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Forecasting Demand and Optimizing Product Ordering in the Supply Chain Using Artificial Intelligence

Mohammadreza Pakbin¹, Yalda Rahmati Ghofrani^{2*}, Kambiz Shahroodi³

¹ Ph.D. Candidate of Department of Business Management, Rasht Branch, Islamic Azad University, Rasht, Iran.

² Assistant Professor, Department of Business Management, Rasht Branch, Islamic Azad University, Rasht, Iran. (Corresponding Author) rahmati@iaurasht.ac.ir, 0000-0001-7855-1249.

³ Associate Professor, Department of Business Management, Rasht Branch, Islamic Azad University, Rasht, Iran. k.shahroodi@yahoo.com, 0000-0001-6392-2799

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ABSTRACT

The purpose of this research is to predict demand and optimize product ordering within the supply chain using artificial intelligence. Employing a purposeful sampling method, 12 managers from Kale were selected as the sample group. This study utilized two Delphi techniques and a neural network. Through semi-structured interviews conducted in a fuzzy Delphi panel, relevant components were identified. Predictions were made using the Multi-Layer Perceptron Neural Network toolbox in MATLAB software. The results from the fuzzy Delphi analysis indicated that the primary factors influencing the forecast included warehouse inventory, sales from the previous week, sales from the previous month, cargo in transit, fluctuations in customer numbers compared to the past, competitors' market status, government regulations, and the company's development plans. After finalizing the Delphi process, the key factors identified were warehouse inventory, sales from the previous week, sales from the previous month, changes in customer numbers compared to the past, competitors' market status, and government regulations. The neural network predictions demonstrated that, due to the fluctuating demand trends, the predicted values closely aligned with the actual values. According to the graphs and the average squared error values, the neural network's predictions were deemed acceptable, even with the rapid fluctuations in actual demand. In the case of Kale Dairy Company, utilizing artificial intelligence for demand forecasting and optimizing product ordering can yield significant benefits. Firstly, more accurate demand forecasting through artificial intelligence algorithms can lead to a reduction in waste and excess inventory within the supply chain. This enables the company to better identify and meet customer needs, ultimately resulting in increased customer satisfaction. ©authors.

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1. Introduction

Forecasting demand and optimizing product ordering are crucial components of supply chain and inventory management. These two concepts enable companies and organizations to enhance their performance by reducing costs, increasing profitability, and improving efficiency in the supply and distribution of goods (Ahmadi et al., 2023). Demand forecasting involves estimating the future demand for products or services. By analyzing historical data, consumption patterns, and economic variables, this process allows organizations to more accurately predict the quantity of goods they need to supply in the future (Groene et al., 2024). By accurately forecasting demand, organizations can optimize their inventory and prevent the accumulation of unnecessary goods in the warehouse. This not only reduces maintenance costs but also frees up capital (Asadabadi et al., 2023). Correct demand forecasting enables companies to deliver goods on time and in the required quantities (Cao, 2023). This, in turn, enhances customer satisfaction and improves service levels (Khairy et al., 2024).

Demand forecasting provides essential information for production, transportation, and distribution planning, enhancing coordination within the supply chain. By utilizing demand forecasting, organizations can mitigate the risks associated with shortages or surpluses of goods. Optimizing ordering involves determining the optimal timing and quantity for ordering goods. The goal of this process is to minimize the costs related to ordering, transporting, and storing goods while ensuring an adequate supply of inventory (Hashemi Petrudi et al., 2024).

By optimizing the ordering process, organizations can reduce costs associated with unnecessary orders and overstocking, thereby increasing profitability (Browning et al., 2023). Effective order optimization ensures that goods are delivered on time, which not only shortens delivery times but also enhances customer satisfaction. Additionally, order optimization allows organizations to refine their processes and boost operational efficiency (Ghosh et al.,

2023). By implementing ordering optimization, inventory levels are maintained at an optimal state, helping to lower maintenance costs and prevent shortages of goods (Nandi et al., 2024).

Demand forecasting and product ordering optimization are two key elements of supply chain management that play a vital role in the success of organizations (Durap, 2023). These processes enable organizations to excel in today's dynamic and competitive business environment by reducing costs, enhancing service levels, increasing customer satisfaction, and mitigating risks. By employing advanced techniques and appropriate tools in this field, organizations can fully leverage the advantages of these processes and elevate their performance to a higher level (Ronchini et al., 2024).

The integration of artificial intelligence and genetic algorithms in demand forecasting and product ordering optimization has revolutionized supply chain management. These technologies enhance the accuracy of predictions and streamline ordering processes (Chervenkova et al., 2023).

By analyzing large and complex datasets, artificial intelligence (AI) identifies hidden patterns and provides more accurate predictions. Unlike traditional methods, AI can swiftly respond to sudden changes in demand and market conditions by learning from historical data (Zejjari et al., 2024). This capability enables organizations to forecast future demand more promptly and accurately, thereby avoiding stockpiling or shortages (Ivanov, 2023). Genetic algorithms, inspired by the principles of natural selection, are highly effective for finding optimal solutions to complex problems, such as product ordering. These algorithms determine the best combination of timing and order quantities by exploring a vast solution space and applying incremental adjustments (Tahmasebifard et al., 2018). This process helps reduce storage and ordering costs, increase profitability, and enhance inventory management (Sawant et al., 2024).

The integration of artificial intelligence and genetic algorithms offers an innovative and

efficient approach to demand forecasting and product ordering optimization. By analyzing large and complex datasets, artificial intelligence uncovers hidden patterns and delivers more accurate predictions. Unlike traditional methods, AI can swiftly adapt to sudden changes in demand and market conditions by learning from historical data. This capability enables organizations to forecast future demand more promptly and accurately, thereby avoiding excess inventory or shortages. Genetic algorithms, which are inspired by the principles of natural selection, are particularly effective in identifying optimal solutions for complex problems such as product ordering. These algorithms determine the best combination of timing and order quantities by exploring a vast solution space and implementing incremental adjustments. This process helps to reduce warehousing and ordering costs, enhance profitability, and improve inventory management.

The combination of artificial intelligence and genetic algorithms offers an innovative and efficient solution for demand forecasting and product ordering optimization. By enhancing accuracy and efficiency, these technologies empower organizations to excel in competitive environments and manage their resources more effectively. Consequently, the research questions are:

What are the key components of an effective demand forecasting model in the supply chain that utilizes artificial intelligence and genetic algorithms?

What is the mathematical model for demand forecasting in the supply chain that utilizes artificial intelligence and genetic algorithms?

2. Literature Review

Supply Chain Management

It is a series of activities that optimizes the economic value of goods and services from their source to consumption by coordinating physical, financial, and informational flows (Mirzaaagha et al., 2016). Additionally, it enhances customer value by meeting their needs and ensuring satisfaction. While the material flow moves forward, the information flow operates in reverse.

Specifically, information related to demand, appropriate costs, and quality is provided to the system by the customer (Mokhtari et al., 2019).

Demand Forecasting

Demand forecasting is the process through which organizations estimate future customer demand for their products or services. This involves analyzing historical data, understanding consumption patterns, and examining various factors such as market trends, economic conditions, and seasonal fluctuations. The primary purpose of demand forecasting is to provide accurate information for decision-making related to production, distribution, and inventory management. By doing so, organizations can effectively allocate their resources and avoid both inventory shortages and surpluses (Shafiei et al., 2021).

Order Optimization

Order optimization is a process through which organizations determine the optimal timing and quantity of goods to order, aiming to minimize the overall costs associated with ordering, carrying, and holding inventory. By employing various techniques and algorithms, including mathematical models and simulations, this process seeks to maintain a balance between having sufficient inventory to meet demand and avoiding both stockpiling and shortages. The primary objective of order optimization is to enhance the efficiency of the supply chain while ensuring access to products at the lowest possible cost (Moslem Bayrami and Yousefinejad Attari, 2021).

Supply chains play a crucial role in enhancing customer experience, controlling costs, and enabling company agility in response to market opportunities and uncertainties. Companies strive for speed, reliability, and traceability while balancing cost requirements, deadlines, and inventory optimization (Collin et al., 2009; Zhang et al., 2016). Supply chain managers must monitor and respond to events and factors that disrupt the supply process, ranging from common incidents such as delivery delays and quality defects to significant events like political unrest, natural disasters, and the

financial instability of suppliers. These factors can contribute to supply chain complexity in uncertain environments. In other words, the era of stable markets is now a thing of the past. Today, companies face highly complex scenarios characterized by unpredictable conditions, including monetary crises, pandemics, climate change, and supply constraints. Furthermore, the increasing demand for fully customized products delivered in the shortest possible time has intensified this situation (Trierweiler & Bauernhanslell, 2022).

According to Mentzer et al. (2001), "a supply chain is a network of organizations that, through upstream and downstream links, are involved in various processes and activities that produce value in the form of products and services provided to the final consumer. To excel in the complex environments in which supply chains operate—and to develop more agile and resilient supply chains—these linkages, processes, and activities must be monitored, predicted, estimated, and optimized.

In recent years, applications based on artificial intelligence have emerged in several different fields, including supply chains (Borges et al., 2021).

It should be noted that supply chain management means balancing supply and demand, improving customer satisfaction, and reducing overall supply chain operating costs through supply chain design, planning, and control, logistics, information flow, and capital flow. Based on the above features, neural networks are currently used in supply chain management mainly in some areas: including optimization, forecasting.

In supply chain management, artificial neural networks can be used for a wide range of applications such as demand forecasting, inventory management, logistics optimization and risk management. Artificial neural networks can analyze historical sales data, customer trends and other relevant factors to accurately predict future demand (Song, 2021) Neural network is the most popular computing technology for solving optimization problems. It is important for supply chain management. Currently, how to use neural networks to solve the optimization

problem of supply chain management, such as store scheduling, warehouse management, transportation route selection, etc., has been studied. Some of these problems are the main problems for building a company's logistics information system. Moreover, compared to other technologies, the neural network has a strong adaptive ability and can quickly consider and accept emerging constraints with real-time processing capabilities.

Demand forecasting is a solid basis for planning and procurement processes that make the supply chain more responsive and efficient (Molov, 2020). Therefore, improving demand forecasting methods has become more important for manufacturers, distributors and retailers (Butani et al., 2021). Various methods have been adapted for demand forecasting. These can be statistical, artificial intelligence-based or hybrid methods that combine the features of a statistical model with a model from the field of artificial intelligence (Benhamida et al., 2020). Statistical methods provide accurate prediction results and are very useful. Currently, due to the increase in data dimensions and data volume, these classical methods face challenges and do not always meet the needs of manufacturing companies (Pasela et al., 2021). Artificial intelligence in the field of supply chain management has proposed new methods that combine traditional time series forecasting with machine learning methods or use artificial neural networks to modify and improve the demand forecasting process (Shen and Chan, 2017). Artificial neural networks can play an important role in the development of supply chain management by improving various aspects of the supply chain, such as demand forecasting, inventory management, logistics optimization and risk analysis. Artificial neural networks are computational models inspired by biological neural networks in the human brain and can learn from data to recognize patterns and make predictions (Zhu and Leo, 2022). It is important to note that although ANNs can provide valuable insights and recommendations, they should be used in conjunction with domain expertise and other analytical methods to make

informed decisions. Also, the availability of high-quality and relevant data is crucial for training accurate and reliable ANN models. To create an artificial neural network, the best predicted network structure should be found through trial and error, along with the selection of a set of input variables (Fenudi et al., 2019).

3. Method

The methodology of this research employs a mixed-methods approach. The study utilizes two techniques: fuzzy Delphi and neural networks. The dimensions and components associated with the features of the demand forecasting model are identified

through Delphi analysis and subsequently refined using a critical evaluation method. This process aims to achieve significant theoretical coherence by employing the multi-layer perceptron neural network toolbox.

This research consists of five steps: identifying the area under investigation, defining the research problem, presenting the research model, designing the structure of the solution algorithms, and generating data for testing and adjusting the parameters of the model and algorithms. The methodology flowchart for this research is illustrated in Figure 1.

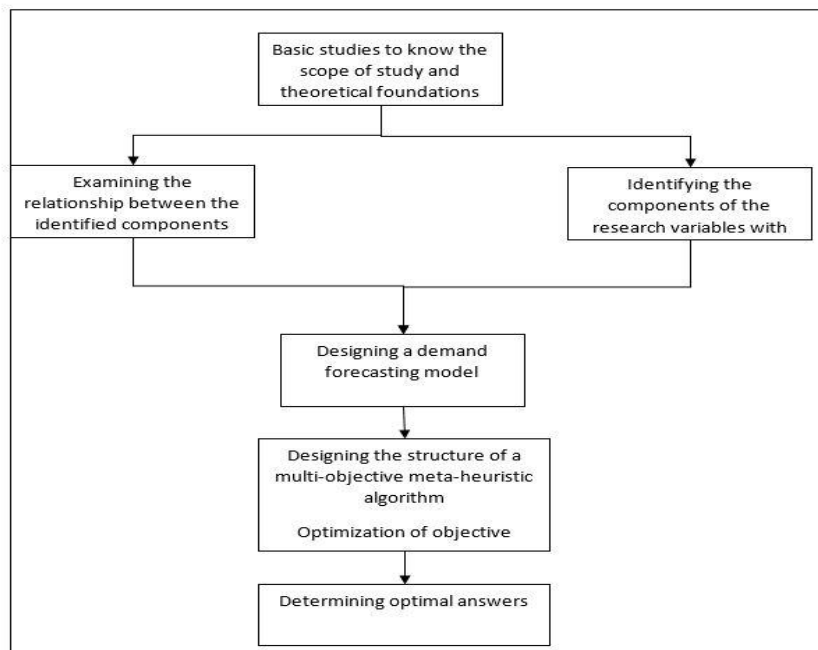


Figure 1. Flowchart of the Current Research Methodology

The statistical population for this study comprised all the experts and managers at Kale Company. Purposeful and judgmental sampling methods were employed. A total of 12 experts and managers from Kale Company were selected to finalize the model components. Specific criteria were established for the selection of these experts. The statistical population of the forecasting department encompasses all products offered by Kale Company. This research aimed to forecast demand and optimize ordering processes due to the large number of targeted sampling products. Consequently, three key strategic

products from the company were chosen as the statistical sample.

- 350 grams of Ana Labneh cheese
- Sondebe Yogurt, 2.2 kg
- 1 liter of full-fat milk from Kale.

Assumptions of the Model

Due to the complexity of demand forecasting and order optimization, there are discrepancies between real-world scenarios and mathematical models. The following assumptions are made for supply and demand management using the methods considered for various materials.

A high capacity is expected from each supplier to minimize defects in raw materials.

The concepts of supply and demand in the field of knowledge refer to the processes and interactions related to the production, distribution, and consumption of knowledge. Demand for knowledge relates to the needs and desires of individuals and organizations to acquire and utilize new information and skills. This need can arise from technological advancements, changes in the labor market, or the necessity to improve organizational performance. Demand is typically generated by employers, students, and researchers seeking to learn and apply knowledge to solve specific problems or enhance their competitiveness.

On the other hand, supply of knowledge pertains to the production and delivery of information, skills, and experiences created by universities, educational institutions, research centers, and experts. The supply of knowledge can include educational courses, training programs, scientific articles, and workshops aimed at transferring knowledge to demanders. In this context, the quality and accessibility of educational and informational resources can significantly impact the ability of demanders to effectively utilize knowledge.

The interaction between the supply and demand for knowledge can lead to the creation of social and professional networks, inter-organizational collaborations, and new innovations. Moreover, in today's world, information and communication technology play a crucial role in facilitating this interaction. Through online platforms and digital resources, demanders can easily access the knowledge and information they need. As a result, the supply and demand for knowledge become a dynamic cycle that contributes to continuous improvement and progress in various societies and industries.

- The following parameters are fixed values for each individual event: unit cost of raw materials, supplier capacity, actual delivery time, available raw materials, discount percentage, order time frame, and the number of free items per order. These

parameters can be adjusted manually by the decision maker.

The maximum time allowed for ordering raw materials is set at 10 days to prevent overstocking and to maintain optimal warehouse performance.

In the identification phase, the fuzzy Delphi technique is utilized within MATLAB software. Furthermore, the implementation of a multi-layer perceptron neural network has advanced the development of the algorithm. The feedforward algorithm governs the process by which the inputs are transformed into an output. However, the feedforward process in a multi-layer perceptron network is more complex than that in single-layer perceptron networks. During the feedforward process in the multi-layer perceptron network, the operations defined in the algorithm are executed across all layers of the network. In this process, the output of each layer serves as the input for the subsequent layer.

Table 1 presents the members of the Delphi panel, along with their positions and educational backgrounds. As shown in the table, the Delphi panel included not only experts but also managers from Kale Company.

Table 1. Characteristics of Delphi panel members

Education	Expert
Ph.D	Manager of sales department of Kale company
MA.	Sales expert of Kale company
MA	Sales expert of Kale company
MA	Sales expert of Kale company
Ph.D	Manager of sales department of Kale company
MA	Sales expert of Kale company
MA	Sales expert of Kale company
MA	Manager of sales department of Kale company
MA	Manager of sales department of Kale company
Ph.D	Manager of sales department of Kale company
MA	Sales expert of Kale company
MA	Sales expert of Kale company

4. Findings

Delphi technique

Eight indicators were finally identified based on the analysis of semi-structured interviews. The Fuzzy Delphi method was used to screen and ensure the importance of the identified indicators and select the final indicators. Experts' opinions about

the importance of each index have been compiled with a 7-degree fuzzy spectrum.

Table 2. Notation of open codes in the Delphi technique

Code	Initial code
C1	warehouse stock
C2	Last week's sale
C3	Last month's sale
C4	load on the way
C5	Change in the number of customers compared to the past
C6	The status of competitors in the market
C7	State laws
C8	Development plans of the company

Table 3. The spectrum of seven fuzzy degrees for the evaluation of indicators

Fuzzy number scale	Fuzzy value	Linguistic variable
(0, 0, 0.1)	$\tilde{1}$	Totally unimportant
(0, 0.1, 0.3)	$\tilde{2}$	very unimportant
(0.1, 0.3, 0.5)	$\tilde{3}$	unimportant
(0.3, 0.5, 0.75)	$\tilde{4}$	average
(0.5, 0.75, 0.9)	$\tilde{5}$	important
(0.75, 0.9, 1)	$\tilde{6}$	very important
(0.9, 1, 1)	$\tilde{7}$	Absolutely important

The opinions of 12 experts about each indicator are shown in Table 4:

Table 4. Fuzzification of the opinion of the expert panel for each open coding

	Expert 1	Expert 2	Expert 3	...	Expert 12
C1	(0.9, 1, 1)	(0.5, 0.75, 0.9)	(0.9, 1, 1)	...	(0.9, 1, 1)
C2	(0.75, 0.9, 1)	(0.5, 0.75, 0.9)	(0.75, 0.9, 1)	...	(0.75, 0.9, 1)
C3	(0.5, 0.75, 0.9)	(0.1, 0.3, 0.5)	(0.5, 0.75, 0.9)	...	(0.9, 1, 1)
C4	(0.1, 0.3, 0.5)	(0.5, 0.75, 0.9)	(0.5, 0.75, 0.9)	...	(0.1, 0.3, 0.5)
C5	(0.9, 1, 1)	(0.5, 0.75, 0.9)	(0.9, 1, 1)	...	(0.9, 1, 1)
C6	(0.1, 0.3, 0.5)	(0.75, 0.9, 1)	(0.9, 1, 1)	...	(0.5, 0.75, 0.9)
C7	(0.5, 0.75, 0.9)	(0.75, 0.9, 1)	(0.3, 0.5, 0.75)	...	(0.9, 1, 1)
C8	(0.1, 0.3, 0.5)	(0, 0.1, 0.3)	(0.1, 0.3, 0.5)	...	(0.5, 0.75, 0.9)

In the next step, the opinion of the experts should be gathered. Various methods have been proposed to aggregate the opinions of n respondents. In fact, these aggregation methods are experimental methods presented by different researchers. Fuzzy average method is used in this study. In this study, the surface center method is used for defuzzification as follows:

Relationship 1

$$DF_{ij} = \frac{[(u_{ij} - l_{ij}) + (m_{ij} - l_{ij})]}{3} + l_{ij}$$

The fuzzy average and the de-fuzzified output of the values related to the indicators are shown in the table. A de-fuzzified value greater than 7 is acceptable, and any index with a score less than 7 is rejected.

Table 5. The results of the first round of the Delphi technique for the identified components

The result of round 1	Definite value	Fuzzy average	upper limit	probable value	lower limit	
Acceptance	0.752	(0.621,0.769,0.867)	0.867	0.769	0.621	C1
Acceptance	0.872	(0.748,0.898,0.969)	0.969	0.898	0.748	C2
Acceptance	0.778	(0.646,0.798,0.89)	0.890	0.798	0.646	C3
Rejection	0.268	(0.239,0.310,0.256)	0.239	0.310	0.256	C4
Acceptance	0.777	(0.623,0.796,0.913)	0.913	0.796	0.623	C5
Acceptance	0.813	(0.681,0.833,0.923)	0.923	0.833	0.6811	C6
Acceptance	0.803	(0.66,0.825,0.923)	0.923	0.835	0.660	C7
Rejection	0.357	(0.267,0.376,0.428)	0.267	0.376	0.428	C8

Fuzzy Delphi analysis continued for the factors identified in the second round. At this stage, 6 indicators were evaluated

based on the views of 12 experts. The results of fuzzy Delphi in the second round are reported in Table 6:

Table 6. Results of the second round of the Delphi technique for open coding

Result of round 2	Definite value	Fuzzy average	Upper limit	Probable value	Lower limit	
Acceptance	0.794	(0.648,0.813,0.921)	0.921	0.813	0.648	C1
Acceptance	0.925	(0.829,0.954,0.992)	0.992	0.954	0.829	C2
Acceptance	0.875	(0.765,0.9,0.96)	0.960	0.900	0.765	C3
Acceptance	0.904	(0.792,0.929,0.992)	0.992	0.929	0.792	C5
Acceptance	0.738	(0.604,0.754,0.854)	0.854	0.754	0.604	C6
Acceptance	0.928	(0.833,0.956,0.996)	0.996	0.956	0.833	C7

The end of the Delphi technique rounds

In the second round, no questions were asked, which is a sign for the end of the Delphi rounds. In general, one approach to the end of Delphi is to compare the

average scores of the last two rounds of questions. If the difference between the two stages is smaller than the very low threshold (0.2), then the survey process is stopped.

Table 7. The difference between the results of the first and second round

Result	Difference	Result of Round 2	Result of Round 1	
Acceptance	0.042	0.752	0.794	C1
Acceptance	0.053	0.872	0.925	C2
Acceptance	0.097	0.778	0.875	C3
Acceptance	0.127	0.268	0.904	C5
Acceptance	0.075	0.777	0.738	C6
Acceptance	0.125	0.813	0.928	C7

Proposed Neural Network

In this research, a two-layer perceptron neural network was employed, along with specific neural network parameters, to predict product demand. Due to the large discrepancy in values, the demand output was divided by 1,000 in the data input table to facilitate the calculation of the mean squared error.

This collection is utilized to obtain the weight parameters of network inputs at the onset of the learning process.

This section is designed to test and evaluate the capabilities of the neural network, which are less extensive than those of the training set.

Validation: This section is utilized to prevent overfitting during the network training process. When the network's learning improves but its generalization ability for the dataset begins to decline, the training process should be halted.

The number of layers in a neural network is a crucial aspect of its design.

The first layer serves as the input layer, while the intermediate layers consist of neurons that perform calculations. The optimal number of intermediate layers is typically determined through trial and error.

The number of neurons in the intermediate layers of neural networks depends on the specific problem being addressed and is typically determined through trial and error. Activation (transfer) functions: The Tansig and Logsig functions are commonly used in the hidden layers of neural networks.

Full-fat milk product

First, the neural network parameters are established using the trial-and-error method. Subsequently, the graphs of the mean squared error and its regression are analyzed.

Table 8. Neural Network Parameters for High-Fat Milk Products

Parameter	Values
The number of hidden layers	2
The number of neurons in each layer	10
The percentage of using data for training	70%
Data usage percentage for validation	15%
Data utilization percentage for testing	20%
First layer transfer function	tansig
Second layer transfer function	logsig
Network training algorithm	Levenberg-Marquardt

The output table of mean squared error and absolute value of error between the actual value and the predicted value is as follows:

Table 9. The mean squared error and the mean absolute value of the error between the actual value and the predicted value

MSA	MSE
Average absolute value of the error	mean squared error
0.23513	0.10456

The above table shows the average squared error and the average absolute value of the error. The mean squared error is equal to the mean error, that is, the error between the actual value and the predicted value (mean squared). Instead of taking the square, the average absolute value of the error takes the absolute value, and its

absolute value is added, that is, the distance between the value predicted by the neural network itself and the actual value to the power of 2 and then their sum. For example, 100 months or 200 months, or any number of months written in the table. But in the average absolute value, instead of taking their difference for each month and raising it to the power of 2 and adding it, it takes its absolute value and adds it, which means that the average squared error is more likely. Its error mean square diagram is as follows:

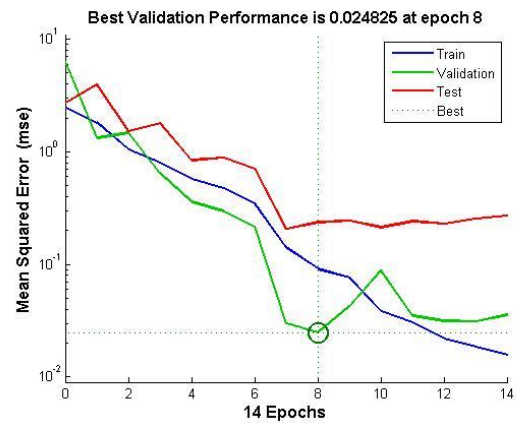


Figure 2. Mean squared error for training, testing and validating the high-fat milk product

Average squared error diagram, as you know, there are three stages in neural network in the average squared error diagram, one is training which is called Train, the other is Validation stage and one is Test stage. The row of this graph actually shows the iterations of the algorithm and its column shows the mean squared error in three graphs. The green graph actually shows the mean squared validation error. In the blue graph, it shows the mean square of the training and the red graph shows the mean square of the test error. In this criterion, the algorithm is stopped in the eighth iteration, which is based on one of the stopping indicators, one of which must happen to stop. Supposedly, one of those indicators is the number of repetitions, which has 1000 repetitions, for example, stopping at the eighth repetition. Another is time, one is performance or mean squared error that stops when it reaches

zero. One is gradient, the other is mu. One is Validation check, which has the right to check up to 6 times, and if the error gets worse, it stops. As can be seen in the first diagram of the high-fat milk product, in this product, Validation always decreases and it decreases compared to Train. In the chart, the red color also decreases. The eighth point is the best. In this graph, the mean square error of validation and testing in the 8th iteration went down and then went up. As a result, in the 8th iteration, the best error for validation is 0.02.

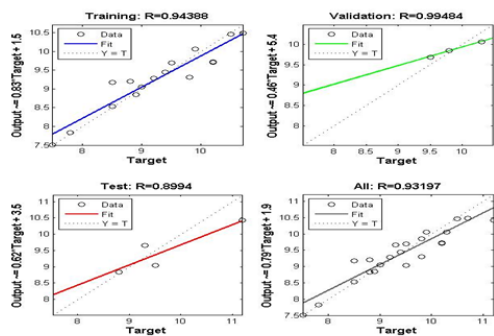


Figure 3. Neural network regression for high fat milk product

Regression means the linear relationship between the actual value and the predicted value. The regression diagram is the relationship between the target and the actual state that exists, compared to the output made in the training state. In the regression diagram, Training is shown on the upper left side, Validation is on the upper right side, Test is on the lower left side, and finally, on the lower right side, the overall state, i.e., the sum of three states, is shown and its regression is plotted. In this graph, the total regression rate is high, also the regression value for the test and validation set and training are close to one and have high values.

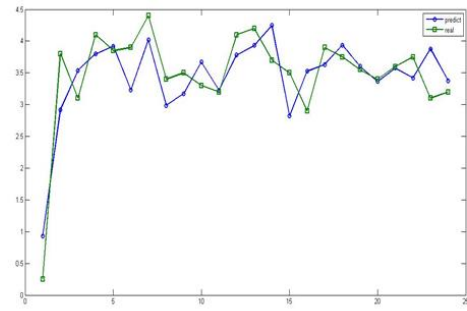


Figure 4. Trend chart of forecast amount and actual amount of high fat milk product

A trend chart actually shows how the actual value changes, with the green color representing the actual value and the blue color representing the forecast value. The closer the two are, naturally, the better. According to the graphs, table values and mean square errors, the prediction of neural network for high-fat milk products is acceptable due to the fast downward and upward trend of actual values. Therefore, in comparison with the years 2019 and 2019, which had complete data, the forecast for the next year (2012) will be as follows:

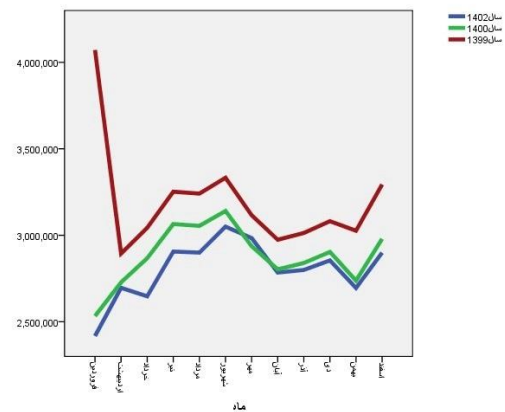


Figure 5. The predicted amount of demand for Kale high-fat milk in 2023

Labneh cheese product

First, the parameters of the neural network are determined based on the trial-and-error method, then the graphs of the average squares of the error and its regression are examined.

Table 10. Neural network parameters of Labneh cheese product

Parameter	Values
The number of hidden layers	2
The number of neurons in each layer	10
The percentage of using data for training	70%
Data usage percentage for validation	15%
Data utilization percentage for testing	20%
First layer transfer function	tansig
Second layer transfer function	logsig
Network training algorithm	Levenberg-Marquardt

The output table of mean squared error and absolute value of error between the actual value and the predicted value is as follows.

Table 11. The mean squared error and the mean absolute value of the error between the actual value and the predicted value

MSA	MSE
Average absolute value of the error	mean squared error
0.36843	0.19677

Its error mean square diagram is as follows:

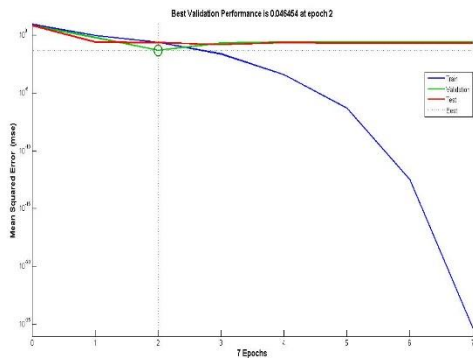


Figure 6. Mean squared error for training, testing and validation of cheese milk product

In this graph, in the second iteration, there is the lowest error difference, the error rate for validation is 0.04.

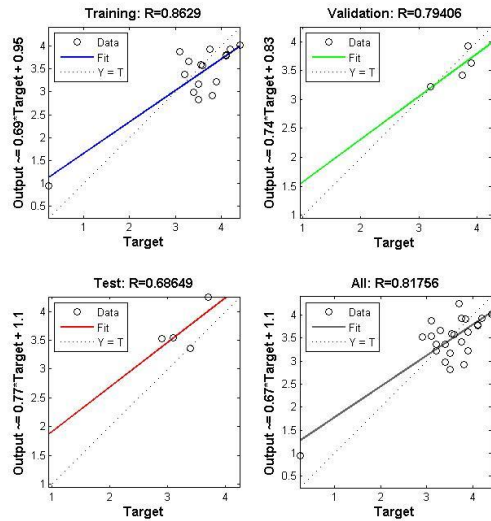


Figure 7. Neural network regression for the product of Labneh cheese

In this graph, the total regression rate is high, and the regression value for the test and validation and training set is close to one.

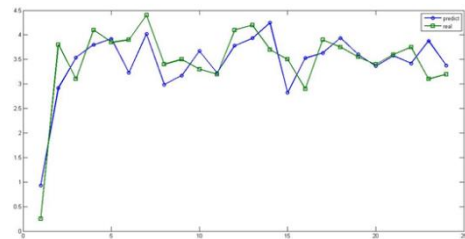


Figure 8. The trend of the predicted amount and the actual amount of the product of Labneh cheese

As can be seen in the graph, according to the upward and downward trend of the demand, the prediction value of the neural network is close to the real value. According to the graphs, the values of the mean squared errors table, this prediction is acceptable due to the rapid downward and upward trend of the actual values.

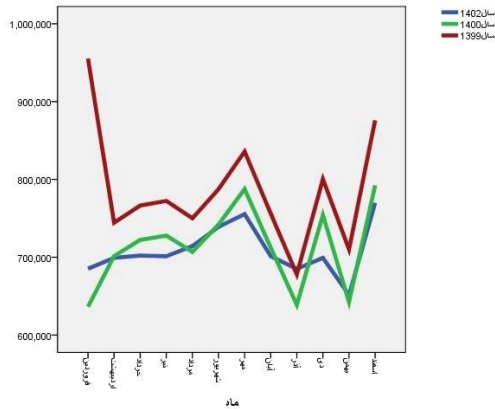


Figure 9. The predicted amount of demand for Labneh Kale cheese in 2023

5. Discussion

Based on the Delphi analysis, factors such as warehouse inventory, last week's sales, last month's sales, changes in the number of customers compared to previous periods, the status of competitors in the market, and government regulations were evaluated. The results indicated that predictions made using the multi-layer perceptron neural network toolbox in MATLAB software closely aligned with actual values, largely due to the upward trend in Venezuelan demand. These findings are consistent with the research conducted by Shafiei et al. (2019), Mokhtari et al. (2019), and Yavari and Graili (2019). Machine learning and artificial intelligence methods have introduced innovative approaches to forecasting problems by modeling the relationships between variables in a deep, layered hierarchy. Techniques such as artificial neural networks, support vector machines, random forests, and deep learning models—including recurrent neural networks and long short-term memory—have recently garnered significant attention from researchers in the field of prediction.

The rapid and inevitable changes in today's world, driven by globalization, have compelled companies to engage more with one another to maintain competitiveness, ensure customer satisfaction, and achieve their goals effectively. Consequently, the concept of

the supply chain has emerged. Sustainable supply chain management involves overseeing the flow of materials, information, and capital, as well as coordinating activities among companies within the supply chain. This management approach considers three dimensions: economic sustainability, environmental impact, and community welfare, all of which are influenced by the demands of customers and stakeholders. Integrating environmental considerations into supply chain management encompasses various stages, including product design, sourcing and selection of materials, the production process, product delivery to customers, and end-of-life management of products after their useful life has expired. Supply chain management can be categorized into three levels: strategic (long-term, related to company strategy and design issues), tactical (mid-term), and operational (short-term, focused on flow management and scheduling). Decisions are made at these levels concerning supply chain procurement, production, and distribution. Reason: Improved clarity, readability, and technical accuracy while maintaining the original meaning.

When a product request is issued by the manufacturer, cost and time are two key factors to consider. According to the timely distribution policy, the appropriate quantity of goods should be delivered at the right time and place, which is crucial for effective distribution. Since logistics costs constitute a significant portion of the total expenses in the supply chain, making simultaneous decisions regarding distribution and inventory planning can substantially reduce overall supply chain costs. Additionally, these decisions play a vital role in determining the level of customer service. Among all supply chain processes, distribution specifically refers to the flow of materials and goods from suppliers to end customers within the chain.

Accurate and precise demand forecasting is critical for all organizations, both in the private and public sectors, in

both theory and practice. Management judgment is often necessary to adjust statistical forecasts in response to specific events. Consequently, forecasting methodology holds significant relevance and application within the field of management. Additionally, demand forecasting is a key management issue. Short-term and random data are essential for accurate forecasting. Demand forecasting serves as a vital tool for supplying goods, planning production, determining necessary inventory levels, and establishing appropriate distribution methods. When a service or product enters a target market, its current size and potential future volume must be estimated accurately. Overestimating or underestimating the actual market can result in substantial profit loss for the supplier. Therefore, the accuracy of the forecasting model is of utmost importance for managers. To enhance the reliability of management forecasts, numerous models have been proposed and utilized to date.

6. Conclusion

Based on the results obtained, artificial intelligence proves to be advantageous in predicting demand for Kale Dairy Company. This technology can identify demand patterns more accurately and swiftly than traditional methods by analyzing large and complex datasets. Utilizing machine learning algorithms, AI considers various factors such as seasonal variations, weather changes, consumer behavior, and market trends in its analyses. These detailed analyses enable Kale to better anticipate customer needs and deliver the required products at the appropriate time.

In addition to enhancing forecasting accuracy, AI enables Kale to dynamically predict demand in real time. This capability allows the company to swiftly respond to market changes and demand fluctuations while optimizing inventory levels. As a result, both inventory holding costs and product waste are minimized, and Kale can also enhance its customer

service. Utilizing artificial intelligence for demand forecasting helps Kale refine its supply and production strategies. By accurately predicting demand, Kale can improve production planning, secure raw materials, and effectively manage its supply chain. This approach will reduce costs, boost productivity, and ultimately increase the company's profitability. Furthermore, this capability allows Kale to maintain its competitive edge in a challenging market and solidify its position as a leader in the dairy industry.

In Kale Dairy Company, the implementation of artificial intelligence to predict demand and optimize the ordering of goods can yield significant benefits. First, enhanced demand forecasting through artificial intelligence algorithms leads to a reduction in waste and excess inventory within the supply chain. This enables the company to more accurately identify and fulfill customer needs, resulting in increased customer satisfaction.

Optimizing the ordering process is a significant advantage of utilizing artificial intelligence in the supply chain of Kale Dairy Company. This technology enables the company to enhance its ordering efficiency by leveraging both historical and real-time data, thereby reducing storage and transportation costs. Such optimization not only boosts the efficiency of the supply chain but also enhances the company's profitability. By incorporating artificial intelligence into demand forecasting and ordering processes, Kale Dairy Company can respond more adeptly to market fluctuations, improving its decision-making capabilities. This increased flexibility allows the company to react swiftly to changes in demand and capitalize on emerging market opportunities, ultimately strengthening its competitiveness within the dairy industry.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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