International Journal of Advances in Intelligent Informatics
Vol. 10, No. 1, February 2024, pp. 159-170

Leveraging hybrid ANN–AHP to optimize cement industry average inventory levels

Edy Fradinata [a,1,*], Muhamad Mat Noor [b,2], Zurnila Marli Kesuma [c,3], Sakesun Suthummanon [d,4], Didi Asmadi[a,5]

[a] Industrial Engineering, Universitas Syiah Kuala (USK), Banda Aceh, 23111, Indonesia
[b] Faculty of Mechanical and Manufacturing Engineering, Universiti Malaysia Pahang, Pekan, Pahang 26600, Malaysia
[c] Statistics Department, Universitas Syiah Kuala(USK), Banda Aceh 23111, Indonesia
[d] Industrial Engineering and System, Prince of Songkla University, Hatyai, Thailand
[1] edy.fradinata@unsyiah.ac.id; [2] muhamad@ump.edu.my; [3] kesumaku@yahoo.com; [4] sakesunn.s@psu.ac.th; [5] didi.asmadi@unsyiah.ac.id
* corresponding author

ARTICLE INFO

Article history
Received February 09, 2021
Revised April, 10, 2023
Accepted August 24, 2023
Available online February 29, 2024

Keywords
Cement industry
Average inventory levels
Hybrid ANN – AHP
Optimization
Warehouse demand

ABSTRACT

In recent years, inventory has been critical due to the production cost and overstock risk related to the expiration date and the fluctuation price risk. This study's minimization of overstock and price fluctuation in the warehouse used a hybridized artificial neural network (ANN) and analytical hierarchy process (AHP) to produce an optimum model. The variables, such as average demand, reorder point, order quantity, factor service level, safety stock, and average inventory level, were used to obtain the optimal condition of the average inventory levels to maximize the profit. Then, the type of inventory system that guarantees the minimum risks in managing the inventory would be selected. The result shows that the data has a mean of 39.2 units, and the standard deviation (SD) was 12.9. This means that the order quantity is 20.2 units, the average inventory level is 57.3, and the average demand is 39. These conditions used the factor z, which is 97% service level. This study concludes that the optimum average inventory level is 91 units, the order quantity is 11 units with the maximum average profit is $1098, and the peak fluctuation condition maximum profit is $1463 when the average inventory level is 7.3, and the inventory policy system used to minimize the risk is the continuous review policy type. The study could be beneficial to reduce production costs and enhance overall profitability and operational efficiency in the sector by mitigating the risks associated with excessive inventory and price volatility while also minimizing the potential for expired inventory.

1. Introduction

Most industries and supply chains worldwide have the problem of inventory cases. Inventory appears to be a dominant cost in the operational management of finances in the factory system. It could be more challenging to manage appropriately the inventory level. The adequate inventory level must be controlled at the minimum to protect the high quantity risk. The risk will appear when the inventory cannot be managed to minimize inventory cost. That appears when the right place and the right time are not relevant. So, the warehouse manager should use forecasting methods to correct predictions for a specific time to minimize the cost risk while satisfying customer demand. Unfortunately, the fill rate of customer demand that is met through immediate stock availability is a complex difficulty to relate decisions that significantly impact the customer service and supply chain cost. In the competitive price of the product, the control system of reducing cost and service level in the warehouse is one of the strategies to determine the price of goods [1]. Customer demand is mandatory to predict the future situation to increase the warehouse's control system manager. The manager in the warehouse is supposed to know the three types of forecasting behaviors: trends, cycles, and seasonal [2], [3]. Lack of prediction should be a problem for the cost to protect the space to do the stockpile in the warehouse. The safety blanket needs to anticipate the degree of uncertainty and variability conditions.

Artificial neural networks (ANN) contain the simulated patterns in huge data sets through specific algorithms [4], [5]. ANN can be applied in some commercial cases, such as in the manufacturing industry, an oil company, trade, agriculture, insurance, electronics, computer, robotics, and even the medical sector [3], [6]. ANN also can be applied in linear or nonlinear, parametric or non-parametric, and continuous datasets [7]–[9]. Some classes of data mining techniques include anomaly detection, learning of rule association, clustering, classification, regression, and summarization. The information on customer prediction by doing effective coordination belongs the manufacturing to the warehouse to get customer satisfaction [10], [11]. All companies tend to make aggressive improvements throughout the warehouse to organize the orders and materials for the customer. Bad coordination in the warehouse will influence poor customer service, missed production schedules, incorrect capacity plans, inefficient shipping, and high costs. Although many companies today are observed, the suppliers and retailers know inventory management. Safety stock utilization was done to predict the demand fluctuation [12]. Optimal buffer inventory and opportunistic preventive maintenance are essential under random production capacity availability [13]. The supplementary demand from suppliers should overreact to manufacture, and the manufacturer will stock the supply inventory greater than the demand of distributor and order to suppliers higher [14]. That case needs inventory level control in the warehouse, which makes it efficient.

The analytical Hierarchy Process (AHP) is an expert method for decision-making based on the criteria and alternatives to choose the goal [15]. The method can be used in many areas to solve problems. This method was introduced by Saaty, 2014 [16]. The criteria have a different scale of importance from one to nine. The alternatives differ in preference for them in every criterion to make tradeoffs. The goal of the problem was defined as the beginning, and the problem was covered to refer to it [17]. The calculation worked with the Expert Choose software and will determine the weight of the output [18], [19].

The inventory must be managed according to customer demand [20]. That is why the inventory level must be kept well because some reasons, such as customer demand being challenging to predict, the life cycle of an increasing number of products, the new competitive product in the marketplace, the uncertainty cost and time of distribution, the delivery of lead time, and the economic scale of delivery by the special transportation on the large quantity [21], [22]. Inventory would be effective if the warehouse manager planned the quantity to order and when and how to get it [23]. The strategy eliminates the uncertainty condition of inventory in the warehouse with the inventory policy system [24]. In this case, the forecasting methods must be selected and applied to get the right method for implementation, replenishment lead time, and time determination. It sends and arrives at the number of different products being measured to the relevance of the budget, makes planning in a proportional time horizon, and considers the inventory holding cost, order cost, and another thing is to determine the certain service level in acceptable condition [25].

The demand is primarily uncertain, so the manager must plan well. Based on the demand, the manager in the warehouse must decide the quantities of stock to meet demand because if the stocks overload, it would be stuck with excess inventory of disposal. On the other hand, if the inventory is minimal, it will produce problems in sales and impact some profits. In this situation, the study has three problem statements: What are the problems in managing the inventory level in the warehouse to the uncertain demand? What inventory policy protects the situation of risks in the warehouse, and what is the optimal average inventory level to obtain optimization profit?

Furthermore, these problem statements aim to identify some variables to get the optimal condition from the average inventory level to the profit. The warehouse's variables are identified in average demand, reorder point, order quantity, factor service level, safety stock, and average inventory level. Then, the type of inventory system would be selected to guarantee the minimum risks in managing the inventory. Lastly, regarding the inventory level related to the average demand, we observe the order quantity to produce the optimal profit.

2. Method

2.1.1. The Lemma

There are policies when managing the inventory in the warehouse [26]. Continue the review policy type and periodic review policy type. Both will be effective if applied in the right situation of the inventory system in the warehouse [27]. The dataset has a pattern observing the customer demand in the function of t, D_t where it is $D_t = \mu + \rho D_t - 1 + \epsilon_t$, and placed an order, q_t to the warehouse. The model tends to the Moving Average (MA) demand characteristic after the autocorrelation is identified at the beginning of the pattern. The customer demand in the warehouse is typically distributed with the variation equation 1, where it increases in variability where it must determine the variance of q_t. It is about the variance of D_t, i.e. with a variance of the demand. The symbol of q_t can be shown as $q_t = y_t - y_{t-1} + D_{t-1}$. The value of q_t is negative, this excess inventory is returned without cost. We write the quantity q_t order by estimating the mean and the standard deviation of lead time demand. The Calculation of the mean and standard deviation will be used for a request, we summarize it the q_t is a sequence of.

$$q_t = \hat{\mu}_t^L - \hat{\mu}_{t-1}^L + z\left(\hat{\sigma}_t^L - \hat{\sigma}_{t-1}^L\right) + D_{t-1} = \left(1 + \frac{L}{p}\right) D_{t-1} - \left(\frac{L}{p}\right) D_{t-p-1} + z(\hat{\sigma}_t^L - \hat{\sigma}_{t-1}^L) \tag{1}$$

Moreover, the variance as follows:

$$Var(q_t) = (1 + \frac{L}{p})^2 Var(D_{t-1}) + (\frac{L}{p})^2 Var(D_{t-p-1})(13)$$

$$-2\left(\frac{L}{p}\right)\left(1 + \frac{L}{p}\right) Cov(D_{t-1}) + (L/p)^2 Var(D_{t-p-1})$$

$$+2z\left(1 + \frac{2L}{p}\right) Cov(D_{t-1}, \hat{\sigma}_t^L) + z^2 Var(\hat{\sigma}_t^L - \hat{\sigma}_{t-1}^L$$

$$= \left[1 + \left(\frac{2L}{p} + \frac{2L^2}{p^2}\right)(1 - \rho^p)\right] Var(D) \tag{2}$$

The level of target inventory followed the equation of $y_t = \hat{\mu}_t^L + z\,\hat{\sigma}_t^L$, where $\hat{\mu}_t^L$ is the estimate of the mean of lead time demand $\hat{\sigma}_t^L$ is the estimate of the standard deviation of the forecast errors above the lead time, and z is chosen to meet a desired service level. To implement this inventory policy, the warehouse estimates the mean and standard deviation of demand based on customer lead time demand observed as $\hat{\mu}_t^L = L\,\hat{\mu}_t$ where the $\hat{\mu}_t$ is the average of previous p observation of demand with the equation 3.

$$\hat{\mu}_t = \frac{\sum_{i=t-p}^{t-1} D_i}{p} \tag{3}$$

The second equation will follow from $Var(D) = \frac{\sigma^2}{1-\rho^2}$ and $cov(D_{t-1}, D_{t-p-1}) = \frac{\sigma^2}{1-\rho^2}\sigma^2$ to further evaluate $\mathrm{Var}(q_t)$, it needs the following lemma:

Lemma 1. If a warehouse uses a simple moving average forecast with an observations p request, and if the requested meets $D_t = \mu + \rho D_t - 1 + \epsilon_t$, then $Cov(D_{t-i}, \hat{\sigma}_t^L) = 0$ for all $i = 1, \ldots\ldots, p$. Therefore, we consider making the lower limit when the increased variability from warehouse use to manufacturer.

Lemma 2. Suppose a warehouse used a simple moving average (MA). In that case, we have a presumption for the observations with p requested to forecasts; its order-up-to inventory policy is defined in $y_t = \hat{\mu}_t^L + z\,\hat{\sigma}_t^L$, but if the request meets the provisions of the variance in the equation $D_t = \mu + \rho D_t - 1 + \epsilon_t\, q^{MA}$, will transfer orders from warehouse to manufacturers, this condition satisfies.

$$\frac{Var\,(q^{MA})}{Var\,(D)} \geq 1 + \frac{2L}{p} + \frac{2L^2}{p^2}(1-\rho^p) \tag{4}$$

where the Var (D) is a variant of customer demand, the different observations can connect from these cases. First, the three functions of these parameters are p, L, and ρ will increase variability from manufacturer to warehouse. p is the number of observations used in the moving average, and L is the lead time between the warehouse and manufacturers. Moreover, ρ is a correlation. The p function showed an increase in the variability of a function of p values when using the observation where it is used in the moving average, and also an increase in the function of L is the lead time.

2.1.2. Hybrid Method

There is a risk in inventory at the warehouse if the sales have not met the target's expectations. The potential exceeds profit; less profit would appear when the goods are already stocked in the warehouse. The correct prediction information with the forecasting tool would assist management in inventory investment. Suppose to explain in general, the methodology is as follows:

2.1.3. Hybrid model ANN-AHP

This study aims to test a hybrid model that combines Artificial Neural Networks (ANN) and Analytic Hierarchy Process (AHP) [28], [29]. The Output of AHP from the six variables (population, the number of buyers, price, GDP, the expectation of future price, promotion, and demand) of the determinant of demand should be the input variable in the input layer, and some data would be the input weight in the hidden layers ANN system. The process of normalized data was used to make the data in the range of 0 to 1 with the AHP; it was made between the ranges of less than 0.01. The ANN runs with the backpropagation network on Levenberg-Marquardt from the output layer [30]. The network uses a backpropagation training function to minimize error value in 'Trainlm" parameter. The stimulus worked to trial to get the error value less than the previous error. The model of the combination method will be reached after the network has done the training and testing. Moreover, output performance is measured using mean square error (MSE). At last, it measured the fitting value to get the result of the model.

2.1.4. Artificial Neural Network

The ANN run on this dataset in the optimal condition with the parameters where it is shown in Table 1.

Table 1. The optimal condition of parameter ANN

Name of parameter	Parameters
Network type	Backpropagation neural network
Training function	Trainlm
Adaption learning function	Learngdm
Number of layers	Two
Transfer function	Sigmoid
Training parameters, min gradient	$1e^{-6}$

The algorithms choose the highly efficient backpropagation algorithm neural network, and the training network updates the bias and weight to get the optimization. The transfer functions calculate the output from the layer where the input comes in. The function of "Learngdm" is as the gradient descent with momentum weight and bias learning function with equation 5.

$$E = \frac{1}{2}\sum_{h}^{M} E_h = \frac{1}{2}\sum_{h}^{M}\sum_{i}^{N}(t_{hi} - O_{hi})^2 \quad (5)$$

where E is the pattern of total error, E_h represents pattern h with its error, the index h ranges over the input pattern set, and i is the i^{th} of the output neuron. This is the desired output for the i^{th} output neuron when pattern h is presented. The transfer function selection is mandatory for the relevance transfer function when data enters the network. This transfer function keeps the training process in the network more stable and speeds up the training process. The data will be run with Sigmoid as the transfer function of the dataset in the network of ANN because it resulted in the smallest MSE.

2.1.5. Neural Network algorithm

The methods worked in the Matlab software. The learning algorithm of the neural network was divided into two sections. They are propagation and weight updates, and the algorithm steps of hybrid ANN-AHP [31] is as in Fig. 1.

Step 1. Defined input and target data
Step 2. Created a Fitting Network
Step 3. Chosen Input and Output Pre/Post-Processing Functions
Step 4. Stetted up Division of Data for Training, Validation, Testing
Step 5. Used Training function of Trainlm (Levenberg-Marquardt Backpropagation)
Step 6. Trained the Network with training network with learning rate, epoch, and show
Step 7. Defined function NN at layer 1 and layer 2
Step 8. **<Input the Weight of AHP>**
Step 9. Choose a Plot Function for performance, trans-state, error, regression, and fit
Step 10. Training the network
Step 11. Defined Performance of error (MSE)
Step 12. Tested the Network with the simulation of network
Step 13. Performance of the network
Step 14. Recalculated Training
Step 15. Plotted training state, plot histogram, target and regression
Step 16. Plotted to perform post-training analysis
Step 17. Result

Fig. 1. Neural network algorithm

The NN-AHP process combines neural network (NN) analysis with Analytical Hierarchy Process (AHP) weights using a systematic approach. Initially, the input and target data are established, forming the foundation for analysis. Afterward, a suitable network is formed, and appropriate pre/post-processing functions are selected to improve data compatibility. The data is subsequently partitioned into training, validation, and testing sets, and then the network is trained using the Levenberg-Marquardt Backpropagation algorithm. The AHP weights prioritize criteria, and functions are chosen for visualization. The network is trained and assessed for performance using Mean Squared Error (MSE) measures. Post-training analysis involves evaluating the network's prediction accuracy and adjusting parameters. Ultimately, the findings are analyzed in order to make inferences about the model's efficacy and ability to predict.

2.1.6. Analytical Hierarchy Process

The Analytical Hierarchy Process (AHP) is a systematic decision-making approach involving a series of essential steps. To begin with, the current issue is precisely articulated, explicitly stating the goals and standards that are part of the decision-making procedure. Subsequently, a hierarchical framework is created, systematically dividing the problem into feasible sub-criteria and alternatives. Subsequently, pairwise comparisons are carried out between every criterion and option, utilizing a scale to evaluate their significance or effectiveness. These comparisons are used to assign numerical values that show the relative relevance of each criterion or option. Afterward, consistency ratios are computed to verify the dependability of the judgments made during pairwise comparisons; if the consistency ratio is less than or equal to 0.01, the judgments are deemed consistent or satisfactory. The AHP enables thorough analysis, prioritization of criteria, and informed decision-making in complex decision-making by following a methodical approach. The steps of the AHP algorithm are as in Fig. 2.

Step 1. Define the problem
Step 2. Do the hierarchical structure
Step 3. Do the pairwise comparison matrix
Step 4. Define pairwise comparison relative important
Step 5. Result if ≤ 0.01 is consistent or good.

Fig. 2. AHP Algorithm

Consistency index can be obtained with equation 6.

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{6}$$

where, CI is an consistency index, λ_{max} represents as a Eigen value, where the eigen biggest matrix value with *n* Orde. If CI is equals to 0, it means that the index is consistent. The calculation of the final weight of each criterion, subcriteria, will be combined to get the score weight of the problem. Fig. 3 is the modified weight from Analytical Hierarchy Process.

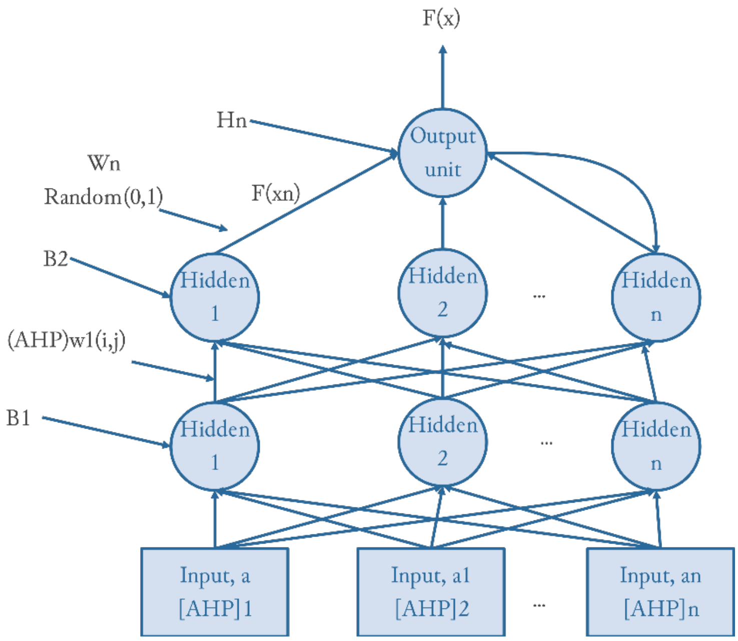

Fig. 3. Combination methods of ANN with Analytical Hierarchy Process

This weight will replace the default weight of the network in the input layer. Then it works with the input from the input layer in the hidden layers, to generate the error better than the initial input.

2.1.7. Order Quantity

The formula for determining the order quantity is expressed as in (7). Continuing from earlier discussions, the order quantity Q is determined to fulfill the prescribed criteria.

$$Q = \sqrt{\frac{2K*AVG}{h}} \tag{7}$$

In this case, the warehouse reviews inventory every period, place, and order to bring its inventory level up to a target level. Observe that, in this case, the review period is one. Hence, the base stock level is calculated as (8).

$$L * AVG + z * SD * \sqrt{L} \tag{8}$$

where AVG and STD are the average and SD of daily (or weekly) customer demand. The constant z is the safety factor. The Avg Inv level is $Q/2 + z$.

2.1.8. The Profit

The profit of the result of the hybrid of ANN-AHP to maximize the profit inventory in the warehouse. For this case follow the overfitting formula from the model moving average. The formula identified that $x1$ (demand), $x2$ (selling price), $x3$ (production cost), and $x4$ (Fixed cost). It can be shown as follow:

$$\text{Profit (x)} = \text{x1 (x2} - \text{x3)} - \text{x4} \tag{9}$$

$$Maximize: \text{g(x)} = -\text{f(x)} = -\text{a} * \text{x4} + \text{b} * \text{x3} - \text{c} * \text{x2} + \text{d} * \text{x} + \text{e} \tag{10}$$

The profit formula identify the $x1$ (demand), $x2$ (selling price), $x3$ (production cost), and $x4$ (Fixed cost) with the maximization of $g(x)$.

3. Results and Discussion

This experiment was carried out to determine the objectives of this study. It should be noted that the run dataset of ANN-AHP in Fig. 4 shows the result for 15 weeks, and the trend is fitted by using the polynomial line to make it smooth. The dataset shows that the trend is moving average, with three peaks on the dataset.

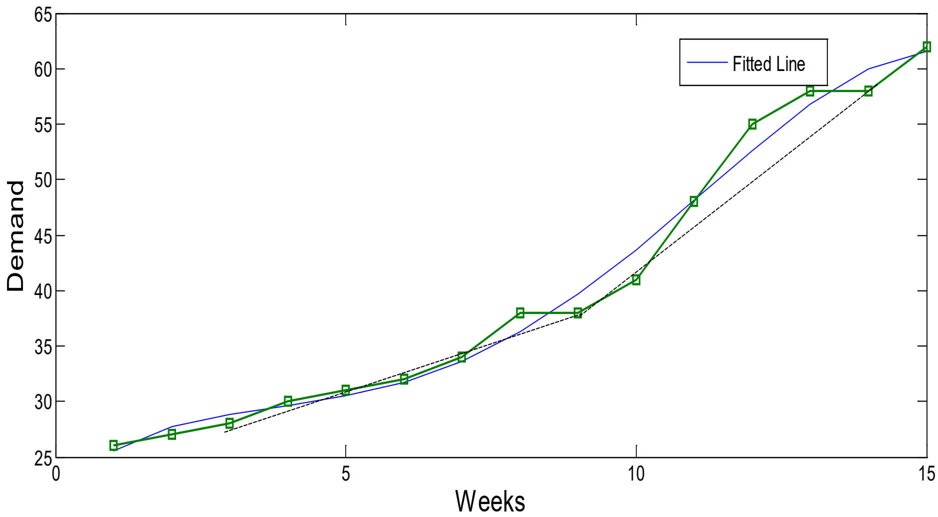

Fig. 4. Demand dataset and fitted line

The figure of the dataset from the independent variable made the demand as the dependent variable change on the centreline. This model influenced the neural network's training since the demand dataset's determinant. The network minimizes the mean square error (MSE) function errors in the overall iteration process on the demand performance.

On the other hand, the demand was formed by the weight, and the input data worked together between nonlinear data, weight, and transfer functions iterated and evaluated the smaller error from the initial error in the network. Then, the iterating was stopped during the overfitting case training. The transfer function of nonlinear, especially Trainlm, has the significant function of forming the pattern because the distribution is continuously differentiable, which is the property of the network learning process and takes the place of the mean and standard deviation value of performance. The model then measured the best validation condition, which is shown in Fig. 5.

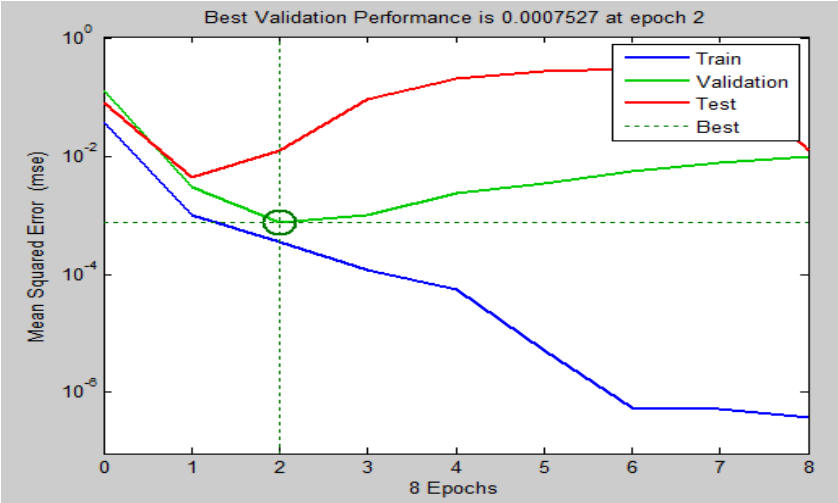

Fig. 5. Best validation performance of dataset

Fig. 5 indicates the validation proses for the network performance of ANN-AHP. It shows that all lines are decreased until iteration 2 (Epoch 2) for the training process, validation, and testing errors. There does not appear to be any overfitting; the green line shows that the validation process to protect the overfitting when it went down the line until iteration 2 (overfitting occurred) started to increase to refuse the overfitting. Fig. 6 shows the plot regression of output.

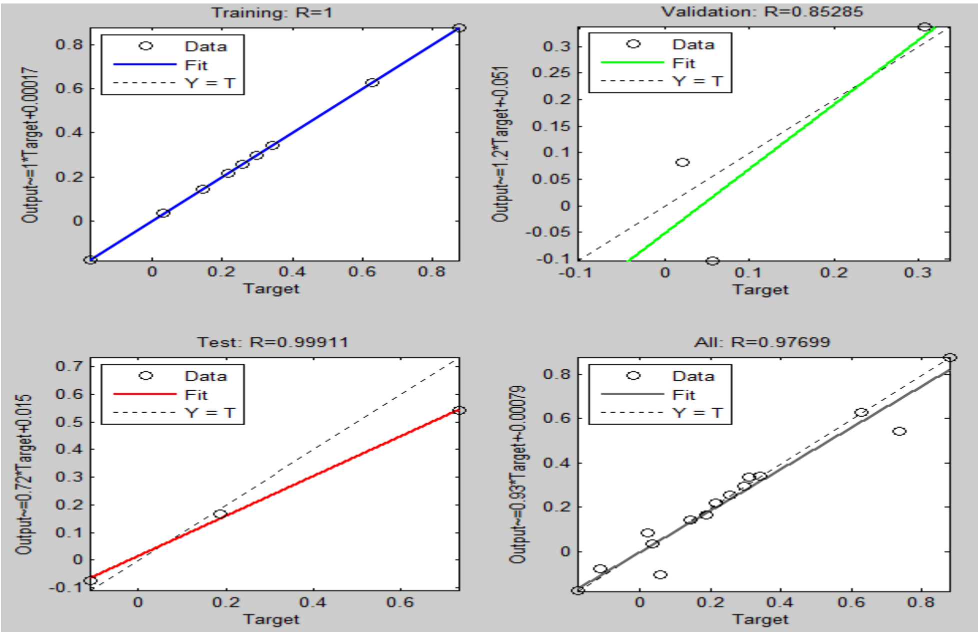

Fig. 6. Plot regression of output

Fig. 6 Describe the validation (R) indicates a good fit. It is 0.85285 (between output and target), the training is 1, and the testing is 0,99911, which means that the validation performs well because the line and the points are close to 1. The dashed line in each axis represents the perfect $result - outputs = targets$, and the solid line indicates the best fit for linear regression between outputs and targets.

Fig. 7 shows some variable activities in the warehouse in a single condition; the factor z is the safety factor associated with the service level. The z refers to the statistical table to guarantee that the probability of stock-outs during lead time is $1 - \alpha$. The average demand shows a value of 50.3, where the warehouse always faces the customer's demand, also called the average demand during lead time. The order quantity (Q) or the economic order quantity (EOQ) is 20.2; this controls the variability in customer demand. It means that the inventory at a certain level or inventory level at one point is at 30.2 since it takes the lead time to receive an order from the customer demand because the demand has variability. On the EOQ position 20.2, the average inventory level rises the quantity for inventory position for order quantity to average demand. In this position, the inventory level is enough to anticipate the demand in the warehouse against shortage until the next order arrives.

Fig. 7. Some variables of inventory system

To predict the maximum profits and the average profit on the inventory position in the warehouse using the model maximization from the fitted polynomial model. It can be seen as follows:

$$\text{Maximize: } g(x) = -f(x) = -0.00025 * x4 + 0.0093 * x3 - 0.12 * x2 + 0.56 * x + 92 \quad (11)$$

The optimization of profit shows the average value is at $1098,- when the order quantity is 11, and the average inventory level is 91. The single maximization on the peak fluctuation has the highest at a profit of $ 1463. It can be seen in Fig. 8.

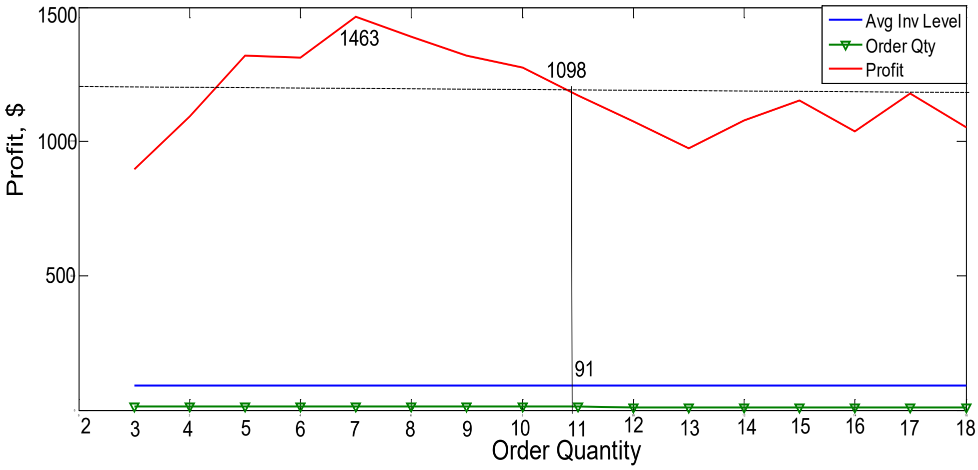

Fig. 8. The optimal condition of average inventory level and optimization of profit

4. Conclusion

This study explored the hybrid AHP-ANN model to predict the optimization of average inventory level and optimization of profit with the factor service level of 97%. Demand oscillations can contribute to the warehouse's risk. It can be uncontrollable inventory, a quality control problem, and a lack of customer service. This risk can increase the cost when the inventory is spent in the warehouse. The result showed that the ANN combination method AHPANN could be the alternative model to predict the average inventory level and profit. This study has three conclusions. First, the determinant of demand variables can determine the accuracy of prediction where the characteristic customer demand of the dataset influences it. Second, the inventory policy system that minimizes risk is a continuous review policy type, and the optimization of profit from the average inventory level can be determined. It can be illustrated as follows: the data has a mean of 39.2, and the standard deviation is 12.9. Moreover, the order quantity is 20.2 units, and the average demand during the period is 57.3 units. The condition uses the service level of z is 97%. This study concludes that the optimum average inventory level is 91 units, the order quantity is 11 units with the quantity that maximizes average profit is $ 1098, and the peak fluctuation in maximum profit is $ 1463 when the average inventory level is 7.3 units order quantity.

Acknowledgment

Authors would like to express their gratitude to Universitas Syiah Kuala, Indonesia and Directorate General of Higher Education, Ministry of Research, Technology and Higher Education of the Republic of Indonesia for their support in this study and Ministry of Higher Education Malaysia through the research project RDU160152 and research grant from Universiti Malaysia Pahang through RDU160352.

Declarations

Author contribution. All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.
Funding statement. The Research funded by Ministry of Higher Education Malaysia through the project of RDU160152 and Universiti Malaysia Pahang through the project of RDU160352.
Conflict of interest. The authors declare no conflict of interest.
Additional information. No additional information is available for this paper.

References

[1] F. Chen, Z. Drezner, J. K. Ryan, and D. Simchi-Levi, "Quantifying the Bullwhip Effect in a Simple Supply Chain: The Impact of Forecasting, Lead Times, and Information," *Manage. Sci.*, vol. 46, no. 3, pp. 436–443, Mar. 2000, doi: 10.1287/mnsc.46.3.436.12069.

[2] R.-B. Esteves and C. Reggiani, "Elasticity of demand and behaviour-based price discrimination," *Int. J. Ind. Organ.*, vol. 32, no. 1, pp. 46–56, Jan. 2014, doi: 10.1016/j.ijindorg.2013.10.010.

[3] T. Kim and B. R. King, "Time series prediction using deep echo state networks," *Neural Comput. Appl.*, vol. 32, pp. 17769–17787, 2020, doi: 10.1007/s00521-020-04948-x.

[4] Z. Zhang, "Multivariate Time Series Analysis in Climate and Environmental Research,". *Cham: Springer International Publishing*, p. 287, 2018, doi: 10.1007/978-3-319-67340-0.

[5] U. Pujianto, D. P. P. Setyadi, and M. I. Akbar, "Prediction of stock purchase decisions using artificial neural network method," *Appl. Eng. Technol.*, vol. 1, no. 2, pp. 23–33, Apr. 2022, doi: 10.31763/aet.v2i1.686.

[6] W. Sulandari, S. Subanar, S. Suhartono, and H. Utami, "Forecasting electricity load demand using hybrid exponential smoothing-artificial neural network model," *Int. J. Adv. Intell. Informatics*, vol. 2, no. 3, p. 131, Nov. 2016, doi: 10.26555/ijain.v2i3.69.

[7] Z. Wu, Y. Xiong, S. X. Yu, and D. Lin, "Unsupervised Feature Learning via Non-parametric Instance Discrimination," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Jun. 2018, pp. 3733–3742, doi: 10.1109/CVPR.2018.00393.

[8] H. Rawat, D. R. Parhi, P. B. Kumar, K. K. Pandey, and A. K. Behera, "Analysis and Investigation of Mamdani Fuzzy for Control and Navigation of Mobile Robot and Exploration of different AI techniques pertaining to Robot Navigation," *Emerg. trends …*, no. April, pp. 1–13, 2018, [Online]. Available at: https://www.researchgate.net/profile/Himanshu-Rawat-2/publication/324156551.

[9] A. Pranolo, Y. Mao, A. P. Wibawa, A. B. P. Utama, and F. A. Dwiyanto, "Optimized Three Deep Learning Models Based-PSO Hyperparameters for Beijing PM2.5 Prediction," *Knowl. Eng. Data Sci.*, vol. 5, no. 1, p. 53, Nov. 2022, doi: 10.17977/um018v5i12022p53-66.

[10] R. N. Bolton *et al.*, "Customer experience challenges: bringing together digital, physical and social realms," *J. Serv. Manag.*, vol. 29, no. 5, pp. 776–808, Nov. 2018, doi: 10.1108/JOSM-04-2018-0113.

[11] H. Rahimpour, V. Ghiasi, A. Fahmi, and Y. Marabi, "Geopolymer vs ordinary portland cement: review of the 3-d printing of concrete," *Appl. Eng. Technol.*, vol. 2, no. 2, pp. 133–152, 2023, doi: 10.31763/aet.v2i2.1010.

[12] E. Fradinata, Z. M. Kesuma, and S. Rusdiana, "Optimal Lot-Sizing Algorithms on Stochastic Demand at the Retailer," in *Emerald Reach Proceedings Series*, vol. 1, Emerald Group Holdings Ltd., 2018, pp. 235–241, doi: 10.1108/978-1-78756-793-1-00010.

[13] R. I. Zequeira, J. E. Valdes, and C. Berenguer, "Optimal buffer inventory and opportunistic preventive maintenance under random production capacity availability," *Int. J. Prod. Econ.*, vol. 111, no. 2, pp. 686–696, Feb. 2008, doi: 10.1016/j.ijpe.2007.02.037.

[14] Y. Yu, S. Zhou, and Y. Shi, "Information sharing or not across the supply chain: The role of carbon emission reduction," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 137, p. 101915, May 2020, doi: 10.1016/j.tre.2020.101915.

[15] G. K. L. Chien and F. T. S. Chan, "Developing an integrated business model in the manufacturing industry – An AHP approach," *Sci. Inf. Technol. Lett.*, vol. 2, no. 1, pp. 16–27, Mar. 2022, doi: 10.31763/sitech.v2i1.611.

[16] T. L. Saaty, "Analytic Heirarchy Process," in *Wiley StatsRef: Statistics Reference Online*, Wiley, 2014, pp. 1–11, doi: 10.1002/9781118445112.stat05310.

[17] P. S. Muttaqin, W. Margareta, and A. D. Zahira, "Green warehouse performance monitoring system design using analytical hierarchy process and supply chain operation reference," *Appl. Eng. Technol.*, vol. 1, no. 3, pp. 146–153, 2022, doi: 10.31763/aet.v1i3.687.

[18] A. Ishizaka and A. Labib, "Analytic Hierarchy Process and Expert Choice: Benefits and limitations," *OR Insight*, vol. 22, no. 4, pp. 201–220, Dec. 2009, doi: 10.1057/ori.2009.10.

[19] F. T. S. Chan, R. W. L. Ip, and H. Lau, "Integration of expert system with analytic hierarchy process for the design of material handling equipment selection system," *J. Mater. Process. Technol.*, vol. 116, no. 2–3, pp. 137–145, Oct. 2001, doi: 10.1016/S0924-0136(01)01038-X.

[20] M. S. Umam, "The hybrid metaheuristic scheduling model for garment manufacturing on-demand," *Sci. Inf. Technol. Lett.*, vol. 2, no. 2, pp. 15–27, 2021, doi: 10.31763/sitech.v2i2.504.

[21] Y. Sha, J. Zhang, and H. Cao, "Multistage stochastic programming approach for joint optimization of job scheduling and material ordering under endogenous uncertainties," *Eur. J. Oper. Res.*, vol. 290, no. 3, pp. 886–900, May 2021, doi: 10.1016/j.ejor.2020.08.057.

[22] T.-M. Choi and Y.-J. Cai, "Impacts of lead time reduction on fabric sourcing in apparel production with yield and environmental considerations," *Ann. Oper. Res.*, vol. 290, no. 1–2, pp. 521–542, Jul. 2020, doi: 10.1007/s10479-018-2838-7.

[23] M. A.-A. Khan, A. A. Shaikh, G. C. Panda, A. K. Bhunia, and I. Konstantaras, "Non-instantaneous deterioration effect in ordering decisions for a two-warehouse inventory system under advance payment and backlogging," *Ann. Oper. Res.*, vol. 289, no. 2, pp. 243–275, Jun. 2020, doi: 10.1007/s10479-020-03568-x.

[24] A. Federgruen, "Chapter 3 Centralized planning models for multi-echelon inventory systems under uncertainty," in *Handbooks in Operations Research and Management Science*, vol. 4, no. C, Elsevier, 1993, pp. 133–173, doi: 10.1016/S0927-0507(05)80183-5.

[25] T. Abu Zwaida, C. Pham, and Y. Beauregard, "Optimization of inventory management to prevent drug shortages in the hospital supply chain," *Appl. Sci.*, vol. 11, no. 6, p. 2726, 2021, doi: 10.3390/app11062726.

[26] Z. Lyu, P. Lin, D. Guo, and G. Q. Huang, "Towards zero-warehousing smart manufacturing from zero-inventory just-in-time production," Robot. Comput. Integr. Manuf., vol. 64, p. 101932, 2020, doi: 10.1016/j.rcim.2020.101932.

[27] A. H. M. Mashud, H.-M. Wee, B. Sarkar, and Y.-H. Chiang Li, "A sustainable inventory system with the advanced payment policy and trade-credit strategy for a two-warehouse inventory system," *Kybernetes*, vol. 50, no. 5, pp. 1321–1348, May 2021, doi: 10.1108/K-01-2020-0052.

[28] G. K. L. Chien and F. T. S. Chan, "Developing an integrated business model in the manufacturing industry – An AHP approach," *Sci. Inf. Technol. Lett.*, vol. 2, no. 1, pp. 16–27, Mar. 2021, doi: 10.31763/sitech.v2i1.611.

[29] S A. Alzahrani and R. A. Khan, "Secure software design evaluation and decision making model for ubiquitous computing: A two-stage ANN-Fuzzy AHP approach," *Comput. Human Behav.*, vol. 153, p. 108109, 2024, doi: 10.1016/j.chb.2023.108109.

[30] L. S. Sundar and K. V. V. C. Mouli, "Experimental analysis and Levenberg-Marquardt artificial neural network predictions of heat transfer, friction factor, and efficiency of thermosyphon flat plate collector with MgO/water nanofluids," *Int. J. Therm. Sci.*, vol. 194, p. 108555, 2023, doi: 10.1016/j.ijthermalsci.2023.108555.

[31] E. Fradinata, S. Suthummanon and W Sunthiamorntut, "Comparison of hybrid ANN models: A case study of instant noodle industry in Indonesia," *Int. J. Adv. Appl. Sci.*, vol. 4, no. 8, pp. 19–28, Aug. 2017, doi: 10.21833/ijaas.2017.08.004.