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OPTIMIZATION

Portfolio design for home healthcare devices production using a new data-driven optimization methodology

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Abstract

Covid-19 pandemic left scars on different industries, and now that we are experiencing the post-pandemic situation, it is essential to plan our next moves. When it comes to home healthcare devices (HHDs), they can be useful in many aspects such as keeping the patients safe at the home. Nowadays, the world is experiencing the post-pandemic situation, then it is needed to adapt to new circumstances as it was done during the pandemic. One of the factors that has been impacted by the new situation is the demand for HHDs which had been increased tremendously during the pandemic. The current study aims to forecast the so-called demand by utilizing machine learning techniques to design a product portfolio considering the shortage cost by benefiting from the Bayesian Best–Worst method (BBWM). A mixed-integer non-linear mathematical model is proposed to reach this goal which designs a portfolio of devices and determines the number of needed machines to produce them. An HHD manufacturing factory has been considered as a real-life case study to approve the functionality of the proposed methodology. Several businesses that have experienced post-pandemic demand fluctuations may benefit from the findings of this study.

Keywords Home healthcare devices · Data-driven optimization · Bayesian best worst method · Time series · Product portfolio design

1 Introduction and literature review

Home health care devices (HHDs) can offer patients a secure and comfortable environment in their own homes, providing excellent value for money while also improving their quality of life (Clemente et al. 2019). HHDs encompass a wide range of devices, including wheelchairs, glucose meters, ventilators, and apnea monitors (FDA 2017). In addition, the use of remote monitoring systems allows doctors to monitor patients from a distance, reducing the need for close contact and ultimately lowering healthcare costs, as reported by Meng et al. (2021). By leveraging the benefits of HHDs and remote monitoring, patients can receive high-quality medical care without the need for frequent hospital visits, while healthcare providers can optimize their resources and deliver better care at a lower cost.

According to Bloomberg's report in 2021, the global home health care market is estimated to expand significantly, with a projected market size of USD 545.1 billion

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by 2028. This growth is primarily attributed to several factors, including the ongoing Covid-19 pandemic, the rising number of elderly individuals, and the increasing prevalence of chronic illnesses such as Alzheimer's and orthopedic-related problems (Bloomberg 2021). As a result, there is a lucrative opportunity for businesses to enter the market and capitalize on the growing demand for home health care services. By tapping into this market, companies can not only meet the rising demand for healthcare services but also contribute to improving the quality of life and health outcomes for patients in need of such services.

Pang et al. (2015) aimed to streamline three key components, including HHDs, services, and patient care, in their efforts to integrate home healthcare. Chaniaud et al. (2020) investigated the importance of educating patients on the proper use of HHDs and explored the potential impact of HHDs on patient outcomes. Keller et al. (2017) surveyed the challenges surrounding the appropriate use of HHDs, particularly among the elderly population, and examined the negative consequences of improper use. Thomson et al. (2013) examined the effects of using healthcare devices at home and found that while patients experienced some psychological benefits, there were also some negative outcomes associated with their use. Overall, these studies highlight the importance of proper education and training for patients using HHDs, as well as the need for healthcare providers to carefully consider the potential benefits and drawbacks of integrating such devices into patient care protocols.

Effective inventory management is a crucial aspect of organizational management, as emphasized by (Masoumi et al. 2021). However, due to the unique characteristics and limitations of each company, there is no one-size-fits-all solution to this issue. As a result, there are various inventory control models available to address specific business needs. The development of an appropriate inventory control model is a top priority for many industries, with the ultimate goal of achieving a balance between stock costs and client service, as noted by Tseng and Yu (2019). In the context of disaster management, Balcik et al. (2016) explored different types of inventory management models and policies used in humanitarian supply chains under critical circumstances. By adopting effective inventory management strategies, organizations can ensure that they have the necessary resources to meet customer demand while minimizing costs and maximizing profits. Hajipour et al. (2021) have also presented a mathmatical model to plan the distribution and the inventory of crucial items during a scenario of disasters.

In today's highly competitive marketplace, accurate and real-time forecasting of product demand is crucial, as emphasized by Chaudhuri and Alkan (2022). However, demand in inventory management models can take different forms. Basic and traditional models typically assume perfect information and deterministic demand, where the demand is exactly certain. However, in real-world scenarios, demand is often uncertain, which can be addressed using Fuzzy and stochastic methods. Stochastic processes, a subfield of probability theory, can be used to model and analyze uncertain demand. Stationary demand has a fixed probability distribution with parameters that can be estimated from collected data and remain constant over time, as reported by Ma et al. (2021) and Sun and Van Mieghem (2019). In contrast, non-stationary demand has time-dependent parameters and distributions that change over time (Azadi et al. 2019; Chen and Rossi 2021; Nagarajan and Shi 2016; Nasr and Elshar 2018). To address these uncertainties, a data-driven approach can be employed, where random variables are modeled with uncertain parameters and observations are used as input data for mathematical programming problems, as suggested by Bertsimas and Thiele (2006). By utilizing these methods, organizations can make informed decisions based on accurate demand forecasts, optimizing their inventory management processes to meet customer needs and maximize profits.

Because of rising in health care expenditures, many countries are experiencing remarkable economic pressure (Mirabnejad et al. 2022). As healthcare costs continue to rise and the demand for healthcare services grows, the need for efficient and well-planned healthcare systems has become a top priority for governments and healthcare managers, as highlighted by Ahmadi-Javid et al. (2017). Inventory management is a critical issue in healthcare systems, requiring a carefully planned approach that takes into account the unique characteristics of these systems. The goal is to minimize inventory costs while maximizing other desirable outcomes, as noted by Saha and Ray (2019). Mathematical modeling has emerged as a useful tool for addressing inventory management challenges in healthcare systems (Dabiri et al. 2017; Paul et al. 2022). Using mathematical models, healthcare organizations can streamline inventory management processes, optimize resource utilization, and improve patient outcomes while minimizing costs. Effective inventory management can ultimately lead to better healthcare services and more sustainable healthcare systems.

Niakan and Rahimi (2015) aimed to propose a mathematical model with multiple objectives to address a routing problem in healthcare inventory management, specifically in the distribution of medical drugs to healthcare facilities. Hovav and Tsadikovich (2015) presented a model for managing inventory of influenza vaccines using mixed-integer programming techniques. Cappanera et al. (2019) developed a mathematical model to manage drug inventory in intensive care units, taking into account the relationships between the three key stakeholders. Tavana et al. (2021) focused on developing an inventory and location mathematical programming model for Covid-19 vaccine distribution in developing countries. Aghsami et al. (2023) proposed a inventory management integrated to location-allocation mathematical problem in a healthcare system. Babaei et al. (2023) presented an efficient inventory control for sustainable vaccination distribution using a multi-objective mathematical model considering risk assessment. However, in mathematical programming, problems are typically solved by assuming that the data are definite, whereas in the real world, data are often uncertain. Hence, addressing uncertainty is a critical aspect of mathematical modeling in inventory management in healthcare systems. By utilizing mathematical models that incorporate uncertainty, healthcare organizations can make more informed decisions, improve resource allocation, and optimize inventory management processes, ultimately leading to better healthcare outcomes and more sustainable healthcare systems.

Mathematical programming involves developing a model based on certain data assumed to be equal to a nominal value. However, this approach does not account for the impact of data uncertainty, which can lead to occasional errors such as non-optimal solutions due to data loss or accidental editing. To address this issue, data-driven optimization combines machine learning, operations research, and management science to create a framework for achieving optimal decisions with specific strategies, as proposed by Bertsimas and Kallus (2020). Recent studies have also applied big data analysis to logistics and supply chain management as a data-driven optimization problem, as reported by Maheshwari et al. (2021). Big data analysis can be applied to various areas of operations management, as explored by Choi et al. (2018). By leveraging the power of data-driven optimization, organizations can make more informed decisions, improve resource allocation, and optimize their operations management processes, leading to enhanced efficiency and better outcomes.

Data mining and machine learning algorithms have proven to be effective in inventory management. Clausen and Li (2022) developed a new data-driven method for the big data-driven newsvendor inventory model, which utilized the principle of empirical risk minimization. Yousefli et al. (2022) proposed a data-driven approach to designing a stochastic rule-based decision support system to help investors infer reliable and near-optimal investment weights. This approach employs optimum knowledge derived from stochastic portfolio problems. Baker et al. (2013) proposed a new algorithmic data-driven model for inventory control of cash in automated teller machines (ATMs) to minimize the amount of cash held in the ATM while satisfying client demand for cash. Cai et al. (2022) investigated the optimal repositioning of empty containers between public hinterlands and ports in a regional port network over multiple time periods, utilizing both numerical and periodical inventory management tactics. By incorporating data mining and machine learning algorithms into inventory management, organizations can make more informed decisions, optimize resource utilization, and improve customer service while minimizing costs. These data-driven approaches offer a promising solution to the complex challenges faced by inventory management in various industries.

Marketers are increasingly leveraging data to improve and refine their marketing strategies and portfolio design, as noted by (Luna et al. 2016). Marketing databases were first developed in the late 1980s to the early 1990s, where data were collected from customers. Over time, these databases expanded, and more features were added, allowing businesses to provide profitable services to their customers. Using data to generate relevant and timely marketing offers is a viable approach to better serve customers, according to Micheaux and Bosio (2019). Data-driven optimization seeks to enhance the performance of optimization methods by utilizing machine learning algorithms, big data analysis, deep neural networks, and other advanced tools, as reported by Pisacane et al. (2021). Ultimately, data-driven optimization can lead to better customer experiences, increased customer loyalty, and improved business performance.

With increasing population growth, civilization, and infectious diseases like Covid-19, there is a growing demand for healthcare devices. Additionally, people are seeking more convenient healthcare options due to the time and cost associated with frequent checkups and traffic congestion. As a result, HHDs are becoming increasingly popular, presenting a golden opportunity to address this issue. This study aims to develop suitable HHDs based on market demand. Firstly, the market needs to be investigated, and demand for the products evaluated. Secondly, machine learning algorithms are utilized to forecast demand. Finally, a new data-driven optimization problem is solved by formulating a mathematical model and considering inventory management concepts and historical data. This optimization problem determines the optimal production quantity for each product. By leveraging these techniques, organizations can optimize their inventory management processes, minimize costs, and improve resource utilization, ultimately leading to better healthcare outcomes for patients.

After conducting a thorough review of the literature and relevant articles, several research gaps have been identified, including the following:

- While many articles have focused on healthcare products, very few have considered home healthcare products, which represents a significant gap in the literature.
- Among the limited number of articles on home healthcare products, almost none have utilized mathematical modeling integrated with inventory management methods, which could significantly enhance the efficiency of inventory management.
- Marketing and novel multi-attribute decision-making (MADM) methods have been rarely observed in the reviewed articles, indicating a potential area for further research.
- Data-driven optimization is widely used in various inventory management models, but it is rarely utilized for inventory management of home healthcare products, which presents an opportunity for future research to improve inventory management processes in this area.

Addressing these research gaps could lead to significant advancements in home healthcare product inventory management, ultimately resulting in better healthcare outcomes for patients and more sustainable healthcare systems. By incorporating mathematical modeling, MADM, and data-driven optimization techniques, organizations can make more informed decisions, optimize resource utilization, and improve their inventory management processes.

The remaining sections of this study are structured as follows. In Section two, the problem is introduced, and a mathematical model is presented. Section three outlines the solution approach utilized in this study. In Section four, the model is applied to real-life examples with smaller dimensions. Section five presents a real-life case study that demonstrates the model's usefulness, along with the corresponding computational results. The sensitivity analysis is conducted in Section six to investigate the impact of various parameters on the model. Section seven provides a useful discussion and managerial insights. Finally, Section eight presents a detailed conclusion and a brief acknowledgment.

2 Problem description and mathematical modeling

2.1 Problem description

HHDs have broad applications for patients of all ages, including elderly individuals, children, those with underlying medical conditions, and those with disabilities. These patients require constant monitoring, which can be time-consuming and costly if done through frequent specialist visits. However, HHDs can significantly reduce the need for such visits, as they allow patients to monitor their health and vital signs from the comfort of their own homes. This convenience not only saves time and money but also provides patients with greater independence and quality of life.

This study considers a factory that produces HHDs and experienced a significant shift in demand due to the Covid-19 pandemic, requiring changes to its production planning. With the world now in a post-pandemic situation, the factory must update its production planning to meet new demands and circumstances. The initial data on the estimated production of each device can be used by the manager to update the factory's layout, including selling some of the current machines and acquiring the necessary ones. To determine the appropriate production quantities for each device, a mathematical model is implemented, taking into account forecasted demand and inventory management methods.

As depicted in Fig. 1, this study comprises two stages. In the first stage, a dataset containing the number of sold devices is collected. A time series model with multiple parameters is utilized to forecast the demand for each device. The most appropriate set of parameters is then selected based on specific performance criteria, as outlined by Ngaffo et al. (2022). The second stage aims to determine the optimal production quantity for each device. Initially, the Bayesian best–worst method (BBWM) is used to identify the shortage costs of each device. Subsequently, a mathematical model is proposed, utilizing the calculated parameters from the previous steps, to determine the decision variables of the model. By following this two-stage approach, this study provides a comprehensive and detailed analysis of the inventory management problem in home healthcare products, with practical insights and recommendations for decision-makers in the healthcare industry.

To formulate the model, several assumptions are made, including:

- Each device has an existing operation process chart (OPC) designed for it.
- The production quantity of each device varies depending on the machine used.
- The cost of producing each device differs depending on the machine used.
- Production planning is conducted on a period-by-period basis.
- Storage capacity is limited and must be taken into account.
- A product portfolio is considered when selecting which devices to produce.
- All parameters are deterministic and not subject to variability.

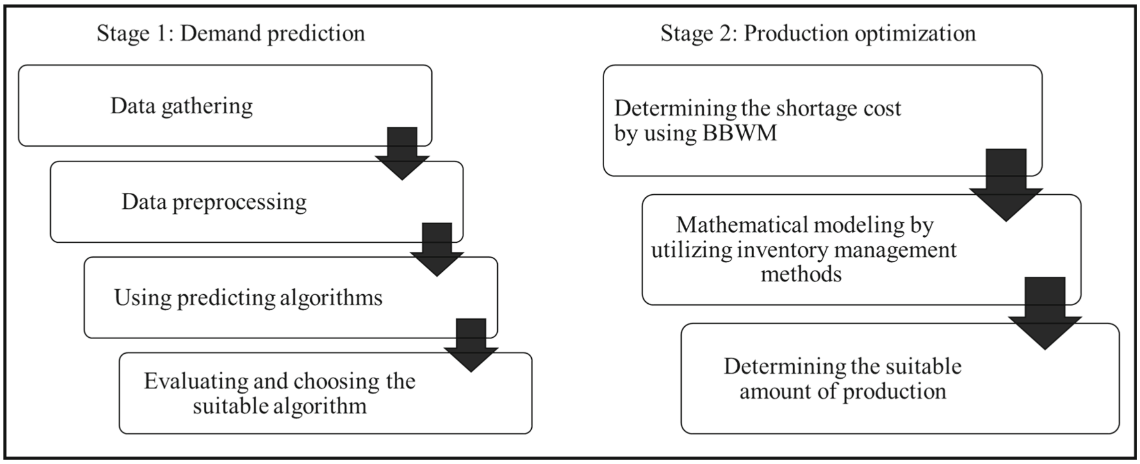


Fig. 1 Stages of the proposed methodology

By taking these assumptions into account, the model's framework is established, providing a basis for effective inventory management strategies in the production of HHDs.

2.2 Mathematical modeling

To reach the optimal amount of production of each device from the portfolio including some devices to set up the factory for the first period, a mixed-integer non-linear programming is proposed. Regarding the OPC, each device requires some machines to be produced. Also, a machine can be used in several OPC of devices. It is obvious a machine will be used if at least one device is produced by this machine.

Table 1 lists a description of the used notations in the mathematical model.

$$Max\ Z = \sum_{i=1}^{i=I}[(R_i - C_i)X_i(1 - Y_i) + (R_i - C_i)D_iY_i - \gamma\pi_i(D_i - X_i)(1 - Y_i)] + \sum_{j=1}^{j=J}(SV_j(N_j - A_j)(1 - Y'_j)) - \sum_{j=1}^{j=J}(P_j(A_j - N_j)Y'_j) \tag{1}$$

Equation (1) maximizes the total profit gained by the production of devices. $[(R_i - C_i)X_i(1 - Y_i) + (R_i - C_i)D_iY_i]$ indicates the profit gained by selling the devices. If the amount of production is greater than the demand, the gained profit is equal to $(R_i - C_i)D_iY_i$ and if the amount of production is less than the demand, the gained profit by selling the devices is equal to $(R_i - C_i)X_i(1 - Y_i)$. The last argument, $\gamma\pi_i(D_i - X_i)(1 - Y_i)$, indicates the shortage cost caused by producing a smaller amount of production than the forecasted demand for device i. $\sum_{j=1}^{j=J}(SV_j(N_j - A_j)(1 - Y'_j))$ represents the value earned by selling the unneeded machines. $\sum_{j=1}^{j=J}(P_j(A_j - N_j)Y'_j)$ shows the cost caused by buying the needed machines.

$$X_i \in \{1, 2, \ldots, I\} X_i \geq D_i - M(1 - Y_i) \tag{2}$$

$$X_i \in \{1, 2, \ldots, I\} X_i \leq D_i + MY_i \tag{3}$$

In constraints (2) and (3), if $Y_i = 1 \Rightarrow X_i \geq D_i$, which shows that the amount of production of device i is more than its demand. If $Y_i = 0 \Rightarrow X_i \leq D_i$, which shows that the amount of production of device i is less than its demand.

$$X_j \in \{1, 2, \ldots, J\} A_j = \left[\left(\sum_{i=1}^{i=I}\frac{O_{ij}X_i}{\mu_{ij}}\right) - \varepsilon\right] + 1 \tag{4}$$

Equation (4) demonstrates the number of needed machines of machine$j$. This equation is obtained based on the Francis method (Richard and Francis 1974; Suby 1975). Using this method, one can determine the number of each machine in a multi-operational process where J machines are supposed to produce a certain number of I products. Here, a very small number called epsilon (ε) is used so that when the value inside the bracket function takes an integer value, the number of machines are calculated correctly. Otherwise, it calculates wrongly the number of machines one more.

$$X_j \in \{1, 2, \ldots, J\} A_j \geq N_j - M\left(1 - Y'_j\right) \tag{5}$$

$$X_j \in \{1, 2, \ldots, J\} A_j \leq N_j + MY'_j \tag{6}$$

In constraints (5) and (6), if $Y'_j = 1 \Rightarrow A_j \geq N_j$, which shows that the number of needed machines of machine j is more than the available number of these machines. If $Y'_j = 0 \Rightarrow A_j \leq N_j$, which shows that the number of needed

Table 1 The used notations

Indexes	
i	Set of devices, $i\epsilon\{1,2,\ldots,I\}$
j	Set of machines, $j\epsilon\{1,2,\ldots,J\}$
Parameters	
R_i	The revenue of selling device i
C_i	The production cost of device i
D_i	The forecasted demand for device i
π_i	The shortage cost of device i
P_j	The cost of buying machine j
SV_j	The selling value of machine j
N_j	The number of available machines of machine j
O_{ij}	If device i is produced by machine j it is equal to 1; otherwise, 0
α	The coefficient used to determine the initial cost of production
γ	The shortage cost caused by the lack of one unit of each device
λ	The coefficient used to determine the maximum storage space during the period
B	The maximum amount of budget dedicated to setting up the factory
μ_{ij}	The number of devices of device i that can be produced by machine j in a period
S_i	The amount of space that device i needs to be stored
F	The maximum amount of storage space
Variables	
X_i	The amount of production of device i
A_j	The number of machines needed of machine j
Y_i	The Boolean variable is 1 if there is a holding cost and is 0 if there is a shortage cost
Y'_j	The Boolean variable is 1 if there is a need to buy machine j and is 0 if there is a need to sell machine j

machines of machine j is less than the available number of these machines.

$$\sum_{j=1}^{j=J}(P_j(A_j-N_j)Y'_j)+\alpha\sum_{i=1}^{i=I}C_iX_i\leq B+\sum_{j=1}^{j=J}(SV_j(N_j-A_j)(1-Y'_j)) \tag{7}$$

Constraint (7) indicates the budget constraint which consists of the cost of purchasing the needed machines ($\sum_{j=1}^{j=J}(P_j(A_j-N_j)Y'_j)$), the initial cost of production of the devices ($\alpha\sum_{i=1}^{i=I}C_iX_i$), and $\sum_{j=1}^{j=J}(SV_j(N_j-A_j)(1-Y'_j))$ the value gained by selling the unneeded machines.

$$\sum_{i=1}^{i=I}\lambda S_iX_i\leq F \tag{8}$$

Constraint (8) determines the maximum capacity of the total storage space.

$$X_i, A_j\geq 0, \text{integer} \tag{9}$$

$$Y_i, Y'_j\in\{0,1\}$$

Constraint (9) indicates that X_i and A_j are positive-integer variables. Furthermore, Y_i and Y'_j are equal to zero or one.

3 Solution approach

3.1 Determining the weight of shortage cost

MADM methods in situations involving multiple criteria are useful in guiding decision-makers (DMs). Mohammadi and Rezaei (2020) have proposed an accurate MADM method called the Bayesian Best–Worst Method (BBWM). BBWM is capable of finding the optimal weightings of several criteria using DM opinions. In this study, different devices are considered, which have different costs of shortage. In determining these different weights of costs, BBWM is used in this study. Its formulas are described below.

$$\mathrm{P}\left(\mathrm{W}^{\mathrm{agg}},\mathrm{W}^{1:\mathrm{K}}|\mathrm{A}_{\mathrm{B}}^{1:\mathrm{K}},\mathrm{A}_{\mathrm{W}}^{1:\mathrm{K}}\right) \tag{10}$$

Equation (10) is the joint probability that calculates the probability of overall optimal weight ($\mathrm{W}^{\mathrm{agg}}$) and each DMs optimal weight ($W^{1:K}$) taking into consideration the amount of the "Best-to-Others" vector (A_B) and the "Others-to-Worst" vector (A_W) for each DM.

$$P(X) = \sum_{y} P(x,y) \tag{11}$$

Equation (11) shows the probability of each variable that can be computed by its marginal probability.

$$P\left(A_W^K | W^{agg}, W^K\right) \tag{12}$$

Equation (12) shows that A_W^K is dependent on W^K, but independent of W^{agg}.

$$\begin{aligned} &P\left(W^{agg}, W^{1:K} | A_B^{1:K}, A_W^{1:K}\right) \\ &\quad = P\left(A_B^{1:K}, A_W^{1:K} | W^{agg}, W^{1:K}\right) \times P\left(w^{agg}, w^{1:K}\right) \\ &\quad = P(W^{agg}) \prod_{k=1}^{K} P(A_W^k | w^k) P(A_B^k | w^k) P(w^k, w^{agg}) \end{aligned} \tag{13}$$

Equation (13) has exploited the Bayes rule for the joint probability considering that $A_W^{1:K}$ is independent of W^{agg} for all DMs. Due to the individual opinions each DM provides and the conditional independence of variables that each DM applies, the final equality is made. In this equation, there are variables and parameters that are dependent upon one another, so there is a chain of relationships between them. That is why it is called a hierarchical model.

$$A_B^k | w^k \sim \text{multinomial}(1/w^k)$$

$$A_B^k | w^k \sim \text{multinomial}(w^k) \tag{14}$$

Equation (14) shows that the multinomial distribution has been used to model $A_B^k \text{and} A_w^k$.

$$w^k | w^{agg} \sim \text{Dir}(\gamma \times w^{agg}) Xk = 1, \ldots, K \tag{15}$$

According to Eq. (15), each DM's weight vector w^k must be adjacent to w^{agg}.γ indicates the concentration parameter, which is non-negative.

$$\gamma = \text{gamma}(a,b) \tag{16}$$

According to Eq. (16), the concentration parameter is a variable that has gamma distribution and (a, b) parameters that satisfy non-negativity constraints.

$$w^{agg} \sim \text{Dir}(\alpha) \tag{17}$$

Equation (17) shows w^{agg} has the Dirichlet distribution with the parameter $\alpha = 1$.

3.2 Demand forecasting

Nowadays, as organizations face sudden and enormous fluctuations that affect the most well-established structures and business sectors require accurate and practical information about the future, forecasts are becoming increasingly critical since they keep the business alive. A forecast is an estimation of a variable's future level. Most of the time, the variable is demand (Alipour-Vaezi et al. 2022). In this study, time series is applied to forecast the demand for the devices during post-pandemic situations. Kurawarwala and Matsuo (1998) examined the forecast performance with regard to seasonal variations of demand using historical data and an autoregressive moving average hypothesis. To enhance forecasting accuracy, Miller and Williams (2003) combined seasonal factors into their model, which are derived from multiplicative models. Miller and Williams' work was expanded by Hyndman (2004) by applying the seasonal Autoregressive Integrated Moving Average (ARIMA) hypothesis to different relationships between trend and seasonality. The seasonal ARIMA is one of the most widely used techniques in time series forecasting (Ravuri and Vasundra 2022).

The ARIMA model is a method to fit time series data so that future points in the series can be better understood or predicted (Fattah et al. 2018). Parameterizing ARIMA models involves three distinct integers (p, d, q). As a result, ARIMA models are written as ARIMA (p, d, q). In datasets, these three parameters address seasonality, trend, and noise.

- p is the auto-regressive component of the model. The influence of previous values is incorporated into the model by including it.
- d represents the integrated component of the model. It appends terms in the model that embeds the amount of differencing (i.e., subtracting past time points from the current value) to be applied to the time series.
- q addresses the moving average component of the model. Consequently, the model's error can be calculated as a linear combination of previous error values at each time point in the past.

To deal with seasonal effects, seasonal ARIMA is applied, which is represented as ARIMA (p, d, q) (P, D, Q)s. As discussed before, (p, d, q) are the non-seasonal parameters, whereas (P, D, Q) are the same as (p, d, q) but have been applied to the seasonal component of the time series. s stands for the periodicity of the time series (4 for quarterly periods, 12 for annual periods, etc.). Due to its multiple tuning parameters, seasonal ARIMA can appear intimidating to beginners.

In this subsection, alongside ARIMA and seasonal ARIMA concise descriptions of the other forecasting models utilized in this study are provided to enhance the comprehensibility of our research.

- Simple Exponential Smoothing (SES): SES is a simple and intuitive approach used in time series forecasting. It employs exponential smoothing to assign weights to previous observations, placing greater emphasis on recent data points. SES proves especially beneficial when there is a lack of prominent trends or seasonal patterns in the data. Its popularity stems from its ease of use and computational efficiency, making it a favored option for forecasting endeavors (Ostertagová and Ostertag 2011).

- Long Short-Term Memory (LSTM): LSTM is a type of recurrent neural network (RNN) that excels at capturing complex temporal dependencies. Unlike traditional feedforward neural networks, LSTM has a memory cell that can retain information over long sequences. This property makes LSTM well-suited for modeling time series data, including demand forecasting, where capturing both short-term and long-term dependencies is crucial (Hochreiter and Schmidhuber 1997).

By utilizing a combination of these diverse forecasting models, we aimed to comprehensively evaluate their performance in demand forecasting. The inclusion of ARIMA, SES, LSTM, and Seasonal ARIMA allowed us to analyze their respective strengths and weaknesses.

The selected models, ARIMA, SES, LSTM, and Seasonal ARIMA, were chosen based on their established effectiveness in time series forecasting. ARIMA and Seasonal ARIMA are widely used for capturing trend and seasonality (ArunKumar et al. 2021), SES is suitable for simple exponential smoothing (Hyndman and Athanasopoulos 2018), and LSTM is known for its ability to capture complex temporal dependencies (Hochreiter and Schmidhuber 1997). By employing these diverse models, we aimed to comprehensively evaluate their performance and identify the most suitable model for demand forecasting.

To explore different parameter combinations iteratively, the grid search will be used. The overall quality of each model is assessed for each combination of parameters and the optimal set of parameters will be selected based on some criteria. To evaluate and compare statistical models fitted with different parameters by ranking them based on their ability to accurately forecast future data points or how well they fit the data, the Akaike Information Criterion (AIC) value will be calculated. Models are evaluated by their AIC, which measures how well they fit the data. Models that achieve the same goodness-of-fit with fewer features will be assigned a lower AIC value than models with more features. So, the model with the lowest AIC will be chosen. Also, there are some other criteria to calculate the error obtained from the difference between the real amount and the forecasted amount.

$$\text{Mean Squared Error (MSE)} = \frac{\sum_{i=1}^{N} e_i^2}{N} \tag{18}$$

Equation (18) shows how close a fitted line is to data points. e_i indicates the error which is calculated by the difference between the real amount and the forecasted amount.

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{\sum_{i=1}^{N} \left| \frac{e_i}{y_i} \right|}{N} \tag{19}$$

Equation (19) shows an average or mean of forecast errors as a percentage. y_i is defined as actual or observed value.

3.3 Mathematical modeling solution

The study uses the Gams software version 25.1.2, Baron solver, and an Asus laptop with 16 GB ram and a Core-i7 CPU to solve a mixed-integer non-linear programming model. The following section illustrates numerical examples for small- and medium-size problems that took only a short time to solve. Because of this low time, the Gams software will be able to solve the real-life case study in a reasonable amount of time as an exact solution.

4 Numerical examples

In this section, the mathematical model is applied to a small-scale and medium-scale problem to verify its functionality. The value of parameters of small-scale and medium-scale problems are shown in Table2.

4.1 Small-scale problem results

The objective function of 257,541 units is calculated by solving the small-scale problem (Table 3). The results are shown in Table 4. For example, 4366 number of device 1 should be produced and 5 number of machine 2 is needed, which means 4 number of machine 1 should be sold due to its entity which is 9.

4.2 Medium-scale problem results

The objective function of 358,803 units is calculated by solving the medium-scale problem. The results are represented in Table 5. For example, 3003 number of devices 1 should be produced and 1 number of machines 1 is needed which means 2 number of machines 1 should be sold due to its entity which is 3. This model is intended to investigate its functionality, so the maximum storage space has been increased, and the objective function is expected to increase as well. According to Fig. 2, increasing the storage spaces has the expected effect of increasing the

Table 2 The values of small-scale problem

i	j	α	B	F	D_1	D_2	D_3	N_1	N_2	N_3	N_4	N_5
3	5	0.1	80,000	70,000	14,000	18,500	9555	4	9	3	6	9

Table 3 The values of medium-scale problem

i	j	α	B	F	D_1	D_2	D_3	D_4
5	7	0.1	80,000	40,000	14,000	18,500	9555	12,000
D_5	N_1	N_2	N_3	N_4	N_5	N_6	N_7	
8500	4	9	3	6	9	7	5	

Table 4 Small-scale problem results

X_1	X_2	X_3	A_1	A_2	A_3	A_4	A_5
4366	12,410	9544	4	5	6	6	3

Table 5 Medium-scale problem results

X_1	X_2	X_3	X_4	X_5	A_1	A_2	A_3	A_4	A_5	A_6	A_7
3003	0	0	0	7003	1	4	0	5	1	2	2

objective function. Therefore, it can be used to solve the case study problem.

5 Real-life case study

To demonstrate the effectiveness of the proposed model and validate its efficiency, a specific factory has been used as a real-life case study. In light of the post-pandemic situation, the demands for devices have changed. Therefore, the factory manager has been seeking to reselect the devices to be manufactured in the next period, which is determined to be six months, to adapt to new circumstances. This factory has a portfolio of 8 devices ($I = 8$) and 10 machines ($J = 10$). Table 6 represents the parameters related to devices, including the revenue of selling devices, the production cost of devices, the forecasted demand for devices which is determined in Sect. 5.2, the shortage cost of devices which is determined in Sect. 5.3, and the amount of space that devices need to be stored. Table 7 shows parameters related to machines, including the cost of buying the machines, the selling value of machines, and the number of available machines. Table 8

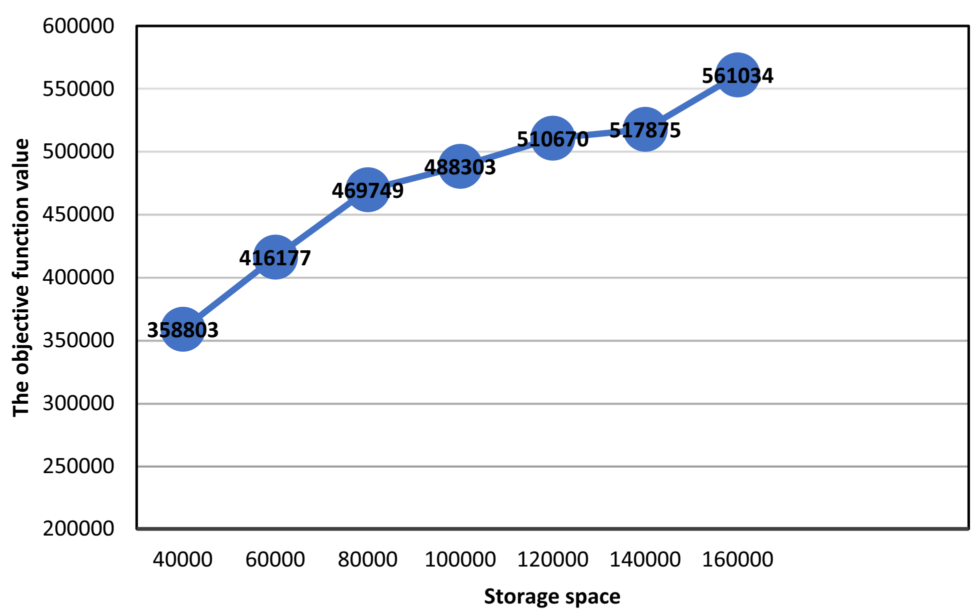


Fig. 2 The impact of storage space on the objective function

Table 6 Parameters related to devices

Device Parameter	1	2	3	4
R_i	175	155	410	110
C_i	135	100	360	80
D_i	4342	4892	4177	6931
π_i	0.197	0.174	0.067	0.199
S_i	15	22	30	23
Device Parameter	5	6	7	8
R_i	55	125	45	560
C_i	35	95	35	500
D_i	7706	5486	9833	4179
π_i	0.088	0.152	0.055	0.068
S_i	10	15	12	39

Table 7 Parameters related to machines

Machine Parameter	1	2	3	4	5
P_j	35,000	30,000	45,000	35,000	21,000
SV_j	24,000	23,000	35,000	25,000	10,000
N_j	2	5	5	4	7
Machine Parameter	6	7	8	9	10
P_j	15,000	15,000	28,000	35,000	55,000
SV_j	10,000	10,000	15,000	20,000	35,000
N_j	6	6	5	3	4

Table 8 O_{ij}(The operation of each device on each machine)

Machine j Device i	1	2	3	4	5
1	1	0	1	0	0
2	1	1	0	1	1
3	0	1	1	0	0
4	0	0	0	1	1
5	0	1	1	0	1
6	1	1	1	0	0
7	0	0	0	1	1
8	0	1	0	1	0
Machine j Device i	6	7	8	9	10
1	1	0	0	0	1
2	0	0	0	1	1
3	1	0	1	0	1
4	1	0	1	1	0
5	1	1	1	1	0
6	0	1	0	1	0
7	0	1	1	0	1
8	0	1	0	0	1

Table 9 μ_{ij}(The capacity of machine j to produce device i)

Machine j Device i	1	2	3	4	5
1	1500	–	2500	–	–
2	2500	1500	–	2000	1000
3	–	2500	4400	–	–
4	–	–	–	5000	3000
5	–	4000	1000	–	2000
6	3000	3000	1500	–	–
7	–	–	–	3000	2000
8	–	1500	–	2500	–
Machine j Device i	6	7	8	9	10
1	1500	–	–	–	3500
2	–	–	–	2000	2000
3	2500	–	1500	–	1500
4	3000	–	1000	2500	–
5	2500	1500	3500	3500	–
6	–	1000	–	2000	–
7	–	2500	2000	–	2000
8	–	3000	–	–	2500

addresses machines needed to produce devices, and Table 9 represents the number of devices that can be produced by machines. The rest of the parameters are represented in Table 10. An appropriate selection of devices must be made based on the proposed parameters in Tables 6, 7, 8, 9, and 10.

5.1 Multi-criteria decision-making results

As explained in Sect. 3.1, BBWM is used to determine the weight of shortage cost of devices. The DMs consist of one factory manager, one production manager, one sales manager, and two marketing specialists. The weights of shortage costs obtained by BBWM are represented in Table 11.

Table 10 The case study details

Parameters	Values
α	0.3
γ	200
λ	0.3
B	100,000
F	60,000

Table 11 Weights of shortage cost of devices

Devices	Weights
1	0.197
2	0.174
3	0.067
4	0.199
5	0.088
6	0.152
7	0.055
8	0.068

5.2 Time series result

This study has taken advantage of the Python programming language which is widely used in various fields, including machine learning and forecasting. As discussed in Sect. 3.2, the seasonal ARIMA model is applied to forecast the demand for the devices. The monthly demand for different devices from January 2016 to July 2022 (79 records) is gathered to build the data set. The data set is separated to train and test data sets. The train data set consists of the demand from January 2016 to April 2021 and the rest make up the test data set. To evaluate the performance of the various model with different sets of parameters, the AIC value has been used. For example, the AIC, MSE, and MAPE values for different sets of parameters for forecasting the demand for device 1 are represented in Table 12. According to this table, the lowest AIC value is 487.2848 which is obtained by the set $\text{ARIMA}(1,1,1) \times (0,1,1)^{12}$. Figure 3 compares the actual and forecasted demand for the test data set obtained by the so-called set. This set is used to forecast the demand for device 1 from August 2022 to January 2023 (6 months). The results of forecasting are represented in Table 13, which indicates the total demand for device 1 is 4342.

Table 12 The performance results of forecasting the demand for device 1

(p,d,q)	$(P, D, Q)^s$	AIC	MSE	MAPE
(0, 0, 0)	$(0, 0, 0)^{12}$	931.8216	418,001	1
(0, 0, 0)	$(0, 0, 1)^{12}$	735.3725	201,554	0.62
(0, 0, 0)	$(0, 1, 0)^{12}$	684.0194	62,446	0.31
(0, 0, 0)	$(0, 1, 1)^{12}$	522.072	54,332	0.29
…	…	…	…	…
(1, 1, 1)	$(0, 1, 1)^{12}$	487.2848	6631	0.06
(0, 0, 1)	$(1, 1, 0)^{12}$	530.0665	65,290	0.33
(0, 0, 0)	$(1, 1, 0)^{12}$	532.3556	66,036	0.34

Based on Table 14, the study conducted a comparative analysis of seasonal ARIMA algorithms with three other popular time series forecasting techniques, namely ARIMA, SES, and LSTM. The comparison was carried out by applying a grid search approach to determine the best set of parameters for each algorithm. The results showed that seasonal ARIMA outperformed the other techniques in terms of forecast error, as it achieved the lowest values for both MAPE and MSE metrics. Therefore, the findings suggest that seasonal ARIMA is a superior forecasting method compared to the other techniques evaluated in the study. This indicates that seasonal ARIMA is better at capturing the underlying patterns and trends in the data, and is able to make more accurate predictions of future demand patterns. This superiority of seasonal ARIMA over the other algorithms can be attributed to its ability to model the seasonality, trend, and noise components of time series data, which makes it particularly effective in forecasting demand for devices. Overall, the comparison in Fig. 4 provides strong evidence for the effectiveness of seasonal ARIMA in forecasting time series data, and suggests that it is a reliable tool to be used in this research.

The LSTM algorithms has the worst results among them. There could be several reasons why the LSTM model has the worst results among the three models (ARIMA, LSTM, and SES). One of them is insufficient data. The LSTM model may require a larger amount of data to learn complex patterns and relationships in the data. If the dataset is relatively small, the LSTM model may not be able to learn meaningful patterns and may perform poorly compared to simpler models like ARIMA and SES. Given the limited dataset of only 79 records used in this study, it is reasonable to expect that the performance of the LSTM model would be less than others due to insufficient data.

5.3 Mathematical modeling results

After determining the weight of shortage cost of the devices and the demand for each device as described in two previous sections, as well as using the other entrance parameters, the mathematical model is solved by the GAMS software to select which and how many devices to be produced among the portfolio. The amounts of production of devices are addressed in Table 15. Based on this

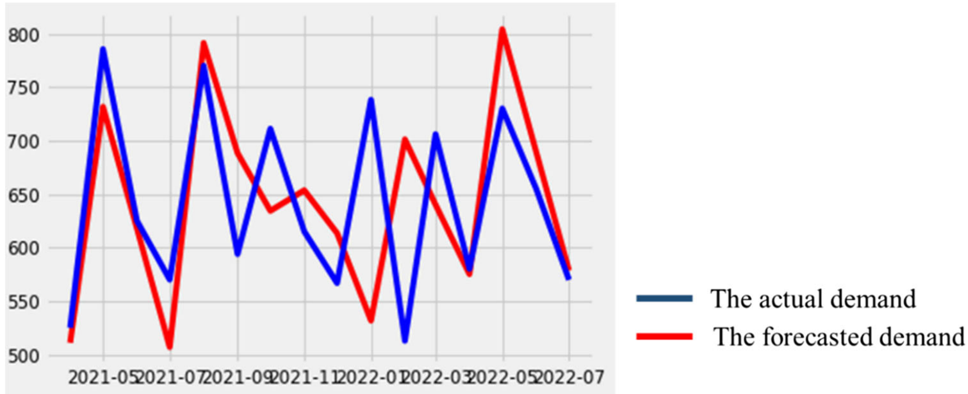


Fig. 3 Comparison between the actual and forecasted demand

Table 13 The results of the forecast of demand for device 1

Date	Demand forecast
August 2022	863
September 2022	760
October 2022	706
November 2022	725
December 2022	685
January 2023	603
The total demand for the period	4342

Table 14 MSE and MAPE values of optimum forecasted algorithms

FORECASTING ALGORITHMS	MSE	MAPE
SARIMA	6631	0.06
ARIMA	12,187	0.13
SES	12,941	0.13
LSTM	40,549	0.26

table, devices 1–4 are selected to be produced. Despite the significant profit gained by producing device 8 which is the most profitable device, it was not selected because of its large storage space and expensive machines needed for producing it.

Table 16 represents the number of needed machines. It can be concluded that machines 1 and 8 should be bought and the other machines should be sold for different amounts which are calculated by the difference between the needed machines (A_j) and the available machines (N_j). For example, 3 machines of machine 1 are needed and 2 machines of this machine are available, which means 3–2 = 1 machine should be bought. Regarding this selection, the objective value is calculated at 159,241 units.

6 Sensitivity analysis

The purpose of the sensitivity analysis in this section is to identify the impact of changing some parameters on the model so that the results can assist the DMs. The impact of R_i, γ, B, and F on the objective function value, summation of the amount of production of devices, and summation of the number of needed machines will be studied.

6.1 Impact of revenue of selling the devices

The impact of changes in revenue from selling devices will be examined in this section. Device 8 is selected as a sample to survey its revenue changes. According to Fig. 5, as the revenue caused by selling device 8 increases, the objective function value improves too. Regarding Fig. 6, the increase in revenue of device 8, at first, makes no changes in its amount of production of device 8 till point 570, then it will boost the amount of production to 2965 units. The amount of production plateau at this level as the revenue increases till point 610. At last, the amount of production reaches 4179 units. Based on Fig. 7, as the revenue increases, the number of needed machines of machine 7 acts as the amount of production, and its overall trend is increasing.

6.2 The impact of γ

The impact of changes in γ will be studied in this section. Based on Fig. 8, as γ increases the objective function value decreases sharply. As shown in Fig. 9, an increase in γ at first will lead to an increase in the summation of the amount of production of devices till point 180. As it continues, the summation does not change due to budget and space constraints. According to Fig. 10, increasing γ will have the same effect on the summation of needed machines as the summation of the amount of production of devices.

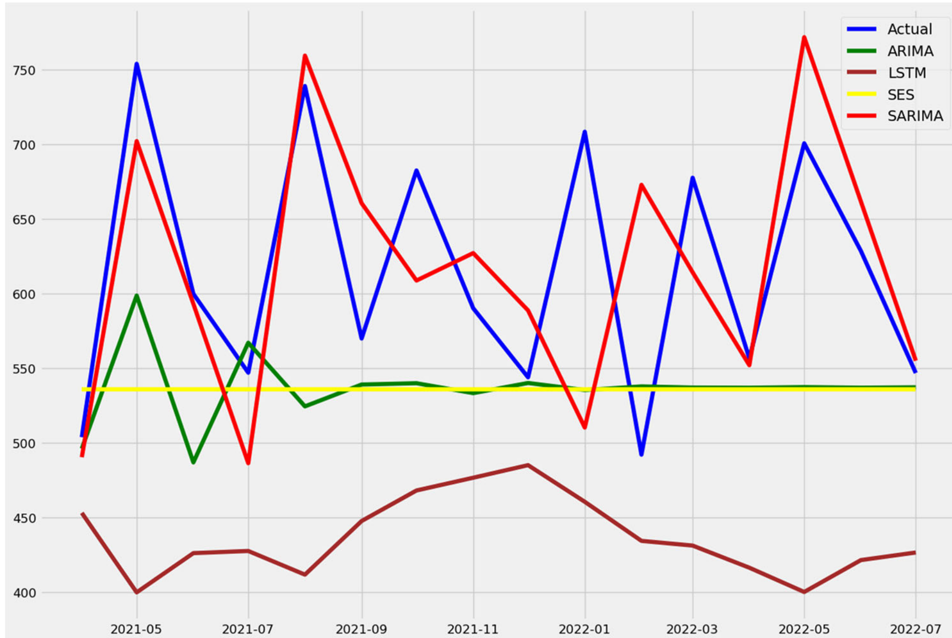


Fig. 4 Comparison between time series algorithms on test data

Table 15 Amount of production of devices

Device	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8
Amount of production	4342	254	949	4367	0	0	0	0

6.3 The impact of budget

In this section, the impact of the budget will be studied. A negative budget means the factory can borrow some money from selling the machines and use it for other purposes. A positive budget shows that the company can invest in the current production. Figure 11 shows that increasing the

Table 16 The needed amount of machines

Machine	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
The needed number of machines	3	1	2	1	2	5	0	5	2	2
$Y\prime$	$Y\prime_1$	$Y\prime_2$	$Y\prime_3$	$Y\prime_4$	$Y\prime_5$	$Y\prime_6$	$Y\prime_7$	$Y\prime_8$	$Y\prime_9$	$Y\prime_{10}$
The machine should be bought or not	1	0	0	0	0	0	0	1	0	0

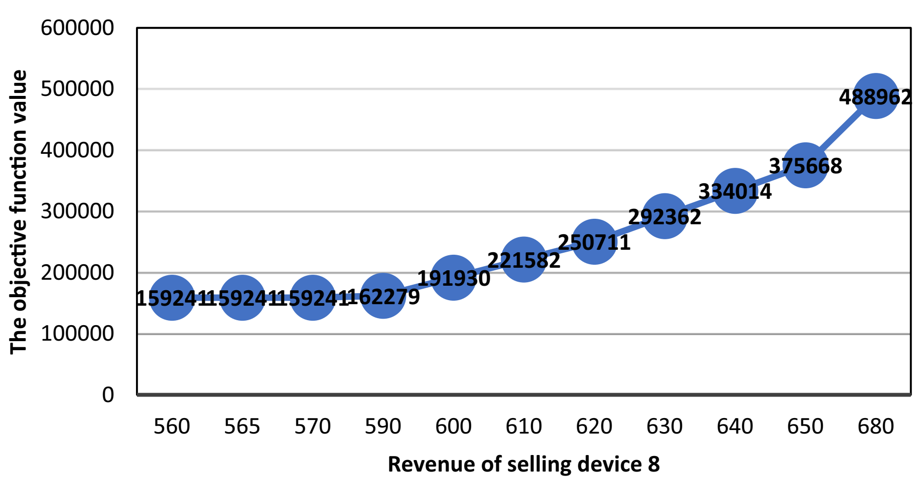


Fig. 5 The impact of revenue of selling device 8 on the objective function value

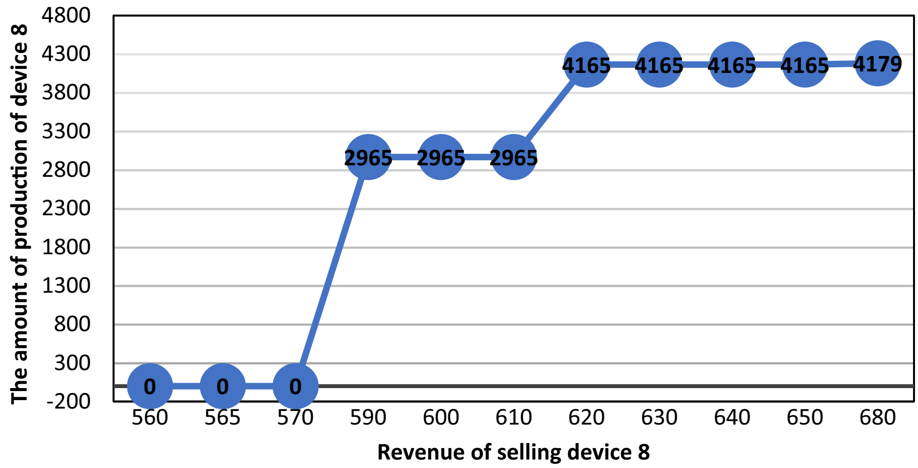


Fig. 6 The impact of revenue of selling device 8 on the amount of production of device 8

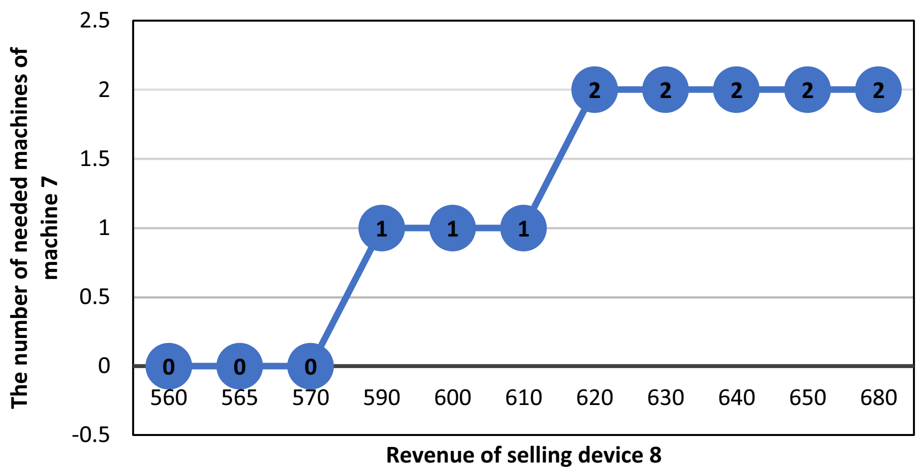


Fig. 7 The impact of revenue of selling device 8 on the number of needed machines of machine 7

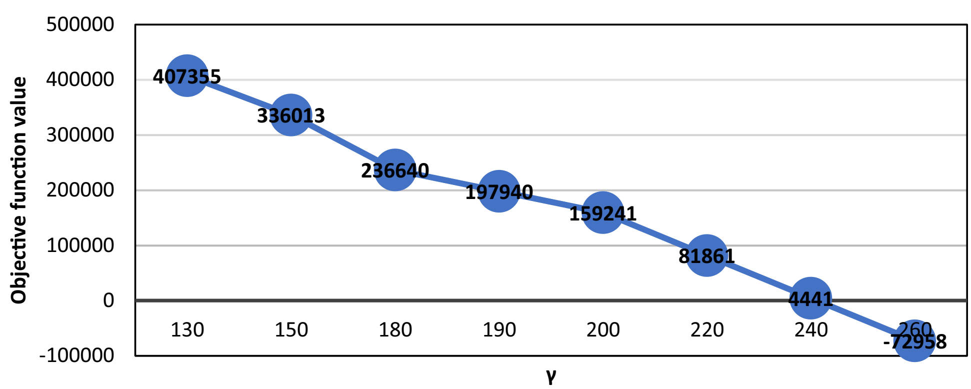


Fig. 8 The impact of γ on the objective function value

budget will lead to an increase in the objection function value at first but makes no changes to the objective function value as it continues because of storage space constraint or greater profit gained by selling the machines instead of producing devices. Based on Fig. 12, an increase in the budget will have the same effect on the summation of the amount of production of devices as it has on the objective function value. According to Fig. 13, increasing the budget will have the same effect on the summation of the number of needed machines as it has on the objective function value.

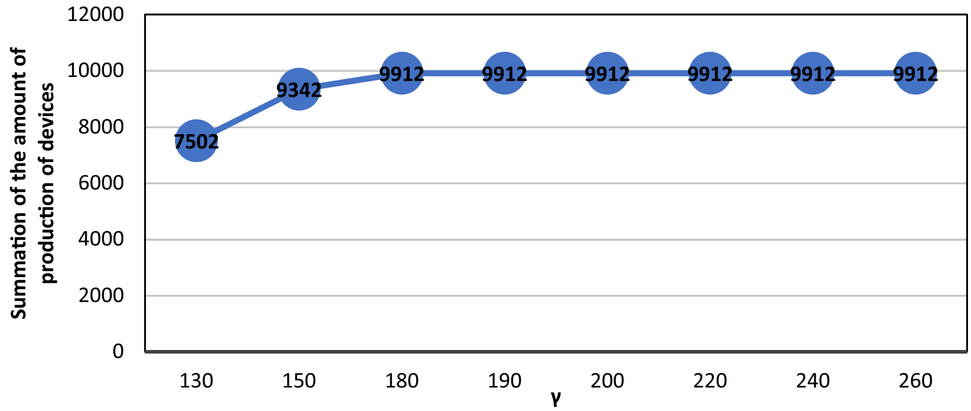


Fig. 9 The impact of γ on the summation of the amount of production of devices

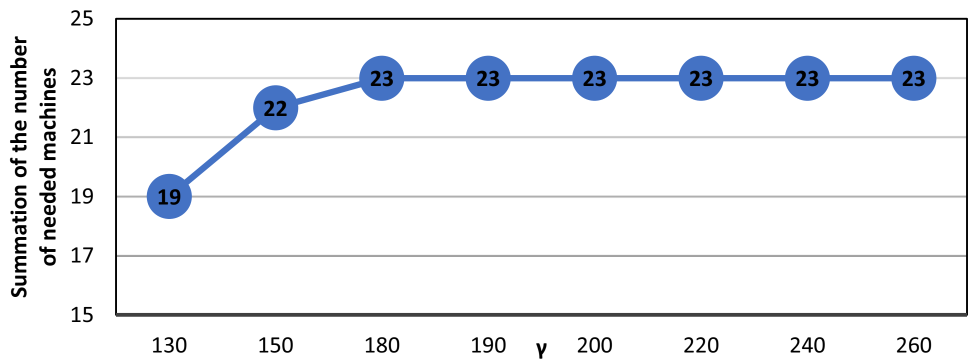


Fig. 10 The impact of γ on the summation of the number of needed machines

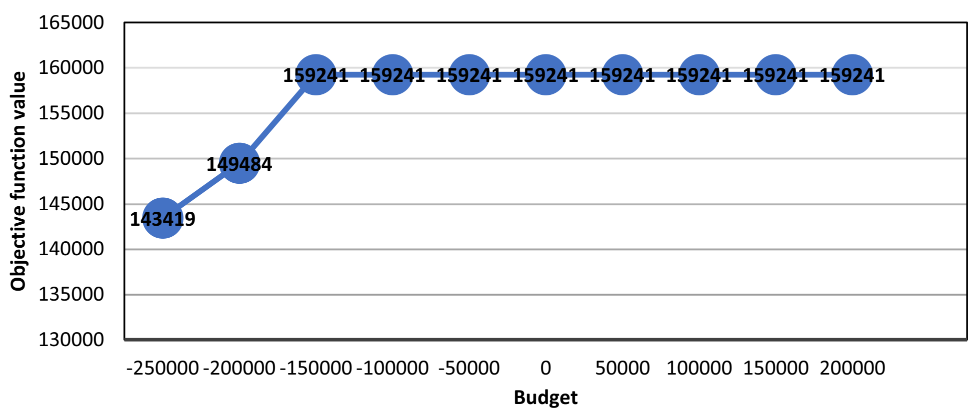


Fig. 11 The impact of budget on the objective function value

6.4 The impact of storage space

The impact of storage space will be examined in this section. Figure 14 shows that increasing the storage space also increases the objective function value. As it goes, it will not affect the objective function value due to other constraints. Based on Fig. 15, an increase in the storage space will lead to the same result on the summation of the amount of production of devices as it has on the objective function value. According to Fig. 16, increasing the storage space will have the same impact on the summation of needed machines as it has on the objective function value.

7 Discussion and managerial insights

In today's highly competitive business environment, managers must remain vigilant of market demand fluctuations when planning production to ensure optimal profitability. To this end, this study proposes a mathematical model that calculates the trade-offs between buying and selling machines and producing devices based on demand, providing decision-makers with a more profitable production schedule. What sets this study apart from others is its use of mathematical modeling and inventory control to create a portfolio of HHDs while also leveraging time series analysis to predict demand in the post-pandemic

Fig. 12 The impact of budget on the summation of the amount of production of devices

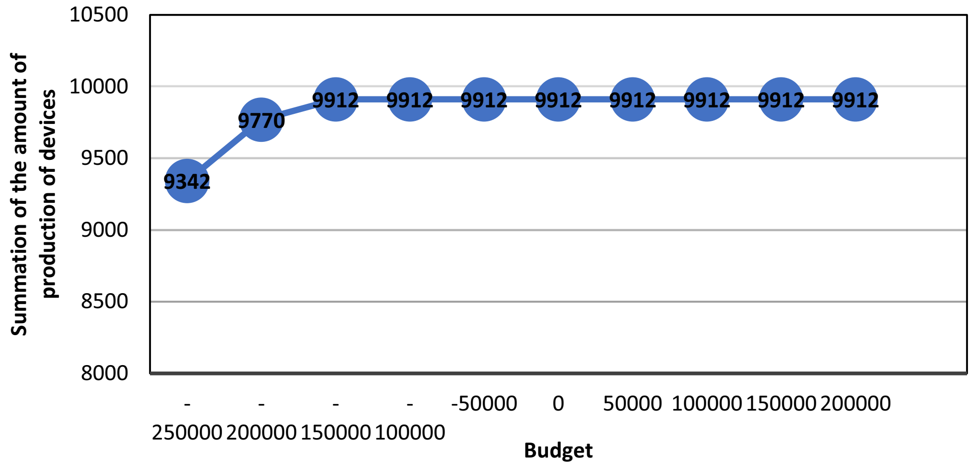


Fig. 13 The impact of budget on the summation of amount of needed machines

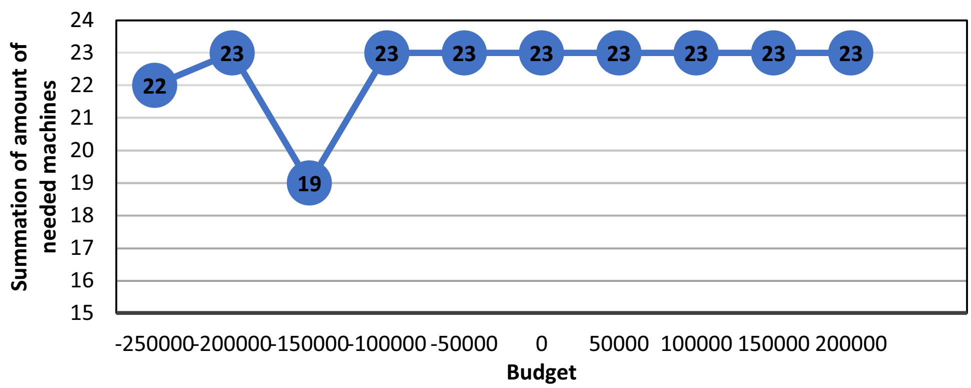
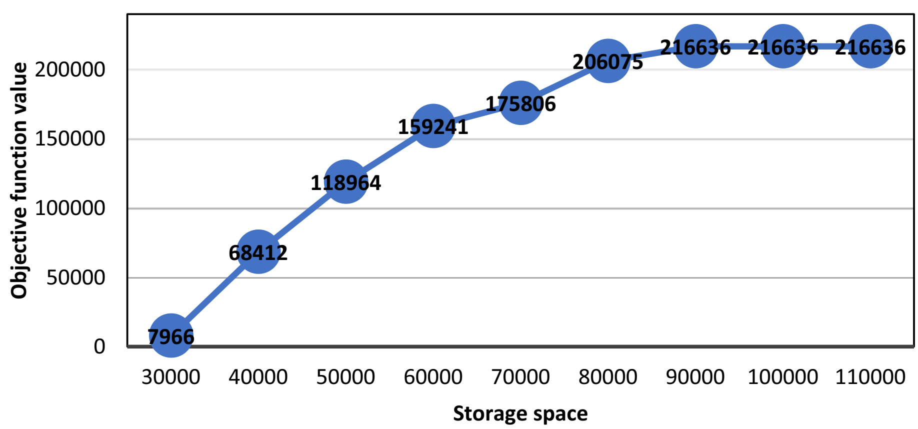


Fig. 14 The impact of storage space on the objective function value



scenario. By taking a comprehensive approach that considers market demand, production costs, and inventory management, this study provides valuable insights for managers seeking to optimize their production processes and achieve greater profitability.

This study provides valuable support for DMs by helping them determine optimal production quantities for each device and the number of machines required. Additionally, by conducting sensitivity analysis, this study generates valuable managerial insights that can inform decision-making.

According to Figs. 5, 6, 7, it is recommended to managers in case of an increase in the revenue of a device, they should increase its production rate step by step, but they should keep in mind that according to Fig. 7, they should allocate a part of this revenue to buy the required machines. It is necessary to consider that the price elasticity of demand for each device should be taken into account, and

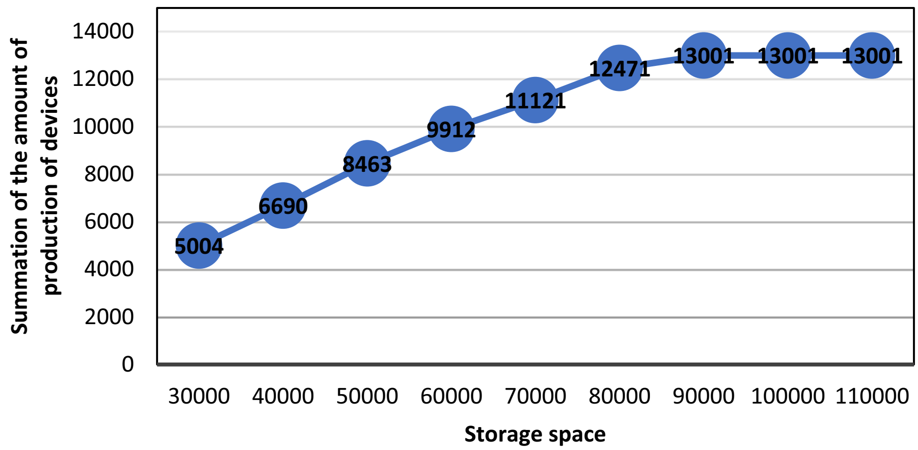


Fig. 15 The impact of storage space on the summation of the amount of production of devices

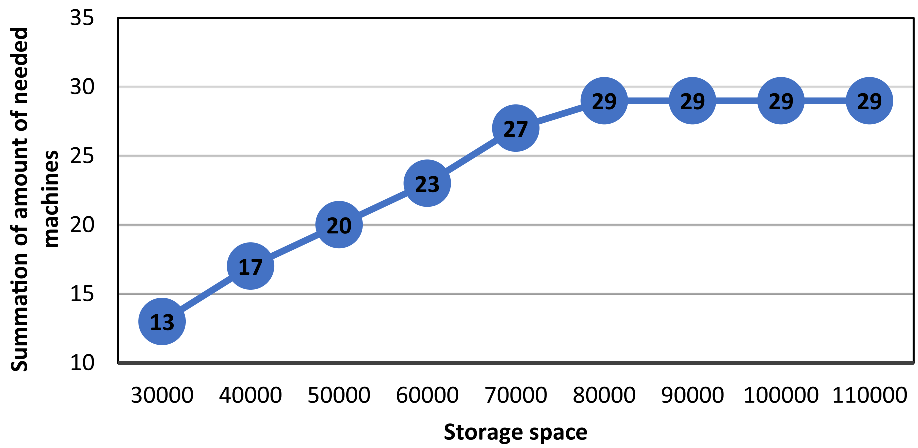


Fig. 16 The impact of storage space on the summation of amount of needed machines

the price increase should be done in consultation with the marketing department.

According to Figs. 9 and 10, increasing γ will make no changes from a point in the amount of production of devices and the number of needed machines due to budget and storage space constraints which leads to a sharp fall in the objective function according to Fig. 8. To overcome this issue, the managers are recommended in case of an increase in γ, to increase the budget and storage space to achieve a higher production to avoid plummeting in the objective function. Besides, based on Fig. 10, it is recommended to the management to increase the number of machines as the shortage cost increases.

Concerning Figs. 11, 12, 13, increasing the budget will not affect the objective function, and the amount of production of devices and the number of needed machines. Moreover, decreasing it makes them plateau as well, till the point –150,000. It means, in addition to the current budget, an extra amount of budget can be obtained from selling the unneeded machines. Thereby, the managers are advised to expend the current budget and the budget gained by selling machines for other purposes like establishing a new production line to produce new devices or expanding the storage space to gain more profit according to Fig. 13.

According to Figs. 14, 15, 16, it is recommended to the management if they want to increase their profits, they can focus on expanding the storage space. Of course, this amount should be increased until it is effective by taking into account other limitations, as provided by the proposed model. It has to be mentioned the profits gained by increasing the storage space should be greater than its expenditures in every step of expansion.

According to Fig. 8, if the shortage cost increases, for example, when the condition of patients worsens or their number increases due to the occurrence of a disaster, in this case, the profit will decrease and according to Fig. 14, the management is recommended to increase the amount of storage space that reduces the decreasing rate of the objective function value. Also, according to Fig. 11, there is no need to increase the budget as it doesn't affect the objective function value.

8 Conclusion

When Covid-19 spreads, it affected industries in different ways. One of its impacts was the change in the demand for HHDs. Obviously, the industries have re-planned the production to meet the demand. Nowadays, in the post-pandemic situation, the demand for HHDs has changed again. Therefore, the industries need to adapt their production to the new circumstances. A mathematical model can be quite useful to determine the optimal amount of production of each device as well as the number of needed machines to gain the maximum profit using the forecasted demand while considering the shortage costs and different constraints.

This study provides a comprehensive system for achieving optimal profitability in the production of a product portfolio, utilizing machine learning techniques, mathematical modeling, and MADM. The system assumes that an OPC has been designed to determine the machines required for each device, and that each device requires a different amount of time to be produced by the needed machines. In the event of new pandemics or disasters that impact demand, the production planning process can be updated using this methodology. The system consists of several stages, with machine learning algorithms used in the first stage to forecast device demand. The weight of shortage cost for each device is then calculated using BBWM. Finally, the optimal amount of production for each device and the required machines can be determined using a mathematical model that is solved by the GAMS program.

This study includes a real-life case study that demonstrates the applicability and effectiveness of the proposed framework. By maximizing profits through the production of devices and the sale of unneeded machines while also considering the costs of shortages and purchasing needed machines, the factory was able to develop a suitable production plan. The findings of this research are highly relevant and valuable for factory management, providing a useful methodology that can be applied not only in HHD factories but also in other industries that have experienced fluctuations in demand due to the pandemic. By utilizing this framework, industries can optimize their production processes and achieve greater profitability, even in the face of challenging external factors.

The current study assumes that planning has been designed for each period, and therefore, there is no need to consider holding costs. However, for future researchers who wish to plan from a multi-period viewpoint, it is recommended that they consider holding costs as well. Furthermore, proposing a layout of machines may be useful for increasing production rates and reducing indoor transportation costs, making it an interesting area of investigation for future studies. Outsourcing some devices could also be a worthwhile assumption to explore in future research. Considering a queueing model integrated with inventory management such as Abbaspour et al. (2022) in a dual channel case for HHDs could be an interesting topic for future research. Additionally, future researchers may benefit from considering work in progress and utilizing scheduling and queueing methodologies to handle it effectively.

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Author contribution MS, AH, and MA-V: conceptualization, methodology, visualization, data curation, writing- original draft preparation, software, data curation, validation. AA: conceptualization, visualization, methodology, investigation, reviewing and editing, supervision. MR: investigation. review and editing validation, supervision.

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Declarations

Conflict of interest Not applicable.

Human participants or animals In addition, this article does not contain any studies with human participants or animals performed by the author. The undersigned authors declare that this manuscript is original, has not been published before, and is not currently being considered for publication elsewhere.

Informed consent Not applicable.

References

Abbaspour S, Aghsami A, Jolai F, Yazdani M (2022) An integrated queueing-inventory-routing problem in a green dual-channel supply chain considering pricing and delivery period: a case study of construction material supplier. J Comput Design Eng 9(5):1917–1951

Aghsami A, Abazari SR, Bakhshi A, Yazdani MA, Jolai S, Jolai F, (2023) A meta-heuristic optimization for a novel mathematical model for minimizing costs and maximizing donor satisfaction in blood supply chains with finite capacity queueing systems. Healthc Anal:100136

Ahmadi-Javid A, Jalali Z, Klassen KJ (2017) Outpatient appointment systems in healthcare: a review of optimization studies. Eur J Oper Res 258(1):3–34

Alipour-Vaezi M, Aghsami A, Jolai F (2022) Prioritizing and queueing the emergency departments' patients using a novel data-driven decision-making methodology, a real case study. Expert Syst Appl 195:116568

ArunKumar K, Kalaga DV, Kumar CMS, Chilkoor G, Kawaji M, Brenza TM (2021) Forecasting the dynamics of cumulative

COVID-19 cases (confirmed, recovered and deaths) for top-16 countries using statistical machine learning models: auto-regressive integrated moving average (ARIMA) and seasonal auto-regressive integrated moving average (SARIMA). Appl Soft Comput 103:107161

Azadi Z, Eksioglu SD, Eksioglu B, Palak G (2019) Stochastic optimization models for joint pricing and inventory replenishment of perishable products. Comput Ind Eng 127:625–642

Baker T, Jayaraman V, Ashley N (2013) A data-driven inventory control policy for cash logistics operations: an exploratory case study application at a financial institution. Decis Sci 44(1):205–226

Balcik B, Bozkir CDC, Kundakcioglu OE (2016) A literature review on inventory management in humanitarian supply chains. Surv Oper Res Manag Sci 21(2):101–116

Bertsimas D, Kallus N (2020) From predictive to prescriptive analytics. Manage Sci 66(3):1025–1044

Bertsimas D, Thiele A (2006) Robust and data-driven optimization: modern decision making under uncertainty. In: Models, methods, and applications for innovative decision making (pp. 95–122). INFORMS

Bloomberg. (2021). Home Healthcare Market Size Worth $545.1 Billion By 2028: Grand View Research, Inc. Retrieved 3/18/2022 from https://www.bloomberg.com/press-releases/2021-09-28/home-healthcare-market-size-worth-545-1-billion-by-2028-grand-view-research-inc

Cai J, Li Y, Yin Y, Wang X, Lalith E, Jin Z (2022) Optimization on the multi-period empty container repositioning problem in regional port cluster based upon inventory control strategies. Soft Comput 26(14):6715–6738

Cappanera P, Nonato M, Rossi R (2019) Stakeholder involvement in drug inventory policies. Oper Res Health Care 23:100188. https://doi.org/10.1016/j.orhc.2019.100188

Chaniaud N, Métayer N, Megalakaki O, Loup-Escande E (2020) Effect of prior health knowledge on the usability of two home medical devices: usability study. JMIR Mhealth Uhealth 8(9):e17983

Chaudhuri KD, Alkan B (2022) A hybrid extreme learning machine model with harris hawks optimisation algorithm: an optimised model for product demand forecasting applications. Appl Intel. https://doi.org/10.1007/s10489-022-03251-7

Chen Z, Rossi R (2021) A dynamic ordering policy for a stochastic inventory problem with cash constraints. Omega 102:102378

Choi TM, Wallace SW, Wang Y (2018) Big data analytics in operations management. Prod Oper Manag 27(10):1868–1883

Clausen JBB, Li H (2022) Big data driven order-up-to level model: application of machine learning. Comput Oper Res 139:105641

Clemente F, Faiella G, Rutoli G, Bifulco P, Romano M, Cesarelli M (2019) Critical failures in the use of home ventilation medical equipment. Heliyon 5(12):e03034. https://doi.org/10.1016/j.heliyon.2019.e03034

Dabiri N, Tarokh MJ, Alinaghian M (2017) New mathematical model for the bi-objective inventory routing problem with a step cost function: a multi-objective particle swarm optimization solution approach. Appl Math Model 49:302–318

Fattah J, Ezzine L, Aman Z, El Moussami H, Lachhab A (2018) Forecasting of demand using ARIMA model. Int J Eng Bus Manag 10:1847979018808673

FDA (2017) Brochure-home healthcare medical devices: a checklist. Retrieved 3/18/2022 from https://www.fda.gov/Medical-Devices/Home-Health-And-Consumer-Devices/Brochure-Home-Healthcare-Medical-Devices-Checklist#:~:Text=Examples%20of%20some%20home%20healthcare,And%20other%20home%20monitoring%20devices

Hajipour V, Niaki STA, Akhgar M, Ansari M (2021) The healthcare supply chain network design with traceability: a novel algorithm. Comput Ind Eng 161:107661

Hochreiter S, Schmidhuber J (1997) Long short-term memory. Neural Comput 9(8):1735–1780

Hovav S, Tsadikovich D (2015) A network flow model for inventory management and distribution of influenza vaccines through a healthcare supply chain. Oper Res Health Care 5:49–62. https://doi.org/10.1016/j.orhc.2015.05.003

Hyndman RJ (2004) The interaction between trend and seasonality. Int J Forecast 20(4):561–563

Hyndman RJ, Athanasopoulos G (2018) Forecasting: principles and practice. OTexts

Keller SC, Gurses AP, Werner N, Hohl D, Hughes A, Leff B, Arbaje AI (2017) Older adults and management of medical devices in the home: five requirements for appropriate use. Popul Health Manag 20(4):278–286

Kurawarwala AA, Matsuo H (1998) Product growth models for medium-term forecasting of short life cycle products. Technol Forecast Soc Chang 57(3):169–196

Luna F, Quintana D, García S, Isasi P (2016) Enhancing financial portfolio robustness with an objective based on ε-neighborhoods. Int J Inf Technol Decis Mak 15(03):479–515

Ma W, Simchi-Levi D, Zhao J (2021) Dynamic pricing (and assortment) under a static calendar. Manage Sci 67(4):2292–2313

Maheshwari S, Gautam P, Jaggi CK (2021) Role of big data analytics in supply chain management: current trends and future perspectives. Int J Prod Res 59(6):1875–1900

Masoumi M, Aghsami A, Alipour-Vaezi M, Jolai F, Esmailifar B (2021) An M/M/C/K queueing system in an inventory routing problem considering congestion and response time for post-disaster humanitarian relief: a case study. J Hum Log Supply Chain Manag.

Meng F, Song F, Guo M, Wang F, Feng X, Wang D, Xu L (2021) Status and influential factors of intelligent healthcare in nursing homes in China. Comput Inform Nurs 39(5):265

Micheaux A, Bosio B (2019) Customer journey mapping as a new way to teach data-driven marketing as a service. J Mark Educ 41(2):127–140

Miller DM, Williams D (2003) Shrinkage estimators of time series seasonal factors and their effect on forecasting accuracy. Int J Forecast 19(4):669–684

Mohammadi M, Rezaei J (2020) Bayesian best-worst method: a probabilistic group decision making model. Omega 96:02075. https://doi.org/10.1016/j.omega.2019.06.001

Nagarajan V, Shi C (2016) Approximation algorithms for inventory problems with submodular or routing costs. Math Program 160(1):225–244

Nasr WW, Elshar IJ (2018) Continuous inventory control with stochastic and non-stationary Markovian demand. Eur J Oper Res 270(1):198–217

Ngaffo AN, Ayeb WE, Choukair Z (2022) Service recommendation driven by a matrix factorization model and time series forecasting. Appl Intell 52(1):1110–1125

Niakan F, Rahimi M (2015) A multi-objective healthcare inventory routing problem; a fuzzy possibilistic approach. Transp Res Part E: Log Transp Rev 80:74–94

Ostertagová E, Ostertag O (2011) The simple exponential smoothing model. In: The 4th International Conference on modelling of mechanical and mechatronic systems, Technical University of Košice, Slovak Republic, Proceedings of Conference

Pang Z, Zheng L, Tian J, Kao-Walter S, Dubrova E, Chen Q (2015) Design of a terminal solution for integration of in-home health care devices and services towards the Internet-of-Things. Enterprise Inform Syst 9(1):86–116

Paul A, Pervin M, Roy SK, Maculan N, Weber G-W (2022) A green inventory model with the effect of carbon taxation. Ann Oper Res 309(1):233–248

Pisacane O, Potena D, Antomarioni S, Bevilacqua M, Emanuele Ciarapica F, Diamantini C (2021) Data-driven predictive maintenance policy based on multi-objective optimization approaches for the component repairing problem. Eng Optim 53(10):1752–1771

Ravuri V, Vasundra DS (2022) An effective weather forecasting method using a deep long–short-term memory network based on time-series data with sparse fuzzy c-means clustering. Eng Optim:1–19

Richard L, Francis RLF, John AW (1974) Facility layout and location: an analytical approach. Prentice Hall

Saha E, Ray PK (2019) Modelling and analysis of inventory management systems in healthcare: a review and reflections. Comput Ind Eng 137:106051

Suby RJ (1975) Facility layout and location—an analytical approach. By R. L. Francis and J. A. White. (New Jersey : Prentice-Hall Inc., 1974.) [Pp. 468.] Price £8–85. Int J Prod Res 13(2), 219–219. https://doi.org/10.1080/00207547508942989

Sun J, Van Mieghem JA (2019) Robust dual sourcing inventory management: optimality of capped dual index policies and smoothing. Manuf Serv Oper Manag 21(4):912–931

Tavana M, Govindan K, Nasr AK, Heidary MS, Mina H (2021) A mathematical programming approach for equitable COVID-19 vaccine distribution in developing countries. Ann Oper Res. https://doi.org/10.1007/s10479-021-04130-z

Thomson R, Martin JL, Sharples S (2013) The psychosocial impact of home use medical devices on the lives of older people: a qualitative study. BMC Health Serv Res 13(1):1–8

Tseng S-H, Yu J-C (2019) Data-driven iron and steel inventory control policies. Mathematics 7(8):718

Yousefli A, Heydari M, Norouzi R (2022) A data-driven stochastic decision support system to investment portfolio problem under uncertainty. Soft Comput 26(11):5283–5296