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RESEARCH ARTICLE

# Application of Internet of Things (IoT) to Food Supply Chain Under Uncertainty-Case: Traditional Dairy Products

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**ABSTRACT** Implementing information technology in production has triggered an increase in Industry 4.0. Owing to this technological advancement, manufacturing tools that can communicate with each other through the Internet of Things are now able to collect real-time data. Under dynamic production conditions, real-time information can enhance production control and supply chain efficiency. To optimize the production process, the food industry must utilize new technologies and the Internet of Things (IoT) to reduce costs, increase productivity, and eliminate waste. This is particularly true with the growing trend in this area. The study created and implemented a manufacturing production planning system that utilized Internet of Things technology, with specialized equipment used in dairy factory operations as the case study. This system collects information on the dairy production process, including material and product inventory, in real-time on Internet of Things devices, then analyzes it with the help of a neural network, and predicts the demand for the next 3 days. The dynamic schedule optimization, optimal timing of milk production, product quantity, and raw materials are determined using two heuristic algorithm methods. Additionally, there are multiple algorithms available for further processing. The optimization results indicate that implementing dynamic scheduling via the Internet of Things can mitigate uncertainty and boost income by 10 to 15%, profit by 13 to 18%, and job shop-level productivity by 13%.

**INDEX TERMS** Food supply chain, Internet of Things, dynamic scheduling, heuristic algorithms, dairy products, uncertainty.

## I. INTRODUCTION

The increasing demand and complexity of expectations along with changes in the competitive environment of the market have led organizations to optimize the supply chain to survive in the market, gain a greater share of product sales in global markets, and respond quickly to the needs of consumers in the shortest time, with the lowest cost and high quality [1]. Therefore, the supply chain must be closely monitored, planned, and managed across all levels, from raw material suppliers to customer distribution. The management of supply chains involves the planning, implementation, and monitoring of all operations related to production storage and distribution to customers [2]. The supply chain is primarily concerned with the integration of operations and information/material flows across all supply chains to provide an organization with a long-term competitive advantage [3].

In the 1970s, supply chain management, and production planning methods became prevalent for food chain integration. This was largely due to changes in how supply chains are managed, which affect demand at each end of the supply chain. Companies such as Walmart and McDonald's have improved the efficiency and reduced costs of their supply chain by using production scheduling optimization methods [4], [5].

Chen et al. [6] applied the IOT to improve transportation and network security. Alfian et al. [7] aimed to improve the efficiency of a perishable food tracking system. Lee et al. [8]

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improved the ability of farmers, researchers, and government officials to analyze current conditions and predict future yields and the correlation of agricultural statistical data in their study of IoT-based production systems. Zhang et al. [9] introduced integrated production planning and warehousing using Internet of Things technology. Tangour et al. [10] proposed the use of IoT for future research after agricultural food planning. Research by Liu [11] applied the Internet of Things to predict the failure rate.

Several investigations have been carried out to decrease the exclusion of food resources, such as Hong et al. [12] Seoul researchers presented a food management system with Internet of Things technology, resulting in improved efficiency and effectiveness. The supply chain's management challenges are particularly challenging when dealing with food that contains perishable and short-lived products. Perishable goods must be traceable due to the challenges of temperature control, storage conditions, production methods, and raw materials. Therefore, effective supply chain management of short-lived products, especially food, is vital [13], [14].

This study aimed to make the simulation more realistic by incorporating dynamic timing instead of regular timing. It reduces demand uncertainty by making modeling as close to the real world as possible by analyzing real-time data to forecast demand using a neural network. It also heuristically uses different approaches to implement dynamic timing so that the model can grow. Then, we extracted the Gantt chart of the schedule and machines for the implemented model with the help of a case study, the type and volume of the manufactured products daily, and we investigated the effect of the Internet of Things on the parameters by comparing the dynamic scheduling and the traditional method.

The rest of the paper is structured as follows: Section II reviews related work and points out our idea. Section III introduces the algorithm and its properties in detail. The experimental Framework and results analysis are presented in Sections IV and V respectively and related discussions are proposed in Section VI. Finally, Section VII provides a general conclusion.

## II. LITERATURE REVIEW

The concept of food supply chain management has been considered seriously since 1983 when J. Hertz published an article entitled ''Introduction to Supply Chain Management,'' in which he explored the field to examine the intricacies of food supply, including their purchase, storage, and distribution [15]. In the following years, many researches were conducted in the field of supply chains, especially in the field of food.

Today, there is great pressure on the food supply chain to improve its revenue and overall sustainability and efficiency [16]. The Internet of Things technology has notably enhanced the food supply chain.

The global population is set to reach nine billion by 2050, resulting in significant changes to the world and increasing competition for the food chain. However, the development of ''Industry 4'' and Internet of Things technology may provide promising solutions [17].

One of the most important achievements of Industry 4.0 is the Internet of Things. The Internet of Things is defined as an information infrastructure in the world that connects physical and virtual objects with the help of communication and information technologies; It transforms and enables advanced services [18].

The Internet of Things in the food supply chain is designed to easily connect machines, equipment, products, and other items in a network. Therefore, an IoT architecture is required for integrated data collection and secure transmission for further analysis [1].

By connecting vehicles to an internet network, the Internet of Things can be utilized in food transportation to provide precise monitoring, management for environmental conditions, forecasting needs (such as pest control measures), optimization of routes, and overall security. This technology helps to reduce food waste, as well as minimize downtime and delays. This strategy offers additional advantages such as enhanced supply chain efficiency, cost reduction, and better fuel economy.

Lacey et al. [19] studied the Internet of Things applications in transportation and logistics. This study outlined ''different uses of the Internet for supply and demand have driven transportation and logistics: machine-to-machine communication, data collection, cargo tracking/tracing along routes with transportation cost reduction''.

One of the reliable papers in the field of the Internet of Things and the use of optimization algorithms to show its effectiveness in the food industry is the research conducted by Zhang et al. [20]. In the stage of distribution and transportation and route improvement, Li et al. [21] proposed a tracking and follow-up system for the food supply chain of ready-to-eat packaged food products using the Internet of Things. Moudoud et al. [22] utilized the Internet of Things to introduce a blockchain architecture, which was intended to facilitate the implementation of 'track and trace' in the food supply chain's transportation and delivery sector. Tsang et al. [23] presented a food product tracking system based on blockchain and the Internet of Things using fuzzy logic for product life, which manages tracking operation and shelf life of perishable products. Current food production control systems are lengthy and complex and face increasing safety risks and constant pressure to produce high-quality and safe food products. All actors in food supply chain systems contribute to the provision of food safety information, which can lead to unforeseen risks due to the sharing of incorrect information or delays [24]. In the study by Oluyisola et al. [25], the concept of planning and intelligent control of production, its use, and its sustainability consequences are introduced in an experimental and research way. Rahmani et al. [26] provided a conceptual framework for intelligent manufacturing and production control planning, which is related to the characteristics of the planning environment and the need for smart manufacturing planning and control, in the review written by Adelke et al. [27] examined more than 44 research articles and critically appraised significant accomplishments and outcomes. In this regard, the research conducted by Liu [11] utilized the Internet of Things to predict the failure rate. Based on this research, it has been demonstrated that IoT technology and neural network prediction can accurately identify errors or malfunctions in Food Machinery equipment. There are many studies in the field of reducing the wastage of food resources, such as Gontarz et al. [28], which examined the types of resource consumption monitoring systems, methods of measuring energy and material consumption, and criteria for evaluating the efficiency of resource consumption monitoring systems.

The research of Garcia-Garcia et al. [29] discussed food waste in developing and developed countries. In this paper, a framework for improving the efficiency of food waste management is presented. Also, Shrouf and Miragliotta [30] represented the Internet of Things for improving energy management in the food industry and production.Using the Internet of Things to collect data is also very practical in Data mining. For example, for the issue of saving and food security, the research by Ji Weng et al. [31] discussed how using data mining in the sustainable food supply chain, it is possible to predict possible risks related to food safety.

Jagtap and Rahimifard [32] showed that a digital food tracking system based on the Internet of Things in a food factory can reduce food waste by 60.7%. In this study, real-time data collection systems were used to collect data related to energy consumption in the food production industry. Alfian et al. [33] did valuable research in this field. This research is about a remote tracking system based on radio frequency identification technology, wireless sensor networks, and data mining to track food products. Regarding food waste as one of the most important issues in this field, a review compiled by Chauhan et al. [34] framework examined factors and challenges related to food loss and waste in the supply chain. Maintaining and managing quality food along with warnings about food conditions is the most important aspect of achieving sustainability in the food supply chain [24]. In this regard, Stewart et al. realized with the help of sensors from the Internet of Things, the data on temperature, humidity, and emitted gases are collected and transferred to the cloud platform. This study suggests that food quality can be improved through an IoT-based system.

Fertility and raw materials are essential components for the food industry's storage. The implementation of Internet of Things (IoT) technology in this sector enables companies to ensure optimal environmental conditions for storing both raw materials and finished goods.

Chen et al.'s research [35] deals with managing the environmental conditions of products with the help of the Internet of Things. The advantages and disadvantages of using radio frequency identification (RFID) technology and wireless sensors in the food product supply chain are examined. Additionally, solutions to enhance supply chain performance are presented. Yan et al. [36] designed a system to control the safety and quality of agricultural products during storage and transportation. Additionally, they introduced an application model of the Internet of Things (IoT) specifically for the agriculture supply chain. Jagtap and Rahimifard [37] examined the use of Internet of Things technology in improving the efficiency of resources in the supply chain, such as managing food energy and material consumption. In this research, the key concepts of the Internet of Things and its applications in different parts of the food supply chain, including agriculture, transportation, storage, and distribution, have been investigated. Also, Barandun et al. [38] indicated that in their investigation, cellulose fibers were utilized for detecting gases that can dissolve in water. A novel approach has been proposed in this paper to manufacture a gas sensor using ribbon electrodes and cellulose fibers at essentially zero expense. Golinska-Dawson et al. [39] investigate a pricing model for demand and food chain quality control using Internet of Things technology. This paper presents a food price and quality control algorithm based on IoT sensor data.

One of the most up-to-date research conducted in the field of correct maintenance and increasing quality in the food supply chain is the use of blockchain, From an IoT perspective, Kayikci et al. [40] explore the potential of blockchain technology in the food chain. In this study, the Internet of Things is used as one of the main tools to collect and transmit data related to the food supply chain, and its role in blockchain implementation is investigated. Skilton and Robinson [41] considered traceability and transparency in the supply chain to be completely related because the result of having a system with traceability is to create transparency. In their research, traceability is considered a process that identifies and validates the various components and timing of events along the supply chain. Abad et al. [42] in research in the field of fish to validate a radio frequency identification smart tag for real-time tracking and cold chain monitoring in food programs have been developed. L. Boquete et al. [43] designed, developed, and tested an IoT-based system to improve logistics during the transportation, storage, and sale of wine bottles by tracking the temperature in different parts of the chain. They have used a system called ZigBee to analyze and display data.

In the field of traceability in transportation, Omar Farooq et al. [44] discussed the problems in the agricultural food supply chain.

Probability can be significantly enhanced by implementing predictive methods that utilize the real-time data generated by the Internet of Things and supply chain transparency. One of the researches that have shown the importance of this issue is the research of Alfian et al. [45]. This paper introduces a monitoring and tracking system for the food supply chain using Internet of Things technology.

In the survey conducted by O. Saeed et al. [46], the importance of the Internet of Things and its successful applications are comprehensively discussed by creating transparency in various stages of agriculture along with challenges and solutions.

The review table 1 was used to evaluate studies that utilized experimental methods, hardware and software, and less mathematical models for optimizing the Internet of Things' input data. Research comparable to the current model has neglected to consider demand uncertainty, which utilizes food industry demand forecasts to make optimal operational decisions and increase production flexibility. From another point of view, in the entire food supply chain, the Internet of Things is generally used in the discussion of reducing waste and managing environmental conditions to maintain product quality, proper storage and transportation of the product, and fewer research discuss transparency in the supply chain and operational decision-making in production have paid [42]. Also, in the field of food production, there are studies for the management of production planning and production scheduling, but there is a gap in the application of smart internet in this field and its effects. Therefore, there has been very little attention paid to the integrated network that can Utilize the benefits of the Internet of Things (IoT) and machine learning to optimize production.

Therefore, to cover this literature gap, this research uses the Internet of Things to create traceability and transparency of production, and at the same time, with the help of a machine learning system, it analyzes the received data to design the most optimal planning and dynamic scheduling for production through simulation.

## III. THE PROPOSED METHOD

Job Shop through IoT was utilized in this study to model the dynamic planning of food industry production using an integer optimization. This model collects the data of the inventory of raw materials and products with the help of the Internet of Things as real-time data and analyzes these data with the help of machine learning through the neural network method to predict the required demand and schedule the production. This model is then solved using two heuristic methods and its results are compared. This schedule is dynamic; it uses a neural network to predict demand based on real-time data. This allows for updates as needed and demonstrates a high response capability to demand uncertainty.

The overall procedure of the algorithm is shown in Figure 1.

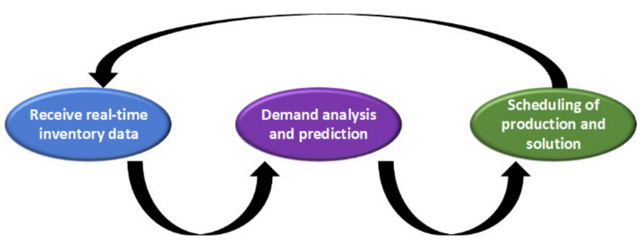


**FIGURE 1.** Model solution structure.

**TABLE 1.** Summary of recent research papers.

| Article | Year | The role of IOT | Linked levels of the chain | | | | |
|---|---|---|---|---|---|---|---|
| | | | Transportation and supply | Manufacturing | Wasted | Maintenance | Transparency |
| [47] | 2013 | Integration of devices and resources | ✓ | | | | |
| [48] | 2014 | Increasing the efficiency and reliability of manufacturing | ✓ | ✓ | | | |
| [49] | 2014 | RFID applications | | | | ✓ | |
| [50] | 2016 | Predictive maintenance | | | | ✓ | |
| [51] | 2017 | - | | | | ✓ | ✓ |
| [52] | 2017 | CPS development case based on IoT platform Thing Worx | ✓ | ✓ | | ✓ | |
| [53] | 2018 | - | ✓ | | | | |
| [54] | 2018 | - | ✓ | | | | |
| [55] | 2018 | Monitoring dynamic manufacturing processes and obtaining real-time information | ✓ | | | ✓ | |
| [56] | 2019 | - | | | | | ✓ |
| [57] | 2019 | - | ✓ | | | | |
| [58] | 2020 | Modeling IoT-driven global | ✓ | | | | |
| [59] | 2020 | - | ✓ | | | | |
| [60] | 2021 | Traceability information | | | | | ✓ |
| [61] | 2021 | - | | | | | ✓ |
| [62] | 2021 | RFID tags | | | | | ✓ |
| [63] | 2021 | Optimization, interoperability, security, and privacy issues | | | | | ✓ |
| [64] | 2021 | Traceability systems | ✓ | ✓ | | | ✓ |
| [65] | 2022 | Access the data | ✓ | | | | ✓ |
| [66] | 2022 | - | ✓ | | | | ✓ |
| [67] | 2023 | - | ✓ | | | | ✓ |
| [68] | 2023 | - | | ✓ | | ✓ | ✓ |

### A. FIRST STEP: PREDICTING DEMAND AS MODEL INPUT USING A NEURAL NETWORK

In this field, artificial neural networks are an important type of machine learning model. As a result of analyzing the input data, the neural network logically determines the relationship between the data, which can be complex and nonlinear. After finding the connection, it performs simulation work for similar possible cases. This network is adjusted by comparing the output with the target, ensuring they closely match [67]. Adaptability and the ability to detect complex patterns in data are among the advantages of neural networks, and neural networks are used in this research to predict demand for products. At first, the information for one year was gained by reporting the special sales scale. Since data preparation can be effective for the better performance of the model, the statistical dispersion method has been used for data preparation and to identify outliers. This method assumes that the distribution of the data of the variable X is a distribution with mean $\bar{X}$ according to Eq.(1) and standard deviation $\sigma$ according to Eq.(2). If a data is out of range ($\sigma$3-$\bar{X}$ $\sigma$ 3 +$\bar{X}$), it will be considered as outlier data.

$$\bar{X} = \frac{\sum_{i=1}^{i=n} X_i}{n} \tag{1}$$

$$\boldsymbol{\sigma} = \sqrt{\frac{\mathbf{1}}{\boldsymbol{n}-\mathbf{1}} \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{i}=\boldsymbol{n}} (\boldsymbol{X_i} - \boldsymbol{X})^{\mathbf{2}}} \tag{2}$$

The best neural network method is chosen by comparing the models with the mean squared error (MSE) criteria according to Eq.(3).

$$\boldsymbol{MSE} = \sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}} \left(\boldsymbol{y_i} - \left(\boldsymbol{y_i^{\wedge}}\right)\right)^{\mathbf{2}} \tag{3}$$

In this Eq. (3), N is the number of samples, $\boldsymbol{y_i}$ is the target value and $\boldsymbol{y_i^{\wedge}}$ is the value predicted by the model for the ith sample.

Approximation in regression refers to a set of techniques and algorithms that try to find an approximate mathematical function using data. In nonlinear approximation methods, attempts are made to build nonlinear models with nonlinear functions (such as power, logarithmic, polynomial, etc.). A better estimation of the relationship between the dependent and independent variables can be achieved by making this adjustment. These methods are selected and applied according to the type of data and the specific problem. Due to the non-linearity of the values in this research, a function should be used to determine the expected time of each device for the specified raw materials and the volume of products. Approximate using the closest values to the input data. For this purpose, we must choose a function that is used both during extrapolation (extrapolation means predicting the values of the function at points outside the range of the available data) and interpolation (interpolation means predicting the values of a function at the data points located in the range of the function and are not available in the original data) have an acceptable performance. By testing the performance of the desired function for approximation during extrapolation and interpolation according to the mentioned points, the exponential function according to Eq. (4) is considered for this problem:

$$\mathrm{Y} = \mathrm{c} + \mathrm{a.x^b} \tag{4}$$

X represents the initial volume of milk for each machine and a, b, and c are estimation coefficients that will be calculated by the least square method to determine the time required for each machine for different amounts of milk and in the next step for the volume of produced products.

The least squares method is a crucial and widely used technique for parameter estimation in mathematical models. It aims to match the model with observed data by finding parameters that minimize the error function and represent the discrepancy between predictions and actual observations.

$$\boldsymbol{E(a\ b\ c)} = \sum_{\boldsymbol{j}=\mathbf{1}}^{\boldsymbol{n}} \left(\boldsymbol{y_j} - \left(\boldsymbol{a} \cdot \boldsymbol{x_j^b} + \boldsymbol{c}\right)\right)^{\mathbf{2}} \tag{5}$$

$$\boldsymbol{E(a\ b\ c)} = \sum_{\boldsymbol{j}=\mathbf{1}}^{\boldsymbol{n}} \left(\boldsymbol{y_j} - \left(\boldsymbol{a} \cdot \boldsymbol{x_j^b} + \boldsymbol{c}\right)\right)^{\mathbf{2}} \tag{6}$$

Eq. (5) and Eq. (6) are used to estimate the coefficients of devices and the volume of production products, respectively. Based on these equations, the time required for each device for varying amounts is calculated, and the final production volume is determined.

### B. SECOND STEP: MATHEMATICAL MODELING

This section proposes the mathematical model, the assumptions, indices, and parameters of the model are defined below.

The implementation of this model in the production job shop will also be according to Figure 2.

The assumptions of the model are:

- The operation is typically a job shop.
- Production machines have a certain maximum and minimum capacity.
- A penalty for perishability has been included for producing over-demand.
- Shortage is not allowed and demand should be covered.
- Raw materials are purchased in proportion to demand.
- First, the inventory is sold, and then we sell the manufactured products. (First in first out (FIFO))
- The time required to set up the machines has been accounted for.
- When product manufacturing starts, stopping is not allowed, and the process must be completed.
- The production time horizon is 3 days.

The objective function of this problem, which seeks to maximize profits for the whole system, is given in Eq. (7) after applying the neural network algorithm to determine the demand as the input to the mathematical model:

$$\boldsymbol{max\ g} = \left(\sum_{\boldsymbol{i}\in\boldsymbol{I}}\Big(\sum_{\boldsymbol{n}\in\boldsymbol{N}}\boldsymbol{x_i^n}\times\boldsymbol{P_i}\Big)\right) - \sum_{\boldsymbol{i}\in\boldsymbol{I}}\left[\sum_{\boldsymbol{n}\in\boldsymbol{N}}\boldsymbol{x_i^n}\times\boldsymbol{cp_i}\right] - \sum_{\boldsymbol{j}\in\boldsymbol{J}}\left[\sum_{\boldsymbol{n}\in\boldsymbol{N}}\boldsymbol{dm_j^n}\times\boldsymbol{cm_j}\right] - \sum_{\boldsymbol{n}\in\boldsymbol{N}}\boldsymbol{D_w n_{\alpha Cw}} - \sum_{\boldsymbol{i}\in\boldsymbol{I}}\boldsymbol{z_i^n}\cdot\left(\boldsymbol{x_i^n}-\boldsymbol{d_i}\right)\cdot\frac{\boldsymbol{M}}{\boldsymbol{Ed_i}}-\boldsymbol{C} \tag{7}$$

Eq. (7) is the target function of the problem, which seeks to maximize the profit of the entire system and comprises the total revenue from the sale of products minus the relevant costs. These costs are, respectively, the direct costs of product manufacture including raw materials, the costs of the use of the machine per minute, which include the cost of depreciation and maintenance, the cost of workforce and perishability, which is considered linearly as a lifetime of each product, in case of excess cost production as penalty. The longer the lifetime, the lower the penalty.

$$x_i^n \geqslant d_i^n + h_i \quad \forall i \in I \tag{8}$$

$$T_j^n \leqslant tmax \quad \forall j \in P \tag{9}$$

$$N_j^n \geqslant 1 \quad \forall j \in P \tag{10}$$

$$N_J^n \leqslant R \quad \forall j = P \tag{11}$$

Eq. (8) is for the minimum production to cover the demand. Eq. (9) is the limitation of the maximum duration of the machine involvement, which can be limited to several machines and serial cases. Eq. (10) represents the series of machines and each serial machine simultaneously can produce only one product. Eq. (11) is about the machines that have more than one inventory and are parallel; similar machines, according to their number, can be involved in manufacturing several products simultaneously.

$$\mathrm{cmin}_j \leqslant \mathrm{ca}_j \leqslant \mathrm{cmax}_j \tag{12}$$

$$h_k^n = \sum_{i\in I}\left(d_i^n - h_i^n\right)\alpha_i^k \tag{13}$$

Eq. (12) reveals the limitation of the capacity of the machines. Eq. (13) calculates the required inventory of raw materials every day. The required inventory of each product is subtracted from the remaining inventory to get the amount of the required product. Then it is multiplied by the raw material conversion rate to determine the needed material.

### C. THIRD STEP: METHOD OF HEURISTIC SOLUTIONS

This research has implemented the optimization by genetic and particle swarming algorithms in two different ways, which we will explain in the following, and discuss its performance after comparing the optimization of these two methods.


**FIGURE 2.** Operational implementation.

**TABLE 2.** Notations table.

| Symbol | Description |
|---|---|
| | Sets |
| I | The index set for the manufactured products i ϵ I |
| J | The index set for production machines j ϵ J |
| N | The index set for day n ϵ N |
| K | The index set for raw materials k ϵ K |
| P | The index set for a subset of production machines p ϵ J |
| | Parameters |
| $p_i$ | Selling price of product i |
| $cp_i$ | Cost of product materials i |
| $cm_j$ | Cost of using machine j per minute |
| cw | A workforce cost per minute |
| $N_j^n$ | Number of products in machine j on day n |
| $dm_j^n$ | Duration of time used by machine j on day n |
| $d_i^n$ | Demand for the product i on day n |
| $h_i^n$ | Inventory of product i in stock on day n |
| $h_k^n$ | Inventory of raw materials k in stock on day n |
| $dw_n$ | Duration of employment of workforce on day n |
| $Ed_i$ | Product lifetime i |
| $ca_j$ | Used capacity of machine j |
| $cmax_j$ | Maximum capacity of machine j |
| $cmin_j$ | Minimum capacity of machine j |
| $tmax$ | Maximum time the machines get involved |
| $\alpha_i^k$ | Conversion rate of raw material k to product i |
| C | Overhead cost |
| M | Perishability coefficient |
| R | Number of similar machines of the same type |
| | Model decision variables |
| $x_i^n$ | Amount of product to be manufactured on day n, an integer |
| $dm_j^n$ | Duration of machine j used on day n, an integer |
| $h_k^n$ | Inventory of raw materials k required on day n, an integer |

#### 1) PARTICLE SWARM OPTIMIZATION ALGORITHM

In the particle swarm algorithm, optimization is performed by a group of individuals (particles) that cooperate and share their information to reach an optimal solution. The optimization steps in the algorithm are as follows, as shown in Figure (3):

- Initialization: The initial position and speed of the particles are determined randomly.
- Movement of particles: each particle moves to a new location according to its current location and speed.
- Information exchange: particles share their information with their neighbors and the best speed and location are updated.
- Location and velocity update: According to shared information and own experiences, the location and velocity of each particle are updated.
- Evaluation: The performance of each particle is evaluated to reach the optimal solution.
- Stopping criteria: The process continues with iteration until it reaches a certain number of iterations or the specified stopping conditions are met [73] and the best position is introduced as the output. The condition of stopping the problem of this research is that the relative change in the best objective function g compared to the last iterations is less than $\mathbf{10^{-6}}$.

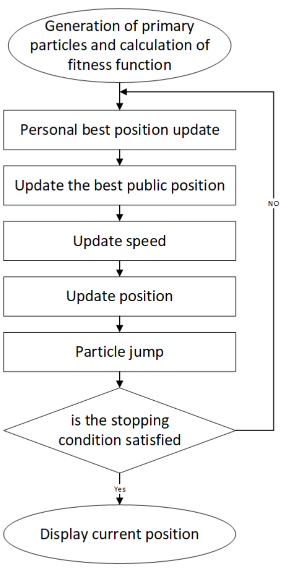


**FIGURE 3. The optimization steps in the PSO algorithm.**

The speed of the particle represents its future location change in the particle swarm algorithm. Therefore, when a particle moves through the optimization space, its velocity determines how fast it moves in a particular direction. This value is updated in each iteration of the search, according to Eq. (14). In this regard, t represents the repetition number and C variables are learning factors or acceleration coefficients. Most sources consider $C_1$ and $C_2$ equal to 2 [70]. r is a uniform random number in the interval (0, 1) and the parameter w represents the inertia weight, which takes an initial value in the interval (0, 1) [71] Inertia weight is the effect of the fast speeds. It controls the current speed, which in this research decreases linearly from 0.8 to 0.3 during the steps of the algorithm.

The term $\boldsymbol{p_i}$ represents the best position that the particle has experienced so far, often referred to as the 'best personal position. 'Meanwhile, $\boldsymbol{p_g d}$ is the best position that has been achieved by the population of particles, known as the' best overall position.

$$V_i(t+1) = WV_i(t) + C_1 r_{1,i}(t)\left(p_i(t) - X_i(t)\right) + C_2 r_{2,i}(t)\left(p_g(t) - X_i(t)\right) \tag{14}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{15}$$

### 2) GENETIC ALGORITHM

Based on the genetic algorithm depicted in Figure 4, optimization is achieved by repeating the process from generation to generation. The chromosomes in each generation are generated from those in the existing population, gradually converging toward an optimal solution. To produce offspring for subsequent generations, the algorithm selects individuals from the current population as parents. The goal of each generation is to surpass the previous one in performance, which is enhanced by crossover and mutation processes. Over successive generations, the population evolves toward an optimal solution until a predefined stopping condition is met.

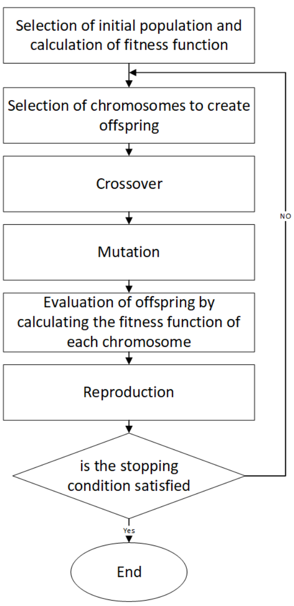


**FIGURE 4. The optimization steps in the GA.**

## IV. EXPERIMENTAL ANALYSIS: THE FRAMEWORK

In this section, the empirical analysis framework of the model is introduced. A case study with its description and analytical case information is presented in section A. The required parameters for the proposed method are discussed in section B, and finally, the sensitivity analysis approach to verify the significance of the results is discussed in section C.

Comparing the optimization method between the two algorithms, the differences and similarities are as follows:

- In the genetic algorithm, the population is generated from different sizes, each of which has the role of an individual. In the particle swarm algorithm, particles move toward optimization by interacting and cooperating.
- In the genetic algorithm, selection and combination of genomes (crossover) and random changes (mutation) are used to produce a new generation. In the particle swarm algorithm, the location and speed of particles are changed based on current and experimental information. In a genetic algorithm, the number of generations is usually more, and improvement is done gradually. The particle swarm algorithm iteratively improves solutions until convergence to either a local or global optimum.

### A. CASE STUDY

The traditional dairy production job shop in Tehran in the southern region has been under study. This job shop manufactures the products after obtaining raw materials from the cattle farm and then sells them in a store in the same area. The products of this job shop include cream, yogurt, and dough; a part of the milk is used to manufacture these products, and the rest is transferred directly to the store for sale.

In this job shop, there are 5 machines, with 2 machines available from machine No. 2. Machines 4 and 5 are designated for the cold room and hothouse, respectively, operating in parallel and capable of accommodating multiple products simultaneously. The values for each set are detailed in Table 3.

**TABLE 3. Size of problems.**

| Symbols | Descriptions | Size of set |
|---|---|---|
| I | Index set for the manufactured products i ϵ I | 4 |
| J | Index set for production Machines j ϵ J | 5 |
| N | Index set for manufactured products n ϵ N | 3 |
| K | Index set for raw materials k ϵ K | 2 |
| P | Index set for a subset of production Machines p ϵ J | 3 |

Table 4 specifies the result of the current depreciation of machines in one year.

Depreciation is calculated using the most conventional method, i.e. straight line, Eq. (16):

$$\textbf{Depreciation} = \frac{\textbf{cost} - \textbf{residual value}}{\textbf{years of useful}} \tag{16}$$

Tables 5 and 6 list the total cost of machines and problem parameters.

### B. MODEL PARAMETERS

The obtained information is related to one year, i.e. 350 working days (15 days off due to Nowruz Tasua and Ashura days) with a special sales scale report.

**TABLE 4. Depreciation of machines.**

| Row | Property items | Cost | Useful life | Cost of current depreciation |
|---|---|---|---|---|
| 1 | 2 barrels | 500,000 | 5 | 100,000 |
| 2 | Cold house and greenhouse | 60,000,000 | 5 | 12,000,000 |
| 3 | Cauldron | 17,000,000 | 5 | 3,400,000 |
| 4 | Milk Cooler | 14,000,000 | 5 | 2,800,000 |
| 5 | Special vessel | 2,000,000 | 5 | 400,000 |

**TABLE 5. Total cost of machines per minute.**

| Counter j | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Total cost of Machines per minute | 8 | 321 | 41 | 2 | 30 | 13 |

**TABLE 6. Parameter values.**

| Description | Milk consumption rate (liter) | Milk powder consumption rate (grams) | Packaging cost (Tomans) | Total cost of materials (Tomans) | Selling price (Tomans) | Lifespan (days) |
|---|---|---|---|---|---|---|
| symbol | $\alpha_i^1$ | $\alpha_i^2$ | - | $cp_i$ | $p_i$ | $Ed_i$ |
| Milk i= 1 | 0 | 0 | 1000 | 18500 | 21500 | 7 |
| Yogurt i=2 | 1,08 | 8 | 3000 | 14203 | 35000 | 5 |
| Dough i= 3 | 1 | 0 | 1000 | 12025 | 20000 | 10 |
| Cream i=4 | 20,83 | 0 | 1000 | 134874 | 190000 | 4 |

In neural networks, careful consideration of the number of layers and the architectural design is particularly crucial. The arrangement and complexity of layers play a significant role in determining the network's ability to learn and generalize from data. To determine the exact number of layers in the neural network, there is no pre-defined and specific structure, and only a series of general rules can be considered, such as the more complex the problems, the higher the number of layers. Also, considering the optimal output and the fact that we stop when the optimal solution is obtained with smaller layer numbers and less time, 45 different layers were tested and, finally, the number of hidden layers for this problem was considered 15.

Also, there are different types of architectures for neural networks. This research investigated three types of feed-forward networks. For network training, three training methods named "Levenberg-Marquardt train (Train LM)", "Train GDX" and "Train BR" have been investigated.

The data in neural network testing is divided as follows: 80% for training, 10% for validation, and 10% for testing.

## V. EXPERIMENTAL ANALYSIS: THE RESULTS AND DISCUSSIONS

In this section, the presentation and analysis of the experimental results of the proposed method are discussed. As the case study has been introduced in the previous sections, the presented method has been implemented to supply the food chain of the case study. The results of the comparison of neural network architecture approaches to choose the best architecture, the comparison of heuristic approaches to determine which method is the most effective, the results of the required production schedule using the proposed method, and the comparison with the traditional method, raw material supply diagrams using the proposed method, effective analysis of management decisions, and finally sensitivity analyses are presented.

### A. NEURAL NETWORK RESULTS

There are different types of architectures for the neural network. In this research, three types of feed-forward net, cascade forward net, and fit net were investigated.

Among them, the feed-forward method showed the best performance and was chosen as the prediction method of this research. One of the important principles in feed-forward neural networks is that there is no connection between the layers, and the information is not fed backward or returned to the previous layers. Also, Loevenberg-Marquardt training has been selected for training networks and used in network training. The performance of this network is shown in Figure 4, which received the data for the past 5 days and will be estimated for the next 3 days.

As shown in Figure 5, the structure of this network is clear, considering the existence of 4 products and having the data of the last 5 days, we have 20 input numbers for the network. The output will be 12 products for 3 days and 4 products. The number of hidden layers of the network is 15 and the last layer is linear. The number of repetitions of the implementation is 12.

Figures 6 - 8 show the results of neural network implementation.

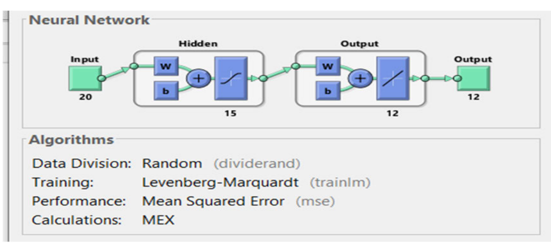


**FIGURE 5.** The structure of the neural network.

As Figure 6. shows, this network after 12 repetitions is finally stopped by the last factor with six rounds of non-improvement. Therefore, the optimal value is determined in the 6th round and the value of 89.27 is gained for its performance. If the curve of the test data demonstrates a substantial increase before that of the validation data, it may suggest the presence of overfitting. Figure 6. reveals that the validation and test data are close to each other and its performance is appropriate.

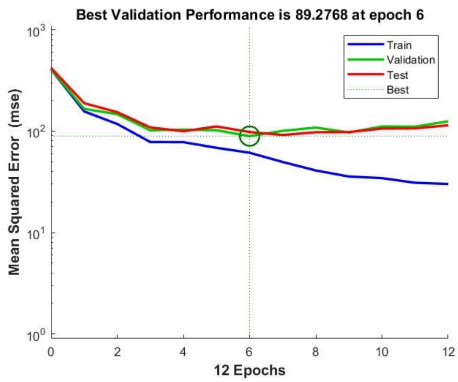


**FIGURE 6.** The mean squares in different iterations.

The next step in network validation is to create a regression plot as shown in Figure 7. that displays the relationship between network outputs and targets. Three graphs illustrate the training, validation, and testing datasets, with the fourth graph portraying the comprehensive performance. The dashed line in each graph represents the perfect result when the outputs are fully on target. The red line represents the best linear regression fit between outputs and targets.

If everything is done correctly, the outputs and goals of the network remain constant throughout the training period; however, in practice, this does not always occur. Therefore, the closer the correlation coefficient (R) number is to 1, the better the model performs. A correlation coefficient of one signifies a perfectly linear relationship between the output and the target variables, while a value approaching zero indicates the absence of such a linear relationship.

In this research model, the test data, training, and validation sets demonstrate a high degree of alignment, as indicated by the correlation coefficient of the entire model, which is close to one, specifically at 0.97. Ultimately, Figure 8 displays the error graph, delineating the distribution of errors between target and predicted values post-training of a neural network. These errors, ranging from $-27.13$ to $+28.5$, represent deviations between predicted and target values, potentially including negative values. Notably, the error closest to zero is $-1.45$, signifying excellent model performance. Following closely, the second most common error value near zero is 2.8. The orange line signifies zero error instances, positioned amidst the highest frequency of errors, reaffirming the model's efficacy in this scenario.

### B. COMPARATIVE RESULTS OF PARTICLE SWARM ALGORITHM AND GENETICS

Considering the problem characteristics and data type, both genetic algorithms and particle swarms can discover optimal

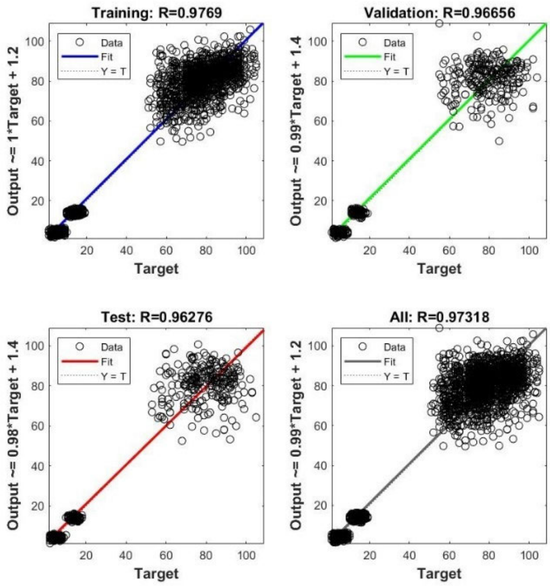


**FIGURE 7.** Neural network regression diagram.

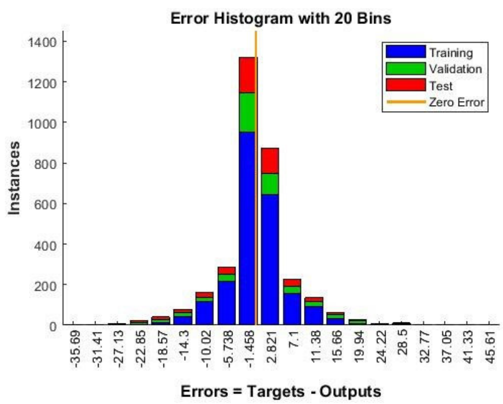


**FIGURE 8.** The neural network error diagram.

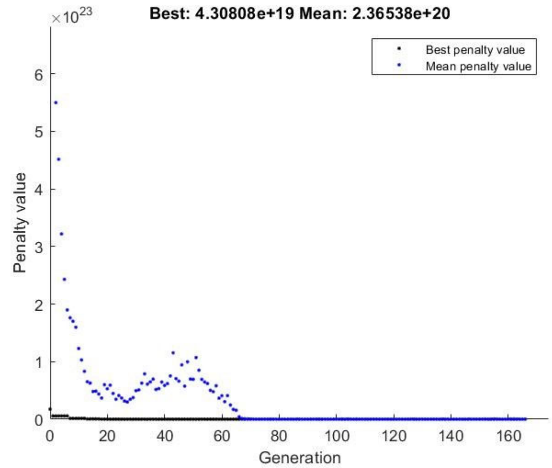


**FIGURE 9.** The genetic algorithm convergence diagram.

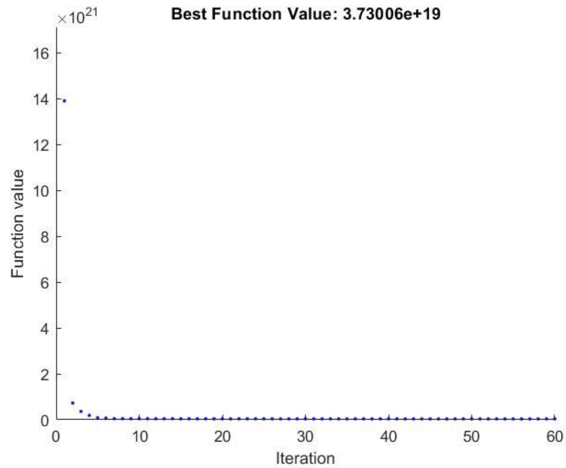


**FIGURE 10.** The convergence diagram of particle swarm algorithm.

or near-optimal solutions. The convergence rate of optimization algorithms reflects the average speed and number of iterations required to reach an optimal or improved solution. Essentially, convergence speed indicates how rapidly the algorithm approaches optimization, or in simpler terms, reduces the distance between the current and the optimal solution.

Figures 9 and 10 demonstrate that the particle swarm method converges faster than the genetic algorithm and exhibits a higher convergence rate.

### C. PRODUCTION SCHEDULING RESULTS

The optimal values represent the products needed for the upcoming three days, considering demand and production capacity. Determined by current inventory levels and product perishability, these values aim to fulfill demand, albeit not necessarily reaching parity. Figure 11. shows the production schedule for each day. This output is displayed in three modes, including heuristic algorithms and the traditional method of this job shop before using the Internet of Things. Following that, we focus on key operational decisions in the job shop, such as machine production scheduling, material volume management within each machine, and the final product output from the process.Production occurs in 3 ways and two types. Number 1 denotes the production of yogurt paired with cream, number 2 entails the concurrent production of yogurt, dough, and cream, and number 3 involves the production of dough alongside cream. Machine No. 2 is available in two numbers and machines 4 and 5 are parallel. The time lasts about five days considering the longest production cycle. The production should be started two days in advance to meet the expected 3 days. The results displayed in Tables 7, 8, and 9 pertain to production scheduling optimization achieved through the genetic algorithm, particle swarm optimization, and traditional methods, respectively. Also, the sequence and scheduling diagram relates to three methods and is presented in Figures 12, 13, and 14.

**TABLE 7.** Production schedule by traditional production method.

| Beginning | End | Machine | Method of production | Materials |
|---|---|---|---|---|
| 1 | 26 | M1 | 2 | 300 |
| 263 | 2010 | M2 | 2 | 300 |
| 2011 | 2265 | M3 | 2 | 300 |
| 2266 | 2381 | M4 | 2 | 300 |
| 2382 | 3828 | M5 | 2 | 300 |
| 2881 | 3142 | M1 | 2 | 300 |
| 3143 | 4890 | M2 | 2 | 300 |
| 4891 | 5145 | M3 | 2 | 300 |
| 5146 | 5261 | M4 | 2 | 300 |
| 5262 | 6708 | M5 | 2 | 300 |

**TABLE 8.** Production scheduling by genetic algorithm method.

| Start time (minutes) | End time (minutes) | Machine name | Name of the production method | Raw materials (liters) |
|---|---|---|---|---|
| 106 | 160 | M1 | 1 | 45 |
| 161 | 171 | M2 | 1 | 45 |
| 172 | 214 | M3 | 1 | 45 |
| 215 | 465 | M4 | 1 | 45 |
| 466 | 1912 | M5 | 1 | 45 |
| 889 | 987 | M1 | 2 | 119 |
| 988 | 2517 | M2 | 2 | 119 |
| 1505 | 1629 | M1 | 3 | 127 |
| 1630 | 3254 | M2 | 3 | 127 |
| 2518 | 2613 | M3 | 2 | 119 |
| 2614 | 2706 | M4 | 2 | 119 |
| 2650 | 2747 | M1 | 1 | 86 |
| 2707 | 4153 | M5 | 2 | 119 |
| 2748 | 2762 | M2 | 1 | 86 |
| 2763 | 2833 | M3 | 1 | 86 |
| 2834 | 3088 | M5 | 1 | 86 |
| 3089 | 4535 | M4 | 1 | 86 |
| 3184 | 3234 | M1 | 2 | 46 |
| 3235 | 4727 | M2 | 2 | 46 |
| 3255 | 3358 | M3 | 3 | 127 |
| 3359 | 3366 | M5 | 3 | 127 |
| 3363 | 4837 | M2 | 3 | 45 |
| 3367 | 4814 | M4 | 3 | 127 |
| 4728 | 4771 | M3 | 2 | 46 |
| 4772 | 4863 | M5 | 2 | 46 |
| 4838 | 4877 | M3 | 3 | 45 |
| 4864 | 6310 | M4 | 2 | 46 |
| 4878 | 4885 | M4 | 3 | 45 |
| 4886 | 6332 | M5 | 3 | 45 |

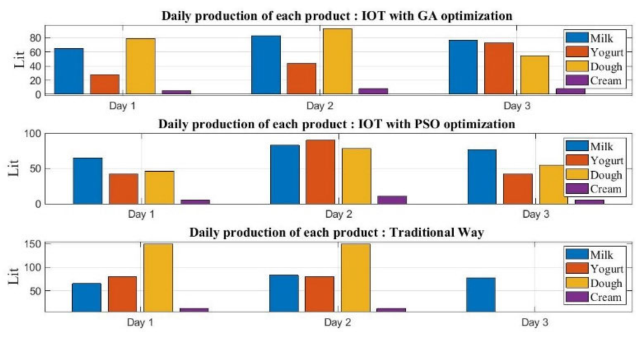


**FIGURE 11.** 3-day production schedule of products.

## D. SUPPLY OF RAW MATERIALS

Ultimately, we address the timely and optimal supply of raw materials to maximize integration throughout the supply chain. In this case study, focusing on milk and milk powder as raw materials, we have determined necessary quantities based on forecasts and current stock levels. This approach empowers buyers to make informed decisions about purchase volume while striving to maintain inventory levels closest to the required amounts to avert shortages and minimize wastage. Figures 15 and 16 depict these quantities separately for three traditional methods and two optimization algorithms.

**TABLE 9.** Production scheduling by particle swarm algorithm method.

| Beginning | End | Machine | Method of production | Materials |
|---|---|---|---|---|
| 29 | 83 | M1 | 1 | 45 |
| 84 | 94 | M2 | 1 | 45 |
| 95 | 137 | M3 | 1 | 45 |
| 138 | 388 | M4 | 1 | 45 |
| 389 | 1835 | M5 | 1 | 45 |
| 1045 | 1143 | M1 | 2 | 119 |
| 1144 | 2673 | M2 | 2 | 119 |
| 1448 | 1515 | M1 | 3 | 81 |
| 1516 | 3059 | M2 | 3 | 81 |
| 2600 | 2750 | M1 | 1 | 136 |
| 2674 | 2769 | M3 | 2 | 119 |
| 2751 | 2770 | M2 | 1 | 136 |
| 2770 | 2862 | M4 | 2 | 119 |
| 2771 | 2879 | M3 | 1 | 136 |
| 2863 | 4309 | M5 | 2 | 119 |
| 2880 | 3139 | M4 | 1 | 136 |
| 2894 | 2947 | M1 | 3 | 72 |
| 2948 | 4475 | M2 | 3 | 72 |
| 3060 | 3126 | M3 | 3 | 81 |
| 3127 | 3134 | M4 | 3 | 81 |
| 3135 | 4582 | M5 | 3 | 81 |
| 3140 | 4586 | M5 | 1 | 136 |
| 4319 | 4373 | M1 | 1 | 45 |
| 4374 | 4384 | M2 | 1 | 45 |
| 4385 | 4427 | M3 | 1 | 45 |
| 4428 | 4678 | M4 | 1 | 45 |
| 4476 | 4535 | M3 | 3 | 72 |
| 4536 | 4543 | M4 | 3 | 72 |
| 4544 | 5991 | M5 | 3 | 72 |
| 4679 | 6125 | M5 | 1 | 45 |

## E. MANAGERIAL INSIGHTS

We will examine the utilization of the Internet of Things and its influence on boosting productivity from a managerial viewpoint to identify the most efficient production method. Consequently, we will compare and analyze profitability, revenue, and production costs across different sectors using both traditional production methods and the approach developed in this model. The model's findings suggest that income could rise by 10 to 15%, and profit by 13 to 18%, depending on the solving method whether the genetic algorithm or particle swarm algorithm—is used. Notably, it's crucial to highlight that even if income doesn't seem to increase initially, the modern method will, in practice, deliver fresher products to customers, a factor that will contribute to long-term income growth due to product perishability considerations. Additionally, given the relatively constant production rate in the traditional method, any product shortages will significantly enhance the positive impact of the developed model on income. Conversely, in scenarios where there is minimal shortage of sales and surplus production in the traditional method, the income disparity between the traditional and developed methods will narrow.

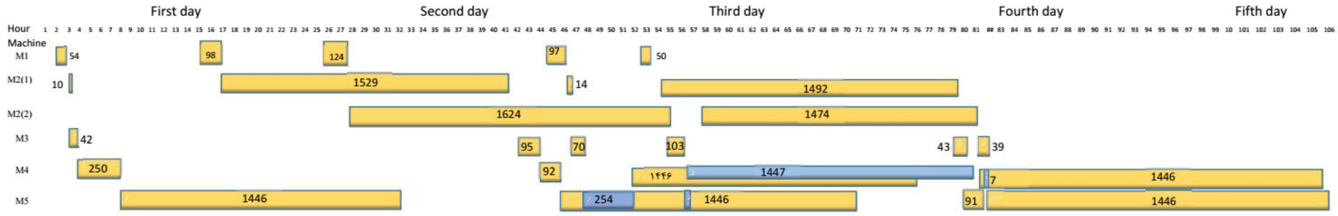


FIGURE 12. The production scheduling by genetic algorithm method.

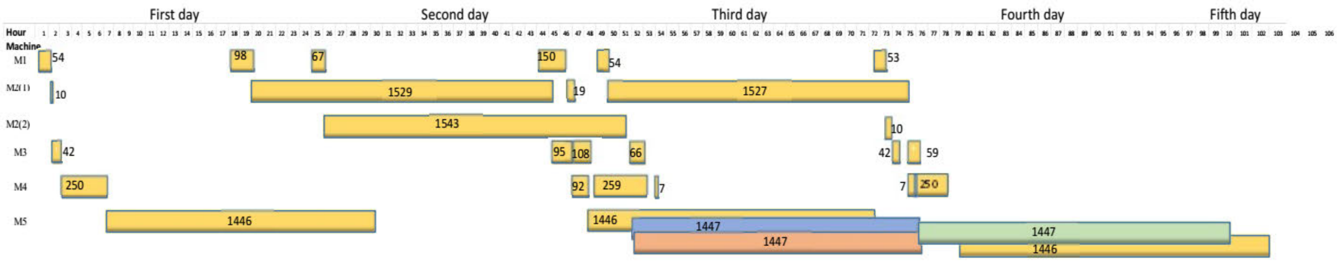


FIGURE 13. The production scheduling by particle swarm algorithm method.

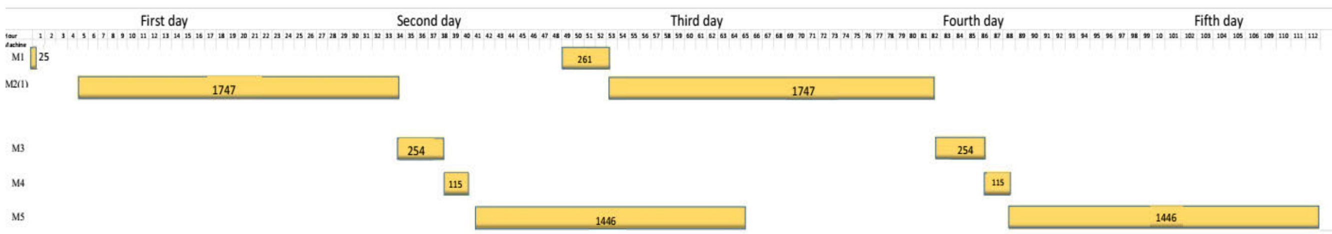


FIGURE 14. The production scheduling by traditional production.

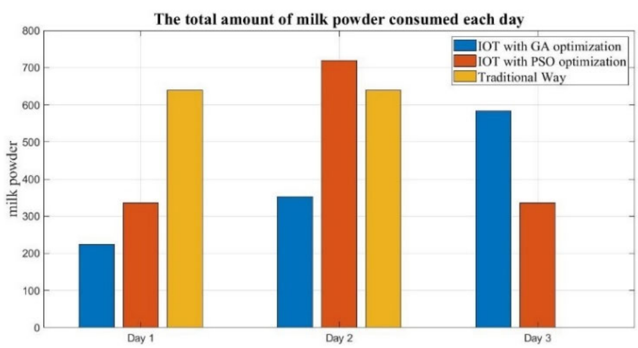


FIGURE 15. Raw milk powder materials for production.

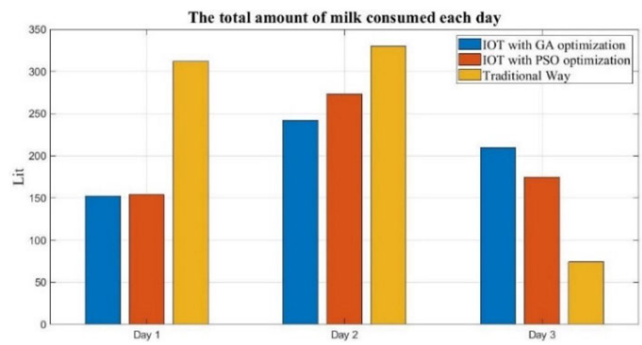


FIGURE 16. Raw materials for milk production.

From a cost perspective, the modern method demands a larger workforce and longer production cycles comparing to traditional methods. Traditional production, which involves larger batches and fewer processing steps, results in shorter overall production times. However, contemporary production methods involve more frequent iterations and smaller, more diverse batches, leading to shorter, more frequent production cycles. This underscores the importance of investing more in human resources, as it ultimately contributes to increased profitability.

The cost of the products in the traditional method is almost constant and product cost in the modern method is determined based on the predicted demand of the neural network. Therefore, when the demand is higher than the number of products produced in the traditional production method, the cost of the products will be higher in the modern method, while the cost of the products may be higher in the traditional method when the demand is lower. Thus, it can be concluded that the modern method enhances system productivity by providing flexibility in production volume to better match demand.

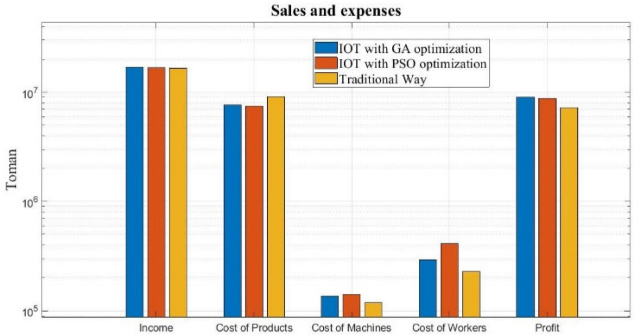


**FIGURE 17. Separation of cost and profit.**

**TABLE 10. Separation of cost and profit.**

| Description (in Tomans) | Traditional way (TW) | Particle swarm Optimization algorithm (PSO) | Genetic algorithm (GA) |
|---|---|---|---|
| Profit | 7209080 | 8290442 | 85067144 |
| Income | 16672500 | 18339750 | 18673200 |
| Total cost of the product | 9116960 | 7456150 | 7621460 |
| Workforce cost | 228042 | 412173 | 292617 |
| Cost of machinery | 118424 | 141694 | 137259 |

This is accomplished by either reducing product costs during surplus production in the traditional method or by averting shortages and consequently boosting sales. In addition to the time of use, the cost of machines also depends on the type of machine and can be lower or higher than the traditional method.

In Figure 17 and Table 10, the results of income, profit, and expenses are displayed separately.

In the traditional method, a combined production approach results in the production of all products in each production cycle, albeit in certain proportions. As depicted in Figure 11, this leads to a higher volume of dough, a lower volume of yogurt, and a fixed quantity of cream being produced. While this may not pose a problem due to the higher sales volume of milk and dough, it is crucial to recognize that cream and yogurt are the most profitable products based on demand and selling price. Therefore, it may be beneficial to occasionally reduce dough production to prioritize cream and yogurt, thereby maximizing profitability.

Furthermore, it is possible to determine if the productivity of the devices has changed based on the schedules, or according to their use.

**TABLE 11. Comparison of the efficiency of machines.**

| Productivity | GA | PSO | Traditional way |
|---|---|---|---|
| Machines | Total time | Total time | Total time |
| M1 | 0.065 | 0.073 | 0.04 |
| M2 | 0.47 | 0.36 | 0.27 |
| M3 | 0.060 | 0.064 | 0.08 |
| M4 | 0.11 | 0.13 | 0.04 |
| M5 | 0.77 | 0.73 | 0.45 |
| Performance of the entire workshop | 0.30 | 0.27 | 0.17 |

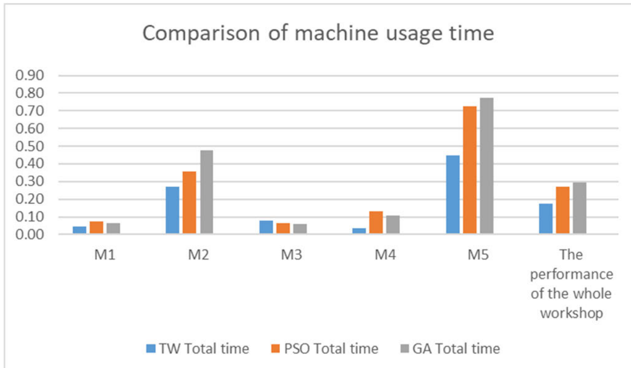


**FIGURE 18. Comparison of workshop productivity.**

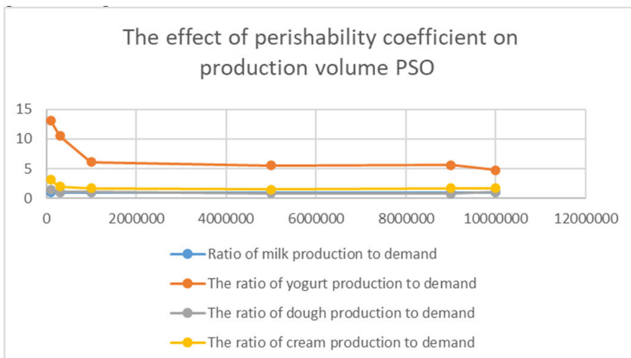


**FIGURE 19. Sensitivity analysis of the perishability parameter in the particle swarm algorithm.**

As Table 11 shows, both optimization methods of genetic algorithm and particle swarm algorithm are better than the traditional method and productivity has increased by 10 to 13 percent.

### *F. SENSITIVITY ANALYSES: PERISHABILITY PARAMETERS AND DEMAND*

In this section, a sensitivity analysis of the model's key parameters will be conducted, specifically focusing on demand and the penalty for perishability. By increasing sensitivity, we seek to evaluate their influence on production

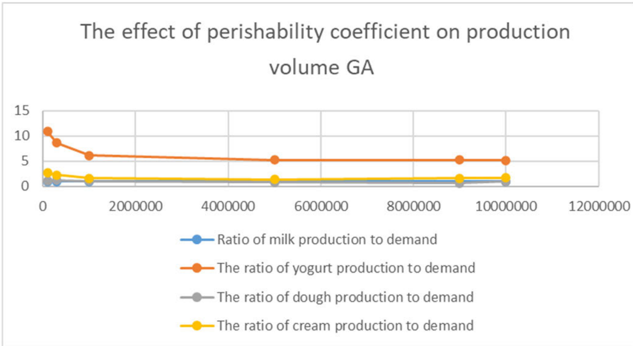


**FIGURE 20.** Sensitivity analysis of the perishability parameter in the genetic algorithm.

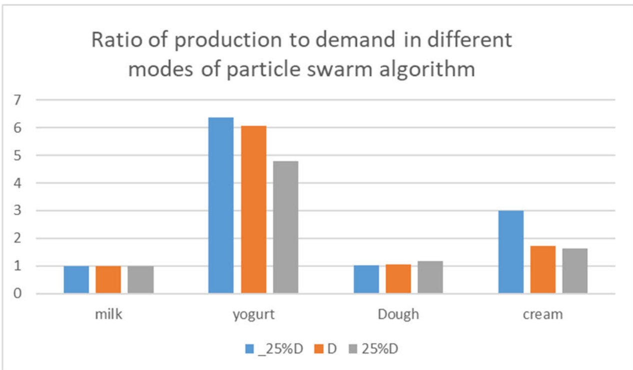


**FIGURE 21.** Sensitivity analysis of the demand parameter in the particle swarm algorithm.

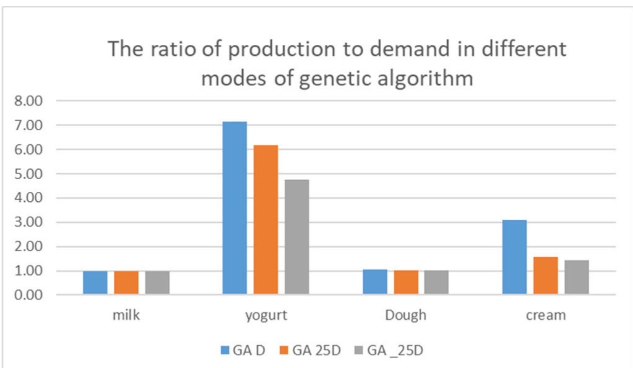


**FIGURE 22.** Sensitivity analysis of the demand parameter in the genetic algorithm.

volume and analyze the model's sensitivity to perishability coefficients. Considering the constraint of no shortages, production will be increased to fully meet demand. Figure 19 demonstrates the impact of perishability on production for the particle swarm algorithm, while Figure 20 illustrates the same for the genetic algorithm.

The demand is considered to be 25% higher and lower than the current state to check the effect of demand on the volume of manufactured products. Then the production volume has been checked based on each of the demand modes. Figures 21 and 22 are drawn for particle swarm algorithms and genetics to measure this problem.

## VI. CONCLUSION

This research seeks to achieve the best scheduling and volume of production so that it delivers fresher products to the final customers and has the most profit for the manufacturer, keeping in mind the perishability of the products and the full coverage of the demand. The production schedule for each machine and the required raw materials and manufactured products have been compiled with a short-term time horizon of 3 days. Production should commence 2 days before, accounting for the longest production cycle. The model should be executed after the production of each product batch to facilitate dynamic scheduling at the workshop level. This allows for the schedule to be updated and re-executed in the event of any changes, which are determined by real-time data and forecasted demand.

This model enables precise determination of raw material usage, resulting in expedited availability and decreased fresh raw material capital consumption. This has been achievable by considering the volume of the required product, the inventory of the warehouse, and the conversion rates so that it can prepare the materials at the operational level and at the right time. This model trains the neural network with the help of the data of the store's one-year demand that can get the production schedule with proper performance. Two genetic and particle swarm heuristic algorithms have been used to solve the model; the particle swarm algorithm provides a higher convergence speed for solving the model.

The results demonstrate that modern job shop performance can increase productivity by 13%. Although the particle swarm algorithm has performed better in the convergence rate, the genetic algorithm has performed better in increasing productivity and has improved productivity by 3% compared to the particle swarm.

The sensitivity analysis of the perishability parameter shows the model has a great tendency to produce in higher volumes and excess by reducing the effect of perishability; The production volume decreases by increasing this coefficient, and this downward trend will gradually decrease according to the required demand coverage. The desired model produces yogurt and cream to a high extent in different demand states. Buttermilk and milk have quantitatively the highest volume of demand and the longest lifespan, and apparently, they should have a larger volume of production as in the traditional method. However, the model is more inclined to produce yogurt and cream. The reason is the higher profit the cream and yogurt contain. This profit is for cream in the first rank and for yogurt in the second according to the volume of demand.

The supply chain for this problem is direct. A closed-loop supply chain can be considered for the development of this research. Thus, if a product of this job shop is not sold or decays, it should be returned to the centers and recovered.

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