Artificial Neural Network Model For Optimization of Forecasting Material Inventory

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ABSTRACT

The increasing competition in the fast-moving consumer goods (FMCG) industry leads to demand fluctuations, negatively impacting the accuracy of demand forecasts and determining optimal lot sizes in material inventory planning. Many companies struggle to adopt appropriate forecasting models, resulting in poor accuracy and higher material costs. This study aims to develop an integrated model for forecasting and material planning using simulation. The artificial neural network (ANN) method is proposed to improve forecasting accuracy, with performance evaluated through mean percentage error (MAPE), mean absolute deviation (MAD), and mean squared error (MSE). The forecast results are then applied to optimize material inventory using the economic order quantity (EOQ) model, considering warehouse capacity constraints. The EOQ model is applied to adjust lot sizes under time-varying demand. The findings highlight the importance of integrating forecasting with inventory planning to provide accurate demand predictions and optimal lot sizing, ultimately minimizing material costs in the FMCG industry. This research contributes to better decision-making in supply chain management by enhancing forecasting accuracy and inventory optimization.

1. Introduction

Demand planning is a critical component for manufacturers, serving as a foundational input for business analysis, sales operations planning, and production projection. It is also essential for estimating material supply procurement, which directly influences production costs [1]. The connection between demand sales and material supply is pivotal in calculating these costs [2]. In today's competitive landscape, particularly within the fast-moving consumer goods (FMCG) industry, manufacturers face increasing demand uncertainty [3]. This uncertainty complicates sales planning and affects supply planning, leading to challenges in determining optimal lot sizes and driving up material inventory costs [2]. As a result, effective demand planning must be closely linked to supply procurement as a core aspect of operational strategy.

FMCG companies often rely on statistical forecasting methods, such as moving averages, exponential smoothing, time series regression, and autoregressive integrated

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moving average (ARIMA) models, to address demand planning challenges [4],[5]. However, these models tend to fall short in environments characterized by high demand volatility, resulting in reduced forecasting accuracy [6]. An alternative approach some companies use is production capacity projection (judgment-based forecasting), which can lead to excess inventory or shortages during planning periods [7]. Overstocking drives up costs and strains warehouse capacity, while shortages result in lower customer service levels and lost sales opportunities [8]. Additionally, prolonged wait times due to shortages can cause customers to switch to competing products, further affecting profitability [9].

Previous research highlights the adoption of forecasting models to address demand uncertainty in the fast-moving consumer goods (FMCG) industry, particularly using artificial neural networks (ANNs) [10]. ANNs are favoured for their ability to handle non-linear data patterns and achieve high accuracy in forecasting through training with historical data. Key input factors for these models include previous demand, average demand, and backorder quantities. Additionally, studies demonstrate that the results of these forecasts can be effectively used to estimate material inventory requirements [11]. Many studies have focused on Material inventory management, with critical approaches including fundamental economic order quantity (EOQ), heuristic models, and algorithmic solutions [12]. Basic EOQ models are commonly used due to their stability over planning periods. However, they struggle to adapt to seasonal demand patterns [13]. Heuristic models, such as lot-for-lot, periodic order quantity, part period balance, silver meal, and least unit cost, are more suited for handling complex material planning scenarios. Meanwhile, algorithmic models, such as the Wagner-Within algorithm, provide optimal solutions using mathematical techniques [14]. Despite these advancements, inventory models must account for capacity limitations.

Research by Bindewald, et al. [15] and Çalışkan [16] has contributed to the development of inventory planning models that utilize mixed integer linear programming (MILP) to handle time-varying demand. These models address both deterministic and stochastic demand conditions to minimize inventory costs. Wang, et al. [17] further developed optimization models, incorporating stochastic demand and integrated order distribution within supply chain planning. A simulation-based approach to inventory management, considering lot sizing, was introduced by Pooya, et al. [18], emphasizing the importance of factors such as bills of materials (BOM), demand, and lead time in simulation inputs [19],[20]. Simulation models have demonstrated their effectiveness in determining optimal lot sizes while minimizing inventory costs. Numerous studies confirm that optimization and simulation-based approaches significantly reduce inventory planning costs, effectively addressing stochastic and deterministic demand scenarios.

Integrating simulation models for demand forecasting and material inventory management under constraints has received limited attention in the literature. Most studies focus on either demand simulation or material inventory optimization without addressing both simultaneously. However, integrating demand and supply simulations is crucial for improving decision-making in planning and enhancing responsiveness to uncertainties [11]. In an integrated model, demand planning must align with supplier relationships, where total demand projections drive the lot size of materials purchased. Previous studies have shown that artificial neural networks (ANNs) achieve high forecasting accuracy, as evidenced by mean percentage error (MAPE) and mean squared error (MSE) indicators [21]. Additionally, researchers have employed optimization techniques in material inventory models with time-varying demand to handle stochastic demand while minimizing inventory costs [2]. These optimization models are often built on operational research frameworks, such as mixed integer linear programming (MILP) [1].

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Although some studies have explored integrated forecasting and material planning models, their results often lack the accuracy needed to optimize material planning costs under specific constraints [4],[22],[23],[24]. The present study develops an integrated model combining ANN-based demand forecasting with MILP-based material inventory optimization to address this challenge. This approach aims to improve managerial decision-making by enhancing demand forecasting accuracy, optimizing lot sizes under warehouse capacity constraints, and reducing inventory costs, including ordering, holding, and material costs [25]. The primary objective of this study is to contribute to demand planning and material inventory management by developing a simulation-based model that integrates ANN forecasting and MILP optimization. This integrated approach bridges the gap in existing research by improving forecast accuracy, determining optimal lot sizes, and minimizing costs under various constraints.

2. Methods

A case study in this research is on a bottled water beverage company located in Bogor Regency, Indonesia. The distribution supply chain in bottled water beverages involves several parties downstream consisting of star outlets, wholesalers, and retailers [26]. The first research stage involves observing and identifying the bottled water beverage company. Identification was started with the interview process in the sales and operation division. Based on the result of the interview, it is found that the company has difficulty determining material inventory planning under capacity, which is caused by fluctuating and proven by unstable demand patterns histories. The second stage is data collection from database sales demand (secondary data) for plotting demand patterns [27]. Observation of company condition is conducted as an internal study to understand demand planning based on the company approach, the ordering process for material, material lead time, horizon planning, lot size material, and warehouse capacity.

In the next stage, we proposed a forecasting method using historical demand sales after the interview process and data collection. Subsequently, data will be processed using the software MATLAB 2015 for forecasting artificial neural networks. The stage of processing data using the artificial neural network method consists of normalization data, determined target data, trial-and-error in the hidden layer, calculation forecast accuracy, and forecasting simulation. The selection of optimal neurons using the performance of mean squared error (MSE) and regression based on the output. Moreover, we developed the result of a forecast artificial neural network to input both optimization and actual models. Input lot size model for material inventory is considered condition capacity warehouse. The stage of optimization material inventory planning consists of identifying the internal study (company), building model mathematics, verification, and validation, calculating lot size using economic order quantity (EOQ) under constraint, and solving the model under horizon planning using mixed integer linear programming (MILP) in LINGO 18.0. The selection of lot size is based on a combination of multi-item EOQ concepts [19] under warehouse capacity [28] and dependent demand using a bill of material. The comparison of model optimization is based on the actual solution of the company in which lot size and purchase order are calculated heuristically [11].

2.1 Normalization and Denormalization

Stage 1 is the normalization process as input forecasting artificial neural network with the change data actual to a range of biner [0,1]. Normalisation aims to increase forecasting performance and reduce redundancy [29]. Equation (1) is the formulation of the transformation process in actual data to normalization. Normalization data is used as

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an input model for forecasting ANNs. Equation (2) is the denormalization process to change range [0,1] to actual data forecast.

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

$$x_{actual} = x_{norm}[max(x) - min(x)] + min(x) \quad (2)$$

x_{norm} = data transformation actual to biner interval (normalization).
$min(x)$ = Minimum data of x
$max(x)$ = Maximum data of x
x_{actual} = data transformation output to actual data (denormalization).

2.2 Proposed Activation Function Model

The performance of the artificial neural network is determined by MSE performance and linear regression on the output layer. We proposed to select a multi-layer perceptron using a hidden layer to increase performance output. In this study, the activation function on the hidden and output layers using TANSIG (tangent sigmoid). TANSIG $\phi(.)$ is continuous or discontinuous activation to overcome non-linearity in the interval between -1 and 1 that can increase performance training data [30]. The activation function TANSIG supports better performance under the backpropagation process. The activation function TANSIG on the neuron is described using Equation (3) as follows:

$$\vec{\phi}^{(m)}(.) = \frac{2}{1+e^{(-2a_j)}} - 1 \quad (3)$$

2.3 Proposed Training Algorithm

The goodness of the output forecast depends on the number of hidden layers applied. This study adopts a trial-and-error strategy to obtain the best performance in the hidden layer. Strategy trial and error in this study using 1 – 10 to determine the best neuron. Data testing is evaluated by analysis of mean squared error (performance). The plot data train uses regression based on the theory of linear regression between data weights, bias, input, and target. Input multi-layer perceptron on the result of regression plot consists of input data training (p) that is converted by normalization ($\vec{x}_p$), weight ($\vec{w}_p$) (estimation parameter), and bias ($\vec{\theta}$) (parameter to intercept in linear regression) [31].

The Equation for the backpropagation process and multi-layer perceptron are referenced by Du, et al. [32]. Equation (4) shows that function input corresponds to layer $(m-1)$ as well as output to layer (M). Equation (5) shows the calculation function using input, weights, and bias in layer m. Equation (6) is processed to calculate error using the result Equation (5) and predicted in neuron j based on the output network $\vec{o}_p$ and target data $\vec{y}_p$ in data set training (p) respectively. Furthermore, the model calculates error using MSE (ε_p) in Equation (7). Meanwhile, Equation (8) changes parameter weight and bias in layer M. However, in the backpropagation process, we applied a generalized error term in Equation (9) to update the parameter. Subsequently, the consequence of updating weights and bias in layer M correspondence with layer m so that applied the rule (chain rule) is shown by Equations (10) based on considered the generalized error term δ. In this study, we use the momentum term in Equation (11) to improve convergence using parameter learning rate (η) and momentum factor (α) with α in the range of $0 \leq \alpha \leq 1$.

$$\vec{x}_p \equiv \vec{o}_p^{(m-1)} \text{ and } \vec{o}_p \equiv \vec{o}_p^{(M)} \tag{4}$$

$$\vec{a}_p^{(m)} = \left[\boldsymbol{W}^{(m-1)}\right]^T \vec{o}_p^{(m-1)} + \vec{\theta}^{(m)} \tag{5}$$

$$\vec{e}_p = \vec{y}_p - \vec{o}_p \tag{6}$$

$$\varepsilon_p = \frac{1}{N}\sum_{p=1}^{N}\left\|\vec{y}_p - \vec{o}_p\right\|^2 \tag{7}$$

$$\begin{cases} \Delta_p w_{ij}^{(M-1)} = \eta e_{p,i}\dfrac{\partial o_{p,i}}{\partial w_{ij}^{(M-1)}} \text{ and } e_{p,i}\left(\dfrac{d\phi_i^{(M)}(a)}{da}\right)_{a=a_{p,i}^{(M)}} o_{p,j}^{(M-1)} \\ \Delta_p \theta_i^{(M)} = \eta e_{p,i}\dfrac{\partial o_{p,i}}{\partial \theta_i^{(M-1)}} \text{ and } \eta e_{p,i}\left(\dfrac{d\phi_i^{(M)}(a)}{da}\right)_{a=a_{p,i}^{(M)}} 1 \end{cases} \tag{8}$$

$$e_{p,i}\left(\frac{d\phi_i^{(M)}(a)}{da}\right)_{a=a_{p,i}^{(M)}} \equiv \delta_{p,i}^{(M)} \tag{9}$$

$$\Delta_p w_{uv}^{(m-1)} = \eta\delta_{p,u}^{(m)} o_{p,v}^{(m-1)} \text{ and } \Delta_p \theta_u^{(m)} = \eta\delta_{p,u}^{(m)} 1 \tag{10}$$

$$\Delta_p w_{ij(t+1)}^{(M-1)} = -\eta\frac{\partial\varepsilon_p}{\partial w_{ij(t)}^{(M-1)}} + \alpha\Delta_p w_{ij(t)}^{(M-1)} \text{ and } \Delta_p \theta_{i(t+1)}^{(M)} = -\eta\frac{\partial\varepsilon_p}{\partial\theta_{i(t)}^{(M)}} + \alpha\Delta_p\theta_{ij(t)}^{(M-1)} \tag{11}$$

Subsequently, we use acceleration backpropagation in momentum using globally adapted learning with function $\vec{w}(t+1) = \vec{w}(t) - \eta_t\vec{g}(t)$, where $\vec{g}(t) = \frac{\partial\varepsilon(\vec{w})}{\partial\vec{w}}$ is the gradient function to fast convergence in the training process which is terms of LEARNGDM. Furthermore, this study uses mathematics interpretation in the Levenberg-Marquardt algorithm second-order acceleration for training data in the artificial neural network.

$$\nabla\varepsilon(t) = \frac{\partial\varepsilon(t)}{\partial\vec{w}(t)} = \vec{e}(t)\frac{\partial e(t)}{\partial\vec{w}(t)} = \boldsymbol{J}^T(t)\vec{e}(t) \tag{12}$$

$$\nabla^2\varepsilon(t) = \boldsymbol{J}^T(t)\boldsymbol{J}(t) \tag{13}$$

$$\vec{w}(t+1) = \boldsymbol{W}(t) - [\boldsymbol{J}^T(t)\boldsymbol{J}(t) + \sigma\boldsymbol{I}]^{-1}\boldsymbol{J}^T(t)\vec{e}(t) \tag{14}$$

Gradient function or Newton methods in Equation (12), where J is the Jacobian matrix of the first derivative of the error function with considering weight vector for the time (t), $\boldsymbol{J}(t) = \boldsymbol{J}(\vec{w}(\boldsymbol{t})) = \frac{\partial\vec{e}(\vec{w})}{\partial\vec{w}}$. when the error function approach is the minimum value, then updating the Equation in (13) for the second method based on the Gauss-newton method. The function modified the Gauss-newton method in Equation (14) where $\sigma > 0, the$ small number or coefficient size of a trust region. I identity matrix for updating inverse hessian matrix. This formula defined by the Levenberg-Marquardt algorithm is invertible for the backpropagation process or in terms of TRAINLM [33].

2.4 Forecast Accuracy

The difference between forecast (F_t) and actual data (A_t) is a forecasting error. The mean absolute deviation (MAD) is the average absolute error for the original series data in Equation (15). Mean percentage error (MAPE) is the percentage using absolute error for evaluation forecasting in Equation (16) [34].

$$\text{MAD} = \frac{1}{T}\sum_{t=1}^{T}|A_t - F_t| \tag{15}$$

$$\text{MAPE} = \frac{1}{T}\sum_{t=1}^{T}\left|\left(\frac{A_t - F_t}{A_t}\right) \times 100\right| \tag{16}$$

2.5 Model EOQ Under Constraint

The EOQ model was developed by adopted research Çalışkan [16],[35]. We proposed the EOQ model approach by combining some items managed in a particular location supplier with purchasing multiple items [36]. Constraints are obtained by the problem conditions of the bottled water beverage company, where the capacity of the warehouse is essential in consideration of the volume size limit [35],[37]. The model uses concept-dependent demand that needs to be calculated based on the bill of material (part).

We use the Lagrange multiplier in an optimization model to determine the partial differential of the proportion optimal value maximum and minimum local to the equality problem. The objective function for the partial differential in EOQ lot size is defined by $\frac{\partial Q_{[j]}}{\partial \lambda}$ where to find λ proportion using GOAL SEEK in MS Excel. In Equation (17) the result of the forecast is converted to the gross requirement based on the bill of material. The gross requirement for each material is calculated by quantity for each item in Equation (18). Furthermore, lot sizing technically uses economic order quantity with capacity constraint and proportion in Equation (19). The capacity warehouse for each material is less than the capacity warehouse in Equation (20). Meanwhile, the company purchase material exceeds the minimum order quantity in Equation (21).

$$X^*_{[j]} = X_{[j]}BOM_{[j]}\ ,\forall j = 1,2,\dots,J \tag{17}$$

$$X^*_{[j]} = \frac{X^*_{[j]}}{SI_{[j]}}\ ,\forall j = 1,2,\dots,J \tag{18}$$

$$Q_{[j]} = \sqrt{\frac{2X^*_{[j]}C_{oj}}{iC_{[j]} + \lambda S_{[j]}}}\ ,\forall j = 1,2,\dots,J \tag{19}$$

$$\sum_{j=1}^{J} Q_{[j]}S_{[j]} \leq S\ ,\forall j = 1,2,\dots,J \tag{20}$$

$$Q_{[j]} \geq MOQ_{[j]}\ ,\forall j = 1,2,\dots,J \tag{21}$$

2.6 Proposed Optimization Material Inventory Model

Model development in this study is a material inventory with time-varying demand based on research by V. Bindewald et al. We proposed a method for solving the problem using mixed integer linear programming (MILP) [38].

The objective function in the mathematical model is presented in Equation (22), which is also used to minimise the total cost of material inventory planning. Equation (23) shows that planned order release is obtained by EOQ calculation. Equation (24), the inventory model is obtained by considering the gross requirement and planned order release with the beginning inventory. Equation (25) is the proportion for EOQ lot size. Furthermore, Equation (26) considers lead time for each material and planned order and inventory greater than the gross requirement in the total planning period. Meanwhile, decision variables in model material inventory planning consist of Equations (27), (28), (29), and (30) to solve the optimization model.

$$minTC = \sum_{j=1}^{J}\sum_{t-1}^{T}(I_{[j][t]}\, iC_{[j]} + Y_{[j][t]}C_{O[j]} + POR_{[j][t]}C_{[j]}) \tag{22}$$

$$POR_{[j][t]} = Q_{[j]}Y_{[j][t]} \qquad ,\forall j = 1,2,\dots,J;\ \forall t = 1,2,\dots,T \tag{23}$$

$$POR_{[j][t]} + I_{[j][t-1]} - X^{*}_{[j][t]} = I_{[j][t]} \;,\forall j = 1,2,\dots,J;\ \forall t = 1,2,\dots,T \tag{24}$$

$$\lambda \geq 0 \tag{25}$$

$$\sum_{t=1}^{T-L_i}(POR_{[j]} + I_{[i]}) \geq \sum_{t=1}^{T} X^{*}_{[j]} \qquad ,\forall j = 1,2,\dots,J \tag{26}$$

$$Q_{[j]} \geq 0, Integer \qquad ,\forall j = 1,2,\dots,J \tag{27}$$

$$POR_{[j][t]} \geq 0, Integer \qquad ,\forall j = 1,2,\dots,J;\ \forall t = 1,2,\dots,T \tag{28}$$

$$I_{[j][t]} \geq 0, integer \qquad ,\forall j = 1,2,\dots,J;\ \forall t = 1,2,\dots,T \tag{29}$$

$$Y_{[j][t]} = \begin{cases} 1\ if\ I_{[j][t-1]} < x_{[j][t]} \\ 0, otherwise \end{cases} \qquad ,\forall j = 1,2,\dots,J;\ \forall t = 1,2,\dots,T \tag{30}$$

2.7 Model Indices, Parameters, and Decision Variables

Notations formulation model EOQ under constraint and material inventory is shown in Table 1. The notation consists of indices, parameters, and decision variables.

2.8 Data and Case Studies

This study uses historical data on sales demand based on 24 periods (long-term) of bottled water beverage companies. The historical data is used to analyze data demand patterns. Data from the historical 24 periods and result normalization is shown in Table 2.

In addition, the company purchased material that consisted of cups, labels, and straws in supplier 1, whereas opp tape and cartons in supplier 2 [39]. Subsequently, the company orders material with a lead time of 1 week for each supplier. This study's EOQ model under constraint is determined to obtain optimal lot size with warehouse limit [36]. The following data on bottled water beverage companies is shown in Table 3.

3. Results and Discussion

3.1 Training Data

Process training data is conducted to determine the best performance neuron and regression between data output and target. In this study, a multi-layer perceptron is applied to increase performance accuracy. In addition, the training data process uses the Levenberg-Marquardt algorithm for fitting and improving weight and bias [40].

Table 1. Indices, parameters, and decision variables of the material inventory model

Notations	Descriptions	Measurements
X_j^*	Demand for item j based on BOM	Unit
t	Period (t = 1,2,…T)	Unit of time
j	Item (j = 1,2,…,J)	Item
C_{Oj}	Ordering cost for item j	Cost/ order
C_j	Material cost for item j	Cost/ item
i	Percentage of holding fraction	Dimensionless
S_j	Warehouse capacity for item j	Volume m^3/ warehouse
MOQ_j	Minimum Order Quantity for item j	Item
BOM_j	Bill of material	Item
SI_j	Quantity for item j	Item
Q_j	Capacity optimal quantity for item j	Item
POR_{jt}	Planned order release	Item
λ	Proportion	Dimensionless
Y_{jt}	Decision	Dimensionless
I_{jt}	Inventory	Item

Table 2. Normalization data

Period	Actual demand	Normalization	Period	Actual demand	Normalization
Jul-20	90641	0.000	Jul-21	132142	0.641
Aug-20	95898	0.081	Aug-21	141658	0.788
Sep-20	94841	0.065	Sep-21	126575	0.555
Oct-20	98834	0.127	Oct-21	120044	0.454
Nov-20	93783	0.049	Nov-21	153128	0.966
Dec-20	104671	0.217	Dec-21	130062	0.609
Jan-21	106353	0.243	Jan-22	132607	0.648
Feb-21	110943	0.314	Feb-22	143070	0.810
Mar-21	106298	0.242	Mar-22	119742	0.450
Apr-21	100261	0.149	Apr-22	123180	0.503
May-21	101250	0.164	May-22	155358	1.000
Jun-21	110393	0.305	Jun-22	131829	0.636

The network type uses feed-forward backpropagation to train the network to recognize patterns from the input to the output layer, as shown in Figure 1. We use learning adaption LEARNGDM, a learning rate process using gradient descent with momentum (Constanta) on weight function and bias [32]. This function is applied to speed up the learning process to find solutions. The solution search algorithm is repeated based on epoch in each iteration, and this study uses plot interval 1000 epochs. The epoch used is 9 iterations to achieve optimal training neurons. Meanwhile, data division divides data into training, testing, and validation. Data is tested using analysis regression in data division respectively in Figure 2. The regression between the data target and output is tested based on fitting. In this study, we select and test data regression approach > 0.95 on each neuron to obtain a high accuracy of output forecast. The robust regression can indicate that the error in MSE has decreased and that the data is fitting.

Table 3. Data model EOQ under constraint and material inventory

Item	Cup	Label	Straw	Opp tape	Carton
Quantity/ unit	5000	160000	153600	72	50
Material cost/ unit (Rp)	500.000.00	5.500.000.00	900.000.00	500.000.00	200.000.00
Ordering cost (Rp)	50.000.00	50.000.00	50.000.00	50.000.00	50.000.00
Fraction holding	0.1%	0.1%	0.1%	0.1%	0.1%
MOQ	60	20	10	20	100
The total box volume	70 cm x 60 cm x 70 cm	90 cm x 50 cm x 50 cm	100 cm x 50 cm x 50 cm	35 cm x 24 cm x 20 cm	70 cm x 80 cm x 80 cm
The volume of the box/ unit	0.3	0.2	0.3	0.02	0.4

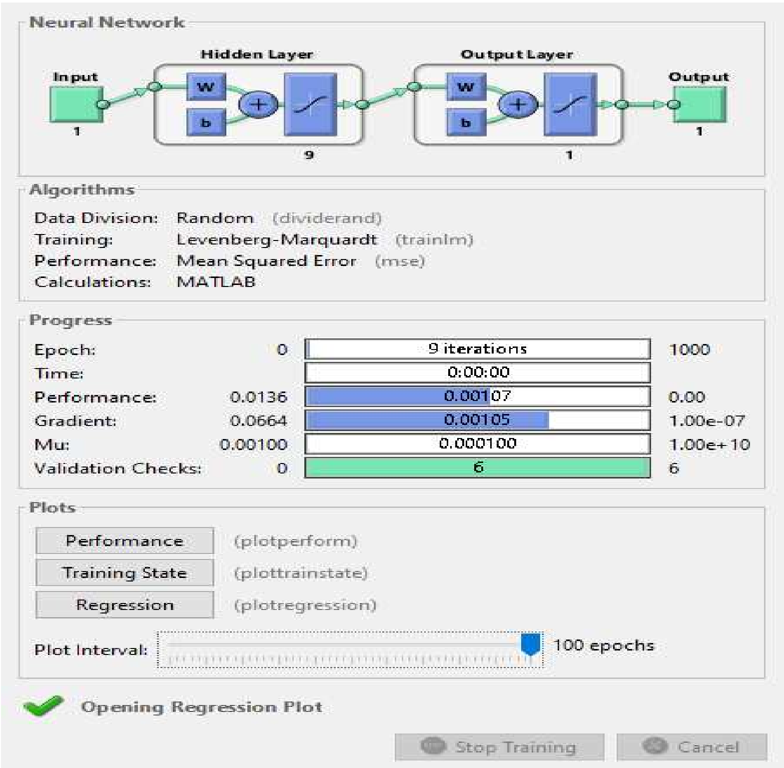

Figure 1. Neural network training

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3.2 Trial and Error Hidden Layer

The data training process on the artificial neural network model is conducted by assessing the accuracy performance. The level of performance is determined by trials and errors on each neuron as shown in Table 4. The neuron selection is based on best performance (mean squared error) and substantial regression > 0.95, respectively.

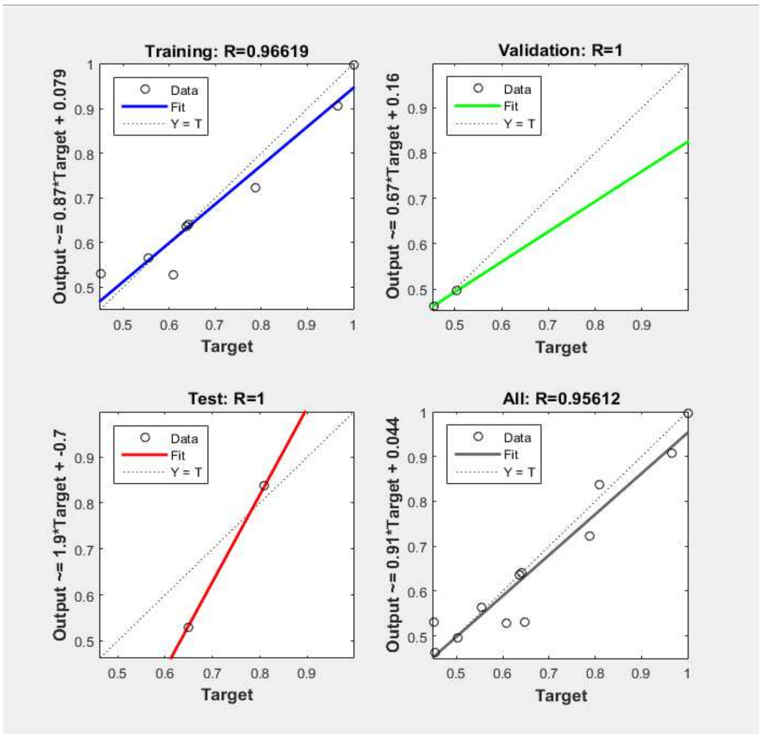

Figure 2. Plot regression

Table 4. Trial and error neuron

Neuron	Performance
1	0.0240
2	0.0277
3	0.0258
4	0.0259
5	0.0103
6	0.0225
7	0.0064
8	0.0047
9	0.0010
10	0.0021

3.3 Forecast Accuracy

The best performance in 9 neurons is conducted testing of accuracy using mean squared error based on output using Equation (6) in

Table 3, whereas in mean absolute deviation and mean percentage error using Equations (11) and (13). Process testing accuracy using comparing data output on a model artificial neural network with data actual (target) on periods 13 to 24. The result of the calculation accuracy forecast is shown in Table 5.

Table 5. Accuracy forecast

Accuracy	MSE (performance)	MAD	MAPE
Result	0.0010	2483.7955	2%

3.4 Forecast Simulation

The result of the multi-layer backpropagation in the hidden layer with 9 neurons and 1 neuron in the output layer, was selected to build an optimal model forecast for 12 periods. Subsequently, forecasting artificial neural networks is conducted using simulations based on function periods 1 = sim (network9, input1) continuously up to function periods 12. The result of the simulation of the artificial neural network is shown in Figure 3.

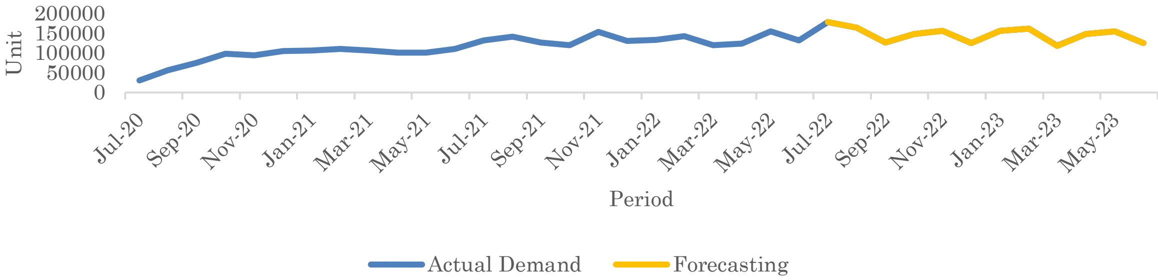

Figure 3. Sales forecast

3.5 Verification Model

Verification is conducted to check that the model developed follows conceptual logic and is mathematically correct. The verification process checks the units (measurement) on the objective functions and constraint. The verification consists of EOQ and material inventory models, shown in Table 6.

Table 6. Verification model

Component model	Measurement	
	Left section	Right section
Objective function (22)	Cost	Cost
Constraint 1 (17)	Unit	Unit
Constraint 2 (18)	Unit	Unit
Constraint 3 (19)	Unit	Unit
Constraint 4 (20)	Volume	Volume
Constraint 5 (21)	Unit	Unit
Constraint 6 (23)	Unit	Unit
Constraint 7 (24)	Unit	Unit
Constraint 8 (26)	Unit	Unit

3.6 Validation and Result

Model validation is conducted on item material to demonstrate that the model can reflect actual conditions in bottled water beverage companies. Validation was conducted in the actual conditions of item material planning with capacity evaluation (internal validity) and based on research by Bindewald, et al. [15] and San-José, et al. [35] as well as (external validity) in bottled water beverage company conditions. To solve the problem, this study uses hypothetical data on bottled water beverage companies. Subsequently, system characteristics are obtained based on observation and discussion with the material and sales department (internal validity).

Table 7. Validation model material inventory

Item	Cup	Label	Straw	Opp tape	Carton
Total MPS (BOM)	87098688	87098688	87098688	1814556	1814556
Material/unit	17420	544	567	110	36291
EOQ	1761	94	237	140	4019
Capacity total	518	21	59	2	1800
EOQ optimal	829	93	214	110	1071
Lagrange value		3.8142			1.6312
Warehouse capacity		320			480
Quantity (Input)	4143649	14919699	32885509	1821600	53571

Table 7 shows the result of lot size EOQ under constraint based on the concept of multi-item. The findings in this study reveal that integration demand forecast and material inventory significantly impact encountering uncertainty in procurement planning. The result shows that forecasts can recognize patterns and can be used as a basis for input material inventory [11]. On the other hand, optimal decisions for determining lot size can reduce inventory costs under particular conditions. For instance, the model EOQ proposed in this study can overcome adjusted material based on warehouse capacity. In addition, lot size optimal can reduce possible overstock in the warehouse so that holding costs can be pressed. However, the lot size proposed in the optimization model can lead to increasing ordering costs. This is because the lot size material proposed is lower than the actual company model (heuristically). The company determines the lot size model using a projection demand approach so that purchase materials tend to over capacity to overcome uncertainty. Consequently, the ordering cost can be minimal with the larger lot size material (reduced frequency order). This condition is aligned based on study A. Mubin et al used a lot size technique under constraint [13]. Furthermore, material inventory with time-varying demand is proposed to calculate material lot sizing alignment based on the planning period and under lead time conditions for each part of the material. The result of the total cost of material inventory for overall period planning is shown in Table 8.

Table 8. Comparison of cost optimization and actual

Component cost	Optimization model	Actual Model	Saving
Material cost (Rp)	18.290.568.024.87	18.316.351.524.76	0.14%
Holding cost (Rp)	40.472.623.58	42.297.358.82	4%
Ordering cost (Rp)	3.300.000.00	3.250.000.00	-2%
Total cost	18.334.340.648.45	18.361.898.883.58	0.15%

3.7 Research Implications

This study's implications have significant theoretical and practical findings in artificial neural networks for material inventory integration problems. The theoretical approach provides holistic insight into artificial neural network models, consisting of multi-layer perceptron, momentum, backpropagation process, and training algorithms using Levenberg-Marquardt in a mathematical approach. Moreover, this study contributed to the literature by implementing a simulation forecast to determine the cost of material inventory planning with time-varying demand. It also highlighted the importance of simulation forecasts to help companies recognize patterns and enhance performance accuracy in dealing with material inventory problems. On the other hand, the applied material inventory model can achieve aims that minimize cost with optimized lot size under a capacity warehouse. In the management approach, this study can help production managers improve tactical-operational planning efficiency, enhance responsiveness, and encounter uncertainty challenges in the era of competition.

This study also provides practical implications for forecasting material inventory. The result shows the importance of determining lot size, including holding, ordering, and material costs. It also confirms that companies should understand data patterns that impact material cost, warehouse capacity, and planning time-varying material. Moreover, the result of the study shows that in a multiple supplier environment, companies can apply planning order quantity with EOQ multi-item to calculate the total requirement for each material simultaneously. This technique can optimize lot size under warehouse capacity for multi-item and is used as the basis for material planning. Furthermore, the model integration using simulation forecast and optimization of material inventory can also be applied to industries with difficulty calculating material inventory cost under demand fluctuation. In addition, the model development can be used to plan supply and demand in industries that encounter uncertain demand sales, which are interconnected with material procurement. Therefore, the findings suggest that integration demand forecasting and material inventory are vital for basis planning, contributing to minimizing inventory costs with better performance accuracy.

4. Conclusion

In conclusion, this research is developing an artificial neural network with the 10-neuron trial for sales demand forecasting. The selected neuron used 9 neurons with a performance output is 0.0010. Based on the result, the artificial neural network obtains an accuracy forecast with MAPE is 2% and MAD is 2483. The output regression with 9 neurons has a strong correlation of 0.95, which can improve the output data sales forecast. Furthermore, the result of the forecast we used to determine material inventory planning. The model includes various costs, such as holding, ordering, and material costs. We select optimal lot sizes in material inventory planning using model EOQ for planned order release (POR). The objective of model material inventory has successfully achieved an optimal solution with a reduction of 0.15% compared to the actual model (heuristically).

However, the limitation of this study in artificial neural networks is that they only use one layer in the hidden layer. In contrast, inventory material is restricted, considering warehouse capacity. Therefore, suggestions for future studies can extend to model artificial neural networks using more hidden layers and varying trial and error algorithms to obtain the best solution performance. Meanwhile, the model can develop in material inventory by adding constraints such as shortage (probability) when the supplier is not fulfilling the material, truck capacity for delivering material, discount factor, limited budget cost, and reverse material. In summary, this study can provide valuable by offering contributions to theoretical and practical solutions in demand-material planning challenges in industries that deal with demand fluctuations while minimizing material inventory costs.

Declarations

Author contribution: DSP: conceptualization, data collection, data analysis, methodology, writing draft, RSW: supervising final draft, funding acquisition, review. Both authors have read and approved the final paper.
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