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Supply Chain Optimization of Industrial Machinery Projects Based on Artificial Neural Networks for Multi-Product Demand Forecasting

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ABSTRACT

Fluctuating demand and diverse products pose significant challenges for supply chain management in manufacturing, leading to production disruptions and increased costs. This study aims to optimize the supply chain of the industrial machinery sector through demand forecasting with artificial neural networks (ANN). Demand data covering 24 months for three products—water tanks, mixer machines, and conveyors—were analyzed using time series clustering based on autocorrelation and complete linkage. Stationarity was tested using the Augmented Dickey-Fuller (ADF) and Box-Cox transformation prior to modeling. The ANN was trained with a learning rate of 0.001, 20 hidden neurons, and PACF-based lag inputs. Results showed that cluster one achieved a MAPE below 30%, indicating strong predictive accuracy, while cluster two achieved a MAPE below 50%, considered acceptable. Predictions for the 25th month from cluster one are recommended for inventory planning. The study demonstrates that ANN-based forecasting effectively supports decision-making and enhances supply chain optimization in multi-product manufacturing.

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INTRODUCTION

The growing competition in the manufacturing industry demands continuous improvement [1]. Supply chain management (SCM) is a key factor in maintaining competitiveness, particularly in the fabrication sector, which faces high demand fluctuations and the risk of product stockpiling [2], [3]. Efficient SCM ensures production sustainability by balancing product availability and operational costs while also coordinating the flow of production, finance, and marketing activities [4], [5]. Challenges remain in managing multi-product data, which often leads to inventory imbalances and production failures [6]. Artificial neural networks (ANN) have been increasingly applied in supply chain forecasting, providing more accurate demand analysis than conventional methods that rely on manual classification [7], [8], [9].

In recent years, the development of artificial neural network models has become increasingly popular in the manufacturing industry, particularly in supply chain management [10]. The application of artificial neural network (ANN) models in the manufacturing industry can help optimize production processes, predict equipment failures, and improve product quality through more effective data analysis [11]. Unlike traditional methods such as exponential smoothing, linear regression, ARIMA, or Holt-Winters, which generally assume linear relationships and tend to be less able to handle multi-product demand volatility [12], [13], [14], ANN is able to capture complex nonlinear relationships and adapt to dynamic changes in supply chain data. This capability makes ANN more effective in addressing challenges such as demand fluctuations, limited information, and multi-product forecasting needs [15]. However, ANN models still require the availability and

quality of complete data for training in order to produce accurate predictions. Incomplete and inaccurate data can result in incorrect predictions [16]. Incorrect predictions risk hindering the optimization process [17].

Artificial neural network demand prediction models are often used in the manufacturing industry to improve the accuracy of predicting demand for goods in industrial machinery production [18]. Artificial neural network technology has been proven to facilitate various supply chain activities through computation [19]. Artificial neural networks are capable of performing multi-product analysis by inputting product data into a data library, which is then processed with pre-built analysis, resulting in output in the form of product data in accordance with demand with a wider variety of products [20]. Similar to transformer manufacturing industries, industrial machinery production shows seasonal patterns and demand fluctuations that require sophisticated forecasting tools to manage supply chain effectively [21]. Artificial neural network models have the ability to learn from historical data and simulations to optimize operational policies.

This study aims to optimize supply chain management for the needs of the manufacturing machinery project industry through an integrated approach that combines autocorrelation-based clustering with ANN for multi-product demand forecasting. While previous studies generally focus on single-product forecasting or rely solely on traditional statistical methods [22], [23] there is still very limited research integrating systematic clustering to address the challenges of multi-product demand volatility. The contribution of this study lies in the systematic preprocessing stage through PACF-based input determination and differentiated performance evaluation

between clusters. This framework not only enables better management of demand fluctuations across multiple products but also provides practical insights to reduce stock imbalances and production failures, thereby strengthening decision-making in supply chain management.

RESEARCH METHOD

Data Collection

The data used in this study consists of demand records for water tanks, mixer machines, and conveyors over the past 24 months. The dataset was obtained directly from the production and sales records of a

manufacturing company located in Surabaya. The verification process was carried out by cross-matching production reports, sales invoices, and inventory records to ensure accuracy and completeness. Missing or inconsistent entries were cleaned and validated before analysis. The verified dataset was compiled using Microsoft Excel, while statistical calculations and ANN modeling were performed using Python on Google Colab. The research stages, including data collection, time series clustering, stationarity testing, ANN modeling, evaluation, and practical implementation in supply chain demand forecasting, are presented in the flowchart in [Figure 1](#)

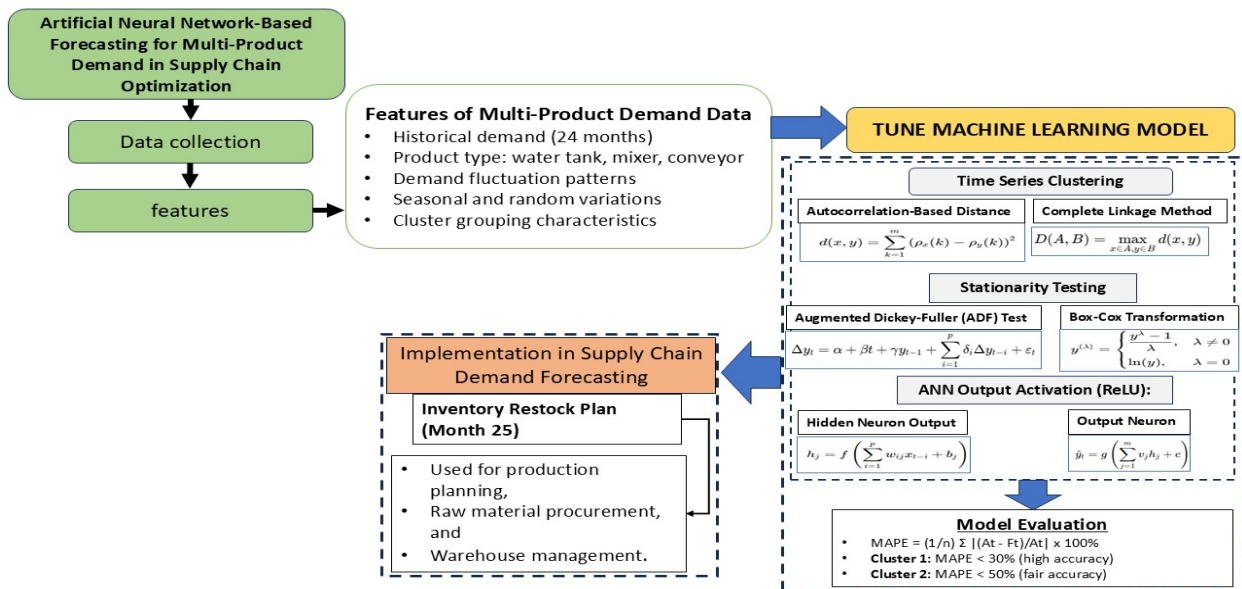


Figure 1 Research Flowchart of ANN-Based Multi-Product Demand Forecasting for Supply Chain Optimization

Understanding the variability of product demand is essential in developing an accurate forecasting model for supply chain optimization. In this study, 24 months of historical demand data were collected for three manufacturing products, namely water tanks, mixer machines, and conveyors. Each product exhibits unique fluctuation patterns that reflect different levels of seasonality,

irregular variations, and demand volatility. Such differences increase the complexity of managing multi-product supply chains, as imbalances in one product category can disrupt overall production planning and inventory control. To illustrate these dynamics, the historical demand trends for the three products are presented in [Figure 2](#).

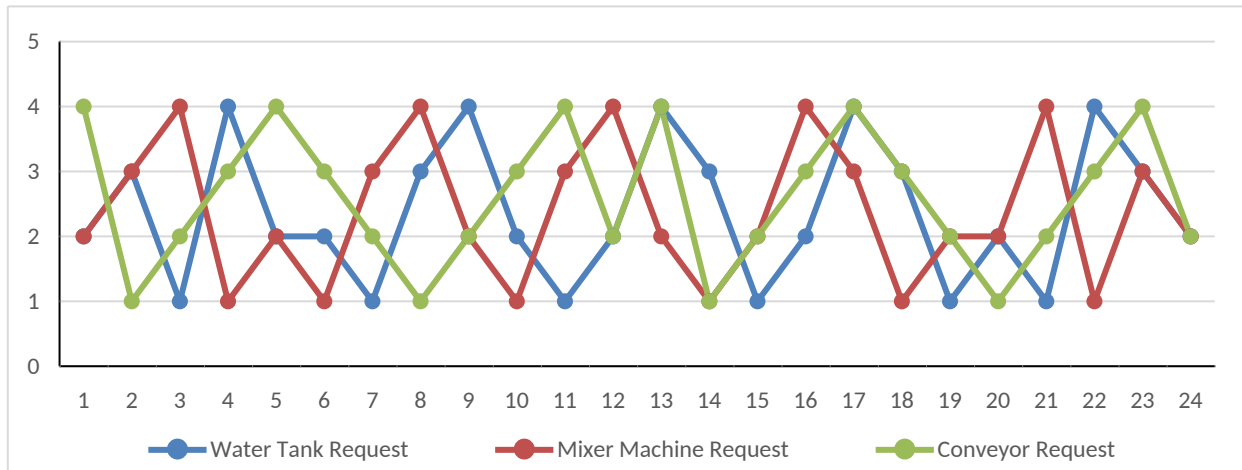


Figure 2 Multi - product demand data for manufacturing companies

Figure 2 presents demand fluctuations over 24 months for the three products. The Water tank shows moderate and consistent variation, Mixer Machine exhibits high volatility, while Conveyor has more stable trends. These patterns help identify similarities across products before applying predictive models.

Data Preprocessing

A time series cluster analysis was applied to the demand data. Distance measures were calculated using autocorrelation-based distances, and cluster membership was determined with the complete linkage algorithm. The optimal number of clusters was identified through dendrogram analysis, formulated as:

$$d_{(xy)z} = \max\{d_{xz}, d_{yz}\}$$

$$T(Y_t) = \begin{cases} \frac{Y_t^\lambda}{\lambda} - 1, \lambda \neq 0 \\ \ln Y_t, \lambda = 0 \end{cases} \quad (1).$$

Clusters that meet the stationary assumption are identified using the PACF plot to determine the observation lags that affect the input data for the ANN model. Normalize the ANN input data using the equation formula:

$$y = x_1w_1 + x_2w_2 + x_3w_3 \quad (2).$$

ANN Model Development

Clusters were identified as input data for the ANN model by creating a time series plot for each cluster to determine the data condition. The dataset was divided into training (80%) and validation (20%) subsets to evaluate model performance. The ANN was trained using backpropagation with a maximum of 1,500 epochs and a learning rate of 0.001. To prevent overfitting, early stopping was applied based on validation error, and weight regularization (L2 penalty) was used during training. Based on the identified input data, an ANN model was created according to the procedure with the equation:

Calculation of hidden neuron output:

$$z_{net_j} = v_{j0} + \sum_{i=1}^m x_i v_{ji} \quad (3).$$

Calculation according to activation function:

$$z_j = f(z_{net_j}) \quad (4).$$

Output neuron calculation:

$$y_{net_k} = w_{k0} + \sum_{j=1}^p z_j w_{kj} \quad (5).$$

Recalculation according to activation function:

$$y_k = f(y_{net_k}) \quad (6).$$

Calculation of δ of output neuron based on output neuron error:

$$\delta_k = (t_k - y_k)f'(y_{net_k}) \quad (7).$$

Calculation of weight change with acceleration rate:

$$\Delta w_{kj} = \alpha \delta_k z_j \quad (8).$$

Calculation of δ hidden neurons based on hidden neuron errors:

$$\delta_{net_j} = \sum_{k=1}^m \delta_k w_{kj} \quad (9).$$

Calculation of the δ factor of hidden neurons:

$$\begin{aligned} \delta_j &= \delta_{net_j} f'(z_{net_j}) \\ \delta_j &= \delta_{net_j} z_j (1 - z_j) \end{aligned} \quad (10).$$

Calculation of the weight change rate

$$\Delta v_{ji} = \alpha \delta_j x_i \quad (11).$$

Calculation of all weight changes:

$$w_{kj}(baru) = w_{kj}(lama) + \Delta w_{kj} \quad (12).$$

Hidden neuron calculations are bias and weighted:

$$v_{ji}(baru) = v_{ji}(lama) + \Delta v_{ji} \quad (13).$$

Calculation of stopping condition test (end of iteration):

$$\hat{y}^{(k)} = f^0 \left[\sum_{j=1}^q [w_j^0 f_j^h \left(\sum_{i=1}^p w_{ji}^h x_{i(k)} + b_j^h \right) + b^0] \right] \quad (15).$$

Evaluation Metrics

The goodness of fit of each cluster model was calculated based on the MAPE value using the equation:

$$MAPE = \sum_{t=1}^N \frac{|PE_t|}{T} \quad (16).$$

MAPE measures the extent to which forecasting results deviate from actual data. The lower the MAPE value, the better the forecasting accuracy. MAPE was chosen because it is intuitive, scale-free, and widely used in supply chain management research and practice, facilitating performance comparisons between products and studies [24], [25]. Furthermore, MAPE presents errors as a percentage, making it easier for practitioners and decision-makers to understand. However, MAPE has limitations, particularly its sensitivity when actual values approach zero, which can result in very high error values [26]. Compared to other metrics such as RMSE or MAE, which indicate the absolute magnitude of error, MAPE is more interpretive in the context of demand forecasting because it presents error information in percentage units, which are relevant for decision-making [27]. Similar performance evaluation approaches have been successfully implemented in various supply chain contexts, where comprehensive performance measurement frameworks help identify both high-performing and underperforming areas, providing basis for strategic improvements [28].

To assess the prediction performance of the Artificial Neural Network (ANN) model used, the Mean Absolute Percentage Error (MAPE) is employed as an accuracy metric. The classification of MAPE values is shown in [Table 1](#).

Table 1 MAPE criteria of ANN model

Nilai MAPE	Information
<10%	Very good predictive ability
10%-20%	Good predictive ability
20%-50%	Fair predictive ability
>50%	Poor predictive ability

[Table 1](#) presents MAPE-based evaluation criteria, where lower values indicate higher accuracy, ranging from very good (<10%) to poor (>50%), and are used to assess the ANN model's demand forecasts.

RESULT AND DISCUSSION

Conceptual ANN Model of Multi-Product Demand Supply Chain

The ANN model is created through several stages aimed at optimizing the supply chain to meet multi-product demand forecasting requirements.

- a. Complete report data input.
Historical demand data (24 months) for three products were used. The assumption is that data must be complete and consistent; missing or poor-quality data may reduce model reliability.
- b. Concept of the ANN supply chain model for multi-product demand prediction.
The ANN was built with a learning rate of 0.001, 20 hidden neurons, and significant PACF lags as inputs. The limitation is its dependence on parameter tuning and the risk of overfitting.
- c. Testing the ANN supply chain model for multi-product demand forecasting.

Performance was evaluated using MAPE. Cluster one showed high accuracy (MAPE <30%), while cluster two achieved fair accuracy (MAPE <50%). The assumption is that MAPE is an appropriate metric,

though it can be sensitive when actual values are very small.

This study was conducted to test the ability of the supply chain ANN model used to meet multi-product demand forecasting needs. The supply chain ANN model was used to improve prediction accuracy based on MAPE input data and compared with the prediction results.

Time Series Cluster Analysis of Multi-Product Demand

Time series cluster analysis of multi-product demand was used in the data preprocessing stage. The analysis was performed to group each multi-product demand that was close in distance. Distance calculations for time series clusters were performed using autocorrelation-based distance, with the weight matrix used being the identity matrix. The algorithm for determining cluster members used a hierarchical method, namely complete linkage.

The dendrogram clustering in [Figure 5](#) [Figure 3](#) shows that Months 6, 7, 10, 14, 15, 18, 21, and 24 form one group (cluster one) which is combined at a relatively low distance on the vertical axis of the dendrogram, indicating that the demand pattern in cluster one tends to be similar, both in terms of quantity and fluctuation. Months 1, 2, 3, 4, 5, 8, 9, 11, 12, 13, 16, 17, 19, 20, 22, and 23 form a cluster two group showing a more varied and dynamic level of demand.

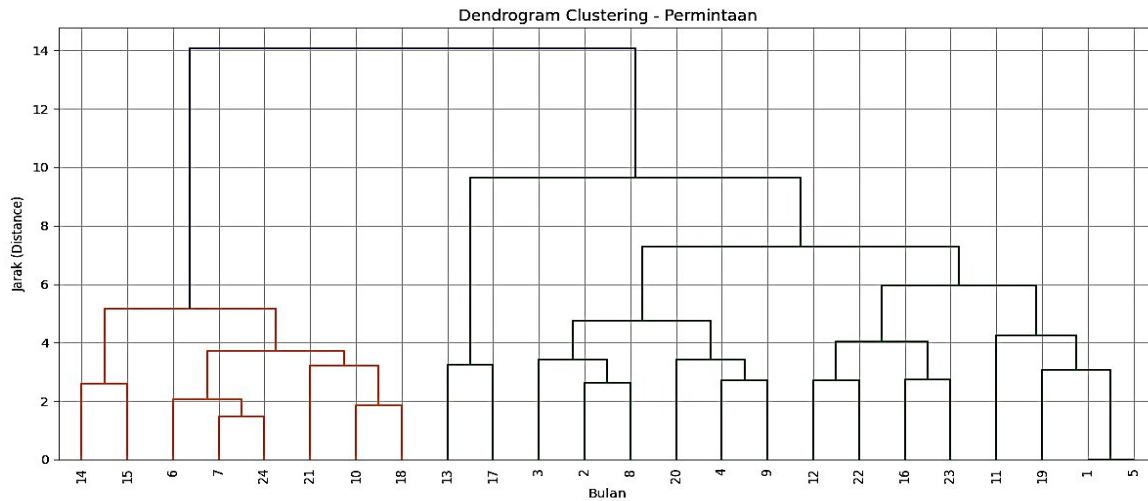


Figure 3 Time series clustering dendrogram graph

Based on [Table 2](#), cluster one shows a tendency for low and stable demand. The average demand for water tanks and conveyors is 2.375, while mixers have a lower average of 1.875. The coefficient of variation shows a small value, with water tanks accounting for 29.30%, mixers 31.97%, and conveyors 36.08%, indicating that the variation in the data relative to the average is quite controlled.

Cluster two shows an average demand reached 2,625 for water tanks, 2,437 for mixers, and 2,562 for conveyors. The coefficient of variation in cluster two increases significantly, reaching 48.04% for mixers and 45.70% for conveyors. The high coefficient of variation indicates that demand in cluster two is more volatile, requiring a more flexible and responsive production strategy

Table 2 Time series cluster calculation

Cluster	Variable	Mean	Max	Min	Std Dev	Coefficient of Variation (%)
1	Water Tank Demand	2.375	3	1	0.69	29.30
	Mixer Machine Demand	1.875	3	1	0.59	31.97
	Conveyor Demand	2.375	4	1	0.85	36.08
2	Water Tank Demand	2.625	4	1	0.92	35.32
	Mixer Machine Demand	2.437	4	1	1.17	48.04
	Conveyor Demand	2.562	4	1	1.17	45.70

[Table 2](#) indicates that cluster one exhibits relatively stable demand with low variation (CV 29%–36%), whereas cluster two shows higher volatility (CV 35%–48%) despite slightly higher average demand. This distinction suggests that products in cluster one are more suitable for *forecast-driven planning*, while products in cluster

two require a more responsive supply chain approach such as an *agile supply chain*. These findings align with Octaviani et al.[\[29\]](#), who emphasized the need for differentiated forecasting strategies based on demand volatility, and Hung et al.[\[30\]](#), who demonstrated that integrating clustering into multi-product forecasting

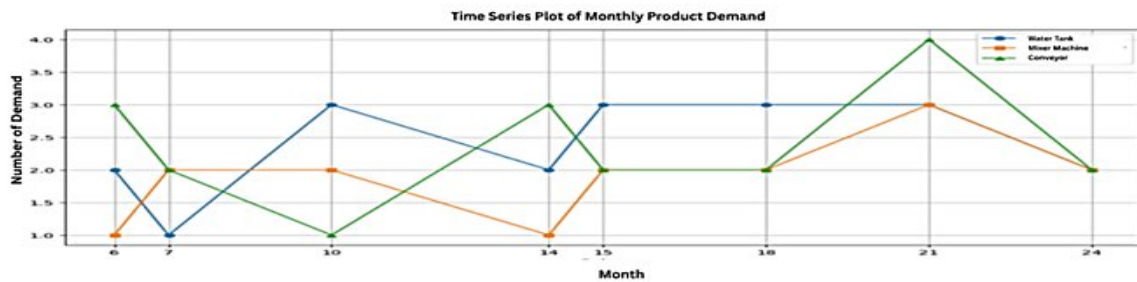
can improve accuracy by tailoring models to specific group characteristics.

Identification of ANN Inputs for Multi-Product Demand

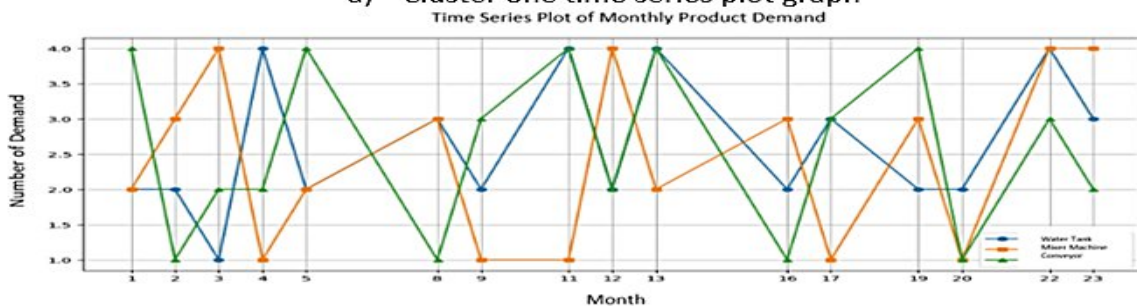
ANN data input is used to identify forecasting models for each cluster. The input data determination procedure is performed by examining significant lags in the PACF plot of stationary data. ANN input data is determined based on significant PACF lags, limited to lag 1 to lag 7. Then, it is evaluated based on the model's goodness-of-fit criterion, namely the smallest MAPE. Forecasting model identification for each cluster is carried out as follows.

The demand cluster in Figure 4 shows that the demand for water tanks decreases in the 7th month with only one unit requested. In the 10th month, demand increases by three units and remains stable at three units from the 15th to the 21st month. The fluctuations in water tank demand indicate that demand tends to be consistent and predictable. The demand for mixer machines in the 6th and 14th

months was at its lowest point of one unit, increasing in the 21st month by three units. Fluctuations in the demand for mixer machines indicate that the demand for mixer machines is unstable. The demand for conveyors in the 6th month was three units, decreased to one unit in the 10th month, and in the 21st month the demand for conveyors increased by four units. The highly fluctuating pattern of conveyor demand indicates that the demand for conveyors is uncertain. Cluster one shows that the demand for water tanks appears to be varied and relatively stable, with demand from 2 to 4. Months 4, 12, and 22 saw an increase in demand, while months 2 and 9 saw a decrease. The demand for mixer machines showed a significant fluctuating pattern. Demand for mixer machines reached its lowest point in months 9 and 17. The demand for conveyors showed a slight stability, but there was a decrease in months 8 and 20. High demand for conveyor products occurred in months 11 and 19, indicating a consistent demand pattern.



a) Cluster one time series plot graph



b) Cluster two time series plot graph

Figure 4 Cluster time series plot graph

The ACF (Autocorrelation Function) plot is used to identify autocorrelation patterns in time series data to determine data stationarity. Based on the graph in the [Figure 5](#), the ACF plot of water tank cluster one demand at lags 1 to 7 shows mild fluctuations, but most are within the confidence limits. At lags 2 and 5, the ACF value is high. The high ACF value indicates that there is no consistent significant autocorrelation, the pattern is random, and the water tank demand data is fairly stationary. The ACF plot of mixer machine demand shows a low ACF value and is within the confidence limits. At lag 6, there is a high negative ACF value. The high negative value indicates that there is no significant autocorrelation pattern in mixer machine demand and the mixer machine demand data appears stationary. Conveyor demand has ACF values at lags 1

to 4 showing significant fluctuations, with lags 2 and 4 being outside the confidence limits. Significant fluctuations indicate that the conveyor demand data is not stationary.

The ACF plot of the water cluster two tank and conveyor demand data shows a significant decrease at lag 1, with autocorrelation values at other lags approaching zero and insignificant. This significant decrease indicates that both demand variables are stationary, meaning that their mean and variance are relatively constant. The demand for mixer machines shows that lag 1 still has a significant autocorrelation value, which means that the mixer machine demand data is not stationary. To ensure the stationarity of the data in the [Figure 5](#) it is necessary to conduct an ADF test.

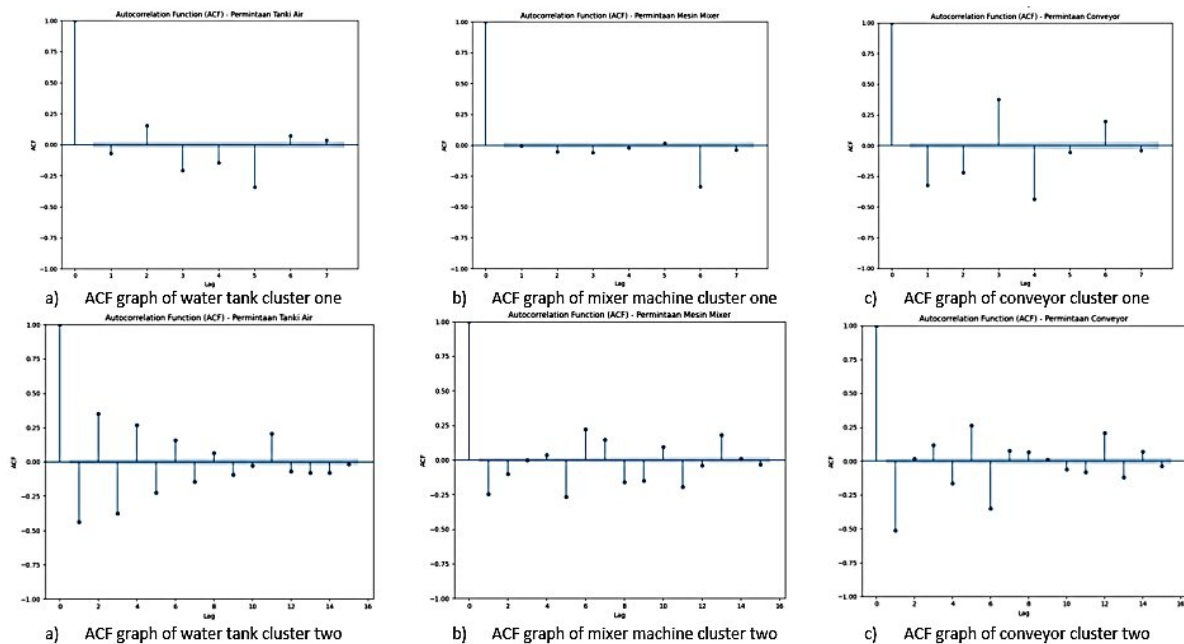


Figure 5 ACF graph of cluster

The initial identification stage is applied to all clusters. It must be ensured that the stationarity assumption in the cluster data is met. There are two types of stationarity: stationarity with respect to the mean and

stationarity with respect to the variance. The Augmented Dickey-Fuller (ADF) test was employed to verify the stationarity of the data with respect to the mean, which is critical for ensuring valid time series

modeling and avoiding spurious regression results [31]. The Box-Cox transformation was applied to stabilize variance and achieve stationarity with respect to heteroscedasticity, thereby improving the reliability of the ANN model inputs [32]. These steps ensure that the demand data meets fundamental assumptions of time series forecasting and enhances the robustness of the subsequent ANN analysis [33]. The ADF test hypothesis is formulated

as follows:

$H_0 : \pi = 0$ (The ACF plot data for the demand variable is not stationary)

$H_1 : \pi < 0$ (The ACF plot data for the demand variable is stationary)

The decision-making condition is to reject H_0 if $P < \alpha$, where $\alpha = 0.05$.

Table 3 Calculation of ADF test

Demand Variable	Dickey-Fuller Statistic	Lag Order	p-value	Conclusion
Water Tank cluster one	-2.415	7	0.137	Non-stationary (fail to reject H_0)
Mixer Machine cluster one	-2.672	7	0.078	Non-stationary (borderline)
Conveyor cluster one	0.231	7	0.973	Non-stationary (fail to reject H_0)
Water Tank cluster two	-2.938	7	0.0411	Stationary (reject H_0)
Mixer Machine cluster two	-4.493	7	0.0002	Stationary (reject H_0)
Conveyor cluster two	-2.648	7	0.083	Non-stationary (fail to reject H_0)

Alternative Hypothesis: The series is stationary.

Based on the Table 3, the demand for water tanks cluster one has a p-value of 0.137. The p-value of 0.137 is greater than the significance threshold of 0.05, so H_0 is accepted, which means the water tank demand data is not statistically stationary. The demand for mixer machines shows a p-value of 0.078. The p-value of 0.078 is close to the significance limit of 0.05 compared to the demand for water tanks, the p-value of the demand for mixer machines is still not low enough to accept H_1 . The demand for conveyors displays a very high p-value of 0.973. The p-value of 0.973 indicates that the conveyor demand data is not stationary and statistically shows strong fluctuations in the data. The variables demand for water tanks, for mixer machines, and for conveyors require a differencing process to make the data stationary. Differentiating serves to eliminate trend components or seasonal

patterns, with the aim of making the data stationary.

The demand for water tank cluster two has a p-value of 0.0411. The p-value of 0.0411 is smaller than the significance limit of 0.05, so H_1 is accepted, which indicates that the water tank demand data is not statistically stationary. The demand for mixer machines shows a p-value of 0.0002. The p-value of 0.0002 is lower than the significance limit of 0.05, the p-value of the demand for mixer machines can accept H_1 . The demand for conveyors displays a very high p-value of 0.083. The p-value of 0.083 indicates that the conveyor demand data is not statistically stationary. The conveyor demand variable requires a differencing process to make the data stationary.

The results of the differencing process are shown in the Table 4, the water tank

demand variable obtained a p-value of 0.00003. The conveyor demand showed quite significant results, with a p-value of 0.000009. The mixer machine demand after differencing showed a p-value of 0.0082. The p-value for the water tank demand, mixer machine demand, and conveyor demand is less than 0.05, so H0 can be rejected, which indicates that after differencing, the data for the water tank demand, mixer machine demand, and

conveyor demand have become statistically stationary. The conveyor cluster two demand variable was subjected to two data differencing processes to obtain a p-value lower than the significance limit. The p-value for conveyor demand is 0.00071, the p-value for conveyor demand is lower than the significance limit of 0.05, indicating that the conveyor demand data is statistically stationary.

Table 4 Calculation of differencing of ADF cluster one test

Demand Variable	Dickey-Fuller Statistic	Lag Order	p-value	Conclusion
Water Tank cluster one	-5.366	7	0.00003	Stationary (reject H ₀)
Mixer Machine cluster one	-3.491	7	0.0082	Stationary (reject H ₀)
Conveyor cluster one	-8.149	7	0.000009	Stationary (reject H ₀)
Conveyor cluster two	-4.177	7	0.00071	Stationary (reject H ₀)

Alternative Hypothesis: The series is stationary
Significance Level: 5%

The λ (lambda) estimation is performed to determine the stationarity of the data with respect to the variance of the demand variable data that has been differencing once to ensure that the stationarity assumption with respect to the variance is met. The λ (lambda) value selected is one that produces a sufficiently small MSE (Mean Squared Error). If the λ (lambda) value is equal to one (or close to it), then the analyzed data is stationary with respect to the variance, and no transformation is required. The results of the λ (lambda) estimation can be seen in the box-cox plot in [Figure 6](#).

Based on the results of the box-cox transformation plot cluster one calculations in the [Figure 6](#), the water tank cluster one demand variable has an optimal λ value of 0.2516, which indicates that the data needs to be transformed using a square root so that its distribution becomes normal. The λ value of 0.2516

indicates that the original data from the water tank demand has a non-normal distribution and requires. The mixer machine demand variable has an optimal λ value of 1.2519. The optimal λ value of 1.2519 is close to 1, which indicates that the data is relatively close to a normal distribution, and requires a little transformation to improve the data. The conveyor demand has an optimal λ value of 0.0625. The optimal λ value of 0.0625 indicates that the data distribution is skewed and requires a power transformation to adjust to a normal distribution. Based on the results of the Cox box re-transformation cluster one in the [Figure 6](#), the value of the water tank demand variable is 1.1762, the value of the mixer machine demand variable is 1.0031, and the value of the conveyor demand variable is 1.0679. The lambda value of the three variables shows that the data is close to the estimated value of $\lambda = 1$, which means that the data of

the three demand variables are considered stationary with respect to variance or normally distributed data.

Based on the results of the box cox transformation plot cluster two in the [Figure 6](#) the water tank cluster two demand variable has an optimal λ value of 0.5088, the lambda value of 0.5088 is close to 0.5, indicating that the data needs to be transformed using a square root to make the data normally distributed. The mixer machine demand variable has an optimal λ value of 1.066. The optimal λ value of 1.066 is close to 1, indicating that the data is relatively close to a normal distribution and no transformation is required. The conveyor demand has an optimal λ value

of 0.5436. The optimal λ value of 0.5436 indicates that a power transformation is needed to adjust to a normal distribution. Based on the results of the box cox re-transformation cluster two in the [Figure 6](#) the optimal lambda value for the water tank demand variable is 0.9718. The lambda value for the water tank demand variable shows that the data is close to the estimated value of lambda = 1, indicating that the data is considered to be normally distributed. The optimal lambda value for the conveyor demand variable is 1.0976. The lambda value for the conveyor demand variable shows that the data is close to the lambda value = 1, indicating that the data is considered stationary with respect to variance.

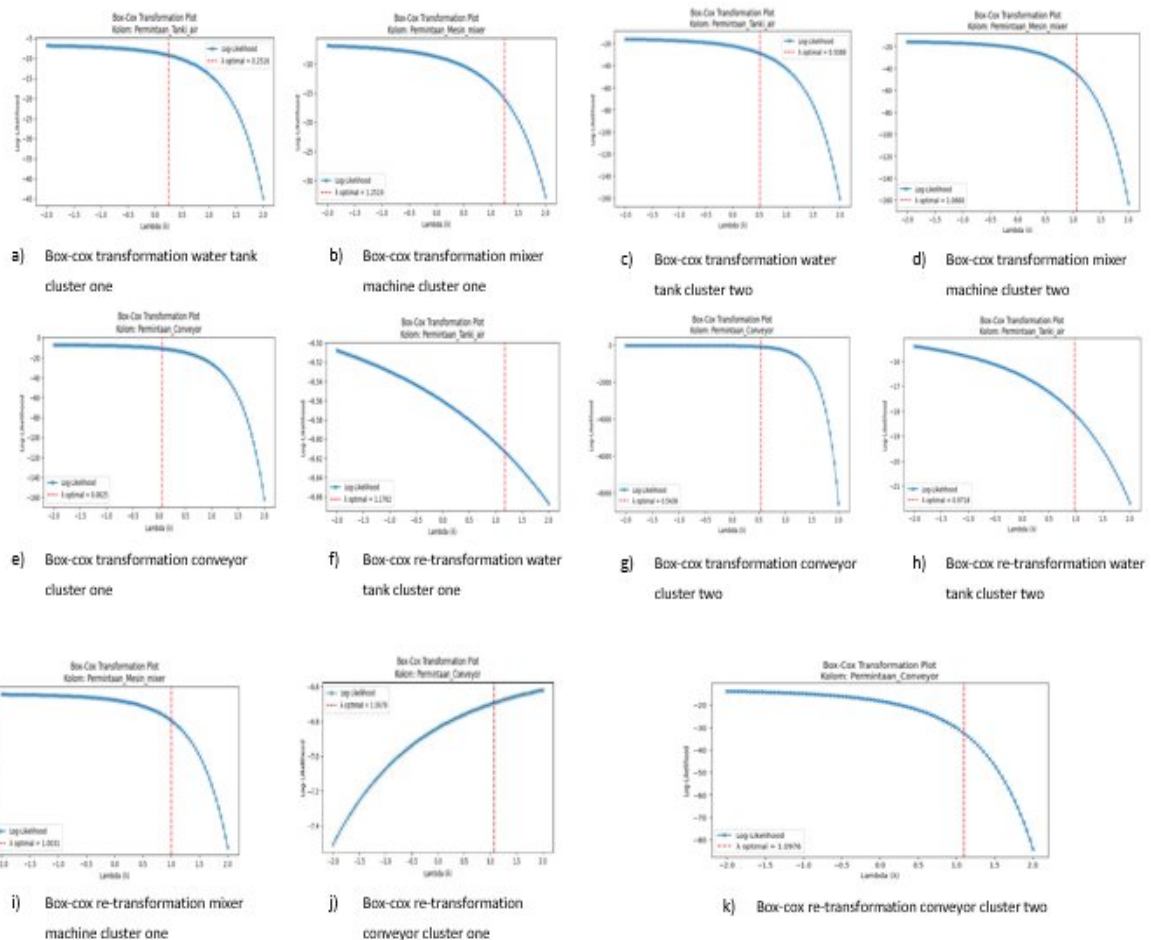


Figure 6 Box-cox transformation graph

Determination of input data for ANN modeling is based on significant PACF lags

limited to lag 7. The PACF plots of the three demand variables can be seen in [Figure 7](#).

Based on the PACF plot of water tank demand, it shows that lag 1 exceeds the significance limit, with a high negative value. The PACF plot of mixer machine demand shows a pattern that exceeds the significance limit at lag 1 and lag 3. The PACF plot of conveyor demand shows a pattern of quite high negative values that exceed the significance limit at lag 1 and lag 2. Lags with negative values that exceed the significance limit can be used as input data for the ANN model.

Based on the results in the [Figure 7](#) significant PACF lags are limited to lag 7.

The PACF plots of the three demand variables can be seen in [Figure 7](#). Based on the PACF plot of the water tank demand, it shows that only lag 1, lag 2, and lag 3 exceed the significance limit, with quite high negative values. The PACF plot of the mixer machine demand shows a pattern that exceeds the significance limit at lag 1, lag 2, lag 5, and lag 7. The PACF plot of the conveyor demand shows a pattern of negative values that exceed the significance limit at lag 1, lag 2, and lag 4. Lags with negative values that exceed the significance limit can be used as input data for the ANN model.

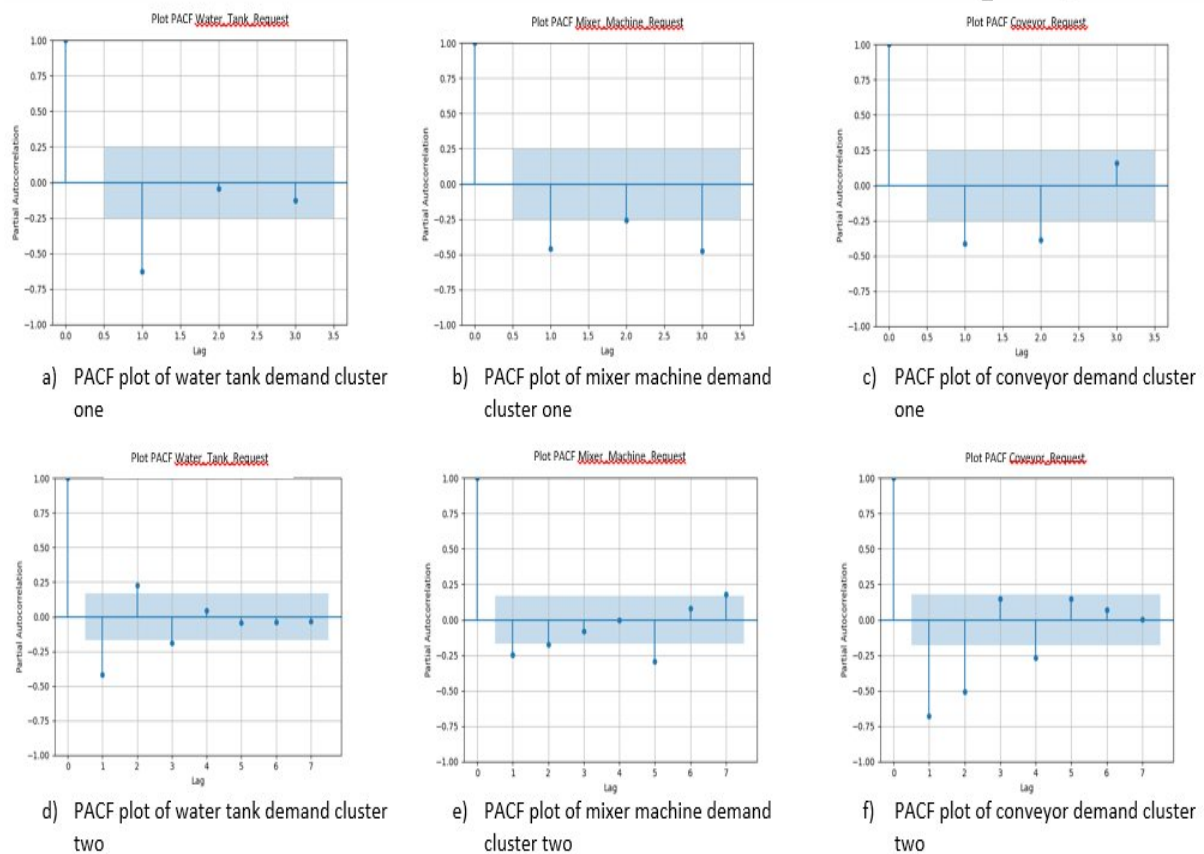


Figure 7 Plot PACF graph

Multi-Product Demand ANN Model

The multi-product demand ANN model is constructed based on significant PACF lags by identifying significant lags in the PACF plot of stationary data. Significant lags

included in the input data for the model are limited to lag 1 to lag 7. The number of hidden neurons used in the multi-product demand ANN model is 20 neurons, with one hundred replications, a learning rate

of 10^{-3} , and a maximum iteration of 1.5×10^3 . The results of the multi-product demand ANN model are shown in [Table 7](#).

Based on the [Table 7](#), cluster one has a more stable prediction performance and a high level of accuracy. The three demand variables in cluster one of the ANN model show relatively low in-sample MAPE values, indicating that the training data process is running well. The out-sample MAPE values of cluster one show fluctuations, but tend to be quite low, ranging below 30%. A MAPE value below 30% indicates that the ANN model can generalize the data well. Cluster one has a prediction result of 1 unit for all three variables in the 25th month. The ANN

model of cluster two experienced a significant decrease in out-sample MAPE performance. The out-sample MAPE values of the mixer machine demand variable and the conveyor demand variable increased sharply to 46.31% and 48.44%, respectively. A MAPE value below 50% indicates that the ANN model is quite good at generalizing the input data. The in-sample MAPE value of cluster two is quite low, indicating that the training data process is running well. Cluster two has predicted results for the water tank demand variable of 1 unit, the mixer machine demand variable of 4 units, and the conveyor demand variable of 3 units.

Table 7 Artificial neural network model prediction results

Cluster	Variable	Input Variables	MAPE (In Sample)		MAPE (Out of Sample)
			In Sample	Out Sample	
1	Water Tank	Y_{t-1}	12,48%	4,32%	1
	Mixer Machine	Y_{t-1}, Y_{t-3}	5,16%	24,68%	1
	Conveyor	Y_{t-1}, Y_{t-2}	18,05%	12,65%	1
2	Water Tank	$Y_{t-1}, Y_{t-2}, Y_{t-3}$	13,76%	20,95%	2
	Mixer Machine	$Y_{t-1}, Y_{t-3}, Y_{t-5}, Y_{t-7}$	6,22%	46,31%	4
	Conveyor	$Y_{t-1}, Y_{t-2}, Y_{t-4}$	7,29%	48,44%	2

[Table 7](#) shows that the ANN model achieved relatively low in-sample MAPE across both clusters, indicating that the training process was effective. In cluster one, out-of-sample MAPE values remained below 30%, demonstrating strong generalization and reliable predictive ability for stable demand patterns. Conversely, cluster two exhibited significantly higher out-of-sample errors, particularly for mixer machines (46.31%) and conveyors (48.44%), reflecting the challenges of modeling highly volatile demand. These results highlight that while ANN can effectively capture stable demand dynamics, its performance may degrade under high variability, consistent with

findings by Bhuiyan et al.[34] and Ali et al.[35], who reported that hybrid models or advanced architectures may be needed to improve robustness in volatile multi-product environments. These findings suggest that manufacturers dealing with volatile product demand may need to complement ANN with hybrid or ensemble forecasting techniques to minimize risks of stock imbalance and production inefficiencies.

CONCLUSION

Based on the results, the ANN model for multi-product demand forecasting demonstrated fairly good accuracy, as

indicated by out-sample MAPE values below 50%. Predictions in cluster one even showed MAPE values below 30%, reflecting high accuracy in product demand forecasting. These findings confirm that ANN is effective in anticipating demand fluctuations in the industrial machinery manufacturing sector. In practical terms, these findings imply improved efficiency in supply chain management. More accurate demand forecasting enables companies to plan inventory more precisely, reduce the risks of overstocking or shortages, and minimize operational costs. In the multi-product context, this approach allows firms to manage demand variability more adaptively compared to traditional methods, thereby supporting production sustainability and strategic decision-making in supply chain operations. The predicted results for cluster one are

recommended as a basis for inventory restock in the 25th month. In practice, these forecasts can guide production scheduling, raw material procurement, and warehouse capacity planning to ensure that stock levels remain aligned with actual demand, reducing the risks of overstocking or shortages. However, this study has certain limitations, including the use of historical data limited to 24 months and only three product types. The ANN model is also highly dependent on data quality, meaning incomplete or inaccurate data may reduce predictive performance. Future research is recommended to explore longer time horizons, include a broader range of products, and compare ANN with other machine learning methods such as Long Short-Term Memory (LSTM) or Gradient Boosting to gain more comprehensive insights.

REFERENCES

















- [1] F. Huang and Y. Deng, "TCGAN: Convolutional Generative Adversarial Network for time series classification and clustering," *Neural Networks*, vol. 165, pp. 868–883, Aug. 2023, doi: 10.1016/j.neunet.2023.06.033.
- [2] H. Kim, S. Park, and S. Kim, "Time-series clustering and forecasting household electricity demand using smart meter data," *Energy Reports*, vol. 9, pp. 4111–4121, Dec. 2023, doi: 10.1016/j.egyr.2023.03.042.
- [3] Y. Wang, Z. Shao, T. Sun, C. Yu, Y. Xu, and F. Wang, "Clustering-property matters: A cluster-aware network for large scale multivariate time series forecasting," in *International Conference on Information and Knowledge Management, Proceedings*, Association for Computing Machinery, Oct. 2023, pp. 4340–4344, doi: 10.1145/3583780.3615253.
- [4] S. Z. Safitri and T. Sukmono, "Comparing of artificial neural network and multiplicative holt winters exponential smoothing methods in forecasting demand," *Journal for Technology and Science*, vol. 1, no. 3, pp. 180–190, Oct. 2024, doi: 10.61796/ipteks.v1i3.215.
- [5] S. Robus, V. Walter, and Z. Kőműves, "An overview of performance measurement for demand forecasting based on artificial neural networks," *Regional and Business Studies*, vol. 14, no. 2, pp. 5–20, Dec. 2022, doi: 10.33568/rbs.4434.

- [6] X. Ding, K. Hao, X. Cai, X. S. Tang, L. Chen, and H. Zhang, "A novel similarity measurement and clustering framework for time series based on convolution neural networks," *IEEE Access*, vol. 8, pp. 173158–173168, 2020, doi: 10.1109/ACCESS.2020.3025048.
- [7] I. Nouiri, D. Malek, and N. Issam, "Forecasting daily water demand using artificial neural networks: A case study of sfax city," in *International Conference on Integrated Environmental Management for Sustainable Development*, 2020, pp. 568–570. [Online]. Available: www.iciem-conference.com.
- [8] A. Aydin et al., "Optimizing iron and steel production through feed-forward artificial neural networks: A demand forecasting approach," 2024. [Online]. Available: <https://www.researchgate.net/publication/378862706>.
- [9] Y. Li and D. C. Anastasiu, "MC-ANN: A mixture clustering-based attention neural network for time series forecasting," *IEEE Trans Pattern Anal Mach Intell*, 2025, doi: 10.1109/TPAMI.2025.3565224.
- [10] J. Kauffmann, M. Esders, L. Ruff, G. Montavon, W. Samek, and K. R. Muller, "From clustering to cluster explanations via neural networks," *IEEE Trans Neural Netw Learn Syst*, vol. 35, no. 2, pp. 1926–1940, Feb. 2024, doi: 10.1109/TNNLS.2022.3185901.
- [11] A. Ranawaka and S. Jawwadh, "Optimization of demand forecasting in the supply chain management of apparel industry," May 16, 2024, doi: 10.21203/rs.3.rs-4330769/v1.
- [12] S. Krishna C. Tulli, "Comparative analysis of traditional and ai-based demand forecasting models," *International Journal of Emerging Trends in Science and Technology*, pp. 6933–6956, Jun. 2020, doi: 10.18535/ijetst/v7i6.02.
- [13] L. Kumar, K. Sharma, and U. K. Khedlekar, "Dynamic pricing strategies for efficient inventory management with auto-correlative stochastic demand forecasting using exponential smoothing method," *Results in Control and Optimization*, vol. 15, Jun. 2024, doi: 10.1016/j.rico.2024.100432.
- [14] C. Lei, H. Zhang, Z. Wang, and Q. Miao, "Multi-model fusion demand forecasting framework based on attention mechanism," *Processes*, vol. 12, no. 11, Nov. 2024, doi: 10.3390/pr12112612.
- [15] J. Feizabadi, "Machine learning demand forecasting and supply chain performance," *International Journal of Logistics Research and Applications*, vol. 25, no. 2, pp. 119–142, 2022, doi: 10.1080/13675567.2020.1803246.
- [16] I. F. Chen and C. J. Lu, "Demand forecasting for multichannel fashion retailers by integrating clustering and machine learning algorithms," *Processes*, vol. 9, no. 9, Sep. 2021, doi: 10.3390/pr9091578.

- [17] Y. Zhao, "Research on e-commerce retail demand forecasting based on sarima model and k-means clustering algorithm," 2024.
- [18] C. Ducharme, B. Agard, and M. Trépanier, "Improving demand forecasting for customers with missing downstream data in intermittent demand supply chains with supervised multivariate clustering," *J Forecast*, vol. 43, no. 5, pp. 1661–1681, Aug. 2024, doi: 10.1002/for.3095.
- [19] E. Prayitno, E. Iskandar, A. A. Subagyo, and I. J. Perdana, "Optimalisasi supply chain management menggunakan integrasi big data dan artificial neural network untuk prediksi permintaan produk umkm," 2024.
- [20] Y. Zhao, "E-commerce demand forecasting using sarima model and k-means clustering analysis," *Journal of Innovation and Development*, 2024.
- [21] E. Oey, G. K. Ayrine, and P. R. D. Yanitra, "Application of forecasting process and techniques— A case study in a transformer manufacturer," *Jurnal Manajemen Industri dan Logistik*, vol. 2, no. 2, 2018, doi: 10.30998/jmil.v2i1.81.
- [22] Y. Ensafi, S. H. Amin, G. Zhang, and B. Shah, "Time-series forecasting of seasonal items sales using machine learning – A comparative analysis," *International Journal of Information Management Data Insights*, vol. 2, no. 1, Apr. 2022, doi: 10.1016/j.jjime.2022.100058.
- [23] J. Feizabadi, "Machine learning demand forecasting and supply chain performance," *International Journal of Logistics Research and Applications*, vol. 25, no. 2, pp. 119–142, 2022, doi: 10.1080/13675567.2020.1803246.
- [24] T. D. Moshood, G. Nawanir, F. Mahmud, S. Sorooshian, and A. Q. Adeleke, "Green and low carbon matters: A systematic review of the past, today, and future on sustainability supply chain management practices among manufacturing industry," Oct. 01, 2021, Elsevier Ltd., doi: 10.1016/j.clet.2021.100144.
- [25] M. Hussain and R. Al-Aomar, "A model for assessing the impact of sustainable supplier selection on the performance of service supply chains," *International Journal of Sustainable Engineering*, vol. 11, no. 6, pp. 366–381, Nov. 2018, doi: 10.1080/19397038.2017.1414898.
- [26] A. Jierula, S. Wang, T. M. Oh, and P. Wang, "Study on accuracy metrics for evaluating the predictions of damage locations in deep piles using artificial neural networks with acoustic emission data," *Applied Sciences (Switzerland)*, vol. 11, no. 5, pp. 1–21, Mar. 2021, doi: 10.3390/app11052314.
- [27] H. Son and C. Kim, "A deep learning approach to forecasting monthly demand for residential-sector electricity," *Sustainability (Switzerland)*, vol. 12, no. 8, p. 3103, Apr. 2020, doi: 10.3390/SU12083103.
- [28] A. Mulyadi, St. N. Meirizha, M. Qurthuby, and M. Sundari, "The analysis of blood supply chain performance based on supply chain operation reference model and causal loop diagram

- approach," *Jurnal Manajemen Industri dan Logistik*, vol. 7, no. 2, pp. 205–218, Oct. 2023, doi: 10.30988/jmil.v7i2.1223.
- [29] E. Octaviani, I. Masudin, A. Khoidir, and D. P. Restuputri, "Material flow analysis for demand forecasting and lifetime-based inflow in Indonesia's plastic bag supply chain," *Logistics*, vol. 9, no. 3, p. 105, Aug. 2025, doi: 10.3390/logistics9030105.
- [30] C. Y. Hung and C. C. Wang, "An approach for multi-item product sales forecasting based on advancing the BCG matrix with matrix-clustering and time modeling techniques," *Systems*, vol. 12, no. 10, Oct. 2024, doi: 10.3390/systems12100388.
- [31] S. Maitra and D. N. Politis, "Prepivoted augmented dickey-fuller test with bootstrap-assisted lag length selection," *Stats (Basel)*, vol. 7, no. 4, pp. 1226–1243, Dec. 2024, doi: 10.3390/stats7040072.
- [32] R. P. Silva, B. B. Zarpelão, A. Cano, and S. Barbon Junior, "Time series segmentation based on stationarity analysis to improve new samples prediction," *Sensors*, vol. 21, no. 21, Nov. 2021, doi: 10.3390/s21217333.
- [33] M. A. Farahani, F. El Kalach, A. Harper, M. R. McCormick, R. Harik, and T. Wuest, "Time-series forecasting in smart manufacturing systems: An experimental evaluation of the state-of-the-art algorithms," *Robot Comput Integr Manuf*, vol. 95, Oct. 2025, doi: 10.1016/j.rcim.2025.103010.
- [34] M. S. M. Bhuiyan et al., "Deep learning for algorithmic trading: A systematic review of predictive models and optimization strategies," Jul. 01, 2025, Elsevier B.V., doi: 10.1016/j.array.2025.100390.
- [35] Y. Ali, F. Hussain, and M. M. Haque, "Advances, challenges, and future research needs in machine learning-based crash prediction models: A systematic review," *Accid Anal Prev*, vol. 194, Jan. 2024, doi: 10.1016/j.aap.2023.107378.

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