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Research Article

The Analysis of the Role of Bullwhip Effects on the Four-Level Supply Chain in Industry Using Statistical Methods

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Nowadays, regarding the technology development and communication means, supply chain management has gained special significance among different industries. The impact of bullwhip is one of the factors that could lessn the supply chain efficiency and increase the cost and delivery time of products and services. In this study, we explored the demand forecasting in supply chain, a four-level chain of retailers, wholesalers, manufacturers, and suppliers. Each level of the chain forecasted demand by moving average method, exponential smoothing, multilayer perceptron artificial neural network, and regression. Also, we provide a hybrid model based on statistics and mathematics to reduce the effect of bullwhip. For this purpose, at first, the supply chain simulation was performed. The results were then evaluated applying analysis of variance and the best combined model to reduce the amount of bullwhip effect was introduced. The model of this research could be useful for other studies. Finally, forecast for retail demand using the regression model; wholesale demand using the exponential smoothing model; manufacture demand using the neural network; and supplier demand using the moving average method have been done.

1. Introduction

In the present study, the effect of combined use of various forecasting methods on the bullwhip effect in a four-level supply chain, including retailers, wholesalers, manufacturers, and suppliers, is investigated. Although a similar issue has been explored in many previous research studies, considering the nature of supply chain components, it is more consistent with reality [1]. For this purpose, first, the supply chain was simulated. The retailer demand received from end customers is assumed to be a Poisson process with rate. This distribution has been selected according to several other research studies that have used this distribution as a demand model in the supply chain [2, 3]. This choice is rooted in the nature and specificity of the Poisson distribution in depicting counting processes. In fact, a look at the process of customers entering the system and registering their demand shows the fact that the process of product demand is a counting process that was well illustrated by the Poisson distribution. This feature has caused more than half of the research studies related to multilevel systems to use this distribution as a demand model [4, 5].

For this purpose, main research question is as follows:

(i). For this purpose, main research question is how can the effect of a bullwhip on supply chain efficiency be measured?

Therefore, main contribution of the paper is as follows:

(i) Predict demand in a four-level supply chain with retailers, wholesalers, manufacturers, and supplier elements.

(ii) Provide a hybrid model based on statistics and mathematics to reduce the effect of bullwhip.

The rest of the article is organized as follows: in Section 2, we present a literature review. In Section 3, we present research methodology. In Section 4, we present results of the paper finally, and in Section 5, we present overall conclusion and further research for future study.

2. Literature Review

In an article with a simulation approach and repeated measurements, Huang et al. [6] presented a spatiotemporal Markov model (STMM) with the probability chain adjustment (STMMPC) to predict states of inventory variation and analyze inventory variation propagation in multistage steel production processes. Jackson I. [7] demonstrated how deep reinforcement learning agents based on the proximal policy optimization algorithm can synchronize inbound and outbound flows if end-to-end visibility is provided. The paper concludes that the proposed solution has the potential to perform adaptive control in complex supply chains. Furthermore, the proposed approach is general, task unspecific, and adaptive in the sense that prior knowledge about the system is not required. Yang et al. [8] modeled the severe effects of seasonal demand in the multistage supply chain and reduced the bullwhip effect, which could not be easily achieved with analytical approaches. Also, she compared the two neural network methods with the ARIMA method and concluded that the neural network method reduces the bullwhip effect. Durán Peña et al. [9] carried out a literature review to determine the causes of the bullwhip effect and the supply chain's quality factors of this phenomenon's perishable products. Updating the demand, the level of deterioration of the product, and the number of intermediaries is the causes of the bullwhip effect most investigated. On the other hand, the product's safety and the quality of the information are the quality factors of the chain of supplies of perishable products more researched. According to this study, important future research will be addressed by causes of human behavior that affect the bullwhip effect in the perishable goods supply chain. Fu et al. [10] investigated the behavioral operations effect in production inventory decision of supply chain consisting of one manufacturer and one buyer, and analyze how the unfairness concerns impact the decision of production inventory in a supply chain system. For this purpose, first a model without the buyer's unfairness concern is established; then, advantage unfairness concern and disadvantage unfairness concern behavior of the buyer are taken into account in the production inventory system. The authors analyze how advantage unfairness concern and disadvantage unfairness concern impact the optimal decisions and channel coordination. Trenggonowati et al. [11] calculated the value of bullwhip effect as well as designing improvements to minimize the bullwhip effect. Based on the research results, the index value of bullwhip effect on longitudinal pipe products is 1.06 and the index value of bullwhip effect on spiral pipe products is 0.80. The improvement design to minimize the phenomenon of bullwhip effect is to build an integrated information system for the customer, manufacturer, and supplier. Zhao et al. [12] employed system dynamics (SD) model to explore the effect of single strategy and combined scenarios on mitigating inventory amplification, i.e., bullwhip effect (BE) in three-echelon SC. Novel scenario simulation is designed to stimulate recovery activities of electronic waste, decrease solid material depletion, and promote clean production. Main thread is as follows: establishing the SD model in line with practical operation mechanism, testing the robustness of model, emulating the effect of single strategy and combined scenarios on mitigating BE, and finally proposing optimal strategies on the optimization of green SC. Cannella et al. [13] presented the mathematical formulation of the supply chain model and conducted a numerical simulation assuming different levels of errors. Results clearly show that Inventory Record Inaccuracy strongly compromises supply chain stability, particularly when moving upwards in the supply chain. Important managerial insights can be extracted from this analysis, such as the role of "benefit-sharing" strategies in order to guarantee the advantage of investments in connectivity technologies. Jaipuria and Mahapatra [14] integrated approach of discrete wavelet transform (DWT) analysis and artificial neural network (ANN) denoted as DWT-ANN is proposed for demand forecasting. Initially, the proposed model is tested and validated by conducting a comparative study between Autoregressive Integrated Moving Average (ARIMA) and proposed DWT-ANN model using a data set from the open literature. Furthermore, the model is tested with demand data collected from three different manufacturing firms. Bray and Mendelson [15] investigated the effect of information exchange between supply chain levels on its bullwhip effect. Bhattacharya and Bandyopadhyay [16] reviewed studies on the factors affecting the effect of bullwhip. Hayya C. [17] investigated the effect of random preparation times, information sharing, and quality of shared information on bullwhip effect. Machuca and Barajas [18] also studied the effect of electronic data exchange on reducing the bullwhip effect and the average cost of inventory using Internet simulation software. Kelepouris et al. [19] investigated the effect of replenishment and information sharing parameters on bullwhip effect. Marko and Rusjan [20] also studied the effect of replenishment policies on this effect. Agrawal et al. [21] investigated the effect of preparation time and information sharing on bullwhip.

One of the factors that many experts believe in its effect on bullwhip is the use of supply chain links by various forecasting methods. One of the factors that many experts believe in its effect on bullwhip effect is the use of supply chain links by various forecasting methods. In this regard, extensive studies have been conducted on the effect of forecasting methods on bullwhip effect such as Chen et al. [22] that studied and compared the effect of two methods of exponential smoothing and moving average on bullwhip effect in a simple two-level supply chain including a retailer and a manufacturer. Chen et al. [23] also investigated the effects of two factors demand forecasting and order supply time on bullwhip effect in a two-level supply chain and generalized the result to multilevel chains. Zhang X. [24] investigated the effect of forecasting methods on bullwhip effect in a simple inventory supply system and concluded

Table 1: Paper classification.

Scope	Author	Year of publication	Goal	Model
Simulation	Huang et al.	2022	Predict state of inventory variation	Spatiotemporal Markov
	Jackson	2022	Deep reinforcement learning agents	Proximal policy optimization algorithm
	Yang et al.	2021	Measured effects of seasonal demand	Artificial neural network
	Fu et al.	2021	Investigation of the behavioral effect in production inventory	Mathematical model
	Zhao et al.	2018	Optimization green supply chain	System dynamic
Forecasting	Ivanov and Sokolov	2013	Presentation of perspective supply chain operation	Mathematical model

Table 2: Scenarios of forecasting methods in the four-level supply chain.

	Retailer	Wholesaler	Manufacturer	Supplier
Scenario 1	Linear regression	Exponential smoothing	Neural network	Moving average
Scenario 2	Linear regression	Exponential smoothing	Moving average	Neural network
Scenario 3	Linear regression	Neural network	Exponential smoothing	Moving average
Scenario 4	Linear regression	Moving average	Exponential smoothing	Neural network
Scenario 5	Linear regression	Moving average	Neural network	Exponential smoothing
Scenario 6	Linear regression	Neural network	Moving average	Exponential smoothing
Scenario 7	Exponential smoothing	Linear regression	Neural network	Moving average
Scenario 8	Exponential smoothing	Linear regression	Moving average	Neural network
Scenario 9	Exponential smoothing	Neural network	Linear regression	Moving average
Scenario 10	Exponential smoothing	Moving average	Linear regression	Neural network
Scenario 11	Exponential smoothing	Moving average	Neural network	Linear regression
Scenario 12	Exponential smoothing	Neural network	Moving average	Linear regression
Scenario 13	Neural network	Exponential smoothing	Moving average	Linear regression
Scenario 14	Neural network	Exponential smoothing	Linear regression	Moving average
Scenario 15	Neural network	Moving average	Exponential smoothing	Linear regression
Scenario 16	Neural network	Linear regression	Moving average	Exponential smoothing
Scenario 17	Neural network	Linear regression	Exponential smoothing	Moving average
Scenario 18	Neural network	Moving average	Linear regression	Exponential smoothing
Scenario 19	Moving average	Neural network	Exponential smoothing	Linear regression
Scenario 20	Moving average	Neural network	Linear regression	Exponential smoothing
Scenario 21	Moving average	Exponential smoothing	Neural network	Linear regression
Scenario 22	Moving average	Linear regression	Neural network	Exponential smoothing
Scenario 23	Moving average	Linear regression	Exponential smoothing	Neural network
Scenario 24	Moving average	Exponential smoothing	Linear regression	Neural network

that forecasting methods are effective on bullwhip effect. Barlas and Gunduz [25] mentioned uncoordinated use of different levels of the chain in forecasting methods as one of the structural roots of bullwhip effect in supply chains. Ivanov and Sokolov [26] presented the first to address the operative perspective of the supply chain dynamics domain. The methodology of this conceptual paper is based on the business and technical literature analysis and fundamentals of control and systems theory. In contributing to the existing studies in this domain, the paper proposes a possible systemization and classification of related terminology from different theoretical perspectives, and important practical problems. For the supply chain dynamics domain, the paper identifies and groups possible problem classes of research, corresponding quantitative methods, and describes the general mathematical formulations. Constantino et al. [27] attempt to evaluation by investigating the interaction of collaboration and coordination in a four-echelon supply chain under different scenarios of information sharing level. In Table 1, we categorized previous studies according to goal and research methodology.

2.1. Research Gap. According to the above, there is no study that can reduce the effect of bull whip on the supply chain using statistical-mathematical analysis simultaneously. In general, only mathematical prediction tools have been used. For this purpose to fill gap in this research, demand forecasting in a four-level supply chain that has retail, wholesale, manufacturer, and supplier elements is done by presenting a hybrid model based on statistics and mathematics.

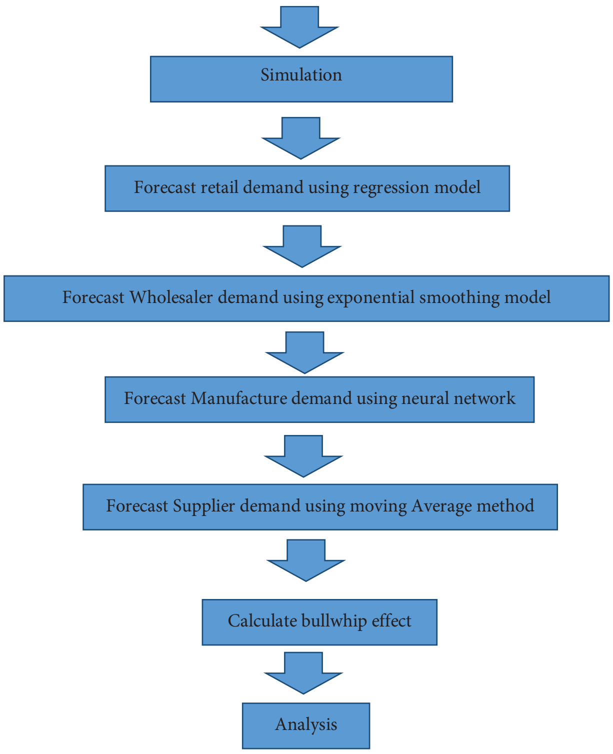

Figure 1: Research framework.

Table 3: Random demand data for customers.

Period	Random demand
1	5
2	1
3	0
4	1
5	1
6	2
7	2
8	2
9	3
10	2
11	0
12	3
13	1
14	2
15	2
16	2
17	4
18	3
19	4
20	3
21	4
22	5
23	7
24	2
25	5
26	4
27	4
28	5
29	5
30	4
31	6
32	6
33	6
34	7
35	2
36	8

3. Methodology

In terms of purpose, it is fundamental and applied research because it is research that finds the best forecasting scenario to reduce the bullwhip effect of in the supply chain and uses the central limit theorem to prove its claim and uses it in a case study and is quantitative in nature.

3.1. Problem Statement. The components of the chain use four methods of moving average, exponential smoothing, regression, and neural network to forecast their demand assuming that none of the components use the same method. Therefore, 24 different combinations of the four available forecasting methods will be investigated. Because the retailer is the lowest level of the chain, it is related to the actual demand of the customers; therefore, the forecasting this level of the chain is based on the actual demand of the customers. At the second level of the chain, the wholesaler is related to the retailer; therefore, the amount of the retailer order is considered as wholesale demand. At the third level of the chain, the manufacturer is associated with the wholesaler. In fact, wholesale order is considered as the demand of this level of the chain. At the highest level of the studied chain, the supplier is associated with the manufacturer. In other words, the amount of the manufacturer's order is considered as the demand of this level of the chain. Therefore, the supplier tries to forecast the demand for the next period based on the previous orders of the manufacturer. First, with the obtained hypotheses, we randomly generate a demand sample with the Poisson process. Then, according to the two-bin ordering policy, the amount of orders at each level is obtained as high-level demand and forecasting is performed. The 24 proposed scenarios are given in Table 2.

Finally, the bullwhip effect in the scenarios was calculated and compared using Minitab, Excel, MATLAB software, and statistical tests, and then, the best scenario was introduced as the lowest amount of bullwhip effect to be used in other 4-level supply chains. Then, the best model introduced in Zarbal Company was used and the result was a reduction in the bullwhip effect of Zarbal Company.

For this purpose, the effect of applying various forecasting methods in a four-level supply chain on bullwhip effect is investigated in this study. The main objective of this project is to provide an approach and model for analyzing various scenarios and evaluating their effects on supply chains. In this study, bullwhip effect is considered as one of the most important performance indicators of supply chain. The demand of four supply chain levels was calculated in such a way that in the forecasting scenarios, none of the supply chain levels were allowed to choose the same method for forecasting. Taking into account this assumption, 24 (four factorial modes) forecasting scenarios were formed in

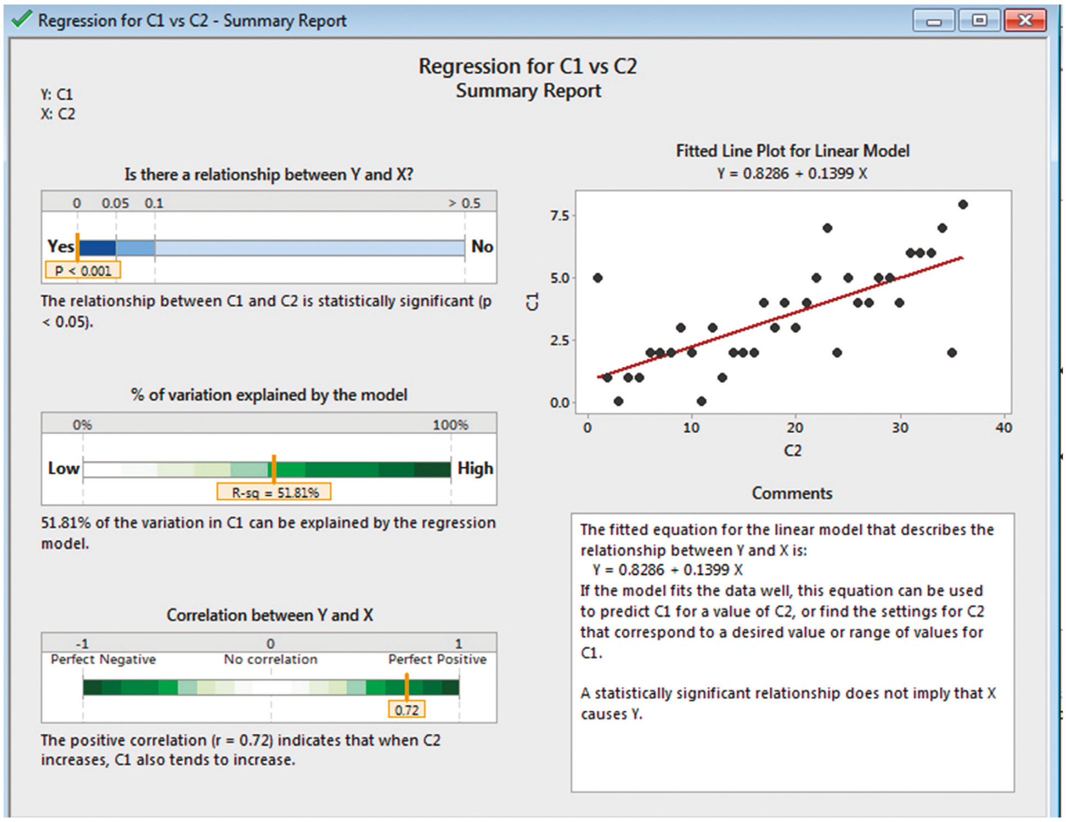

Figure 2: Correlation diagram of customer demand.

which the chain levels forecasted by moving average, linear regression, exponential smoothing, and multilayer perceptron neural network. In Figure 1, research methodology framework is shown.

3.2. Simulation. First, the intended supply chain was simulated and by Minitab 17 software, 36 random numbers were generated with Poisson distribution with parameter 4, and the random values of which are shown in Table 3.

Then, according to Scenario 1, the steps of demand forecasting and ordering were formed by the two-bin method (2 and 6).

3.3. Forecasting Retail Level Demand Using Regression Method. According to Figure 2, the correlation hypothesis between random data was confirmed; then, the retailer demand was forecasted using the Minitab and regression method. Because $p -$ value < 0.5, the value of the null hypothesis is rejected and the two variables X and Y are correlated:

$$\begin{cases} H_0: \rho = 0 \\ H_1: \rho \neq 0 \end{cases}. \tag{1}$$

The formula $Y = 0.8286 + 0.1399\,X$ shows the regression equation performed to forecast retail level demand. The two-bin ordering system used in Table 4 is performed using two bins (boxes). The capacity of the smaller bin is equal to the amount of inventory required at the order point (equivalent to 2 units). When the products arrive at the warehouse, bin number 2 (smaller bin) is always filled first and then the rest of the inventory is kept in bin number 1 (total volume of the warehouse). Consumption starts from bin number 1, and when the inventory of this bin is finished, the inventory has practically reached the order point. At this time, in order to resupply the products, the order will be issued at a fixed and determined amount. Upon receipt of the ordered products, consumption will take place from bin number 2. As stated in previous chapters, inventory quantities are zero at the beginning of the period, and since the ordering system is two-bin (6 and 2), in the first stage, it needs to be ordered in a quantity that, in addition to meeting the expected demand, fills the maximum warehouse volume. Since the total demand forecasting of stages 2, 3, and 4 in Table 3 does not cause the inventory to reach less than 2 units, the order quantities of these periods are zero; therefore, orders are made in way that the amount of warehouse inventory should not be less than 2 units (smaller bin) and also the amount of inventory should not exceed 6 units. This logic of two-bin ordering system (6 and (2) was defined in Excel software for all levels of the supply chain so that all levels of the supply chain can order with this ordering system. Table 4 shows retail demand forecasting value using regression formula, retail order quantities, and retailor inventory over different time periods.

3.4. Forecasting Wholesaler Level Demand Using Exponential Smoothing Method. Using the quantities of retailer order by the exponential smoothing method and coefficient $\alpha = 0.33$,

Table 4: Demand forecasting and retail order by the regression method.

Period	Demand	Order	Warehouse
1	0.97	6.97	6
2	1.11	0	4.89
3	1.25	0	3.64
4	1.39	0	2.26
5	1.53	5.27	6
6	1.67	0	4.33
7	1.81	0	2.52
8	1.95	5042	6
9	2.09	0	3.91
10	2.23	4.32	6
11	2.37	0	3.63
12	2.51	4.87	6
13	2.65	0	3.35
14	2.79	5.43	6
15	2.93	0	3.07
16	3.07	5.99	6
17	3.21	0	2.79
18	3.35	6.55	6
19	3.49	0	2.51
20	3.63	7.11	6
21	3.77	0	2.23
22	3.91	7.67	6
23	4.05	4.05	6
24	4.19	4.19	6
25	4.33	4.33	6
26	4.47	4.47	6
27	4.61	4.61	6
28	4.75	4.75	6
29	4.89	4.89	6
30	5.03	5.03	6
31	5.17	5.17	6
32	5.31	5.31	6
33	5.45	5.45	6
34	5.59	5.59	6
35	5.72	5.72	6
36	5.86	5.86	6

Table 5: Demand, order, and wholesaler warehouse by the exponential smoothing method.

Period	Demand	Order	Warehouse
1	2	8	6
2	3.64	0	2.36
3	2.44	6.08	6
4	1.63	0	4.37
5	1.09	0	3.27
6	2.47	5.2	6
7	1.66	0	4.34
8	1.11	0	3.23
9	2.53	5.3	6
10	1.7	0	4.3
11	2.56	4.26	6
12	1.72	0	4.28
13	2.76	4.47	6
14	1.85	0	4.15
15	3.03	4.88	6
16	2.03	0	3.97
17	3.34	5.37	6
18	2.24	0	3.76
19	3.66	5.9	6
20	2.45	0	3.55
21	3.99	6.44	6
22	2.67	0	3.33
23	4.32	7	6
24	4.23	4.23	6
25	4.22	4.22	6
26	4.25	4.25	6
27	4.32	4.32	6
28	4.42	4.42	6
29	4.53	4.53	6
30	4.64	4.64	6
31	4.77	4.77	6
32	4.9	4.9	6
33	5.03	5.03	6
34	5.17	5.17	6
35	5.31	5.31	6
36	5.44	5.44	6

the wholesaler demand was forecasted. Table 5 shows the quantities of demand and wholesaler order and the amount of inventory in different periods.

The logic of two-bin (6 and 2) wholesaler like the other levels is that a quantity is ordered at the beginning of the period that in addition to meeting the demand at the beginning of the period, it maximizes the amount of inventory at the beginning of the period. In other words, it fills larger and smaller bins and the forecasted demand quantities, the larger bin is used first and as soon as the larger bin is finished, it is the reorder point, a new order is issued, and the smaller bin is used until the new order arrives and fills both bins.

3.5. Forecasting Manufacturer Level Demand Using Neural Network. Manufacturer demand was forecasted using the multilayer perceptron neural network method. A multilayer perceptron network with hidden two-layer specifications was used to model the data. Using coding in MATLAB software, time series data were arranged according to intelligent guesses and determined optimal time delays and interruptions. Levenberg-Marquardt was used to train the neural network because it is the fastest method of progressive neural networks with medium to high size up to several hundred weights, and using the trial and error method, different values were considered for middle layer neurons. Finally, the number of middle layer neurons was selected based on the outputs. The activity functions tansig

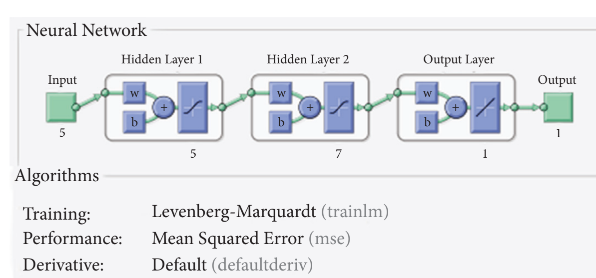

Figure 3: Neural network.

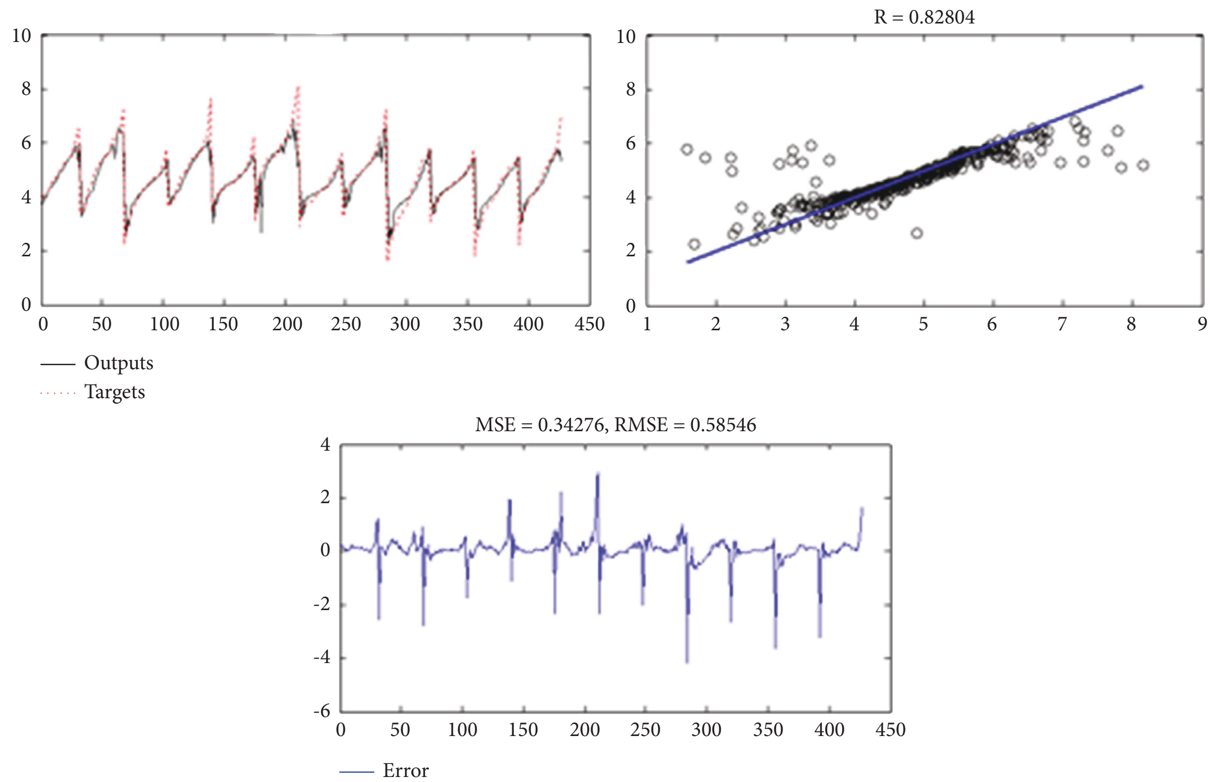

Figure 4: Diagram of forecasted demand and expected demand of the neural network.

and purelin were also written as sigmoid functions for output. After giving the historical input data to MATLAB software, using the given functions and time delays, MATLAB software receives 60% of the data for training, 20% for validation during training, and the remaining 20% for the test. Finally, it compares the forecasted output with the expected output with the mean squared error index. Figure 3 shows the neural network.

As shown in Figure 4, left-top, the red dots are the expected demand values and the black dots are the forecasted demand of the neural network. And the top-right diagram shows the dispersion of the points. The bottom diagram shows the MSE error value, which indicates good forecasting of the neural network with a slight error. Table 6 shows the demand by the neural network method and order by two-bin method and the manufacturer warehouse quantities.

3.6. Forecasting the Supplier Level Demand Using the Moving Average Method. Then, using the manufacturer's order quantity, the supplier demand was forecasted by the moving average. Note that the amount of inventory at the beginning of the period is considered zero. As can be seen from the data in Table 7, the order amount of the first period is equal to the demand of the first period plus the maximum amount of warehouse volume (larger bin) and for the second period, because we have no demand, no order is placed and the inventory remains the same. And for the third period, because the amount of demand is more than the amount of inventory, the order is placed as much as the amount of demand. The amount of demand and orders continues in the same way until the sixth period, and the amount of demand is the size that the inventory does not become less than 2 units (smaller bin) so no order is placed. This process of two-bin ordering system continues until the last period.

4. Results

4.1. Calculating the Bullwhip Effect. For this purpose, firstly we define the predetermined parameter for using regression prediction in Minitab and the neural network in MATLAB as follows:

(i) Variance of manufacturer order = 13.34
(ii) Variance of retailer demand = 2.17
(iii) Bullwhip effect value = 6.14

Using regression prediction in Minitab and neural network prediction in MATLAB, the logic of different scenarios is written in Excel software and the bullwhip effect for the first 36 random data in 24 scenarios is shown according to Table 8.

4.2. Introducing the Superior Model. Now, taken from the central limit theorem in probability theory, it states that under certain conditions, the mean of a large number of independent random variables, each with a known value and a certain variance, will have an approximately normal distribution. Therefore, this experiment was repeated 50 times

Table 6: Demand, order, and manufacturer warehouse by the neural network method.

Period	Demand	Order	Warehouse
1	4.05	10.05	6
2	2.06	0	3.94
3	5.34	7.4	6
4	2.73	0	3.27
5	3.46	6.19	6
6	1.22	0	4.78
7	3.47	4.69	6
8	2.69	0	3.31
9	1.04	0	2.27
10	3.09	6.82	6
11	0	0	6
12	2.76	0	3.24
13	5.96	8.72	6
14	3.62	0	2.38
15	4.88	8.5	6
16	2.08	0	3.92
17	4.27	6.35	6
18	3.45	0	2.55
19	4.28	7.73	6
20	1.83	0	4.17
21	4.07	5.9	6
22	2.8	0	3.2
23	1.54	4.34	6
24	7.22	7.22	6
25	0	0	6
26	3.74	0	2.26
27	4.78	8.52	6
28	5.25	5.25	6
29	5.03	5.03	6
30	2.96	0	3.04
31	5.67	8.63	6
32	6.38	6.38	6
33	4.77	4.77	6
34	4.9	4.9	6
35	0.07	0	5.93
36	5.17	5.24	6

and the results of the bullwhip effects were obtained in Table 9.

Rest of Table 9. Values of bullwhip effect resulting from the simulation.

Now, the hypothesis is tested whether the mean of bullwhip effect in different forecasting scenarios is significantly different from each other?

$$\begin{cases} H_0\colon \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = \mu_6 = \mu_7 \\ = \mu_8 = \ldots\ldots \mu_{22} = \mu_{23} = \mu_{24}. \\ H_1\colon \end{cases} \quad (2)$$

At least two of the means are not equal.

According to Table 10, because the value of $F = 1.22$ is greater than the value of $F_{.05,\ 23,\ 1176}$, the null hypothesis is rejected at the significant level of 5% and it can be claimed that the difference of the means at the level of 5% is significant. Using the one factor analysis of variance in Minitab software, as the results of analysis of variance show, the null hypothesis about the equality of the mean of bullwhip effect

Table 7: Demand and order and supplier warehouse by the moving average method.

Period	Demand	Order	Warehouse
1	10.05	16.05	6
2	0	0	6
3	7.4	7.4	6
4	0	0	6
5	4.36	4.36	6
6	3.4	0	2.6
7	3.4	6.8	6
8	2.72	0	3.28
9	2.72	5.44	6
10	1.17	0	4.83
11	2.88	4.05	6
12	1.71	0	4.29
13	1.71	0	2.59
14	3.89	7.3	6
15	2.18	0	3.82
16	4.31	6.49	6
17	4.31	4.31	6
18	3.71	0	2.29
19	3.71	7.42	6
20	3.52	0	2.48
21	3.52	7.04	6
22	3.41	0	2.59
23	3.41	6.82	6
24	2.56	0	3.44
25	4.37	6.93	6
26	2.89	0	3.11
27	2.89	5.78	6
28	3.94	0	2.07
29	3.44	7.38	6
30	4.7	4.7	6
31	4.7	4.7	6
32	4.73	4.73	6
33	5.01	5.01	6
34	4.95	4.95	6
35	6.17	6.17	6
36	4.01	4.01	6

Table 8: Values of bullwhip effects for different forecasting scenarios.

Scenario	Bullwhip effects
1	6.14
2	2.42
3	4.9
4	2.42
5	4.8
6	3.51
7	6.69
8	2.09
9	3.6
10	2.09
11	11.34
12	0.62
13	6.36
14	8.84
15	7.54
16	6.49
17	4.88
18	5.1
19	2.39
20	1.35
21	4.1
22	7.35
23	1.9
24	1.9

Table 9: Values of bullwhip effect resulting from the simulation.

Period		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	1	6.14	13.34	2.86	10.45	15.21	27.42	18.91	6.08	17.89	3.58	6.3	1.23	3.39	5.58	4.65	3.68	4.05
	2	2.42	15.78	3.65	10.69	16.32	27.85	19.65	6.28	18.56	3.09	6.58	1.88	1.5	4.08	4.9	8.21	5.79
	3	4.9	14.03	2.45	9.08	14.59	26.7	19.98	6.59	17.73	3.96	6.89	2.54	3.61	4.52	5.3	6.83	5.4
	4	2.42	13.05	4.03	11.89	17.57	28.09	20.05	7.51	17.45	4.51	5.11	2.91	5.38	4.88	4.83	7.97	5.66
	5	4.8	14.94	4.056	11.52	17.2	26.63	20.68	7.89	16.96	4.85	5.98	3.55	3.18	4.36	4.27	7.18	3.05
	6	3.51	12.25	4.99	9.63	21.4	27.61	21.21	9.44	16.32	4.12	6.35	3.83	3.73	5.29	7.9	4.52	4.68
	7	6.69	13.19	5.13	11.36	16.06	28.91	22.56	8.76	15.69	3.9	7.12	6.34	4.44	5.39	6.24	8	6.41
	8	2.09	14.05	7.27	12.35	15.63	28.29	22.9	9.41	16.84	4.8	7.44	3.65	3.54	5.7	6.32	5.97	5.58
	9	3.6	14.46	7.4	12.76	20.18	29.11	23.54	8.09	18.26	5.74	6.96	8.07	7.36	8.2	6.47	8.33	8.43
	10	2.09	13.69	5.84	13.25	17.68	29.36	24.02	9.77	15.03	5.6	6.2	4.62	5.27	6.24	6.77	6.54	5.4
	11	2.09	13.69	5.84	13.25	17.68	29.36	24.02	9.77	15.03	5.6	6.2	4.62	5.27	6.24	6.77	6.54	5.4
Predictive scenarios	12	0.62	13.75	5.23	12.67	17.43	27.48	23.66	10.07	14.69	6.95	6.3	7.66	3.83	7.59	5.97	5.47	6.87
	13	6.36	12.28	5.02	13.98	18.15	28.69	22.86	9.62	14.02	5.33	7.21	4.41	5.61	3.6	5.4	6.73	3.93
	14	8.84	13.49	7.12	12.45	15.92	20.94	17.39	8.85	13.95	5.87	7.03	3.91	4.89	6.78	6.09	2.78	4.16
	15	7.54	13.46	6.39	13.23	18.52	27.44	18.04	7.23	12.58	6.32	7.76	1.63	4.19	5.42	3.83	3.72	4.35
	16	6.49	11.79	5.33	12.6	1.084	15.25	19.7	7.85	10.54	6.94	6.92	0.55	3.3	4.69	4.37	2.52	2.78
	17	4.88	7.48	4.78	5.82	14.84	25.25	15.67	8.08	9.34	0.83	6.31	3.57	2.67	4.29	3.7	3.33	4.7
	18	5.1	13.03	7.05	13.12	17.69	26.35	22.54	8.65	14.01	5.22	5.38	2.75	3.71	4.47	3.75	3.9	5.43
	19	2.39	13.21	5.74	11.98	15.28	27	22.03	9.65	14.23	4.89	6.38	3.85	4.11	4.86	4.25	3.73	5.69
	20	1.35	14.04	6.31	11.25	14.87	26.45	23.13	10.21	14.58	5.41	7.51	3.12	3.83	5.15	4.56	4.9	6.2
	21	4.1	15.36	7.14	12.61	13.28	23.1	26.39	10.55	15.33	6.01	6.28	2.85	4.34	5.86	6.48	5.31	7.36
	22	7.35	15.05	7.58	13.12	14.74	26.89	25.46	9.68	16.02	6.21	5.75	4.73	5.13	7.25	6.89	5.46	6.39
	23	1.9	14.45	8.01	12.35	15.02	27.31	24.93	8.7	16.78	6.02	6.64	4.44	5.29	6.66	7.26	7.42	6.43
	24	1.9	14.011	7.81	12.41	15.69	26.06	25.11	9.29	15.8	5.97	7.44	8.35	5.38	7.9	7.05	6.19	7.46

Period		18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
	1	15.46	12.48	9.23	0.64	2.28	3.61	2.9	8.26	5.24	0.88	3.8	10.46	13.28	8.3	18.08	6.08	1.92
	2	15.63	13.55	9.36	0.75	3.57	4.51	2.58	9.62	5.82	0.76	4.48	11.23	12.56	10.2	17.64	6.18	1.78
	3	14.36	13.48	9.98	4.63	2.65	5.8	1.82	6.08	5.07	0.091	3.71	10.28	12.025	8.97	17.05	6.27	1.62
	4	14.8	12.75	10.45	1.02	3.73	4.21	4.98	7.18	5.72	0.16	4.54	10.36	12.09	8.28	17.45	6.2	148
	5	13.7	15.84	10.1	1.05	4.36	5.26	5.37	7.64	5.64	0.27	7.54	10.94	13.47	8.07	16.96	6.09	1.23
	6	12.53	15.46	14.57	0.52	4.91	2.07	7.81	6.02	5.11	2.58	3.28	10.06	12.6	9.33	16.38	6.11	1.87
	7	15.82	12.08	11.21	4.7	3.88	5.31	10.54	7.33	8.14	4.82	9.58	12.31	14.35	9.34	15.69	6.82	1.34
	8	14.09	13.65	11.87	1.19	4.12	9.05	9.83	8.14	8.94	1.08	6.2	11.64	13.48	9.18	18.09	6.94	1.55
	9	12.43	18.04	12.45	4.59	12.83	10.44	6.04	8.79	8.26	7.12	5.55	17.67	15.48	8.46	19.49	9.28	6.33
	10	13.98	14.54	13.21	1.25	3.88	5.26	7.55	8.53	8.55	1.02	4.38	14.38	13.87	9.17	16.84	11.76	2.08
	11	13.98	14.54	13.21	1.25	3.88	5.26	7.55	8.53	8.55	1.02	4.38	14.38	13.87	9.17	16.84	11.76	2.08
Predictive scenarios	12	12.79	14.48	15.37	6.32	2.64	4.051	4.37	7.89	8.46	4.59	3.9	12.37	10.48	9.55	15.03	6.81	2.09
	13	12.6	11.35	12.02	1.06	4.05	3.65	4.92	7.68	9.24	1.08	5.09	11.08	15	10.25	10.88	6.08	2.31
	14	13.73	12.84	11.65	1.58	5.09	2.89	6.02	5.18	9.08	1.67	4.87	8.39	0.65	10.35	11.37	7.18	2.44
	15	13.43	12.53	10.03	1.49	2.16	3.75	7.05	9.18	9.82	1.09	6.043	12.34	15.2	10.05	14.02	5.04	2.01
	16	0.94	11.49	13.01	1.41	4.88	4.93	6	9.77	3.73	1.22	6.49	8.24	7.99	9.87	6.34	7.31	2.51
	17	13.77	12.53	9.35	1.37	4.67	5.68	4.58	4.28	9.67	1.54	5.62	14.02	13.65	9.02	12.58	7.48	2.81
	18	12.19	10.77	11.58	1.9	3.87	3.26	5.47	10.6	9.28	1.62	6.28	13.84	15.09	10.25	12.57	7.64	1.98
	19	15.31	14.96	12.96	1.81	2.93	2.67	4.87	8.96	8.74	1.08	9.23	13.97	14.37	9.08	13.62	7.8	2.57
	20	14.63	14.47	12.13	1.09	3.54	3.33	5.36	8.27	8.64	3.36	5.95	13.25	15.09	10.37	14.01	7.41	2.66
	21	16.39	15.28	13.05	1.3	4.68	4.28	6.62	9.16	8.91	1.84	4.61	13.2	14.37	9.022	14.23	7.29	2.35
	22	15.61	14.97	13.85	2	4.08	3.65	4.87	9.18	9.23	1.09	6.16	14.05	15.83	10.44	14.58	7.66	3.87
	23	14.84	14.43	14.01	2.05	3.92	4.65	5.28	10.08	9.08	1.14	5.48	13.28	15.6	9.83	15.33	7.09	2.35
	24	15.91	13.72	13.25	2.09	4.8	7.43	4.62	9.64	9.13	1.39	8.62	13.46	14.39	10.8	16.02	8.33	2.77

Table 9: Continued.

Period	35	36	37	38	39	40	41	42	43	44	28	45	46	47	48	49	50
	1	4	1.3	5.67	12.45	3.44	15.36	2.65	8.25	2.33	4.3	2.22	7.45	11.69	6.38	5.05	2.97
	2	3.55	0.6	5.37	10.05	4.68	16.2	3.68	9.13	3.81	4.58	3.03	6.96	11.28	6.04	4.66	2.58
	3	3.46	3.27	5.41	10.76	3.54	15.1	2.94	8.01	3.69	3.88	2.91	6.54	1.89	5.88	4.32	1.88
	4	3.85	1.86	5.88	11.15	4.98	15.97	5.23	9.03	4.01	4.41	3.06	6.03	11.91	6.14	4.78	2.13
	5	3.27	0.054	5.31	11.43	7.67	17.41	6.39	12.47	3.8	7.5	2.11	5.67	1.9	5.77	3.85	1.46
	6	3.64	0.041	9.4	12.21	3.06	14.65	3.02	8.05	2.63	3.66	1.84	6.23	11.45	5.45	3.21	1.22
	7	4.65	5.49	5.89	10.77	9.69	18.92	7.07	12.05	3.65	9.09	1.51	13.47	11.12	4.8	2.51	0.89
	8	4.88	4.18	6.08	8.91	6.32	15.42	5.63	9.62	4.15	6.43	4.69	8.95	13.63	7.96	6.29	3.15
	9	6.33	9.55	8.11	7.65	5.89	14.33	4.12	8.05	0.075	5.86	8.91	10.78	15.81	8.01	4.89	1.79
	10	3.79	0.26	6.34	7.4	4.65	13.28	3.09	7.89	0.093	4.92	4.15	8.11	12.69	6.95	5.01	2.45
	11	3.79	0.26	6.34	7.4	4.65	13.28	3.09	7.89	0.093	4.92	4.15	8.11	12.69	6.95	5.01	2.45
Predictive	12	3.53	0.44	6.4	9.62	3.76	18.4	3.06	7.63	2.58	9.35	2.89	6.13	11.02	5.3	3.6	2.33
scenarios	13	4.68	0.06	6.09	7.25	5.88	11.69	4.89	7.02	0.12	5.69	0.96	5.35	10.21	5.02	3.52	2.69
	14	5.02	0.347	2.39	6.15	4.23	11.21	3.86	6.32	0.456	4.08	1.254	6.39	10.56	5.23	3.93	3.58
	15	5.29	0.64	6.72	5.82	6.08	10.58	5.06	6.91	0.76	6.33	1.01	5.68	9.65	4.71	3.03	2.98
	16	5.3	0.29	4.27	6.39	6.59	9.47	5.39	6.35	0.33	6.79	0.54	4.66	6.38	4.11	3.04	3.05
	17	5.84	0.54	6.54	5.24	5.3	4.72	5.48	6.03	0.57	5.81	0.78	4.87	8.98	4.58	2.46	2.74
	18	5.21	0.42	6.22	5.09	6.35	11.58	4.95	7.41	0.43	6.03	0.63	5.05	8.22	4.12	4.64	2.02
	19	4.92	0.29	6.8	9.66	9.11	14.58	8.64	10.85	2.88	9.13	0.52	4.15	10.02	6.03	3.9	3.99
	20	5.06	0.24	7.11	8.71	5.61	12.96	5.22	7.64	1.85	5.08	0.42	3.69	11.4	6.89	5.16	4.57
	21	5.14	0.36	7.92	9.03	4.12	12.05	4.02	6.93	2.11	4.96	0.68	4.33	12.03	7.24	6.12	5.46
	22	5.22	0.51	7.83	9.55	6.04	14.13	6.11	8.75	3.04	6.25	0.86	5.21	13.02	7.84	6.58	6.02
	23	5.34	0.42	10.84	10.25	5.37	13.57	5.1	7.86	2.55	5.68	1.85	6.11	13.95	8.2	7.14	6.86
	24	5.18	0.59	7.38	10.01	8.51	14.85	7.88	10.23	3.1	8.81	2.13	7.56	13.99	8.61	7.88	7.45

Table 10: Analysis of variance.

Source	DF	Adj-SS	Adj-MS	F-value	P value
Model	23	848.3	36.88	1.22	0.217
Error	1176	35556.0	30.23		
Total	1199	36404.2			

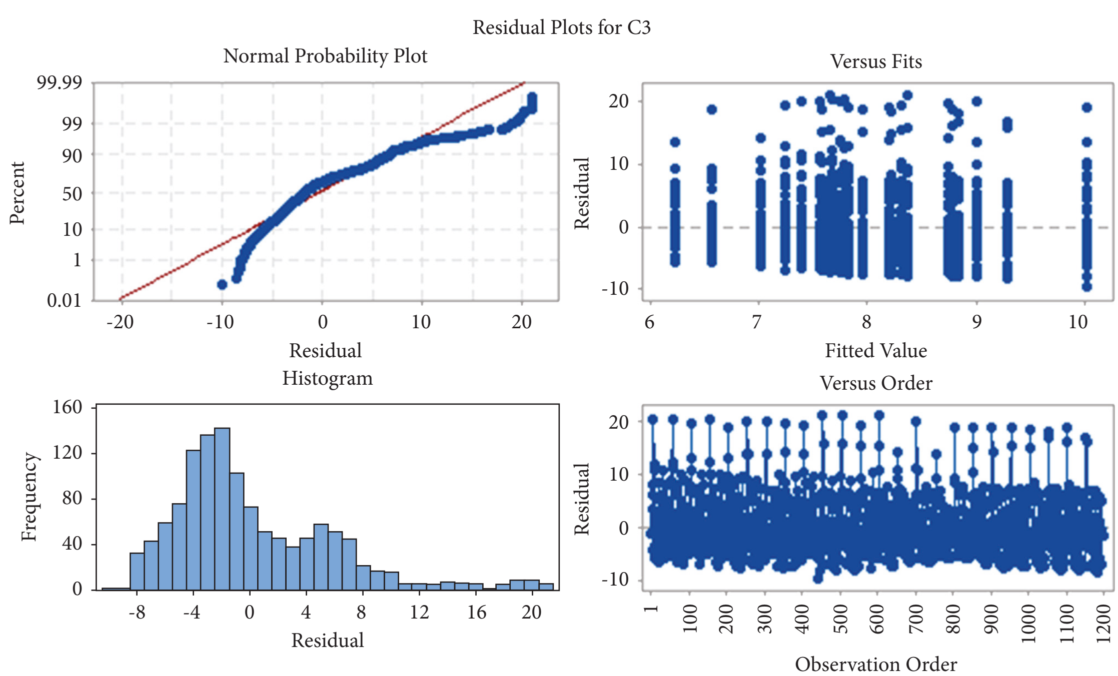

Figure 5: Review of analysis of variance results.

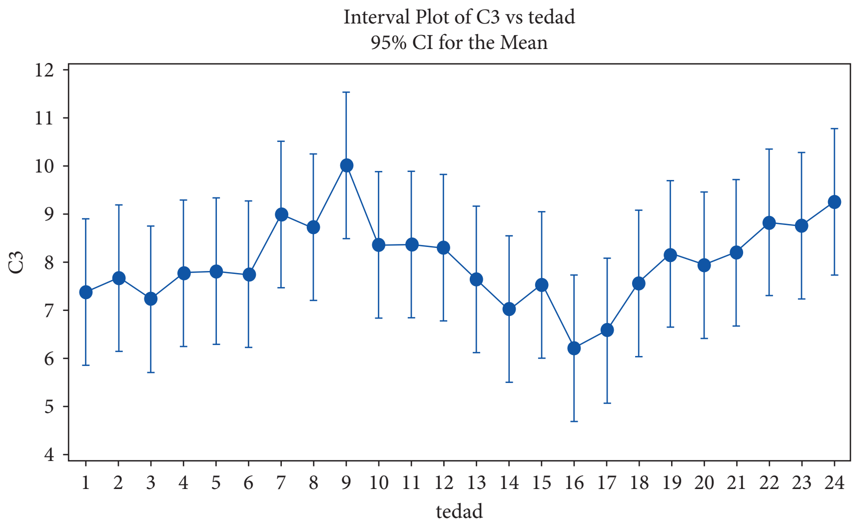

Figure 6: Results of analysis of variance.

in the 24 proposed scenarios is not accepted at 95% confidence level and it can be said that there is a significant difference between different scenarios.

The last issue is related to investigating the accuracy of the hypotheses of the analysis of the variance model. In fact, the method of analysis of variance is based on hypotheses that, if not established, will invalidate the results. The basic hypotheses of analysis of variance are that the model errors of independent random variables have a normal distribution with zero mean and common variance. These hypotheses are investigated in Figure 4. In this figure, the first plot (top left corner) is the normal probability plot of the residuals, which shows that the residuals have a normal distribution with a satisfactory approximation. Normal probability plot is a graphical method for examining the normality of a set of data that plots observations against their cumulative frequency on a sheet called normal probability sheet. If the observations on this sheet are concentrated around a straight line, it indicates that the dataset is normal. As can be seen, the residuals of the analysis of variance are concentrated with a very good percentage around the straight line in the normal probability plot, which is evidence that the residuals are normal. Regarding the equality of variance of errors, the plot of residuals is used in relation to the fitted values (top-right corner). If this plot does not show a specific nonrandom pattern, it indicates that the variance of the errors is equal. As can be seen in the plot, in the present test, this plot shows that the variance of the errors is constant.

The last plot (bottom right corner) also shows the plot of residuals in relation to the time of data collection, which indicates a random pattern. In fact, this plot should not show any specific pattern such as trend and cycle. These methods are fully presented in Montgomery's book.

As shown in Figure 5, the results of analysis of variance, the null hypothesis about equality of the means of bullwhip effect in the 24 proposed scenarios is not accepted at the 95% confidence level and it can be said that there is a significant difference between the different scenarios. Tukey's multiple comparison test was used to detect this difference. Finally, it was proved that Scenario 9 is significantly different from other scenarios, Scenario 16 is also significantly different from other scenarios, and the rest of the forecasting scenarios are not significantly different; therefore, according to the form and findings of the analysis of variance, the best scenario (lowest bullwhip effect) was for Scenario 16. And also, Scenario 9 was introduced as the worst scenario. Significant differences between the mentioned scenarios are shown in Figure 6.

In fact, based on the results of the above analysis, it can be stated that if in the four-level system with the desired hypotheses, retailer, wholesaler, manufacturer, and supplier use neural network, linear regression, smoothing exponential, and moving average, respectively, to forecast their demands, considering impossibility of eliminating errors in the forecast results, the amount of bullwhip effect resulting from this combination of forecasting methods will be less than any other combination, and as a result, this combination will help reduce the bullwhip effect and its negative effects on the supply chain.

4.3. Implication Real Case in Zarbal Company. In the case study, Zarbal Poultry Production Company with four levels of suppliers was considered, and the Zarbal Complex companies in northern Iran are located in the Caspian Sea region and are one of the largest and most experienced chicken meat production companies. In addition to providing part of the domestic and foreign market needs for a day-old broiler chickens, this complex is also active in the field of chicken meat production. Zarbal Company has started its activity in the Iranian poultry industry since 1975, and during this period, by offering superior products, it has always maintained its superiority in terms of quality. In the studied supply chain of Zarbal Company, we consider the community of four Zarbal agencies in Babol City as the

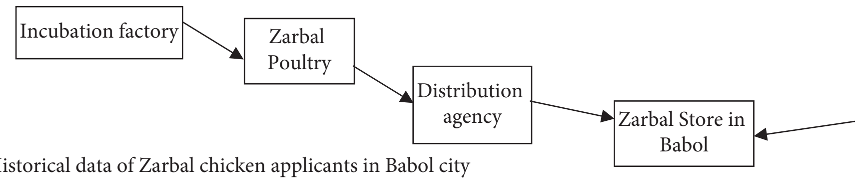

Figure 7: 4-level supply chain of Zarbal Company.

retailer level, the Zarbal exclusive distribution agency as the wholesale level, the Zarbal broiler poultry hall as the manufacturer level, and the Zarbal incubator factory as the supplier level. The two-bin ordering method (300 and 2000) was used for all levels of the supply chain. As the results of analysis of variance showed, the best scenario for forecasting the four-level supply chain, Scenario 16, i.e., the neural network method for the retailer level, the linear regression method for the wholesale level, the moving average method for the manufacturer level, and the exponential smoothing method for the supplier level were introduced, which is as follows for the case study. Figure 7 shows Zarbal Company's 4-level supply chain.

4.3.1. Forecasting Retailer by Neural Network Method in Agencies Other than Babol City. Using historical data of customer demand from the total of four Zarbal distribution centers in Babol City and by the artificial neural network of multilayer perceptron, the demand of Babol retailers was forecasted. The results of neural network forecast are shown in Table 11.

4.3.2. Forecasting Zarbal Company Agency by Regression Method. The null hypothesis of the correlation test indicates the absence of a correlation relationship, and the alternative hypothesis confirms the existence of a correlation relationship. As shown in Figure 8, because p value < 0.05, the null hypothesis is rejected, and the two variables X and Y are correlated. Forecasting was performed using the linear regression method and the following equation. Table 12 shows forecasting Zarbal Company agency by the linear regression method:

$$\begin{cases} H_0\colon \rho = 0 \\ H_1\colon \rho \neq 0 \end{cases} \quad (3)$$

$$Y = 1841 + X5.988.$$

4.3.3. Forecasting Zarbal Poultry by Moving Average Method. Zarbal distribution agency was forecasted by the moving average method with $p = 4$. The demand forecast values of Zarbal poultry and orders obtained by the two-bin method are shown in Table 13.

4.3.4. Forecasting Zarbal Company Incubator Factory by Exponential Smoothing Method. Using the order quantity obtained in the previous period at the level of Zarbal poultry and forecasting the demand of the previous period at the level of Zarbal incubation with a coefficient $\alpha = 0.33$, the demand for the next period at the level of Zarbal poultry was forecasted by exponential smoothing method, and the results of which are shown in Table 14.

Table 11: Forecasting the demand of agencies other than Babol city by the neural network method.

Period	Demand	Order
1393/02/06	1882	2000
1393/02/09	1868	1868
1393/02/13	1862	1862
1393/02/15	1856	1856
1393/02/18	1853	1853
1393/02/22	1862	1862
1393/02/25	1856	1856
1393/02/28	1856	1856
1393/02/31	1850	1850
1393/03/04	1864	1864
1393/03/07	1877	1877
1393/03/10	1882	1882
1393/03/13	1894	1894
1393/03/17	1807	1907
1393/03/21	1917	1917
1393/03/24	1927	1927
1393/03/27	1931	1931
1393/03/31	1942	1942
1393/04/04	1957	1957
1393/04/09	1973	1973
1393/04/14	1983	1983
1393/04/17	1995	1995
1393/04/21	2005	2005
1393/04/25	2006	2006
1393/04/29	2015	2015
1393/05/02	2019	2019
1393/05/06	2026	2026
1393/05/12	2020	2020
1393/05/14	2025	2025
1393/05/16	2027	2027
1393/05/18	2031	2031
1393/05/20	2031	2031
1393/05/22	2031	2031
1393/05/25	2031	2031
1393/05/29	2031	2031
1393/06/03	2040	2040

Finally, the value of bullwhip effect for these levels of Zarbal Company chain using the combination of forecasting methods presented in Scenario 16 is 3.892. This is while the value of bullwhip effect for this level of the chain with traditional and mental methods was 8.428. And this super-good growth is the combined forecasting method of the proposed model.

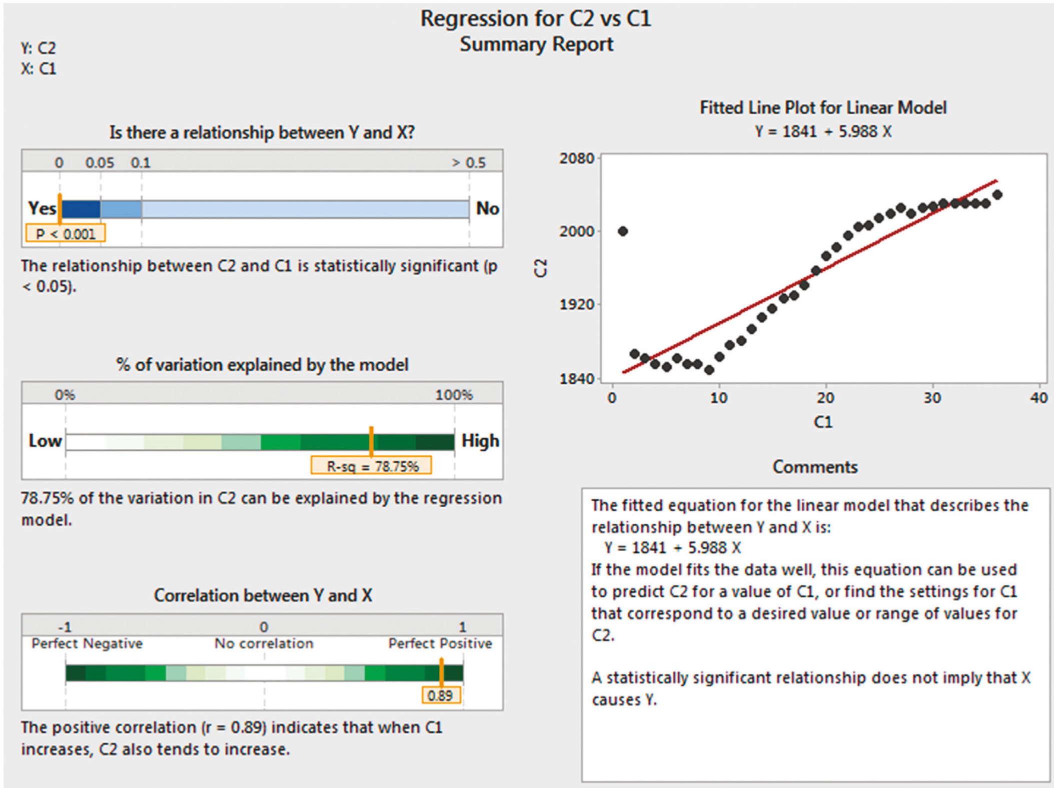

Figure 8: Diagram of correlation of Zarbal distribution agency demand.

Table 12: Forecasting Zarbal Company agency by the linear regression method.

Period	Demand	Order
1393/02/06	1847	3847
1393/02/09	1853	1853
1393/02/13	1859	1859
1393/02/15	1865	1865
1393/02/18	1871	1871
1393/02/22	1877	1877
1393/02/25	1883	1883
1393/02/28	1889	1889
1393/02/31	1894	1894
1393/03/04	1900	1900
1393/03/07	1906	1906
1393/03/10	1912	1912
1393/03/13	1918	1918
1393/03/17	1924	1924
1393/03/21	1930	1930
1393/03/24	1936	1936
1393/03/27	1942	1942
1393/03/31	1948	1948
1393/04/04	1954	1954
1393/04/09	1960	1960
1393/04/14	1966	1966
1393/04/17	1972	1972
1393/04/21	1978	1978
1393/04/25	1984	1984
1393/04/29	1990	1990
1393/05/02	1996	1996
1393/05/06	2002	2002
1393/05/12	2008	2008

Table 12: Continued.

Period	Demand	Order
1393/05/14	2014	2014
1393/05/16	2020	2020
1393/05/18	2026	2026
1393/05/20	2032	2032
1393/05/22	2038	2038
1393/05/25	2044	2044
1393/05/29	2050	2050
1393/06/03	2056	2056

Table 13: Forecasting Zarbal Company with the moving average method.

Period	Demand	Order
1393/02/06	1870	1870
1393/02/09	1853	1853
1393/02/13	1859	1859
1393/02/15	1865	1865
1393/02/18	2356	2356
1393/02/22	1862	1862
1393/02/25	1868	1868
1393/02/28	1874	1874
1393/02/31	1880	1880
1393/03/04	1886	1886
1393/03/07	1892	1892
1393/03/10	1897	1897
1393/03/13	1903	1903
1393/03/17	1909	1909
1393/03/21	1915	1915
1393/03/24	1921	1921
1393/03/27	1927	1927
1393/03/31	1933	1933
1393/04/04	1939	1939
1393/04/09	1945	1945
1393/04/14	1951	1951
1393/04/17	1957	1957
1393/04/21	1963	1963
1393/04/25	1969	1969
1393/04/29	1975	1975
1393/05/02	1981	1981
1393/05/06	1987	1987
1393/05/12	1993	1993
1393/05/14	1999	1999
1393/05/16	2005	2005
1393/05/18	2011	2011
1393/05/20	2017	2017
1393/05/22	2023	2023
1393/05/25	2029	2029
1393/05/29	2035	2035
1393/06/03	2041	2041

Table 14: Forecasting Zarbal incubator factory by the exponential smoothing method.

Period	Demand	Order
1393/02/06	1700	1400
1393/02/09	2416	2416
1393/02/13	2230	2230
1393/02/15	2108	2108
1393/02/18	2027	2027
1393/02/22	2136	2136
1393/02/25	2045	2045
1393/02/28	1987	1987
1393/02/31	1949	1949
1393/03/04	1926	1926
1393/03/07	1913	1913
1393/03/10	1906	1906
1393/03/13	1903	1903
1393/03/17	1903	1903
1393/03/21	1905	1905
1393/03/24	1909	1909
1393/03/27	1913	1913
1393/03/31	1918	1918
1393/04/04	1923	1923
1393/04/09	1928	1928
1393/04/14	1934	1934
1393/04/17	1940	1940
1393/04/21	1946	1946
1393/04/25	1951	1951
1393/04/29	1957	1957
1393/05/02	1963	1963
1393/05/06	1969	1969
1393/05/12	1975	1975
1393/05/14	1981	1981
1393/05/16	1987	1987
1393/05/18	1993	1993
1393/05/20	1999	1999
1393/05/22	2005	2005
1393/05/25	2011	2011
1393/05/29	2017	2017
1393/06/03	2023	2023

4.4. Discussion and Comparison. Many researchers have studied the effect of forecasting methods on bullwhip, which was mentioned in the literature review. However, Najafi and Zanjirani Farahani [28] compared the effect of various forecasting methods such as moving average, exponential smoothing, and regression in creating or intensifying the bullwhip effect in a four-level supply chain on bullwhip effect and by three demand models, used the pairwise comparison test to analyze his results. Esmaili et al. [29] also investigated the two methods of moving average and exponential smoothing on eight demand models in a two-level chain. In analyzing their results, they used the pairwise comparison of means. Accordingly, the method based on designing experiments and analysis of variance used in the present study can be considered as a distinct aspect of it from previous studies, which gives more stability to the results. In other study, Razavi Hajiagha et al. [30] investigated the effect of combined application of forecasting methods on bullwhip in three-level supply chains with a simulation approach and the assumption of dissimilarity of forecasting methods in a combined scenario and they analyzed the results using analysis of variance. Kohansal used three smoothing methods of Holt-Winters, ARIMA, and artificial network to forecast the egg price. Based on the results, the forecast of the neural network method is closer to reality. According to the above comparison, there is no study that can reduce the effect of bullwhip on the supply chain using statistical-mathematical analysis simultaneously. In general, only mathematical prediction tools have been used. For this purpose to fill gap in this research, forecast for retail demand using regression model; wholesale demand using exponential smoothing model; manufacture demand using neural network, and supplier demand using moving average method have been done.

5. Managerial Insights and Practical Implications

By moving from the bottom of the chain to the top of the supply chain, small changes at the bottom cause large changes at the top. These changes will cause large fluctuations in the supply chain because it has been shown that the sources of change in the supply chain are very wide. If these changes are transferred to the higher levels of the supply chain with a time delay, they will delay the production and transportation of goods to the lower categories and will have the effect of a bullwhip.

6. Conclusion

In this study, we explored the demand forecasting in supply chain, a four-level chain of retailers, wholesalers, manufacturers, and suppliers. Each level of the chain forecasted demand by moving average method, exponential smoothing, multilayer perceptron artificial neural network, and regression. Also, we provide a hybrid model based on statistics and mathematics to reduce the effect of bullwhip. For this purpose, main contrition of the paper is predicting demand in a four-level supply chain with retailers, wholesalers, manufacturers, and supplier elements. Also, we provide a hybrid model based on statistics and mathematics to reduce the effect of bullwhip. Therefore, in this study, using four methods that most researchers used to forecast, including moving average, exponential smoothing, linear regression, and multilayer perceptron neural network, the demand value of the four-level supply chain was forecasted with the assumption that none of the forecasting scenarios use any similar method. For this purpose, main results of the paper are as follows:

(i) Forecast retail demand using the regression model.

(ii) Forecast wholesale demand using the exponential smoothing model.

(iii) Forecast manufacturer demand using the neural network.

(iv) Forecast supplier demand using the moving average method.

Also, the quantities of orders were obtained using the two-bin method; then, the effect of the bull whip was calculated by calculating the variance of supplier orders to the variance of retailer demand. And by the analysis of variance and pairwise comparison test, the best combined scenario with the least bullwhip effect in the four-level supply chain was introduced. In the case study of Zarbal Company, with the best bullwhip effect, Scenario 16, the demand of Zarbal chicken stores (retailer) by the neural network method, Zarbal chicken distributors (wholesaler) by the linear regression method, Zarbal poultry (manufacturer) by the moving average method, and the incubator factory (supplier) by the exponential smoothing method forecasted, which reduced the bullwhip effect. Suggestions for the development of this article are as follows. Considering the uncertainty in the calculations, we develop a simulation model and introduce a hybrid approach based on simulation and statistics.

Data Availability

All data are given in the article file.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] J. A. Durán Peña, Á. Ortiz Bas, and N. M. Reyes Maldonado, “Impact of bullwhip effect in quality and waste in perishable supply chain,” *Processes*, vol. 9, no. 7, p. 1232, 2021.

[2] A. C. Braz, A. M. De Mello, L. A. de Vasconcelos Gomes, and P. T. de Souza Nascimento, “The bullwhip effect in closed-loop supply chains: a systematic literature review,” *Journal of Cleaner Production*, vol. 202, pp. 376–389, 2018.

[3] A. Pourghader Chobar, M. A. Adibi, and A. Kazemi, “A novel multi-objective model for hub location problem considering dynamic demand and environmental issues,” *Journal of Industrial Engineering and Management Studies*, vol. 8, no. 1, pp. 1–31, 2021.

[4] M. Rezaei Kallaj, M. Abolghasemian, S. M. Pirbalouti, M. Sabk Ara, and A. P. Chobar, “Vehicle routing problem in relief supply under a crisis condition considering blood types,” *Mathematical Problems in Engineering*, vol. 2021, Article ID 7217182, 10 pages, 2021.

[5] R. H. A. Seyed Hossein, A. Hadi, and U. Laia, “The effect of combined application of forecasting methods on bullwhip effect in multi-level supply chains,” *Management Improvement, Year*, vol. 6, no. 4, pp. 96–113, 2012.

[6] J. Huang, Y. Meng, F. Liu, C. Liu, and H. Li, “Modeling and predicting inventory variation for multistage steel production processes based on a new spatio-temporal Markov model,” *Computers & Industrial Engineering*, vol. 164, Article ID 107854, 2022.

[7] I. Jackson, “Deep Reinforcement Learning for Supply Chain Synchronization,” in *Proceedings of the 55th hawaii international conferences on system conferences*, Honolulu, January 2022.

[8] Y. Yang, J. Lin, G. Liu, and L. Zhou, "The behavioural causes of bullwhip effect in supply chains: a systematic literature review," *International Journal of Production Economics*, vol. 236, Article ID 108120, 2021.
[9] J. A. Durán Peña, Á. Ortiz Bas, and N. M. Reyes Maldonado, "Impact of bullwhip effect in quality and waste in perishable supply chain," *Processes*, vol. 9, no. 7, p. 1232, 2021.
[10] K. Fu, Z. Chen, and B. R. Sarker, "Behavioral operations effect of fairness and unfairness concern in the decision of the supply chain production-inventory system," *Journal of Modelling in Management*, 2021.
[11] D. L. Trenggonowati, M. Ulfah, A. Ridwan, and R. Arthafia, "Proposed improvement on supply chain system to minimize the bullwhip effect phenomenon with Monte Carlo simulation approach," *Journal of Innovation and Technology*, vol. 2, no. 2, pp. 40–45, 2021.
[12] Y. Zhao, Y. Cao, H. Li et al., "Bullwhip effect mitigation of green supply chain optimization in electronics industry," *Journal of Cleaner Production*, vol. 180, pp. 888–912, 2018.
[13] S. Cannella, J. M. Framinan, M. Bruccoleri, A. P. Barbosa-Póvoa, and S. Relvas, "The effect of inventory record inaccuracy in information exchange supply chains," *European Journal of Operational Research*, vol. 243, no. 1, pp. 120–129, 2015.
[14] S. Jaipuria and S. S. Mahapatra, "An improved demand forecasting method to reduce bullwhip effect in supply chains," *Expert Systems with Applications*, vol. 41, no. 5, pp. 2395–2408, 2014.
[15] R. L. Bray and H. Mendelson, "Information transmission and the bullwhip effect: an empirical investigation," *Management Science*, vol. 58, no. 5, pp. 860–875, 2012.
[16] R. Bhattacharya and S. Bandyopadhyay, "A review of the causes of bullwhip effect in a supply chain," *International Journal of Advanced Manufacturing Technology*, vol. 54, no. 9-12, pp. 1245–1261, 2011.
[17] C. Hayya, "The bullwhip effect - impact of stochastic lead time, information quality, and information sharing: a simulation study," *Production and Operations Management*, vol. 13, no. 4, pp. 340–353, 2004.
[18] J. A. D. Machuca and R. P. Barajas, "The Impact of Electronic Data Interchange on Reducing Bullwhip Effect and Supply Chain Inventory Costs," *Transportation Research Part E: Logistics and Transportation Review*, vol. 40, 2004.
[19] T. Kelepouris, P. Miliotis, and K. Pramatari, "The impact of replenishment parameters and information sharing on the bullwhip effect: a computational study," *Computers & Operations Research*, vol. 35, no. 11, pp. 3657–3670, 2008.
[20] J. Marko and B. Rusjan, "The effect of replenishment policies on the bullwhip effect: a transfer function approach," *European Journal of Operational Research*, vol. 184, no. 3, pp. 946–961, 2008.
[21] S. Agrawal, R. N. Sengupta, and K. Shanker, "Impact of information sharing and lead time on bullwhip effect and on-hand inventory," *European Journal of Operational Research*, vol. 192, no. 2, pp. 576–593, 2009.
[22] F. Chen, J. K. Ryan, and D. Simchi-Levi, "The impact of exponential smoothing forecasts on the bullwhip effect," *Naval Research Logistics*, vol. 47, pp. 269–286, 2000.
[23] F. Chen, Z. Drezner, J. K. Ryan, and D. Simchi-Levi, "Quantifying the BullwhipEffect in a simple supply chain: the impact of forecasting, lead times, and information," *Management Science*, vol. 46, pp. 436–443, 2000b.
[24] X. Zhang, "The impact of forecasting methods on the bullwhip effect," *International Journal of Production Economics*, vol. 88, no. 1, pp. 15–27, 2004.
[25] Y. Barlas and B. Gunduz, "Demand forecasting and sharing strategies to reduce fluctuations and bullwhip effect in supply chains," *Journal of the Operational Research Society*, vol. 62, pp. 458–473, 2011.
[26] D. Ivanov and B. Sokolov, "Control and system-theoretic identification of the supply chain dynamics domain for planning, analysis and adaptation of performance under uncertainty," *European Journal of Operational Research*, vol. 224, no. 2, pp. 313–323, 2013.
[27] F. Costantino, G. Di Gravio, A. Shaban, and M. Tronci, "The impact of information sharing and inventory control coordination on supply chain performances," *Computers & Industrial Engineering*, vol. 76, pp. 292–306, 2014.
[28] M. Najafi and R. Z. Farahani, "Comparison of the effect of different forecasting methods on Bullwhip effect," in *Proceedings of the Fifth International Conference on Industrial Engineering*, pp. 24–36, Tehran, October 2007.
[29] M. Esmaili, R. Tat, and M. Akbarzadeh, "Comparison of the Effect of Different Forecasting Methods on Bullwhip Effect in the Supply Chain," in *Proceedings of the 8th International Conference on Industrial Engineering*, pp. 88–102, Tehran, June, 2012.
[30] S. H. Razavi Hajiagha, H. Akrami, and H. A. Mahdiraji, "Approximation of bullwhip effect function in a three-echelon supply chain," in *Proceedings of the International Conference on Business*, pp. 109–126, Management and Governance 2011, Chennai, India, December 2011.