SCM) is a critical function that influences the efficiency and competitiveness of manufacturing industries. Demand forecasting plays a pivotal role in optimizing production schedules, inventory control, and resource allocation. However, traditional statistical methods often fail to capture the complexities of fluctuating demand patterns due to their linear assumptions. To address this challenge, this study employs an Artificial Neural Network (ANN) model with a backpropagation algorithm to improve demand forecasting accuracy. The research is conducted in a steel tower manufacturing company in Aceh, Indonesia, using historical production data from 2020 to 2022. Data normalization is applied to enhance model convergence, and the ANN is trained and validated using Mean Square Error (MSE), correlation coefficient (R), and Mean Absolute Percentage Error (MAPE) as performance indicators. The results demonstrate that the ANN model effectively predicts a total demand of 4,226 units over 12 production periods, with the highest demand occurring in period 11 (491 units) and the lowest in period 1 (183 units). The model achieves an MSE of 0.000985 and an R-value of 0.99393, highlighting its superior predictive capability. These findings confirm the ANN model's potential as a powerful forecasting tool for dynamic supply chain environments. The study contributes to the growing research on machine learning applications in SCM by providing empirical evidence of ANN's effectiveness in complex, non-linear demand forecasting scenarios.

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1. Introduction

Supply chain management (SCM) is a system of optimization networks that consist of organizations, information, and other resources that collaborate to create or deliver a product or service from the supplier to its networks ((Sentia et al., 2022; Syahputra et al., 2022). In its application, SCM involves the integrated planning and execution of processes to manage the flow of materials, information, and financial capital in operations such as demand planning, procurement, manufacturing, inventory control and handling, transportation (or logistics), and product return (Denny Sentia et al., 2022)

As a complex management system, one of the main concerns of SCM is the constant change in managing customer demands, while at the same time, companies are pressured to reduce production costs and improve capital margins. Different layers of supply chain demand exist, including independent demand (driven by external market needs) and dependent demand (determined by internal production requirements). To function optimally, SCM requires a combination of conducive strategy planning, specialized software, and collaborative work between each entity within the network. Consequently, forecasting methods and approaches have been widely used in precision management to anticipate customer expectations and optimize inventory management (Murray et al., 2015) Therefore, there is a rising emphasis on forecasting consumption behaviors and demand preferences by utilizing customer data patterns and records to achieve an effective supply chain network (Arifin et al., 2022; Seyedan & Mafakheri, 2020). Demand uncertainty, in particular, significantly impacts SC performance, affecting production capacity, inventory planning, and the logistic functions of a company (Kochak & Sharma, 2015). In this regard, demand forecasting is considered an essential strategy for dealing with the dynamics of supply chain uncertainty.

For demand forecasting in SCM, a range of statistical and artificial intelligence (AI) approaches have been explored, including traditional time-series models (e.g., ARIMA, exponential smoothing) and machine learning methods (e.g., ANN, support vector machines)(Abbate et al., 2022; Malekian & Chitsaz, 2021a) ANN has emerged as one of the most effective methods in time-series forecasting and regression analysis due to its ability to capture non-linear relationships. ANN represents a computational model inspired by the human brain, capable of learning from historical data through a backpropagation mechanism (Malekian & Chitsaz, 2021b) Unlike conventional models, ANN excels in handling non-linear and complex patterns, making it particularly useful for supply chain forecasting where demand fluctuations may not follow strict statistical assumptions (Park & Lek, 2016)

Among machine learning approaches, the Backpropagation algorithm is widely used for training feedforward neural networks, enabling more accurate gradient calculation of loss functions (Goh, 1995; Ian Goodfellow et al., 2016) This algorithm iteratively adjusts network weights to minimize forecasting errors, making it superior to traditional statistical models when data exhibits non-stationary behavior. Compared to methods such as ARIMA, which is effective in modeling linear dependencies but struggles with complex nonlinear relationships, or Support Vector Machines (SVM), which require extensive feature engineering, ANN provides a more flexible approach with automatic feature extraction and adaptation to changing patterns. Moreover, ANN does not rely on strict statistical assumptions like many traditional techniques, making it better suited for dynamic and uncertain environments such as supply chain demand forecasting. Comparative studies suggest that hybrid approaches combining ARIMA and ANN often yield improved forecasting accuracy, highlighting the need to evaluate their performance in real-world applications (Ghiassi et al., 2005; Kochak & Sharma, 2015)

Despite the widespread adoption of ANN, research gaps remain in its application to multi-layered supply chain demand forecasting. Existing studies primarily focus on short-term predictions without considering the hierarchical nature of supply chain networks, which include raw material procurement, production scheduling, and final distribution(Cannas et al., 2024). Furthermore, while ANN models demonstrate high predictive accuracy, their interpretability remains a challenge, limiting their practical deployment in SCM decision-making processes. Addressing these gaps, this study explores the effectiveness of ANN with a backpropagation algorithm for forecasting demand in a steel tower production company in Indonesia, with a particular emphasis on improving prediction accuracy and model validation(Feizabadi, 2022; Kosasih et al., 2024).

This study is organized as follows: Firstly, this paper analyzes data obtained from a steel tower production industry in Indonesia. To ensure valid assumptions, the data in this study is transformed into normalized values. Secondly, the normalized data is explored using ANN methodology with a backpropagation algorithm, and its predictive performance is compared with conventional forecasting techniques. Lastly, the credibility of the model is assessed using Mean Square Error (MSE), correlation coefficient (R), and Mean Absolute Percentage Error (MAPE) during the data testing process. This research aims to bridge the gap between statistical and machine learning forecasting approaches by investigating the influence of historical data patterns and recommending optimal demand prediction strategies

2. Methodology

2.1. Data acquisition and preprocessing

This study is conducted through a field observation at a steel tower production company in Indonesia. The company sources raw material components from multiple suppliers while also managing global distribution. Due to the complexity of its supply chain system, forecasting plays a critical role in ensuring operational efficiency by enabling timely inventory replenishment, capacity planning, and sales optimization (Treiblmaier, 2014) Additionally, accurate demand forecasting enhances managerial decision-making and facilitates strategic business growth. This study analyzes historical production and demand data from 2020 to 2022.

To improve computational efficiency, the data is first normalized within a range of 0 to 1. Normalization stabilizes the gradient descent process, facilitating faster convergence in the neural network (Vafaei et al., 2015). The normalization process is performed using Equation (1) (Aksu et al., 2019):

$$y = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

Where:

- y is the normalized data,
- x is the original data value.

2.2. Artificial Neural Network (ANN) Model

An Artificial Neural Network (ANN) is a computational model inspired by biological neural structures. The ANN model used in this study follows a feedforward architecture with a backpropagation learning algorithm. The transformation of input data through hidden layers is formulated as follows: (Latif et al., 2020)

$$X = \sum_i A_j X_i + b_j \quad (2)$$

$$F_1 = \sigma(X) \quad (3)$$

$$F_2 = W_{kj} F_1 + b_0 \quad (4)$$

where:

- X represents the weighted sum of inputs,
- X_i denotes the input variables,
- A_j is the weight of the input layer,
- F_1 is the hidden layer activation function,
- F_2 is the output layer activation function,
- W_{ij} is the connection weight between input and hidden neuron j ,
- b_j is the bias term for hidden neuron j,
- W_{kj} is the connection weight between hidden neuron j and output neuron k ,
- b_0 is the bias term for the output neuron k.

2.3. Backpropagation algorithm

The backpropagation algorithm is used to train the ANN by iteratively adjusting the connection weights to reduce prediction error. the learning process in backpropagation consists of the following steps (Huang et al., 2018):

- forward Propagation: The input data is passed through the network layers, and the output is computed using activation functions.
- Error Calculation: The difference between the predicted and actual values is measured using an error function, such as Mean Square Error (MSE).
- Gradient Calculation: The partial derivatives of the error function with respect to each weight are computed using the chain rule.
- Weight Update: Weights are updated using the learning rate and momentum to minimize the error.

The formula for adjusted weight is calculated as follow (Guang-Bin Huang, 2003):

$$W_{new} = W_{old} - \eta \frac{dE}{dW} \quad (5)$$

where:

- W_{new} is the updated weight,
- W_{old} is the previous weight,
- η is the learning rate,
- $\frac{dE}{dW}$ is the computed gradient

2.4. Neural network architectural design

The optimal number of neurons in the hidden layer is determined using empirical trials. To optimize the architecture, the number of hidden neurons H is approximated using the following empirical formula (Syaharuddin et al., 2022):

$$H = \sqrt{m + N} + a \quad (6)$$

where:

- H represent the number of hidden neurons,
- m is the number of output neurons,
- N is the number of input variables,
- a is an adjustment factor to optimize model accuracy.

2.5. Data training and testing

The dataset is divided into training and testing subsets to evaluate the predictive performance of the ANN model. Training is conducted using the Mean Square Error (MSE) and correlation coefficient (R) as performance indicators. The MSE is computed as follows(Jayan et al., 2024; Nurfadilah et al., 2024):

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \quad (7)$$

where:

- Y_i is the actual observed value,
- $\hat{Y}_i$ is the predicted value,
- n is the number of observations.

The correlation coefficient (R) measures the relationship between input data (X_i) and predicted outputs (Yi) (Georige Athanasopoulos, 2018)

$$R = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2} \quad (8)$$

A high R value (close to 1) indicates a strong correlation between the ANN predictions and actual values, confirming the model’s reliability. Mean Absolute Percentage Error (MAPE) is also employed to achieve a proper fitness in the forecast accuracy. The MAPE model used in this is defined in formula *(9)*

$$MAPE = \sum_{i=1}^{n} \left|\frac{X_i - P_i}{X_i}\right| x\ 100\% \quad (9)$$

where X_i is equals to the actual data in year i, and P_i depict the forecast value in year i. Furthermore, data denormalization is performed against the simulation results to determine the original value of the forecasting findings. Data denormalization using equation 2 below.

2.6. Data Denormalization

Once the ANN model generates predictions, the normalized values are converted back to their original scale using the following denormalization formula (Aksu et al., 2019) :

$$y = a + (b - a) \times \hat{Y}_i \tag{10}$$

where:

- y is the deformalized value,
- a is the minimum observed value in the dataset,
- b is the maximum observed value in the dataset,
- $\hat{Y}_i$ is the ANN-predicted normalized value.

3. Research Result

3.1. Data prepossessing and network architecture setting

In this research, ANN model is applied to predict the forecasting data for a supply chain demand in the next period of supply. Previous historical demand data from 2020-2022 are selected as input variables for the proposed model. To obtain a normal distribution data within the variable, data normalization is conducted. The activation fn in this study is the binary sigmoid which has variable range of 0-1. is used in this. The results of data normalization are shown in Table 1. Therefore, based on the calculations in Table 1. the data has been normalized within the range of 0 to 1, allowing the data set to be validated for the next neural network procedure. The determination of the neural network architecture in this research is constructed based on several trial repetitions between each variable. Although the determination of neuron variable in research is determined based on Equation still there is no provision to deduce the other exact parameter to obtain a minimum error score. As a result, multiple trials are required to acquire the most optimal findings.

Therefore, based on several trial-and-error sequences, the neural 3-10-1 network design with a learning rate (lr) of 0.1, constant momentum (mc) of 0.95, epoch iteration of 1000, and epoch between iteration of 20 has the parameter value that provides the slightes error.

Table 1
Normalized data

Input	Periods											
	1	2	3	4	5	6	7	8	9	10	11	12
X1	0	0.030	0.086	0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165
X2	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654	0.060	0.605	0.293
X3	0	0.199	0.282	0.714	0.376	0.808	0.429	0.684	0.259	0.124	0.650	0.203

3.2. Data Training

The normalized data will be divided into two datasets, training and testing data, throughout the process of developing the optimum network architecture. The data separation is intended to ensure that the network receives adequate training and testing data to assess training achievement based on the MSE and R value (Sentia., 2022). Table 2. Shows the dataset used for data training sequences. The trainrp training function is used to determine the weight changes and bias in this training, while the MSE and R function is used to calculate the error.

Table 2
Data training

Input data												Output
X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Y1
0.000	0.030	0.086	0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233
0.030	0.086	0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049
0.086	0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150
0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000
0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323
0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639
0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564
0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.0	0.323	0.639	0.564	0.312
0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654
0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654	0.060
0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654	0.060	0.605
0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654	0.060	0.605	0.293

to evaluate model performance and reliability, the paper employs training error analysis and regression evaluation as key validation metrics. The training error analysis aims to assess the network's ability to minimize errors over successive learning iterations, ensuring effective convergence. Meanwhile, the regression evaluation measures the relationship between predicted and actual values, providing insight into the model's predictive accuracy. By utilizing these metrics, the study seeks to develop a robust neural network model capable of producing reliable and precise predictions, contributing to advancements in data-driven decision-making and optimization tasks. Therefore, Figure 1 presents a graphical representation of the best training performance achieved during the model's learning process. The network architecture utilized consists of a 12-10-1 configuration, which includes an input layer with 12 neurons, a hidden layer with 10 neurons, and an output layer with a single neuron. The training process is conducted with a learning rate (lr) set at 0.1, ensuring a controlled and efficient weight update mechanism to facilitate convergence. Additionally, a constant momentum (mc) of 0.95 is applied to enhance stability and prevent oscillations during the optimization process. This configuration is carefully chosen to achieve an optimal balance between training efficiency and generalization capability.

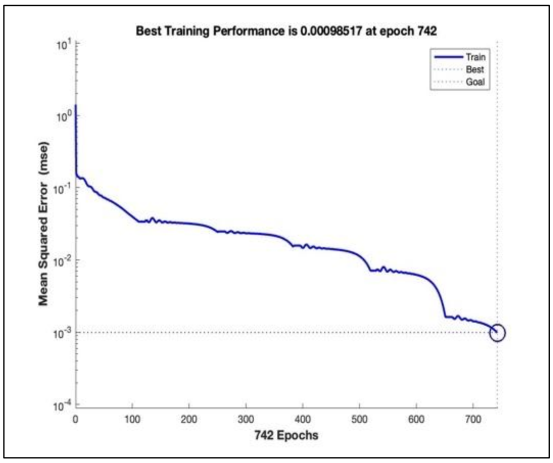

Fig .1.MSE analysis for data Training

As result, According to Fig. 1, the training results converged after 742 epoch iterations. The training set produce an MSE value attained of 0.00098517. There was an indication of a rapid drop at the start of the training, this is due to the fact that the training function employed trainrp function. However, the line appears to steadily diminish. To evaluate predictive accuracy and reliability, the paper employs regression analysis as a key validation metric. Figure 2 illustrates the correlation between predicted and actual values, with the regression line indicating the model's performance. The strong alignment demonstrates effective generalization, minimizing overfitting risks. This approach ensures the development of a reliable neural network model for data-driven decision-making and optimization.

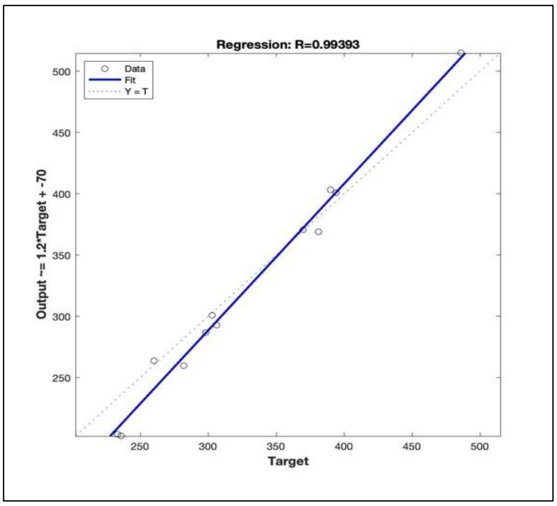

Fig .2. Regression analysis for data training

The result of the training process produces a regression value of 0.99393, where higher degree of association is displayed when the R reach a close value to 1. This suggests that the real variables with ANN in training have a high correlation attribute, even if several results did not distribute accordingly to the intended fit or goal line.

Furthermore, as shown in Figure 3, a nonsignificant difference between the ANN data training outcomes is presented to target data. This shows that the total ANN output model matches the target data. The MSE value achieved is 0.00098517, reflecting the network's lowest and most optimum target value. As a result, the data training process produces an ideal predicting result.

As a result, based on the MSE and R correlation measurement, only a minimal variance is pretended in both predictive measurement, which implies a stronger the

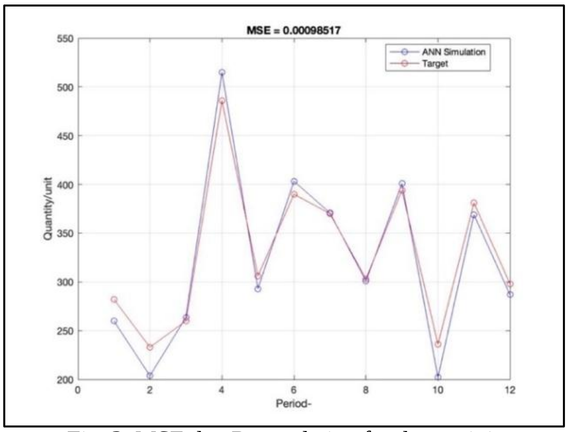

Fig .3. MSE dan R correlation for data training

relationship between the input and the output variable. Then, the high degree of connection between the associated variables leads to the conclusion that ANN creates enough fitness to anticipate supply chain demand.

3.3. Data testing

The primary objective of data testing is to evaluate the performance of the neural network by comparing its predicted outputs with the actual target values derived from the input data variables. This process serves as a critical validation step to determine the model's accuracy and generalization capability. The specific input data utilized for the data testing analysis is systematically presented in Table 3, providing a detailed overview of the dataset used in this phase. If all testing metrics meet the predefined performance criteria, the neural network can advance to the deployment stage, ensuring its readiness for real-world applications.

To facilitate this evaluation, the binary logarithmic sigmoid (logsig) function and the pure linear (purelin) function are employed as activation functions within the data testing procedure. These functions play a crucial role in processing input values and generating output predictions, contributing to the overall effectiveness of the model. The graphical representation of the data testing results is illustrated in Figure 3, offering insights into the network's predictive accuracy and validation performance.

Table 3
Data Testing Sequences

Input data												Output Data
X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	Target
0.000	0.030	0.086	0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233
0.030	0.086	0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049
0.086	0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150
0.632	0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000
0.353	0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323
0.639	0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639
0.301	0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564
0.748	0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.0	0.323	0.639	0.564	0.312
0.120	0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654
0.477	0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654	0.060
0.365	0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654	0.060	0.605
0.165	0.233	0.049	0.150	1.000	0.323	0.639	0.564	0.312	0.654	0.060	0.605	0.293

To ilustrate the comparison between the neural network's predicted outputs and the actual target values over multiple periods. Figure 4. provides insight into the model's predictive accuracy, with deviations indicating areas for potential refinement. MSE value displayed at the top serves as a key performance metric, quantifying the overall error between predictions and actual values. This evaluation is crucial in determining the reliability of the trained neural network before deployment**.**

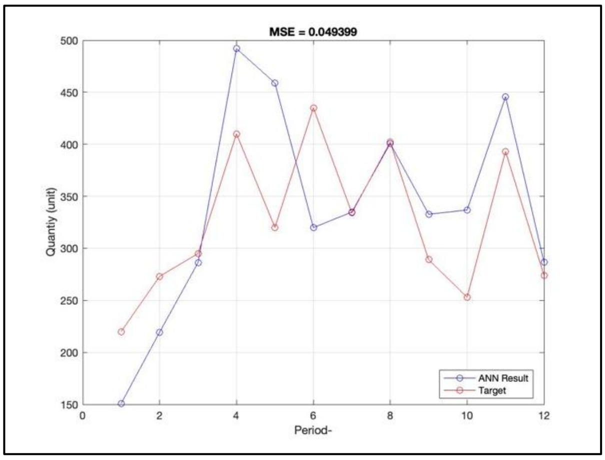

Fig .4. Data Testing result

Therefore, the data testing produces an MSE value of 0.04399, the data testing has a lower MSE score compared to the Data training procedure. In addition, it appears that there are some variations between the target and the ANN outcome data. The variation may be caused by the different network architecture set in the data testing sequence although these variances are not too substantial. Therefore, the model can be accepted since the MSE value is lower than 0.

The correlation coefficient and MSE value obtained throughout the data testing procedure demonstrate that the algorithm is showing a satisfactory result to anticipate product demand. However, both of these numbers may be increased by expanding the training data and adjusting network performance factors such as error targets, number of epochs, network design, type of activation function, and so on.

To further investigate the fitness of the model, an MAPE testing is proposed to measure testing accuracy of the statistic model. MAPE validation is performed to evaluate the ANN network's performance in identifying actual data patterns. The MAPE calculation result is shown below to compare the real data with the ANN results. Table 4. contains information about MAPE computations.

Table 1
Normalized data

Period Index	Xi	Pi	Xi-	|Xi-Pi|	|Xi-Pi|/Xi
1	220	183	37.0	37.0	0.168
2	273	270	3.0	3.0	0.011
3	295	329	-34.0	34.0	0.115
4	410	453	-42.6	42.6	0.104
5	320	458	-138.1	138.1	0.432
6	435	395	40.2	40.2	0.092
7	334	423	-88.9	88.9	0.266
8	402	334	67.6	67.6	0.168
9	289	340	-50.6	50.6	0.175
10	253	286	-32.8	32.8	0.130
11	393	491	-98.4	98.4	0.250
12	274	264	9.9	9.9	0.036
				Total	1.948
				MAPE	16.236 %

Therefore, based on Table 4, it can be seen that the overall MAPE value obtained is 16.236%. Although there is a slight variance between the output and the ANN result, the level of accuracy of the forecasting results is considered as good because it has a MAPE value that ranges between 10-20%. Therefore, the model can be considered as valid.

3.4. ANN forecasting

After obtaining the validated training and testing result, the best architectural model can be utilized to anticipate the amount of supply chain demand for the next 12 periods. To determine the original value, the ANN forecasted results are normalized. Therefore, Table 5 shows the results of forecasting demand for the steel tower production, where the highest demand should be anticipated in period-11 (491 units) and the lowest demand should be anticipated in period 1 (183 units).

Table 5
The Result of Ann Forecasting

Period	Forecasted demand
1	183
2	270
3	329
4	453
5	458
6	395
7	423
8	334
9	340
10	286
11	491
12	264
Total	4,226

The table provided delves into the forecasting of steel tower production demand using an Artificial Neural Network (ANN) model. ANNs are a powerful class of machine learning models that excel in identifying complex patterns and relationships within data. By leveraging the ANN model, the goal is to anticipate the demand for the next 12 periods with greater accuracy. The process begins with model training and validation, ensuring that the architectural design chosen is the most effective for capturing the intricacies of demand fluctuations. Normalization of the forecasted results is a crucial step, as it ensures that the output values are scaled appropriately before being reverted to their original form, making the data interpretable and actionable for practical use. The results presented in Table 5 reveal a detailed forecast of demand across 12 periods, highlighting the dynamic nature of production needs. The highest demand is forecasted for period 11 with 491 units, indicating a significant peak that necessitates advanced planning and resource allocation. In contrast, period 1 shows the lowest demand with 183 units, suggesting a time of reduced production activity. These extremes underscore the importance of having a flexible and responsive production system that can adjust to varying demand levels. The total forecasted demand across all periods sums to 4,226 units, providing a comprehensive view of the overall production requirements for the year.

From an academic standpoint, the use of ANNs for demand forecasting is well-justified due to their ability to model non-linear relationships and interactions within the data. This capability is particularly beneficial in the context of supply chain management, where demand patterns can be influenced by a multitude of factors, including market trends, seasonal variations, and economic conditions. The normalization process further enhances the model's utility by ensuring that the predictions are on a comparable scale, thereby facilitating accurate interpretation and decision-making. This methodological rigor not only improves forecast accuracy but also supports strategic planning and operational efficiency.

In analyzing the demand distribution, it is evident that the production facility must be prepared for significant variability. The peak in period 11 suggests a potential seasonal or cyclical pattern, which could be influenced by external factors such as market demand spikes or project timelines. Conversely, the low demand in period 1 might indicate a period of low market activity or a post-peak slowdown. Understanding these patterns is critical for optimizing inventory management, workforce planning, and production scheduling. By anticipating these fluctuations, the production facility can better align its resources, minimize waste, and enhance overall productivity, ultimately leading to more efficient and cost-effective operations.

4. Conclusion

This study investigates the application of an Artificial Neural Network (ANN) with a backpropagation algorithm for demand forecasting in Indonesia’s steel tower production industry. By utilizing historical demand data from 2019–2022, the ANN model was trained and validated to predict future demand with high accuracy. The optimal ANN architecture (12-10-1) achieved a **training MSE of 0.000985** and an **R-value of 0.99393**, indicating strong predictive capability. During testing, the model maintained **an MSE of 0.04399** and a **MAPE of 16.236%**, confirming its reliability despite minor deviations between predicted and actual values.

The demand forecast for the next 12 periods revealed **notable fluctuations**, with the highest demand projected in **period 11 (491 units)** and the lowest in **period 1 (183 units)**. These variations underscore the importance of adaptive production planning and inventory management in the steel tower industry. The results validate ANN's effectiveness in capturing non-linear demand patterns, making it a valuable tool for improving supply chain decision-making.

While ANN has demonstrated strong forecasting accuracy, alternative deep learning models such as Recurrent Neural Networks (RNN), particularly Long Short-Term Memory (LSTM) networks, may further enhance performance by capturing sequential dependencies. Future studies should explore hybrid models integrating ANN with RNN-based architectures to improve predictive robustness and adaptability.

From a managerial perspective, the implementation of ANN-based forecasting can optimize inventory control, mitigate production bottlenecks, and enhance supply chain resilience. By leveraging machine learning-driven demand predictions, manufacturers can improve resource allocation, reduce operational costs, and increase overall efficiency.

Future research should focus on refining neural network architectures to enhance forecasting accuracy. This includes optimizing hyperparameters such as activation functions, learning rates, and dropout rates to prevent overfitting and improve generalization. Additionally, incorporating external macroeconomic factors, seasonal demand variations, and supply chain disruptions can provide a more comprehensive forecasting model.

Another promising direction is the integration of hybrid models combining ANN with advanced deep learning techniques such as LSTM, Gated Recurrent Units (GRU), or Transformer-based architectures. These models can capture both short-term fluctuations and long-term demand trends, leading to more robust predictions. Furthermore, explainability and interpretability of AI-driven forecasting should be improved by integrating feature importance analysis and attention mechanisms, ensuring managerial trust and adoption.

Finally, real-world implementation and validation of ANN-based forecasting in different manufacturing industries should be explored. Case studies on real-time deployment, scalability, and integration with enterprise resource planning (ERP) systems would provide valuable insights into the practical feasibility of AI-driven supply chain management solutions.

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