Int. J. Nonlinear Anal. Appl. 15 (2024) 4, 65–78
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2023.28672.3956

Present a mixed approach of neural network and bat algorithm to predict customer demand in the supply chain to reduce the Bullwhip effect

Milad Rezaeefard[a], Nazanin Pilevari[b,c,*], Farshad Faezy Razi[d]

[a] *Department of Industrial Management, College of Management and Economics, Science and Research Branch, Islamic Azad University, Tehran, Iran*

[b] *Department of Industrial Management, West Tehran Branch, Islamic Azad University, Tehran, Iran*

[c] *Visitor Professor of Science and Research Branch, Islamic Azad University, Tehran, Iran*

[d] *Department of Industrial Management, Semnan Branch, Islamic Azad University, Semnan, Iran*

(Communicated by Seyed Hossein Siadati)

Abstract

Many studies have addressed supply chain that shows the importance of the subject and the competition in the supply chain consisting of several companies. The previous studies address the issue of reducing the Bullwhip Effect in the supply chain, which is possible by predicting the correct amount of customer demand. This paper improves the accuracy of the model prediction and reduces the existing error in the previous models to attain an accurate and very close-to-reality forecast and also to reduce the Bullwhip Effect in the supply chain. Literature shows the absence of research on the presentation of a metaheuristic algorithm consisting of a neural network and bat algorithm to forecast supply chain demand in manufacturing companies; therefore, this article is innovative. On the other hand, no researchers have addressed Bullwhip Effect reduction using mixed metaheuristic algorithms. Therefore, this article improves the previous models, reduces the number of errors in demand forecasting, and reduces the Bullwhip Effect. For this purpose, the scalable gradient algorithm method is used for better network training. The results indicate the optimal performance of neural network training with a comparable gradient and bat algorithm on reducing the Bullwhip Effect.

Keywords: Bullwhip effect, Bat algorithm, Neural network, Demand forecasting, Supply chain
2020 MSC: 90B06

1 Introduction

Demand planning is an critical step in production planning, which is based on demand data in the supply chain [16]. The main task of production planning is to choose a suitable demand forecasting method. Therefore, companies are concerned about the correct demand forecast because the production stages planning will be based on the obtained

*Corresponding author
Email addresses: milad.rezaeifard@yahoo.com (Milad Rezaeefard), nazanin.pilevari@gmail.com (Nazanin Pilevari), f.faezi@semnaian.ac.ir (Farshad Faezy Razi)

Received: October 2022 *Accepted:* May 2023

information from this step [9]. A direct supply chain includes raw materials transfer, and product flows from producers to end users, and a reverse supply chain includes reverse product flows from end users to producers [13].

Organizations and factories constantly face problems in one part of the supply chain part, which will be transferred to other parts and will become bigger and bigger. Forecasting plays a critical role in this problem management in the supply chain, to control unsustainable production programs, excess costs, reduction of storage, etc.[17]. Therefore, the correct demand forecasting in the supply chain can reduce this effect, which is known as the bullwhip effect or customer demand uncertainty, and reduces costs and excess activities of companies and organizations [1].

The company's demands for correct identification and quick response to the demands is the key to success. A lack of proper forecasting of demand in business interactions can lead to capital loss and an increase in storage costs. Therefore, the companies benefit from demand forecasting investment in business interactions. Nonetheless, the process requiring information volume when deciding to forecast demand, and the ambiguity and complexity of these interactions, have complicated the demand forecasting problem [5].

Currently, we consider organizations with their position in a supply chain. Thus, some experts believe that now, the competition has been transferred from companies to chains. The supply chain discussion has developed in the last two decades, and many large international organizations have gradually adopted it [2]. Organizations gain significant competitive advantages by establishing closer relationships with others, and they can reduce related time and costs depending on how they manage the supply chain. In a competitive environment, a successful supply chain benefits empowering the organization's competitive advantages. An organization will work more effectively when it has a mutually beneficial relationship with its business partners based on trust, knowledge sharing, and integrity [4]. The rapid growth in data quantities collected by information systems inclined marketers to adopt data-based decision support tools to improve and modify marketing decisions [10]. The possibility of mass production of goods and services has provided the necessary ground to increase the supply, relevant to the demand. The producers must satisfy the customers, and the market and supply scope may not be interpreted by the limited tools of the past [12]. This article provides a study of supply chain performance with a realistic framework. Therefore, the current incompleteness of information in many organizations results in impractical model presentation, even if considered a full-scale supply chain performance measurement.

2 Research Background

Gupta and Saxena [7] predicted the demand load of power grids through a hybrid intelligent model. This article sought to develop a feed-forward neural network model for predicting electricity load demand at different times of the year. In this article, the geographic optimization algorithm (GPSO) was used as a new training method to improve neural networks' performance. The results showed that this model can significantly improve prediction accuracy and training performance.

Zougagh et al. [18] predicted the number of sales in the supply chain through big data analysis. He identified the impact of data explosion on production forecasting and how to improve it. This article focused on the time series of data, but it also sought to discover how to use this data to achieve consumer behavior and the impact of such information on organizational forecasting.

Lin et al. [11] titled " A Simple and strong approach to demand forecasting in the supply chain", presented a simple yet strong approach based on recent developments in time series. They concluded that such a technique based on algebraic methods is more suitable for supply chain work.

Rezaei et al. [14] entitled "Bullwhip Effect in the closed loop supply chain", seeks to find a solution to reduce the Bullwhip effect in the supply chain. They concluded that closing a supply chain can reduce the Bullwhip effect, causing positive effects on supply chain environmental performance.

Nguyen et al. [15] looked for a comparison of demand predition models for natural gas demand in urban areas. The models prediction were based on past temperature, predicted temperature and time variables. The models have been trained and tested based on gas consumption models data, and the two neural network and linear regression models showed the best results compared to other methods.

Goel et al. [6] titled "Demand forecasting by online information generated by users and based on finding key points in past research". concluded that their findings differ from previous studies. In this study, they found that predictive criteria such as exponential distribution outperforms in the case of online information.

Harrison [8] sought to predict the air transport industry demand using the hybrid approach of SARIMA and support vector regression. The hybrid model proposed in this study can be used for future capacities of management and target planning. The time series in this study has been analyzed by SARIMA. In the following, four hybrid models were used to predict future statistical indicators in this industry. The results indicated that the research model shows better results than other methods.

Zarandi and Moghadam [3] titled "Forecasting Tourist Demand Based on Enclosed Neural Networks, automatic neural networks (NNAR) have been used to improve the prediction accuracy. At first, they developed and forecasted two raw and closed neural models for tourism demand series and compared the results. As a result, it can be seen that closed neural networks are more useful for improving the accuracy of predictions of automatic neural networks.

3 Methodology

This article adopts a neural network in addition to the bat algorithm for prediction. At first, this paper obtains effective indicators on buyers' exchanges. Then, the paperoptemizes weights through the seasonal data of buyers, using the bat algorithm and through the signals sent in this method. Then, the preditions are made using the neural network with the help of MATLAB software. Also, the scalable gradient algorithm is used to improve the Bullwhip Effect of the neural network. Finally, the results of the research model are compared with the results obtained from the neural network and the combination of the neural network and the particle swarm algorithm to show the accuracy of the model, followed by tested the extent of the reduction of the Bullwhip Effect.

First step:

First, the main and general indicators affecting the demand were identified in the litreature, and the final indicators were obtained using the Fuzzy Cognitive Mapping method (FCM) along with the data collected from the seasonal buyers purchase amount.

Second step:

Data normalization: We use the minimum-maximum transformation method for normalization, because each unit properties and their changes scope differs from others in many cases, and according to the fact that the artificial neural network for normalized data outperforms other methods.

$$N_i = X_i - X_{\min}/X_{\max} - X_{\min}$$

where,

N_i = Standardized values

X_i = Real values

$X_{\min}$ = Minimum real values

$X_{\max}$ = Maximum real value

Third step:

Neural network formation: In this research, we use a feed-forward neural network in two successive layers:

$$y_i = g_i\left(\sum_{i=1}^{n} \omega_{ij} \times u_i + b_j\right), \quad i \in [0, m] \;\; j \in [0, n].$$

In this network, the supervised learning method based on updating the weights is used to reduce the error, and for this purpose, the Mean Square Error (MSE) method is used:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - z_i)^2.$$

Fourth step:

Network training and weight optimization with bat algorithm: The bat algorithm structure must first be formed to train the neural network to improve the weights of the network. The purpose of choosing the bat algorithm is to send the frequency and reflect it to calculate the distance to the destination, and the shorter the distance to the destination, the closer the frequency reflection is to zero. The following equation is used to calculate the frequency:

$$f_k = c_1 \times \sum D/aa_i = 1$$

where,

$f_k =$ Bat sound frequency

$c_1 =$ Pulse rate

$D =$ The data matrix $(a \times b) \cdot b$ is the data column of the input variables

$a =$ Virtual bats whose number is obtained by trial and error method.

The value of the initial frequency is randomly selected between zero and one, referring to Yang's article. The value of c_1 is automatically adjusted when the bat approaches or moves away from the target, and its value is calculated by the following equation:

$$c_1 = c_2 \times Ek_2 \times P_k$$

where,

$c_2 =$ The bat learning rate and its value is constant and equal to 1.112.

$E_k =$ The bat movement error, its value is close to zero when it approaches the destination.

$P_k =$ New position of bat.

The desired destination for virtual bats is the share price, which is used to calculate the distance to the destination by the following equation:

$$S = f_k \times D_k \times w_t$$

where, $S =$ The distance of the virtual bat k to the desired destination

$f_k =$ Sound frequency of the virtual bat k

$D_k =$ virtual bat k data matrix

$w_k =$ The weight matrix is a value between zero and one that is chosen randomly.

Fifth step:

Network training with scale gradient algorithm

$$S_k \approx \frac{E(w_k + \sigma_k q_k) - E(w_k)}{\sigma_k} + \lambda_k q_k, \qquad 0 < \sigma_k \ll 1.$$

The sixth step:

Implementation of the model by MATLAB software and testing and validation of the model through test and validation data

Seventh step:

Comparing network outputs with real data and neural network and neural network and particle swarm to detect the better performance of the research model.

Eighth step:

Measuring the effect of Bullwhip Effect after running the model and comparing it with before running the model

$$\frac{var(Q)}{var(D)} \geq 1 + \frac{2L}{p} + \frac{2L^2}{p^2}.$$

4 Bat algorithm

To simplify the work, the following assumptions are used [17]:

- All bats use echolocation to detect distance, and they can also detect the difference between food, prey, and obstacles.
- Bats randomly use speed v_i at position x_i with frequency $f_{\min}$, variable wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength or frequency of emitted pulses and regulate the pulse emission rate r according to the proximity to the prey.

- It is assumed that the loudness of the sound changes from a large positive value of A_0 to a constant value of at least $A_{\min}$.
- The frequency is considered in the $[0, f_{\max}]$ range. Higher frequencies have shorter wavelengths and travel a shorter distance. For bats, a typical range is about several meters. The pulse sending rate or r is also in the range $[0, 1]$, where one indicates the maximum pulse sending rate [12].

In addition to the mentioned assumptions, instead of using the wavelength, the frequency can be changed and λ is assumed to be constant because the product of f_λ is constant. The pseudo code of this algorithm is given in the figure below

Bat algorithm pseudocode

Objective function $f(x)$, $x = (x_1, \ldots, x_d)^T$
Initialize the bat population x_i, v_i, $i = (1, 1, \ldots, n)$
Define pulse frequency f_i at x_i
Initialize pulse rates r_i and the loudness A_i
While ($t <$ Max number of iterations)
Generate new solutions by adjusting frequency,
and updating velocities and locations/solutions [equations (2) to (4)]
If (rand $> r_i$)
Select a solution among the best solutions
Generate a local solution around the selected best solution
End if
Generate a new solution by flying randomly
If (rand $< A_i \& f(x_i < f(x^*))$
Accept the new solutions
Increase r_i and reduce A_i
End if
Rank the bats and find the current best x^*
End while
Postprocess results and visualization

The relations of speed and position update in this algorithm have similarities with the relations in particle mass prediction. It can be said that the bat algorithm is a combination of this algorithm and local search, which is controlled by the loudness of the sound and the pulse sending rate. The new positions x_i and speed v_i at time t are as follows [7]:

$$\begin{aligned} f_i &= f_{\min} + (f_{\max} - f_{\min})\beta \\ v_i^t &= v_i^{t-1} + (x_i^t - x^*) f_i \\ x_i^t &= x_i^{t-1} + v_i^t \end{aligned} \tag{4.1}$$

where, β is a random vector in the interval $[0, 1]$ and is obtained from a uniform distribution. Here, x^* is the best current global position, which is determined after comparing all positions obtained by n bats. In the bat algorithm, the loudness and the pulse sending rate should also be updated during the iterations. The loudness of the sound decreases as the bat approaches the prey, and the value of A is zero when the bat finds the prey. On the other hand, the rate of sending the pulse reaches its maximum value and becomes one after finding the prey [18].

$$\begin{aligned} A_i^{t+1} &= \alpha A_i^t \\ r_i^{t+1} &= r_i^0[1 - \exp(\gamma^t)] \end{aligned} \tag{4.2}$$

where, α and γ are constant. In fact, α is similar to the cooling factor in the SA algorithm. For every value $0 < \alpha < 1$ and $\gamma > 0$, when t tends to infinity, A_i^t tends to zero and r_i^t tends to the value r_i^0, in other words:

$$A_i^t \to 0, \;\; r_i^t \to r_i^0 \;\; \text{as} \quad t \to 0.$$

First, each bat has different values of loudness and pulse sending rate. These parameters are initially chosen randomly. Then their value is updated. For the local search part, when a solution is selected among the best available solutions, the new position for each bat is determined locally by random walk as follows [11]:

$$x_{new} = x_{old} + \varepsilon A^t \tag{4.3}$$

where, ε is a random number in the interval $[-1, 1]$ and A^t is the average loudness of all bats at this time.

5 Discussion Fuzzy mapping

The appropriate resources were selected by searching the customer demand in the supply chain keyword in each of the databases, but considering that this term is a general word and most of the sources found include unreleavant topics, so this term was limited to the compound term of customer demand in the supply chain, and since some researchers consider the term customer demand in the supply chain to be equivalent to demand, the term demand strategy was also considered when searching for sources in the databases. To search for sources in domestic databases, in addition to the term customer demand in the supply chain, customer demand strategy in the supply chain was also explored as its synonym. It should be noted that the total number of articles found considering the input criteria is 208 studies (Persian and English), after reviewing all of them and considering the output criteria from the perspective of content criteria or lack of access, finally the results extracted from 93 studies (86 English studies and 7 Persian studies) were reviewed and analyzed. In the following, appropriate exclusion and inclusion criteria have been considered to find comprehensive studies related to the research topic to review them, according to [16] in this research.

Table 1: Search method, inclusion, and exclusion criteria

NUMBER OF INITIAL FINDINGS	EXCLUSION CRITARIA	NUMBER OF INITIAL FINDINGS	INCLUSION CRITRIA		SEARCH	DATABASE
			SECOND STAGE FILTER	FIRST STAGE FILTER		
15	Irrelevant in terms of content/lack of access	208	English language	Article title, Abstract, Keywords /1980 to present	“To Predict Customer Demand”	science direct
		101	Article, conference paper, Book chapter			
11	Irrelevant in terms of content/lack of access	53	English language	Article title, Abstract, Keywords /1980 to present	”To Predict Customer Demand In The Supply Chain”	
		6	Article, conference paper, Book chapter			
44	Irrelevant in terms of content/lack of access	133	English language	Article title, Abstract, Keywords /1980 to present	“To Predict Customer Demand”	IEE
			Article, conference paper, Book chapter			
7	Irrelevant in terms of content/lack of access	57	English language	Article title, Abstract, Keywords /1980 to present	”To Predict Customer Demand In The Supply Chain”	
			Article, conference paper, Book chapter			
5	Irrelevant in terms of content/lack of access	9	English language	Abstract /1980 to present	“To Predict Customer Demand”	Proquest
			Book, conference papers, Dissertation & thesis			
0	Irrelevant in terms of content/lack of access	2	English language	Abstract /1980 to present	”To Predict Customer Demand In The Supply Chain”	
			Book, conference papers, Dissertation & thesis			

1	Irrelevant in terms of content/lack of access	1	Conference articles, journal articles, e-books	Title, keyword, summary of the article/1981 until the current year	Demand customer in the supply chain	CIVILICA
0		0	Conference articles, journal articles, e-books	Title, keyword, summary of the article/1981 until the current year	Strategy customer demand in the supply chain	
0		0	Conference articles, journal articles, e-books	Title, keyword, summary of the article/1981 until the current year	Strategy/ prediction demand in the supply chain	
1	Irrelevant in terms of content/lack of access	1	Contents of all member journals	Title, author's name, abstract and keywords	Strategy/ demand customer in the supply chain	magiran
4		4	Contents of all member journals	Title, author's name, abstract and keywords	Strategy/ demand customer in the supply chain	
1		1	Contents of all member journals	Title, author's name, abstract and keywords	Strategy/ prediction customer demand in the supply chain	
0	Irrelevant in terms of content/lack of access	0	Searching in articles with and without full text	Title, abstract and keywords/1981 until the current year	Strategy/ demand customer in the supply chain	SID
0		0	Searching in articles with and without full text	Title, abstract and keywords/1981 until the current year	Strategy/ prediction demand customer in the supply chain	

Extracting findings' and evaluating the quality of each study Every study must have acceptable validity, reliability and objectivity; and thus, qualitative study and systematic review are not exclusions. In systematic review studies, a comprehensive search leads to finding many releavant studies. However, all these studies may not enjoy sufficient quality each reviewed study should be evaluated by appropriate tools and in accordance with the defined criteria prior to inclusion in the study and only good quality articles are included in the analysis. This article adopts a checklist including many criteria to evaluate papers and rank them as high, low, and average quality. The papers are ranked to increase the validity of the study with the appropriate tool of the checklist and to exclude low-quality studies from the synthesis process.

Table 2 shows an example of the evaluation checklist of 5 studies based on Carlsen et al. model.

Table 2: An example of the evaluation checklist of 5 studies based on Carlsen et al. model

	Criteria / **Study**	**Study 1**	**Study 2**	**Study 3**	**Study 4**	**Study 5**
1	Sampling strategy	x	x	x	x	?
2	Data collection	x	x	x	x	x
3	Data analysis method	x	x	x	x	x
4	Research plan consistency with the research objective	x	x	x	x	x
5	Clear statement of findings	x	?	x	x	x
6	Appropriate justification of the research result	x	x	x	x	?
7	Consistency between the guiding paradigms of the research project with the chosen methods	x	x	x	x	?
Quality level (high/low/medium)		High	Medium	Low	High	Medium
Comments			Needs to be reviewed by a third reviewer	Needs to be reviewed by a third reviewer		Needs to be reviewed by a third reviewer

At this stage, the extracted sources were independently examined by at least two "reviewers" and examined according to the criteria mentioned in Table (2) and in case of rejection, the relevant reason is also mentioned. In case of disagreement between reviewers, "the third reviewer" will review the paper.

The Kappa test determines the "degree of agreement" between two reviewers. The value of kappa index, known as Cohen's kappa, fluctuates between zero and one. The closer the value of this measure is to one shows the more agreement between the reviewers. But when the kappa value is closer to zero, then we see less agreement between the two reviewers. In this study, the Kappa index is 0.71, which indicates a high agreement between the two reviewers. Finally, all the included articles in the study are controlled and approved by an expert in that field. The sources are available to the "reviewer" with the name of the author, the institution and the relevant journal are covered.

5.1 Selection of FCM method and analysis of study findings

If a fuzzy perceptual map with n number of nodes is given, the value of each node in each iteration can be calculated as follows [16]:

$$A_i(t) = f\left(A_i(t-1) + \sum_{j=1}^{n} A_j(t-1).W_{ji}\right) \tag{5.1}$$

where, $A_i(t)$is the value of the concept C_i at time t and the $A_j(t-1)$ is the value of the concept C_j at time $t-1$, W_{ji} correspond to the fuzzy weight between two nodes and f is a threshold function that converts the result of the multiplication into a number in the interval $[0, 1]$. The non-linear function f allows the concept of activation to take an allowed value. The f function has various types as that of equations (4.2), (4.3), (5.1) and (5.2) [3]:

- **Bivalence:**

$$f(x) = \begin{cases} 0, & x \leq 0 \\ 1, & x > 0 \end{cases} \tag{5.2}$$

- **Trivalence:**

$$f(x) = \begin{cases} -1, & x \leq -0.5 \\ 0, & -0.5 < x < 0.5 \\ 1, & x \geq 0.5 \end{cases} \tag{5.3}$$

- **Logestic:**

$$f(x) = \frac{1}{1+e^{-cx}} \tag{5.4}$$

- **S:**

$$f(x) = \tanh(x) \tag{5.5}$$

The most common threshold function is the logistic function, where it determines the slope of the continuous function f. Tsadiras has compared the effects of bivalence, trivalence and sigmoid threshold functions in fuzzy perceptual mapping and gives guidance to users of fuzzy perceptual mapping to choose the most appropriate type in their fuzzy perceptual mapping [14]. The key point is that fuzzy perceptual maps grow through feedback. The fuzzy perceptual maps work like experts who work with artificial intelligence computer programs along with long chains of if-then rules. Fuzzy perceptual maps may be considered as a neural network and a dynamic system can be made from it, with a possibility of re-examining information and its circulation, like a two-way associative memory. In this system, it is possible to reach and converge to one point, as well as to reach the equilibrium state [8].

5.2 Clustering of fuzzy perceptual maps

The fuzzy perceptual mapping model is a cause and effect diagram that shows the relationships between basic components in complex systems. Experts familiar with the components of the system and the relationships between them may determine the relationships in the fuzzy cognitive mapping model. In case of a big number of factors we intent to categorize the factors in modeling in specific areas, the problem is that with the increase of their number and the relationships between them, the error of examining the factors increases. An expert cannot easily determine the correct cause and effect relationships between factors. Therefore, to solve the problem in classifying factors, it is necessary to consider a mechanism to facilitate the process of classifying factors and specifying the correct cause and effect relationships in the factors final matrix [11].

Cause and effect graph clustering or fuzzy perceptual mapping not only allows similar nodes to be identified, but also makes it possible to reduce the problem dimensions and convert a big number fuzzy perceptual map nodes to fuzzy perceptual mapping with less number of nodes. Identifying similar nodes and placing them in a cluster gives the analysts a better understanding of the graph nodes or in a better way, the same key variables. After clustering and labeling the clusters based on their properties, the clusters are converted into named-categories. Therefore, key factors can be identified based on their properties with a single name [14].

5.3 Modeling of factors affecting the forecasting of customer demand in the supply chain to reduce bullwhip effect

At this stage of the research, the factors affecting the prediction of customer demand in the supply chain are modeled by fuzzy perceptual mapping. After determining the effective factors in the previous stages, the research experts identify and weigh the causal relationships between the factors in each area in this stage. The influence of the factors on each other in the form of fuzzy linguistic variables {very low, low, medium, high and very high} is entered into the fuzzy system with the help of fuzzy triangular numbers, and with the help of the non-fuzzification method, and is converted into definite numbers in the range of -1 and 1. The closer the obtained number is to -1 or 1, it means that two factors have more influence on each other. The closer the number is to zero, the weaker the influence of the factors on each other. In figure 1 shows the linguistic variables membership functions and Table 3 shows the used linguistic variables.

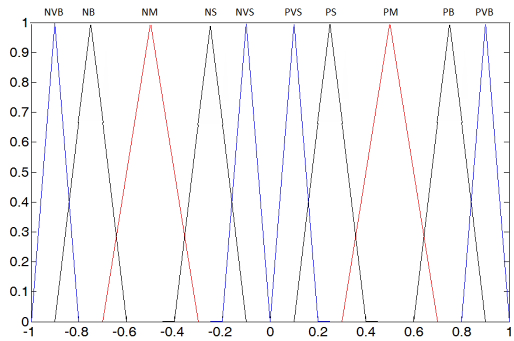


Figure 1: Membership functions of linguistic variables

Table 3: Linguistic variables used in the fuzzification process

Linguistic variable	**Fuzzy number**
Very much positive (PVB)	(0.8,0.9,1)
Very positive (PB)	(0.6,0.75,0.9)
Moderate positive (PM)	(0.3,0.5,0.7)
Low positive (PS)	(0.1,0.25,0.4)
Very low positive (PVS)	(0,0.1,0.2)
Very low negative (NVS)	(-0.2,-0.1,0)
Low negative (NS)	(-0.4,-0.25,-0.1)
Moderate negative (NM)	(-0.7,-0.5,-0.3)
Very negative (NB)	(-0.9,-0.75,-0.6)
Very much negative (NVB)	(-1,-0.9,-0.8)

In this research, maximum average method is used for de-fuzzification. Thus, the average is taken from the center of the obtained fuzzy numbers according to the experts. For example, if nine experts answered the question of the influence of the factor C_i on C_j, the linguistic variables "very much", "very much", "very", "very", "very", "very", "very much", "moderate" and "very", that is, the opinion of 5 people is "high", 3 people are "very much" and one person is moderate. In this case, the fuzzy numbers equivalent to linguistic variables are averaged and placed in the relationship matrix of FCMapper software.

After the implementation, the fuzzy perceptual mapping model is drawn to be analyzed and used by managers and experts. In the following, the stages of drawing fuzzy perceptual mapping model in the "forecasting customer demand in the supply chain" of the buyers of Aftab oil factory will be explained.

5.4 Modeling of factors affecting customer demand forecasting in the supply chain with the help of fuzzy perceptual mapping

According to the above stages, the causal weights are adjusted with the help of learning methods after determining the effective factors on predicting customer demand in the supply chain and causal relationships, and the amount of primary effects.

Figure 2 shows the initial fuzzy perceptual mapping. This mapping includes factors that are nodes and causal relationships between factors that are shown by edges. FCMapper software was used to draw the map. In the FCMapper software, nodes can be drawn according to the input-output degree of the node, that is, any node that has a greater sum of input and output weight (centrality) has a higher degree and is therefore more important and it is shown bigger. Also, edges that show causal relationships and the degree of influence of relationships are dark and light according to their weight. Therefore, the closer the edge weight is to one, the darker it is displayed. In this graph, the final long-term goal of predicting customer demand in the supply chain is shown with a rhombus and the outputs affecting the long-term goal are shown with a circle. Factors affecting the outputs are classified in six categories, including demand segmentation, demand forecasting, sales and operation planning, demand management support, demand management performance, and supply chain operator. Inputs include customer, retailer and wholesaler. Figure 3 shows the fuzzy perceptual mapping of the field of customer demand forecasting in general. This figure shows the same concepts in general symbols. Due to the large number of causal relationships between the concepts and the crowdedness of the fuzzy perceptual mapping in Figure 3, we keep the relations with a weight greater than 0.7 and redraw the fuzzy perceptual mapping of the area of customer demand prediction. Figure 4 shows the fuzzy perceptual mapping of customer demand prediction with relationships with a weight greater than 0.7. In this figure, due to the elimination of many relationships, the variables are drawn in the same size and the centrality approach is not used in the drawing. This fuzzy perceptual mapping shows the most important relationships more clearly.

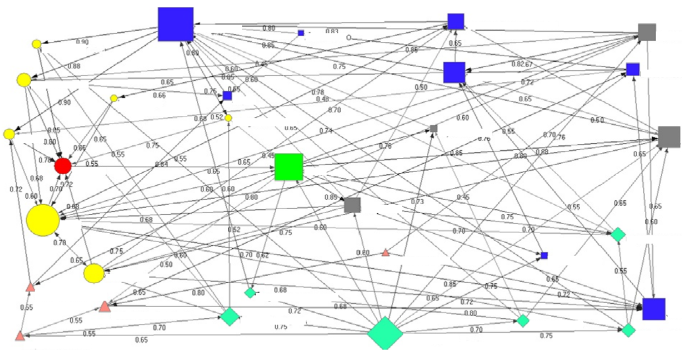
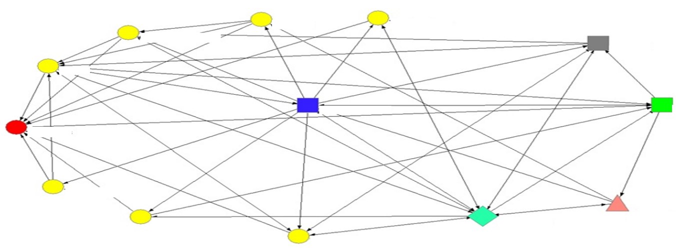


Figure 2: Fuzzy perceptual mapping of customer demand forecasting with expert opinion



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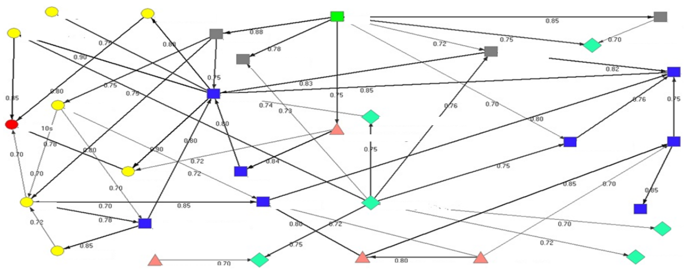

Figure 4: Fuzzy perceptual mapping of customer demand forecast with expert opinion with weights greater than 0.7

6 Calculate Bullwhip Effect

All inventory operates in four stages under the inventory-on-demand policy. Each stage order is placed in a predetermined review period for the supplier due to the stock-on-demand policy. The scope and amount of this order is the difference between the considered level and the effective stock level at the time of review. The effective level refers to the amount of inventory in the order minus the retailer's order shipment or the amount allocated to the product. The safety time here is the distance between the order and receipt. Periodic review refers to the number of weeks between two reviews. Safety time indicates safe inventory or the number of weeks with average demand. The forecast is calculated with a moving average, so the future demand forecast is continuously updated when new demand is met. In the central model, the moving average with Bullwhip Effect is calculated using the following equation [15].

Order = considered level (inventory + ordered - retailer's back order)

Considered level = prediction * (decision deadline + periodical inspection + safety time)

Bullwhip Effect = order variance / demand variance

If the Bullwhip Effect value is equal to (1) the variance of the order is equal to the variance of the demand. In other words, there will be no increase in variance. If the value of the Bullwhip Effectis greater than 1, there will be a Bullwhip Effect. If the whiplash effect is less than 1, the smoothing scenario is created.

6.1 Bullwhip Effect considering different algorithms

Table 4: Measuring Bullwhip Effect using neural network algorithm

m	Retail seller	Wholesaler	Factory (manufacturer)
1	1.60000	32.00000	36.52000
3	0.24888	3.55555	6.72444
5	0.11520	1.28000	4.31520
10	0.04480	0.32000	3.28480
15	0.02702	0.14222	3.08924
20	0.01920	0.08000	3.01920
25	0.01484	0.05120	2.98604
30	0.01208	0.03555	2.96764
35	0.01018	0.02612	2.95631
40	0.00880	0.02000	2.94880
45	0.00774	0.01580	2.94354
50	0.00691	0.01280	2.93971

Table 4 shows that the use of neural network algorithm to predict customer demand in the supply chain to reduce the Bullwhip Effect shows the Bullwhip Effect of 1.920.

Table 5: Measuring Bullwhip Effect using neural network algorithm trained with scale gradient algorithm

m	Retail seller	Wholesaler	Factory (manufacturer)
1	0.80000	32.00000	34.58000
3	0.10666	3.55555	5.44222
5	0.04480	1.28000	3.10480
10	0.01520	0.32000	2.11520
15	0.00853	0.14222	1.93075
20	0.00580	0.08000	1.86580
25	0.00435	0.05120	1.83555
30	0.00346	0.03555	1.81902
35	0.00287	0.02612	1.80899
40	0.00245	0.02000	1.80245
45	0.00213	0.01580	1.79793
50	0.00188	0.01280	1.79468

Table 5 shows that the use of trained neural network algorithm with scale gradient algorithm and PSO to predict customer demand in the supply chain to reduce the Bullwhip Effect shows the Bullwhip Effect of 0.780.

Table 6: Measuring Bullwhip Effect using trained neural network algorithm with scale gradient algorithm and PSO

m	Retail seller	Wholesaler	Factory (manufacturer)
1	0.40000	32.00000	33.74500
3	0.04888	3.55555	4.94944
5	0.01920	1.28000	2.64420
10	0.00580	0.32000	1.67080
15	0.00302	0.14222	1.49024
20	0.00195	0.08000	1.42695
25	0.00140	0.05120	1.39760
30	0.00108	0.03555	1.38164
35	0.00088	0.02612	1.37200
40	0.00073	0.02000	1.36573
45	0.00063	0.01580	1.36143
50	0.00055	0.01280	1.35835

Table 6 shows that the use of trained neural network algorithm with scale gradient algorithm and bat algorithm to predict customer demand in the supply chain to reduce the Bullwhip Effect shows the Bullwhip Effect of 0.345.

Table 7 shows that the use of trained neural network algorithm with scale gradient algorithm and bat algorithm to predict customer demand in the supply chain to reduce the Bullwhip Effect shows the Bullwhip Effect of 0.220.

Tables 4 to 7 show that trained neural network algorithm with scale gradient algorithm and bat algorithm prduces the most effective result, among the different algorithms and different trainings applied on the neural network algorithm.

Validation to check the validity of the research, the output of this treatise was compared with the articles of Yousefi et al. [16], De Paula et al. [9], Rezaeefard et al. [13], and Zhang et al. [17].

Table 7: Measuring Bullwhip Effect using the trained neural network algorithm with the scale gradient and bat algorithm

m	**Retail seller**	**Wholesaler**	**Factory (manufacturer)**
1	0.26666	32.00000	33.48666
3	0.03160	3.55555	4.80716
5	0.01208	1.28000	2.51208
10	0.00346	0.32000	1.54346
15	0.00173	0.14222	1.36396
20	0.00108	0.08000	1.30108
25	0.00076	0.05120	1.27196
30	0.00058	0.03555	1.25613
35	0.00046	0.02612	1.24658
40	0.00038	0.02000	1.24038
45	0.00032	0.01580	1.23612
50	0.00028	0.01280	1.23308

Table 8: Measuring Bullwhip Effect

The reviewed study	**The reviewed algorithm**	**Bullwhip Effect**
Yousefi et al. [16]	ANN	2/52
De Paula et al. [9]	Fuzzy multi-criteria methods, genetic algorithm	1/97
Rezaeefard et al. [13]	FCM and AMOS	4/48
Zhang et al. [17]	VMD-SVM	1/32
Current study	Neural network trained with bat and scale gradient	0/220

Table 8 shows the method adopted by this paper is the most effective method on the Bullwhip Effect and this shows the efficiency of the trained neural network with scale gradient algorithm, and bat algorithm.

7 Conclusion

Most economic activities growth and even survival in the developing countries depends on the suuply of demands. Therefore, the countries authorities try to control the supply and demand parameters of consumption amount appropriately by predicting the edible oil consumption as accurately as possible and planning correctly in guiding the consumption.

This article results showed that each of the techniques can be efficient according to the consumption of each product. In general, these three techniques, especially artificial neural networks, show better results in all evaluation indices than regression equations. In this paper, an attempt was made to use and compare trained neural network algorithms with the gradient algorithm and particle swarm, artificial neural networks and trained neural network algorithms with scale gradient algorithm and bat algorithm for prediction in the field of consumption. The results indicate the optimal performance of trained neural network with scale gradient and bat algorithm on reducing the Bullwhip Effect.

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