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Optimisation of Warehouse Location and Inventory Management for an Industrial Textile Manufacturer Company in Türkiye

Tutku TUTKUN[1], İrem Nur NERGIZ[1], Rukiye KAYA[1], Uğur SATIÇ[1*]

[1]*Abdullah Gül University, Industrial Engineering Department, Kayseri, Türkiye*
(ORCID: 0009-0008-5176-2722) (ORCID: 0009-0005-1602-7130) (ORCID: 0009-0003-5881-0305)
(ORCID: 0000-0002-9160-0006)

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Abstract
In this study, we consider the demand forecasting, facility location, and inventory management problems of an industrial textile manufacturer company in Türkiye. First, we begin with the demand forecasting problem for thirty-two different products and employ ABC analysis to categorise the products. Then we test multiple forecasting methods and find out that Exponential Smoothing and Croston's TSB methods perform better in our categories. Using the demand forecast results in the facility location problem, we search for a location in Europe for a warehouse. For the facility location problem, we use a mixed-integer nonlinear mathematical model to minimise the transportation cost, and warehouse rental cost. We solve the model by using GAMS Solver. Then, we handle the inventory management problem and determine the quantity of the products that are sent from the factory and the warehouse to the customer. We propose a genetic algorithm approach that generates reorder quantities and reorder points for both the factory and the warehouse to minimise the total logistics costs, including holding, ordering and stockout costs. We use simulation models to calculate the logistics costs then we use these costs as fitness values to choose the best reorder quantities and reorder points. The proposed approach offers improvement in demand forecasting, inventory management, and facility location problems and brings up a 26% reduction in total logistic costs.

1. Introduction

In this research, we considered an industrial textile manufacturer company which has a wide product range from yarn production and carpets to various kinds of fabrics. Approximately 20% of the company's production capacity serves one main customer, which is an international furniture retailer. This furniture retailer provides a forty-eight-week order forecast to the company. However, only the first five weeks of this forecast represent actual orders, while the remaining forty-three weeks can be altered by the retailer at any time. This forecasting structure creates significant challenges for the company, as fluctuations such as changed or cancelled orders disrupt the production process. Consequently, the company experiences instability in both its production planning and its inventory management, leading to inefficiencies and increased costs. The first stage of this research focuses on addressing the demand forecasting problem experienced in the supply process while dealing with orders from the furniture retailer. This stage employs a variety of forecasting techniques tailored to the specific needs of the company's product lines. Methods such as ABC analysis, Moving Average, Exponential Smoothing, Linear Regression, and Croston's TSB method are utilised to improve forecasting accuracy. The literature has highlighted the importance of these techniques in managing demand variability and enhancing production efficiency. For instance, Tadayonrad and Ndiaye [1] emphasise the importance

*Corresponding author: ugur.satic@agu.edu.tr *Received: 13.09.2024, Accepted: 22.11.2024*

of accurate demand forecasting on the efficiency of the inventory management. Abolghasemi et al. [2] state that demand variability is a key challenge for supply chain management since it causes significant forecast errors, disruption in operations and additional costs. The authors investigate 843 real demand time series with different values of coefficient of variations which indicates the volatility in series. They emphasise the challenge of forecasting with this variability and offer a hybrid model to forecast demand. Song and Lu [3] also indicate that uncertain demand makes it difficult to match demand and supply and manage inventory without shortage. Moayedi and Sadeghian [4] present that demand uncertainty and changes in production processes affect supply chain management in a variety of aspects including environmental effects such as excess carbon emission. The authors consider demand, supplies, processing, transportation, shortage and capacity expansion costs as uncertain parameters and offer multi-objective stochastic programming for green supply chain management under uncertainty.

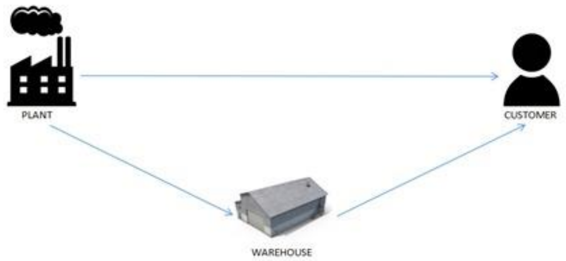

Figure 1. Suggested Operational Flow of the Company's Supply Chain

The second stage of this research addresses the facility location problem. The company requires a warehouse strategically located in Europe to respond more quickly and effectively to orders from the continent. Figure 1 represents the suggested system where some customers will be served from the plant and some customers will be served from the warehouse. The importance of strategic warehouse location is well-documented in the literature. Santosa and Kresna [5] explore the Single Stage Capacitated Warehouse Location Problem (SSCWLP) and emphasise the significance of optimising warehouse locations to reduce logistical costs and improve service levels. Szczepański et al. [6] also discuss the impact of optimal warehouse placement on transportation time and inventory management, noting that proper location selection can lead to substantial operational improvements and cost reductions. In this study, we use a mixed-integer nonlinear mathematical model (MINLP) to optimise the warehouse location, with the objective of minimising total costs, including transportation and warehouse rental costs. Due to the problem structure of the facility location problem, integer programming is extensively adopted in the literature as a solution methodology. Basciftci et al. [7] emphasise the significance of the determination of facility location for decision-dependent demand and offer MILP for the problem. Kchaou Boujelben et al. [8] also uses mixed integer linear programming for multi-period facility location problem. Aboolian et al. [9] handle both facility location and design optimisation in the context of competition with existing facilities. The authors incorporate the uncertainty of customer demands and different design strategies into the approach and offer a generalised facility location and design problem (GFLDP). They also utilise mixed integer nonlinear programming (MINLP) as a part of the solution methodology.

Finally, the third stage of this study is to handle the inventory management problem and generate an effective stock management strategy that sorts out stock-related problems caused by disruptions in the order forecast. One of the significant factors influencing high service levels is the effective management of stocks. By effective stock control company can meet customer demand on time, minimise stockouts, and avoid excess inventory. However, due to the lack of reliable and consistent order forecasts the company is not able to manage their stocks effectively. The company need a robust stock management system to align its stock levels with actual demand and keep the service level high. In this study, we propose an approach based on genetic algorithm to generate optimal reorder quantities and reorder points for the products.

Genetic algorithm (GA) is a stochastic search technique inspired by the natural selection theory of Charles Darwin. The advantages of GA, such as versatility, flexibility, simplicity, and capability to search effectively in large and poorly understood search space with little information, permit it to solve NP-hard optimisation problems across many disciplines [10]. GA offers robustness in navigating complex, nonlinear problem spaces with multiple constraints, making them particularly advantageous over traditional optimisation methods in inventory management [11].

The integration of genetic algorithms in inventory management has been extensively studied. Hernandez and Süer [12] suggested a GA approach to obtain the reorder quantity for an incapacitated, no shortages allowed, single item, single-level situation lot sizing problem by minimising the sum of holding and ordering costs. Lo [10] considered a production-inventory management model and suggested a GA approach to obtain reorder quantities and reorder points by minimising the average total cost. Pasandideh et al. [13] designed the multi-product, single-supplier inventory management problem as an economic order quantity model and proposed a GA approach which generates order quantities and order levels by minimising the total inventory cost of the supply chain. GA combined with the economic order quantity (EOQ) models, provides a robust solution for improving inventory management, ensuring that the company can maintain optimal stock levels while minimising costs. Babai et al. [11] demonstrates the effectiveness of genetic algorithms in minimising total logistics costs by optimising inventory levels and order intervals in a real-world case study. This approach is particularly relevant for handling complex, nonlinear inventory problems like those encountered by the textile manufacturer in this research. Mahjoob et al. [14] handled a multi-product multi-period inventory routing problem and used a modified adaptive genetic algorithm for the problem. The results present the efficiency of the proposed algorithm. Vidal et al. [15] also emphasise the importance of effective inventory management and propose a decision support system for effective inventory management. They adopt fuzzy MCDM methods to determine and rank SKUs according to importance. Then they develop a ML model which combines genetic algorithm (GA) and artificial neural network (ANN) to forecast demand for these SKUs. The forecast results indicate a significant enhancement in the accuracy of the demand forecast for SKUs compared to the previous forecast of the company. The proposed approach enhances both the responsiveness and the effectiveness of the company's decision-making process in inventory management.

In conclusion, this study integrates advanced forecasting methods, strategic facility location modelling, and genetic algorithms in inventory management to improve the overall efficiency of the company's supply chain operations by improving the production planning of the company and reducing the inventory and transportation costs.

2. Material and Method

Our three-staged study requires different approaches in each stage. The first stage, the demand forecasting problem requires data analysis consisting of data cleaning and categorising the products with ABC analysis. Then different forecasting methods will be selected for each product class (e.g. A, B and C classes). In the second stage which is the facility location problem, a mixed integer nonlinear programming approach using GAMS will be used. In the third stage which is the inventory management problem, we will suggest a genetic algorithm approach.

2.1. The Demand Forecasting Problem

In this stage of the study, we handle the demand forecasting problem. We acquired sales data of 32 products for the years between 2019-2023 from the sales and marketing department of the company. Given the significant impact of the COVID-19 pandemic on sales for the years between 2019-2021, the number of products sold before the pandemic was compared with the number of products sold after the pandemic. There were significant differences between the sales during the COVID-19 pandemic period and after the pandemic period. Thus, we removed the data of the COVID-19 pandemic period from our data set and we only used the data from 2022 and 2023 in this research.

Firstly, we investigated the demand type of the 32 products with ABC analysis. ABC analysis is a critical component of inventory management, categorising inventory items into three categories (A, B, and C) based on their importance and frequency of demand. Alfawaer [16] uses ABC analysis for the design of a forecasting inventory classification model. We used it for the same purpose. We applied ABC analysis to categorize the products based on their order frequency. Firstly, we segmented the sales data into weekly intervals. Then we calculated the frequency of orders by recording the number of weeks in which the product was ordered. Then we calculated the relative percentages of order frequencies. We ranked the products in descending order according to their order frequency percentages. Then we calculated the cumulative values of these relative percentages. Based on the relative percentages, we classified the products into three categories: the products from 0% to 40% are categorised as A, the products from 41% to 80% are categorised as B, and the remaining products are categorised as C. Category A represents products with the highest order frequency, category B includes products with moderate order frequency, and category C consists of products with the lowest order frequency. This method allows for the systematic prioritization of inventory based on demand patterns.

Dutta et al. [17] suggest that the choice of forecasting method can be determined based on the categories determined by ABC classification. Fattah et al. [18] emphasise the importance of selecting appropriate forecasting methods based on demand categorization. They recommend the use of moving average and exponential smoothing for products with stable demand patterns, highlighting their effectiveness in smoothing out fluctuations and capturing underlying trends. Similarly, Chau [19] advocates for the application of linear regression and exponential moving average, particularly in scenarios where demand trends are linear and consistent over time. These methods provide a robust foundation for forecasting in environments characterized by predictable and steady demand, ensuring accurate predictions and efficient inventory management. In contrast, for products with sporadic and intermittent demand, the use of methods such as Croston's TSB is strongly advocated by Rožanec et al. [20] who highlight their effectiveness in reducing forecasting errors and improving accuracy in industries where demand patterns are volatile.

According to our ABC analysis, 8 products fall into category A, representing the highest priority items. 12 products were categorised as category B. Although ABC classification does not indicate which forecasting method to use for each category, it guides the selection of forecasting techniques for each category according to the specifications and demand patterns of them. Categories of A and B are characterized by high and consistent demand, and we used moving average, exponential smoothing and linear regression methods as demand forecasting methods. The moving average method is a fundamental technique used to analyse time series data. It predicts the next data point in a time series by averaging the data over a given time interval. This method is particularly useful in smoothing out short-term fluctuations and highlighting longer-term trends [21]. Exponential smoothing was utilised to respond to small trend changes, giving more weight to recent observations. This method is effective for time series without significant trends or seasonality, as it adapts quickly to short-term fluctuations, making recent data more relevant [18]. The exponential moving average method is a frequently used method in statistics and financial time series. This method tries to make a forecast by giving more weight to the latest data [22]. On the other hand, the linear regression method is implemented to identify the relationship between time and demand, aiming to improve trend forecasts. This method models demand changes over time, making it particularly effective for datasets with trends offering more accurate predictions of future demand based on historical data [20]. We used these methods for 10-week demand forecasting for each product. Since the exponential smoothing method provided more reliable forecast results among these methods, we adopted this method for classes A and B. The remaining 12 products were categorised as category C by ABC classification. This category exhibits irregular and intermittent demand patterns, and we used Croston, Croston's TSB, bootstrap, and Syntetos-Boylan methods for this category. Croston’s method decomposes demand into two separate processes: the demand size and the interval between demand occurrences, making it particularly effective for slow-moving items where traditional methods struggle to provide accurate forecasts [23]. The bootstrap method which is a non-parametric resampling technique estimates statistical measures and their variability without assuming a specific population distribution. It helps create robust forecasts and confidence intervals by resampling the original data multiple times [19]. On the other hand, the Syntetos-Boylan method refines Croston's method by incorporating a correction factor to reduce bias in forecasts [15]. It categorizes demand into intermittent, regular, and quiet periods, improving accuracy for low-volume, sporadic demand. Among the methods for category C, Croston TSB and bootstrap methods provided more reliable predictions for irregular demand. The results are given in detail in section 3.

2.2. The Facility Location Problem

After the demand forecasting problem, we handled the facility location problem. Facility location decision is a strategic decision due to its high cost and long-term effects [16]. We adopted mixed integer nonlinear programming for the facility location problem in this study. In the literature, application of integer programming is extensively observed. Boujelben et. al. [8] used MILP for the facility location problem. They propose a two-phase solution approach. In the first phase, they evaluate the average distances and transportation costs from the distribution centres to customers using an exact clustering procedure based on a set-partitioning formulation. These evaluated costs are then used as input for the second phase, where the facility location problem is formulated as a mixed-integer nonlinear program and solved with a state-of-the-art commercial solver. On the other hand, Branco et al. [24] also utilised MINLP for the location of sugarcane mills.

In this study, firstly we carried out the sales forecast of 32 products, then we continued our research with the facility location problem that the company faced since they want to respond to the orders from Europe more quickly and less costly. 12 possible warehouse locations were considered by the company. The suggested warehouse locations are shown in Table 1. Only one warehouse can be opened.

Table 1. Possible Warehouse Location

County	City
Poland	Warsaw
Bosnia and Herzengoniva	Sarejevo
Romania	Bucharest
Lithuania	Vilnius
Netherlands	Amsterdam
Italy	Rome
Macedonia	Skopje
Bulgaria	Sofia
Hungary	Budapest
Serbia	Belgrade
Germany	Berlin
Portugal	Lisbon

Products can be delivered to customers in two different ways which are from the factory or the warehouse. The company has five customers in Poland, and one customer each in Romania, Bosnia, Portugal, and Lithuania. The demands of the customers are different from each other. A mixed integer nonlinear approach was used for this problem to minimise the total cost which consists of the transportation costs for all alternative routes, the fixed costs of opening a warehouse, and the holding costs for safety stock. A Nomenclature table for this model is shown in Table 2.

2.2.1. Objective function

$$Min\ Z = \sum_i^I \sum_k^K \left(c_{i,k}^{fw} \sum_j^J \left(d_{j,k}\beta_{i,j}\right)\right) + \sum_j^J \sum_k^K \left(c_{j,k}^{fc} d_{j,k}\alpha_j\right) + \sum_i^I \sum_j^J \sum_k^K \left(\left(c_{i,j,k}^{wc} + h_i\right) d_{j,k}\beta_{i,j}\right) + \sum_i^I (\gamma_i g_i) + \sum_i^I \sum_k^K h_i s \sqrt{\sum_j^J g_i \beta_{i,j} \sigma_{j,k}^2} \tag{1}$$

Equation (1) shows the objection function of this model. The objective function calculates the total cost by adding up the transportation costs (composed of factory to warehouse $\left(\sum_i^I \sum_k^K \left(c_{i,k}^{fw} \sum_j^J \left(d_{j,k}\beta_{i,j}\right)\right)\right)$, factory to customer $\left(\sum_j^J \sum_k^K \left(c_{j,k}^{fc} d_{j,k}\alpha_j\right)\right)$ and warehouse to customer $\left(\sum_i^I \sum_j^J \sum_k^K ((c_{i,j,k}^{wc} + h_i) d_{j,k}\beta_{i,j})\right)$ costs), the rent of a warehouse $\left(\sum_i^I (\gamma_i g_i)\right)$, and the holding costs for safety stock $\left(\sum_i^I \sum_k^K h_i s \sqrt{\sum_j^J g_i \beta_{i,j} \sigma_{j,k}^2}\right)$. The purpose of the function is to minimise the total cost.

The transportation costs are created from many parameters such as customs fees, the fee paid to the vehicles and the driver, and gasoline prices. Additionally, holding costs for only taken into account for the safety stocks. Holding costs amount is obtained from the company.

Table 2. Nomenclature of the MINLP model

Nomenclature	**Description**
I, J, K	Set of warehouse locations i, set of customer j, set of products k
$c_{i,k}^{fw}$	Transportation cost of one unit k type product from the factory to warehouse i
$c_{j,k}^{fc}$	Transportation cost of one unit k type product from the factory to customer j
$c_{i,j,k}^{wc}$	Transportation cost of one unit k type product warehouse i to customer j
h_i	Holding cost at warehouse locations i
g_i	Rent cost of warehouse locations i
$d_{\mathrm{j,k}}$	(Annual mean) demand of k type product at customer j
$\sigma_{j,k}$	Standard deviation of the demand of k type product at customer j
t_i^{fw}	Transportation duration from the factory to warehouse i
t_i^{fc}	Transportation duration from the factory to customer j
$t_{i,j}^{wc}$	Transportation duration from warehouse i to customer j
p_k	Annual capacity of producing k type product
x_i	The capacity of the warehouse i
s	Desired level of safety factor
m	Threshold for the weighted lead time
α_j	1 if customer j is served by factory, 0 otherwise
$\beta_{i,j}$	1 if customer j is served by warehouse i, 0 otherwise
γ_i	1 if warehouse i is opened, 0 otherwise

2.2.2. Constraints

$$\sum_i^I \sum_j^J (d_{j,k}\beta_{i,j}) + \sum_j^J (d_{j,k}\alpha_j) \leq p_k, \quad \forall k \in K \tag{2}$$

$$\sum_k^K \sum_j^J \left(d_{j,k}\beta_{i,j}\right) + \sum_k^K s\sqrt{\sum_j^J \left(\sigma_{j,k}^2 t_i^{fw}\beta_{i,j}\right)} \leq \gamma_i x_i, \ \forall i \in I \tag{3}$$

$$\sum_j^J \sum_k^K \left(d_{j,k}\left(\sum_i^I \left(t_{i,j}^{wc}\beta_{i,j}\right) + t_i^{fc}\alpha_j\right)\right) / \sum_j^J \sum_k^K d_{j,k} \leq m \tag{4}$$

$$\beta_{i,j} \leq \gamma_i, \quad \forall i \in I \ \& \ \forall j \in J \tag{5}$$

$$\sum_k^K s\sqrt{\sum_j^J (\sigma_{j,k}^2 t_i^{fw}\beta_{i,j})} \geq 0, \quad \forall i \in I \tag{6}$$

$$\sum_j^J (d_{j,k}\beta_{i,j}) \ \geq 0, \quad \forall i \in I \ \ \& \ \forall k \in K \tag{7}$$

$$\alpha_j + \sum_i^I \beta_{i,j} = 1, \quad \forall j \in J \tag{8}$$

$$\alpha_j, \beta_{i,j}, \gamma_i \in (1,0), \quad \forall i \in I \ \& \ \forall j \in J \tag{9}$$

Equation (2) ensures that the total amount of product that leaves the factory to the warehouse $\left(\sum_i^I \sum_j^J (d_{j,k}\beta_{i,j})\right)$ or directly to customers $\left(\sum_j^J (d_{j,k}\alpha_j)\right)$ cannot exceed the production capacity (p_k) for each product type k. Equation (3) ensures that the total amount of product $\left(\sum_k^K \sum_j^J (d_{j,k}\beta_{i,j})\right)$ in the warehouse j including the safety stock $\left(\sum_k^K s\sqrt{\sum_j^J (\sigma_{j,k}^2 t_i^{fw}\beta_{i,j})}\right)$ cannot exceed the capacity of the warehouse j $(\gamma_i x_i)$. Equation (4) ensures that the weighted average lead time (composed of the lead time from warehouse to customers $\left(\sum_i^I \left(t_{i,j}^{wc}\beta_{i,j}\right)\right)$, from factory to customers $\left(t_i^{fc}\alpha_j\right)$ and a weighting function of demand $\left(d_{j,k}\right)$) is under the desired threshold (m). Equation (5) ensures that a customer can only be served from an existing warehouse. Equation (6) ensures that the safety stock cannot be negative. Equation (7) ensures that the amount of product sent to the warehouse j cannot be negative. Equation (8) ensures that the customers cannot be served by the warehouse $\left(\beta_{i,j}\right)$ and factory $\left(\alpha_j\right)$ at the same time. Equation (9) represents that these variables are binary.

2.3. The Inventory Management Problem

In this stage of the study, we consider the inventory management problem of the warehouse. Since this problem includes the inventory management of a future warehouse, we assumed that the demand is uncertain. Thus, the weekly shipment quantities from 2021 to 2023 have been examined and a probabilistic distribution of 32 products was found.

This inventory management problem where the demand is stochastic is addressed using a genetic algorithm (GA) to optimise the reorder quantity (Q) and reorder point (R) for 32 products. EOQ equations of the reorder quantity (Q) (i.e., Equation (10)) and reorder point (R) (i.e., Equation (11)) are used to determine holding, ordering and penalty costs.

$$Q_k = \sqrt{\frac{2D_k O_k}{h_i}} \tag{10}$$

$$R_k = D_k L + S \tag{11}$$

Here, D_k is the demand of the product k which is a random variable. O_k is ordering cost per order of product k. h_i is the holding cost of a single unit product in the selected warehouse. L is the lead time. S is the safety stock amount.

GA is a class of optimisation algorithms inspired by the process of natural selection [23]. The GA was implemented using Python [25] and optimisation libraries such as SciPy for efficient computations [26]. The goal of the GA was the minimisation of the total costs (Equation (12)) which includes holding costs (Equation (13)), ordering costs (Equation (14)), and penalty costs.

$$Min\ (total\ cost) = \ holding\ costs + \ ordering\ costs + penalty\ costs \tag{12}$$

$$holding\ costs\ = \ Average\ inventory\ during\ the\ period\ *\ h_i \tag{13}$$

$$ordering\ costs = Number\ of\ orders\ placed\ in\ the\ period * O_k \tag{14}$$

The key steps of GA are as follows: initialisation and iteration. The initialization step consists of the generation of the first population by generation combination of random Q and R values, and evaluation of the fitness values of the first population. We used the total cost as the fitness value. The fitness values of each individual are calculated with a simulation process, where each individual is used in a scenario and based on its Q and R values the sum of the holding cost, penalty cost, and ordering cost are calculated.

The iteration step of GA consists of elitist selection, crossover, mutation and evaluation. The elitist selection is the selection of some individuals with the highest fitness value from the population and transferring them to the next generation without any change. This approach guarantees that our next generation will be worse than its predecessor. The remaining population of the next generation is generated by the crossover phase. In this approach, two individuals are randomly selected from the current population which are called father and mother individuals. A new individual is generated by mixing genes (Q and R values) of the father and mother individuals. We used the one exchange point method where a random exchange point is decided. Then genes are transferred from the mother to the new individual till the exchange point and the remaining genes are transferred from the father after the exchange point. The mutation represents a random change in one gene. All individuals who are generated with the crossover phase may enter the mutation phase by random chance. In this phase, a random gene is selected, and its Q and R values are replaced with a random value. After that in the evaluation phase, the fitness values of the newly generated generation are calculated. The initialisation step only occurs once at the beginning of the algorithm then the iteration step repeats until the termination condition is met.

3. Results and Discussion

3.1. Results of the Demand Forecasting Problem

We investigated the demand type of these 32 products with ABC analysis. The ABC analysis result is shown in Table 3. The analysis revealed that 8 products fell into category A, representing the highest priority items. 12 products were categorised as category B. The remaining 12 products were categorised as category C.

We assessed various forecasting methods such as moving average (3 and 6 periods), exponential smoothing, and linear regression methods for A and B class products, and Croston, Croston TSB, bootstrap and Syntetos-Boylan methods for C class products to determine the best fit for the product classes.

Table 3. ABC Analysis Results

Item	# of week	%	Cumulative	ABC Analysis
A1	86	5.71%	5.71%	A
A2	85	5.64%	11.35%	A
A3	83	5.51%	16.85%	A
A4	74	4.91%	21.77%	A
A5	68	4.51%	26.28%	A
A6	67	4.45%	30.72%	A
A7	65	4.31%	35.04%	A
A8	63	4.18%	39.22%	A
B1	62	4.11%	43.33%	B
B2	61	4.05%	47.38%	B
B3	54	3.58%	50.96%	B
B4	52	3.45%	54.41%	B
B5	49	3.25%	57.66%	B
B6	48	3.19%	60.85%	B
B7	47	3.12%	63.97%	B
B8	44	2.92%	66.89%	B
B9	44	2.92%	69.81%	B
B10	44	2.92%	72.73%	B
B11	39	2.59%	75.32%	B
B12	39	2.59%	77.90%	B
C1	38	2.52%	80.42%	C
C2	35	2.32%	82.75%	C
C3	35	2.32%	85.07%	C
C4	35	2.32%	87.39%	C
C5	29	1.92%	89.32%	C
C6	28	1.86%	91.17%	C
C7	27	1.79%	92.97%	C
C8	24	1.59%	94.56%	C
C9	22	1.46%	96.02%	C
C10	22	1.46%	97.48%	C
C11	19	1.26%	98.74%	C
C12	19	1.26%	100.00%	C

Using the prediction results generated by these methods and the actual outcomes, we calculated the mean absolute percentage error (MAPE) values to compare the performance of the mentioned forecasting methods. MAPE is the average absolute percentage difference between the predicted values and the actual values. MAPE values are calculated as below:

$$\frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right| x100 \qquad (13)$$

Here, A_t is the actual value at time t, F_t is the predicted value at time t, and n is the number of observations. Low MAPE values mean that the prediction method is performing well, and its prediction is close to the actual values. High MAPE values mean that the prediction method performs poorly, and its prediction deviates from the actual values.

Table 4. Comparison of MAPE Values on A and B Types Products

Product Code*	Moving Average 3P	Moving Average 6P	Exponential Smoothing	Linear Regression
A-1	0,34	0,55	**0,27**	1,09
A-2	0,33	0,32	**0,21**	0,54
A-3	**0,57**	1,24	0,61	0,83
A-4	0,36	0,45	**0,25**	0,36
A-5	2,42	2,15	**1,85**	3,43
A-6	0,64	0,95	**0,47**	0,73
A-7	0,78	0,90	0,59	**0,58**
A-8	0,08	0,13	**0,04**	0,58
B-1	0,58	1,03	**0,49**	1,81
B-2	0,84	1,26	**0,54**	1,65
B-3	0,10	0,08	**0,07**	0,73
B-4	0,24	0,45	**0,18**	0,20
B-5	0,31	0,39	**0,21**	0,39
B-6	0,91	1,98	**0,77**	2,17
B-7	0,12	0,15	**0,08**	0,11
B-8	0,11	0,11	**0,07**	0,10
B-9	0,35	0,51	**0,26**	0,49
B-10	16,23	13,19	**9,53**	12,85
B-11	0,42	0,56	**0,29**	0,78
B-12	0,67	0,91	**0,50**	1,45

*Product codes are replaced for anonymity

Performance comparison of method that applied to A and B class products are shown in Table 4. According to Table 4, exponential smoothing generated the lowest MAPE values for most products except for one product where the moving average with 3 periods generated the lowest result and another product where linear regression periods generated the lowest result. Performance comparison of methods that applied to C class products are shown in Table 5. Croston's TSB method generated the lowest MAPE values for all products. Based on the results presented in the tables, we suggest that exponential smoothing should be used for demand forecasting of A and B class products and Croston's TSB method for C class products.

Table 5. Comparison of Mape Values on C Type Products

Product Code*	Croston TSB	Bootstrap	Croston	TSB
C-1	**0,13**	0,42	0,72	0,46
C-2	**0,09**	1,16	0,69	0,76
C-3	**0,11**	1,56	0,77	0,72
C-4	**0,13**	0,76	0,73	0,73
C-5	**0,12**	0,70	0,80	0,43
C-6	**0,03**	2,20	0,63	1,43
C-7	**0,10**	0,73	0,72	0,65
C-8	**0,13**	1,34	0,84	0,74
C-9	**0,06**	1,19	0,76	0,53
C-10	**0,11**	0,41	0,84	0,57
C-11	**0,11**	4,00	0,84	1,52
C-12	**0,02**	2,42	0,78	0,75

*Product codes are replaced for anonymity

3.2. Results of the Facility Location Problem

The facility location problem described in Section 2.2 is solved by a MINLP approach on GAMS solver in 9.22 seconds on a laptop computer with an Intel i5-1155G7 CPU with 2.50 GHz clock speed and 8 GB of RAM.

Our MINLP model, identified Warsaw, Poland as the optimal warehouse location with €197,004.78 profit where both absolute and relative gaps are at 0%. The model specified which customers are to be served directly by the factory and which are to be served via warehouses. The model also calculated the lead times from locations to customers which are shown in Table 6. Additionally, the model calculated the annual quantities of products to be sent to the warehouse and customers which will be used as an input in the inventory management problem.

Establishing a warehouse in Poland not only reduces logistics costs but also improves lead times and service levels for customers in European markets. A strategically placed facility can enhance operational efficiency and responsiveness, thus potentially improving the company's competitive position within the industry.

Table 6. Customer Served by locations

From Factory		From Warehouse	
Customer location	Lead Time (hour)	Customer location	Lead Time (hour)
Poland-City 1	73	Romania-City 1	12
Poland-City 2	61	Poland-City 3	2
Bosnia-City 1	39	Poland-City 4	3
Portugal-City 1	104	Poland-City 5	3
Lithuania-City 1	77		

*City names are replaced for anonymity

3.3. Results of the Inventory Management Problem

Multiple GA parameters are tested to find the best settings to minimise the total costs and it is observed that the minimum cost can be achieved with a population size of 100, a maximum generation number of 1000, an elitist rate of 0.1, the mutation rate of 0.4 and the stopping criteria are either reaching the maximum number of generations or if the best solution remains unchanged for 50 generations.

By implementing the genetic algorithm-based inventory management approach, the company has not only minimised holding and ordering costs but also enhanced stock availability, thus improving customer satisfaction.

3.4. Cost and Savings Analysis

Finally, we compared the existing system with the suggested system where a warehouse is opened in Poland-Warsaw and the ideal stock quantity (Q) and reorder point (R) determined by GA.

The direct shipment costs in the existing system were compared in detail with the shipment costs in the optimised system, which uses a warehouse-based approach. This comparison examined all logistical components, including product costs, direct and warehouse shipment transportation costs, delay costs associated with shipment delays, warehouse rent, and operational expenses. In this comparison, we used recent cost elements, such as 2024 fuel prices, driver services, warehouse rent, and other operational expenses, allowing for a comparison between shipments made from the new warehouse location and those previously made directly from the factory. In this process, customer locations and order quantities were evaluated as critical factors for determining the optimal warehouse location.

Through the optimisation model and genetic algorithm, the ideal stock quantity (Q) and reorder point (R) for the designated warehouse location abroad were calculated based on historical data and cost analysis. These values help optimise stock costs while supporting an on-time delivery process that enhances customer satisfaction.

As a result of these comparisons, the suggested warehouse-based system was found to provide a 26% cost saving compared to the existing non-warehouse-based system. This outcome clearly demonstrates the cost advantages of the suggested system that uses optimisation methods such as MINLP and GA approaches. Our study offers a strategic solution that reduces logistics costs and enhances operational efficiency.

3.5. Long Term Effects

The suggested system in this research contributes to the company’s long-term strategic goals and long-term benefits towards customer satisfaction and supply chain management. Our cost saving analysis shows that the suggested system promises a significant 26% cost reduction opportunity compared to the current system on the logistic costs involving storage and transportation costs. However, the cost reduction is not the only benefit of the suggested system. The system suggested warehouse with the optimal location and stock management strategy found by GA also promise reduction in delivery times that enhances customer satisfaction. The increased capacity to respond to customer demands more quickly and efficiently improve both customer loyalty and service quality. These long-term benefits will increase the firm’s competitive advantage and improve its position in the market.

4. Conclusion and Suggestions

This study addresses critical issues in the supply chain of a textile manufacturer company in Türkiye. Advanced forecasting techniques improved production planning and stock management accuracy. Methods like ABC analysis, Exponential Smoothing, and Croston's TSB method were used.

A mathematical model for facility location and inventory management optimised the Poland warehouse, reduced logistics costs, and improved delivery times. Combining EOQ with Genetic Algorithms minimised inventory costs and ensured optimal stock levels. Overall, the study enhanced efficiency, reduced costs, improved customer satisfaction, and resulted in a 26% profit increase.

Although the suggested system is designed for the considered textile company, its adaptability extends far beyond the textile sector and can be applied to other sectors or scenarios that involves supply chain and inventory management. For example, in the food and retail sectors, where consumption cycles and product lifespans are short, our suggested system may help to optimize the inventory levels and reduces waste. Especially in the electronics industry, where stock holding costs are high and demand chance quickly, our suggested system may lead significant cost savings. In the pharmaceutical and healthcare industries, our system helps to select optimal warehouse locations to ensures consistent availability of essential supplies. Through these diverse applications, our suggested system also increases the service levels and enhances the customer satisfaction.

Future research should explore the integration of emerging technologies such as machine learning and artificial intelligence to further enhance demand forecasting and inventory management. Additionally, continued evaluation of warehouse operations and logistics strategies will be essential to maintain and improve the firm's competitive edge.

Contributions of the authors

T.Tutkun: literature review, designing the study, methodology and performing the Experiments, writing, editing

İ. N. Nergiz: literature review, designing the study, methodology and performing the Experiments, writing, editing
R. Kaya: literature review, designing the study, methodology, writing and editing
U. Satıç: literature review, designing the study, methodology (only GA), writing and editing

Conflict of Interest Statement

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The study is complied with research and publication ethics.

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