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Design of Dual-Channel Supply Chain Network Based on the Internet of Things Under Uncertainty

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Abstract: In this paper, a mathematical model of a dual-channel supply chain network (DCSCN) based on the Internet of Things (IoT) under uncertainty is presented, and its solution using algorithms based on artificial intelligence such as genetic algorithm (GA), particle swarm optimization (PSO), imperialist competitive algorithm (ICA), and gray wolf optimizer (GWO). The main goal of this model is to maximize the total DCSCN profit to determine the amount of demand accurately, price in direct and indirect channels, locate distribution centers, and equip/not equip these centers with IoT devices. The results show that with the increase in the uncertainty rate, the amount of demand and corresponding transportation costs have increased. This issue has led to a decrease in the total DCSCN profit. By analyzing the mathematical model, it was also observed that deploying IoT equipment in distribution centers has increased fixed costs. Examining this issue shows that by increasing the savings factor by 0.2, the total DCSCN profit has increased by 6.5%. By ranking the algorithms with the TOPSIS method, the GA was ranked as the most efficient algorithm, followed by PSO, ICA, and GWO. This IoT-enhanced dual-channel supply chain model not only aims to optimize traditional supply chain metrics but also introduces advanced, data-driven strategies for improving demand management, pricing, and infrastructure allocation, ultimately driving profitability in uncertain environments.

Keywords: dual-channel supply chain network; internet of things; fuzzy programming; robust possibilistic programming; algorithm based on artificial intelligence

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1. Introduction

In today's competitive world and the production space, manufacturers produce and provide products according to customer needs. The more manufacturers pay attention to meeting customers' needs, the more they can gain a larger market share and make significant profits. Therefore, to gain more market share, manufacturers consider the total process of supplying raw materials, production, and distribution to customers in the form of a supply chain. In fact, the supply chain manages the flow of goods from suppliers to customers to reduce total costs or increase revenues [1]. One of the most essential tasks of the supply chain is pricing products in the competitive market so that it can provide the most appropriate price and quality, in addition to gaining a greater share of sales. In the DCSCN, products are usually sold to customers through intermediaries and without intermediaries. This issue leads to creating a complex supply chain system, which requires the presentation of a mathematical model to achieve the optimal solution. Dual channels are intricate due to the interplay between direct and indirect sales, where pricing, demand allocation, and competition between channels must be balanced to maximize profitability. Their complexity arises from non-linear relationships, demand fluctuations, and channel-specific costs. An optimal solution can be mathematically derived using multi-objective optimization techniques that navigate these complexities by identifying trade-offs and converging on solutions that maximize total profit while satisfying operational constraints.

With the rapid development of e-commerce and information technology, many manufacturers have engaged in e-commerce and selling their products to customers through direct channels. Direct sales development channels have many advantages over indirect or intermediary channels, such as reducing total costs, increasing production efficiency, creating various products, saving time, etc. However, direct sales marketing is challenging due to the presence of intermediaries. In both markets, there is competition for more market share [2].

Direct sales become problematic when intermediaries are present due to potential channel conflicts, as intermediaries may feel undermined and reduce their promotional efforts or switch to competitors. Additionally, direct sales create competition for the same customers, leading to pricing challenges and market confusion. Managing both channels increases operational complexity and costs, as companies must maintain direct platforms and logistics while ensuring intermediary support. This delicate balance requires strategic pricing and relationship management to optimize dual-channel operations effectively.

The competition between the two channels is to achieve more market share. Therefore, each two-channel is trying to convince consumers to buy from them. Among the factors that influence the increase in demand in the direct sales channel are proper access, fast delivery, and price of goods [3]. Among these factors, the most critical factor that will create competition with the indirect sales channel is the cost of goods for the consumer. Therefore, the main competition between the two sales channels occurs through determining the appropriate price to attract a larger market share and increase profits. The first study of DCSCN was initiated by Balasubramanian [4] in dual channel price competition. Since then, much research has been conducted in this field, reflected in DCSCN decision-making, DCSCN conflict, DCSCN pricing strategy, and DCSCN coordination mechanisms [5].

The development of research related to the DCSCN and the increase in customer demand for various products have led to uncertainty in product manufacturing. When there is uncertainty in customer demand, it is difficult to price products and determine the optimal amount of production and distribution. Many studies have shown that uncertainty has led to increased operational costs, including costs related to strategic and tactical decisions [6].

In order to deal with this uncertainty in the supply chain, various methods have been used in the literature, such as stochastic programming (SP), fuzzy programming (FP), RPP, etc. Most of these methods seek robust, uncertain parameters to make optimal decisions [7]. In this paper, to solve this issue, a DCSCN model with three echelons of production centers, distribution centers, and customers has been considered, in which there is uncertainty in the demand and transportation costs. Four different methods were used to deal with uncertain parameters in this supply chain network, such as BPCCP, RPP-I, RPP-II, and RPP-III. These methods try to control the amount of customer demand in such a way that the best decision can be made in line with the pricing of products in the direct channel (online sales) and the indirect channel (offline sales).

However, what distinguishes the DCSCN studied in this research is using IoT tools to increase the supply chain's performance and reduce operating costs. IoT technology can automate and digitize supply chain processes to achieve maximum operational efficiency while lowering operational costs. The massive proliferation of IoT devices has revolutionized the supply chain. In the supply chain, IoT devices track and trace shipments using the latest real-time monitoring technologies, including GPS. IoT devices are also used for asset management using NFC technology and RFID tags. IoT devices are generally used in almost every step of the supply chain process. The research on supply chain management based on the IoT is still developing [8]. This issue's importance has led to the modeling of the DCSCN in conditions of uncertainty; IoT tools should also be used in the problem. So, the use and non-use of IoT in the mathematical model is part of the important decisions that must be taken to maximize profit.

In this study, the aim is to maximize the total profit of a dual-channel supply chain by integrating IoT under uncertainty. Key research questions include the following: How can IoT enhance demand forecasting accuracy, optimize pricing in direct and indirect channels, and determine the strategic location and IoT-equipment decisions for distribution centers? The objectives are to develop a robust model that leverages IoT for precise demand management, dynamic pricing, efficient infrastructure allocation, and overall supply chain resilience and profitability.

Equipping or not equipping distribution centers with IoT is a part of strategic decisions along with the location of distribution centers. Also, determining the optimal amount of production, choosing the type of vehicle, determining the amount of product demand, and its pricing in direct and indirect channels to maximize the total profit are other decisions of the DCSCN based on the IoT. To solve the mathematical model in this paper, algorithms based on artificial intelligence, such as GA, PSO, ICA, and GWO, are used. In general, the flowchart of this paper is shown in Figure 1.

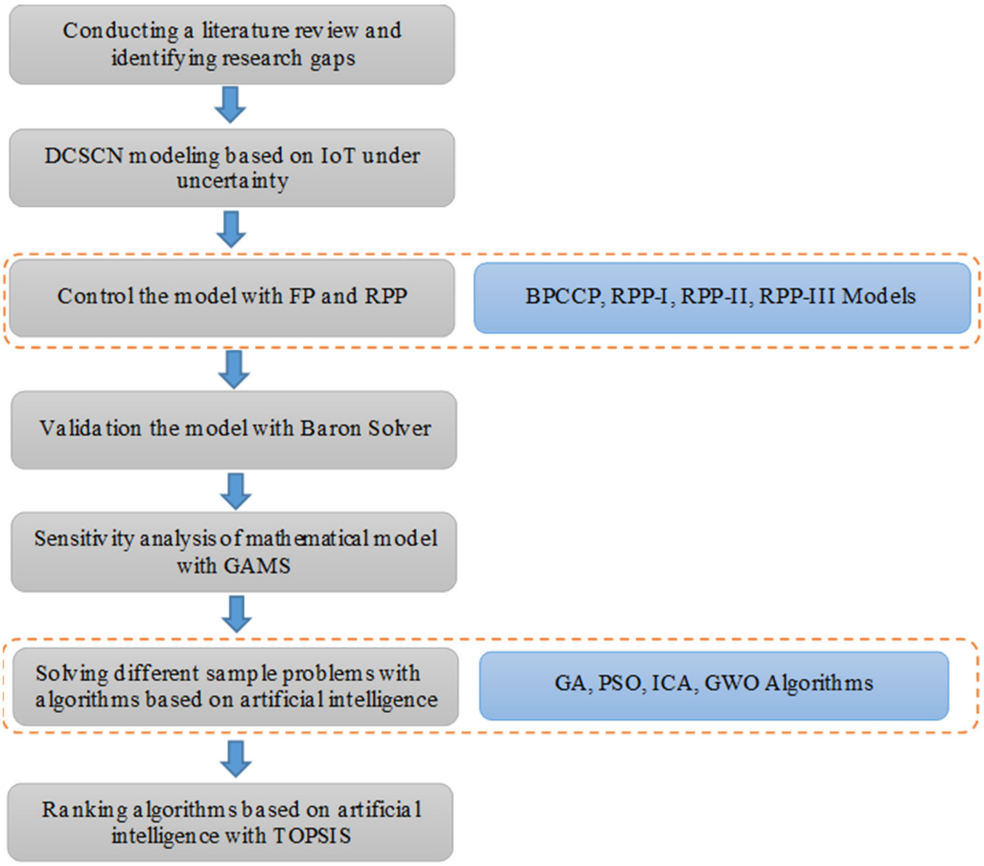

Figure 1. Research flowchart.

This article has six sections. The Section 2 discusses the literature review and the review of various articles in this field. Finally, the research gap is extracted and presented. The Section 3 presents a mathematical model of the DCSCN based on the IoT under uncertainty. A BPCCP, RPP-I, RPP-II, and RPP-II models were used to control the uncertainty parameters of demand and transportation cost. In the Section 4, algorithms based on artificial intelligence and initial solution design are introduced. The Section 5 discusses the analysis of different sample problems with different solution methods. Also, sensitivity analysis and algorithm efficiency are discussed in this chapter. Finally, in the Section 6, conclusions are discussed.

2. Literature Review

Determining the selling price of the product of each of the sales channels in the DCSCN is a critical issue. Customers have different expectations in each of these channels. Most of the research uses game theory to investigate the pricing problem in the supply chain, but it cannot be used to cover this problem due to its mathematical complexity. However, some researchers, such as Yu et al. [9], investigated the pricing problem with mathematical programming, leading to the model's non-linearity.

Gan et al. [10] presented a mathematical model to determine pricing factors in a dual-channel system, where products have a short life cycle. They considered a closed-loop supply chain that included the collector, manufacturer, and retailer in addition to the manufacturer. The new product is distributed through the traditional channel and sold through the direct channel. According to different government policies, Javadi et al. [11] presented the pricing problem in a DCSCN. Due to the growth of e-commerce and green production, some companies have changed their direction to provide environmentally friendly products and use online sales channels to increase competition. Modak and Kelle [12] investigated a DCSCN under stochastic customer demand dependent on price and delivery time. They considered five decision variables, price and order quantity for retail and online channels, and delivery time for online channels. The results showed that uncertainty often occurs in retail and online channels. Ranjan and Jha [13] investigated the pricing strategies and coordination mechanisms between members in a DCSCN. In this study, three models (centralized, decentralized, and cooperative) were investigated. A manufacturer offers a new interchangeable green (eco-friendly) product through the direct channel and a non-green (traditional) product through the offline retail channel.

He et al. [14] considered a dual-channel closed-loop supply chain where a manufacturer can distribute new products through an independent retailer and remanufactured products through a third-party company or platform in the presence of possible government subsidies. He et al. [15] studied a single-retailer–single-vendor DCSCN model in which the vendor sells perishable products through direct online and indirect retail channels. In addition to the deterioration in the quantity, the quality of the products also decreases over time. Peng et al. [7] discussed a buy-online–delivery-store (BODS) strategy in which the manufacturer sells products through online and offline channels and the offline retailer delivers online orders from the retailer's warehouse. Sales apply. By comparing the strategies, the manufacturer manages the online channel, and the retailer manages the offline channel independently. Zhang et al. [16] discussed a dynamic pricing strategy and green issues for a DCSCN that includes a manufacturer and a retailer. In addition, they discussed pricing and green strategies under decentralized and centralized decision-making scenarios.

IoT technologies have proven vital in strengthening supply chain resilience by enabling real-time data collection and analytics. These capabilities allow organizations to promptly identify and mitigate risks, such as delays or environmental disruptions. The real-time tracking of goods, for instance, facilitates immediate responses to unexpected changes, significantly reducing potential losses [17].

Despite its benefits, IoT implementation in supply chains faces various obstacles. Ahmad et al. [18] identified regulatory compliance, network complexity, and data security as significant challenges. Their study emphasized the importance of collaborative strategies and comprehensive planning to overcome these barriers and fully realize IoT's potential. The IoT has demonstrated its value in temperature-sensitive supply chains by continuously monitoring environmental conditions, such as temperature and humidity, and thereby maintaining product quality. This capability ensures that perishable goods remain within specified parameters, thereby reducing spoilage and safeguarding product integrity [18].

The combination of IoT with other advanced technologies, including artificial intelligence (AI) and blockchain, has further enhanced supply chain operations. For example, AI processes IoT-generated data to predict disruptions and optimize decision-making. At the same time, blockchain technology fosters transparency and security by ensuring the integrity of data shared across the supply chain network [17].

IoT is expected to play a central role in creating more integrated and intelligent supply chain systems capable of autonomously managing uncertainties. Advances in IoT technologies, supportive regulatory policies, and industry collaborations will likely drive the development of more resilient and adaptive supply chains [19].

Fan et al. [20] developed game theory models in a supply chain under traditional retail channels and dual-channel structures to investigate whether the manufacturer adopts an assembly delegation policy. Liu et al. [21] investigated the optimal pricing strategies of a manufacturer and a retailer in a DCSCN with overconfident consumers. They first introduced the concept of consumers' overconfidence level, in addition to consumers' channel preferences. Mu et al. [22] developed and analyzed DCSCN mathematical models for expected profit maximization under centralized, decentralized, and coordinated decision structures. In this paper, a decision framework is presented for a DCSCN that considers credit sales competition and stochastic demand. Li and Mizuno [23] studied a periodic survey, joint dynamic pricing, and inventory problem for a DCSCN with one manufacturer and one retailer, where demand is stochastic and price sensitive. Pal et al. [24] studied the production of environmentally friendly, innovative green products and their effects on the environment. Considering the complexity of the problem in different players' pricing decisions, the level of green innovation and promotional efforts under centralized policies, they used the Stackelberg model and Nash equilibrium. He et al. [25] modeled the two-period optimal pricing strategy of the manufacturer and the retailer and investigated how consumer channel preference, price competition, and market change affect the strategy's equilibrium. Zhao and Zhao [26] investigated pricing strategies in a DCSCN under uncertainty, focusing on profit optimization under different conditions by adjusting the market potential. To solve the problem, they used the following three focused decision models: Stackelberg of the manufacturer, Stackelberg of the retailer, and the vertical Nash model. Liu et al. [27] in a study on the decision-making and optimal coordination problem of a dual-channel fresh agricultural product supply chain analyzed the effect of information sharing on optimal decisions and proposed a coordination mechanism to encourage supply chain members to share information. Gao et al. [28], in order to help managers make sustainable economic and environmental decisions, investigated a sustainable and environmentally friendly closed-loop supply chain network with two channels (an online and offline channel).

The literature review shows that various models have been presented for the DCSCN regarding greenness, pricing, and centralized and decentralized policies. However, the use of IoT tools in DCSCN models has not been seen in the meantime. In this study, the previous research is advanced by integrating IoT into a dual-channel supply chain model, focusing on maximizing profitability under uncertainty. Unlike similar studies, it incorporates IoT-driven real-time data for precise demand forecasting, dynamic pricing, and strategic decisions on the location and IoT-equipping distribution centers. The model uniquely addresses the cost–benefit analysis of IoT implementation and provides a comprehensive framework for managing uncertainty, making it more practical and adaptable for modern supply chain networks. This paper's IoT tools deviate from prior dual-channel supply chain network models by directly addressing uncertainties through real-time data collection, predictive analytics, and enhanced visibility. Unlike traditional models that often rely on static or historical data, IoT-enabled tools in this research provide dynamic insights into demand fluctuations, supply disruptions, and market volatility. These tools allow for more precise forecasting, adaptive pricing strategies, and responsive decision-making, making the model more robust and effective in managing the complexities and uncertainties inherent in dual-channel operations. Therefore, the innovations of this research can be stated as follows:

- Using the concept of the IoT in the form of a mathematical model;
- Development of a DCSCN model with the IoT;
- Using four different uncertainty methods to control model parameters;
- Using four algorithms based on artificial intelligence to solve problems.

3. Problem Definition

The literature review showed that the implementation of the infrastructure of IoT tools in the modeling of the DCSCN to optimize the total system has not been comprehensively studied. Therefore, based on the research gap, this section presents a DCSCN model based on the IoT under uncertainty. Since the uncertainty in demand and transportation costs can lead to the wrong management decisions, the BPCCP model and different RPP models have been used to control these two parameters. The model presented in this article is a three-echelon supply chain model consisting of production centers, distribution centers, and customers. To illustrate the issue, consider Figure 2, which shows two different channels in the supply chain that meet customer demand. In the direct channel, customer demand is met directly by production centers, and in the indirect channel, customer demand is fulfilled by distribution centers. In the DCSCN based on the IoT, the pricing of products in direct channels (from the production center) and indirect channels (from the distribution center) depends on the elasticity of the product price according to demand, and this demand can affect the pricing of products in two channels. Since IoT tools can reduce the costs of the total supply chain and increase the total DCSCN profit. In this paper, the implementation of the IoT infrastructure in the location of distribution centers is considered. Thus, by creating the infrastructure of the IoT and equipping the distribution centers with various IoT tools, operational and energy costs can be reduced, although the cost of equipment will lead to a decrease in profitability.

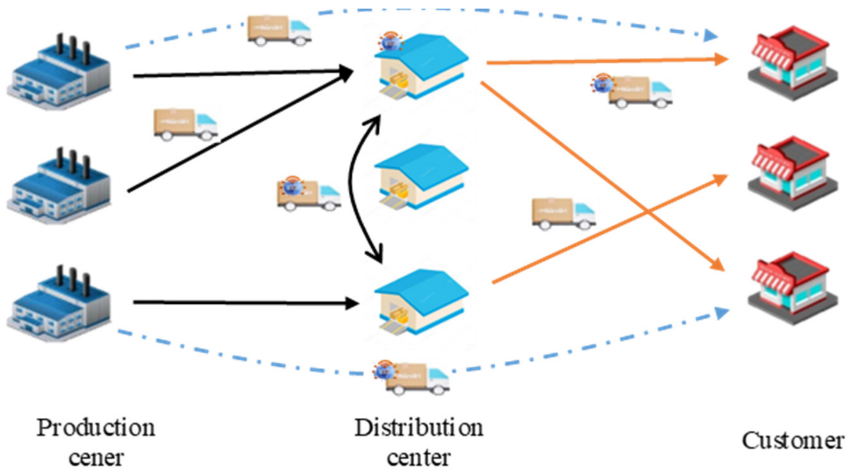

Figure 2. DCSCN-based IoT.

The proposed mathematical model is superior due to its comprehensive integration of IoT-driven real-time data and multi-objective optimization to address demand forecasting, dynamic pricing, and strategic infrastructure decisions in a dual-channel supply chain under uncertainty. Its complexity lies in handling non-linear relationships, uncertainty parameters, and the trade-offs between cost, efficiency, and profitability. By incorporating IoT-equipped and non-equipped options for distribution centers and balancing direct and indirect channel dynamics, the model provides a robust, scalable framework, surpassing conventional models in adaptability and decision-making precision.

Various decisions are made to maximize the total DCSCN profit, which can be the location of distribution centers, equipping/not equipping distribution centers with IoT, allocating vehicles to each route, pricing products in direct and indirect channels, and determining the exact amount of the demand indicated in these channels. Each mathematical model also includes a set of assumptions that covers the general scope of the mathematical model. Therefore, the assumptions of the mathematical model of the DCSCN based on the IoT are as follows:

- it is a multi-product and single-period model;
- demand and transportation costs are considered trapezoidal fuzzy numbers;

- vehicles are considered heterogeneously with different capacities;
- the capacity of the distribution and production centers is known;
- various IoT tools have been considered, and using several tools leads to more cost reduction;
- the potential demand of each channel is uncertain and the actual demand is a function based on price elasticity;
- it is possible to transfer products between distribution centers.

According to the above assumptions, the mathematical model's sets, parameters, and decision variables are defined as follows (Table 1):

Table 1. Sets, parameters, and decision variables.

Sets	
K	Set of production centers $k \in K$
J	Set of distribution centers $j \in J$
I	Set of customers $i \in I$
T	Set of IoT tools $t \in T$
P	Set of products $p \in P$
V	Set of vehicles $v \in V$
Parameters	
$\widetilde{d}_{ip}$	Potential demand of product $p \in P$ for customer $i \in I$
λ_{ip}	Price elasticity of alternative product $p \in P$ in the direct channel for customer $i \in I$
λ'_{ip}	Price elasticity of alternative product $p \in P$ in the indirect channel for customer $i \in I$
γ_i	Price elasticity based on customer demand $i \in I$ in the direct channel
γ'_i	Price elasticity based on customer demand $i \in I$ in the indirect channel
$\widetilde{\rho}_v$	Transportation cost each product unit by vehicle $v \in V$
f_j	Fixed cost of choosing location $j \in J$ to build a distribution center
ϖ_{jp}	Maximum capacity of product $p \in P$ for distribution center $j \in J$
χ_{ip}	Maximum capacity of product $p \in P$ for production center $i \in I$
o_j	Operation and energy cost of distribution center $j \in J$
g_{jt}	The cost of equipping the distribution center $j \in J$ to the IoT tool $t \in T$
β_t	Coefficient of saving energy and operational costs due to the use of IoT tools $t \in T$
Decision Variables	
D_p	The price of product $p \in P$ in the direct channel
I_p	The price of product $p \in P$ in the indirect channel
φ_{ip}	Actual demand of product $p \in P$ for customer $i \in I$ in direct channel
ω_{ip}	Actual demand of product $p \in P$ for customer $i \in I$ in indirect channel
X_{kjpv}	The amount of product $p \in P$ transferred from production center $k \in K$ to distribution center $j \in J$ by vehicle $v \in V$
Y_{jipv}	The amount of product $p \in P$ transferred from distribution center $j \in J$ to customer $i \in I$ by vehicle $v \in V$
Z_{kipv}	The amount of product $p \in P$ transferred from production center $k \in K$ to customer $i \in I$ by vehicle $v \in V$
$W_{jj'pv}$	The amount of product $p \in P$ transferred from distribution center $j \in J$ to distribution center $j' \in J$ by vehicle $v \in V$
N_j	1; if distribution center is chosen in location $j \in J$ 0; otherwise
M_{jt}	1; if distribution center $j \in J$ is equipped to IoT tool $t \in T$ 0; other wise

The mathematical model of the DCSCN based on the IoT under uncertainty is as follows:

$$\begin{aligned} Max\ P = & \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} I_p Y_{jipv} + \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} D_p Z_{kipv} - \sum_{j\in J} f_j N_j - \sum_{j\in J} o_j N_j \\ & -\sum_{j\in J}\sum_{t\in T} g_{jt} M_{jt} - \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} \widetilde{\rho}_v Y_{jipv} \\ & -\sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} \widetilde{\rho}_v Z_{kipv} - \sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V} \widetilde{\rho}_v X_{kjpv} \\ & -\sum_{j'\in J}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V} \widetilde{\rho}_v W_{j'jpv} + \sum_{j\in J}\sum_{t\in T} \beta_t o_j M_{jt} \end{aligned} \tag{1}$$

$$s.t:$$

$$\varphi_{ip} = \widetilde{d}_{ip} - \lambda_{ip} D_p + \gamma_i I_p, \ \ \forall i \in I, p \in P \tag{2}$$

$$\omega_{ip} = \widetilde{d}_{ip} - \lambda'_{ip} I_p + \gamma'_i D_p, \ \ \forall i \in I, p \in P \tag{3}$$

$$\sum_{j\in J}\sum_{v\in V} Y_{jipv} \le \omega_{ip}, \quad \forall i \in I, p \in P \tag{4}$$

$$\sum_{k\in K}\sum_{v\in V} Z_{kipv} \le \varphi_{ip}, \quad \forall i \in I, p \in P \tag{5}$$

$$\sum_{k\in K}\sum_{v\in V} X_{kjpv} + \sum_{j'\in J}\sum_{v\in V} W_{j'jpv} - \sum_{j'\in J}\sum_{v\in V} W_{jj'pv} = \sum_{i\in I}\sum_{v\in V} Y_{jipv}, \quad \forall j \in J, p \in P \tag{6}$$

$$\sum_{i\in I}\sum_{v\in V} Y_{jipv} \le \varpi_{jp} N_j, \quad \forall j \in J, p \in P \tag{7}$$

$$\sum_{i\in I}\sum_{v\in V} Z_{kipv} + \sum_{j\in J}\sum_{v\in V} X_{kjpv} \le \chi_{ip}, \quad \forall i \in I, p \in P \tag{8}$$

$$M_{jt} \le N_j, \quad \forall j \in J, t \in T \tag{9}$$

$$D_p, I_p, \varphi_{ip}, \omega_{ip}, X_{kjpv}, Y_{jipv}, Z_{kipv}, W_{jj'pv} \ge 0 \tag{10}$$

$$N_j, M_{jt} \in \{0,1\} \tag{11}$$

Equation (1) shows the problem's main objective function, which includes maximizing the total DCSCN profit. Equations (2) and (3) determine the size of actual customer demand based on potential demand and the price elasticity of the substitute product and market in two direct and indirect channels. Equation (4) shows the amount of product transported between distribution centers and customers using different vehicles. This amount of transmission will be as much as the customers' demand in the indirect channel. Equation (5) shows the customer demand in the direct channel. Equation (6) shows the balance of the product transfer flow in the distribution center. Equation (7) guarantees that the amount of product transferred from each distribution center to customers will not exceed the capacity of that center. Equation (8) guarantees that the amount of product transferred from each production center in the direct and indirect channel will not exceed the capacity of that center. Equation (9) shows that if a distribution center is selected and built, that center can be equipped with all kinds of IoT tools. Equations (10) and (11) show the type of decision variables.

Due to the uncertainty of potential demand and transportation costs in the presented model, various methods have been used to control these parameters.

3.1. BPCCP Model

The indeterminacy of the parameters of the mathematical model and the lack of access to historical data have led to such data being considered by experts' opinions and in the form of trapezoidal fuzzy numbers. Therefore, to face uncertainty limits, the uncertainty rate α is used. To control the uncertainty in demand and transportation cost, the basic model is considered as follows, where the vectors $p, f, \tilde{c}, \tilde{d}$, and s, respectively, represent the selling price of the product, fixed cost, transportation cost, demand, and capacity. Also, a and b are the matrix of coefficients and finally X and Y are continuous and binary variables, respectively. Now, it is assumed that the vectors $\tilde{c}, \tilde{d}$ in the above model are presented as uncertainty parameters. According to the general form of uncertainty-limited programming, the expected value of the objective function and the pessimistic FP should be obtained to deal with the objective function and the uncertainty constraint, respectively. Now, according to the basic model, the BPCCP model is in the form of Equation (12):

$$\begin{array}{lcl} \text{Basic Model} & \text{BPCCP Model} & \text{Script Model} \\ Max\ pX - fY - \tilde{c}X \ \Rightarrow & Max\ pX - fY - \mathrm{E}[\tilde{c}]X \ \Rightarrow & Max\ pX - fY - \left(\frac{c^1+c^2+c^3+c^4}{4}\right)X \\ s.t.: & s.t.: & s.t.: \\ aX \leq \tilde{d} & NEC\{aX \leq \tilde{d}\} \geq \alpha & aX \leq (1-\alpha)d^3 + \alpha d^4 \\ bX \leq sY & bX \leq sY & bX \leq sY \\ Y \in \{0,1\},\ X \geq 0 & Y \in \{0,1\},\ X \geq 0 & Y \in \{0,1\},\ X \geq 0 \end{array} \tag{12}$$

According to the above relationships, the BPCCP model of the DCSCN based on the IoT will be as follows:

$$\begin{aligned} Max\ P = & \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} I_p Y_{jipv} + \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} D_p Z_{kipv} - \sum_{j\in J} f_j N_j - \sum_{j\in J} o_j N_j \\ & - \sum_{j\in J}\sum_{t\in T} g_{jt} M_{jt} - \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) Y_{jipv} \\ & - \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) Z_{kipv} - \sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) X_{kjpv} \\ & - \sum_{j'\in J}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) W_{j'jpv} + \sum_{j\in J}\sum_{t\in T} \beta_t o_j M_{jt} \end{aligned} \tag{13}$$

$s.t.:$

$$\varphi_{ip} = \left(\alpha d_{ip}^4 + (1-\alpha) d_{ip}^3\right) - \lambda_{ip} D_p + \gamma_i I_p,\ \ \forall i \in I, p \in P \tag{14}$$

$$\omega_{ip} = \left(\alpha d_{ip}^4 + (1-\alpha) d_{ip}^3\right) - \lambda'_{ip} I_p + \gamma'_i D_p,\ \ \forall i \in I, p \in P \tag{15}$$

Equations (4)–(11) (16)

3.2. RPP-I Model

In uncertainty models, the minimum level of confidence to establish the uncertainty constraint should be determined by decision-making preferences. As can be seen, in the presented model, the objective function is not sensitive to the deviation from its expected value, which means that achieving stable solutions in the basic model is not guaranteed. In such cases, a high risk may be imposed on the decision-making in many real cases, especially in strategic decisions where the stability of the solution is critical to a large extent. Therefore, to deal with this inefficient situation, the non-deterministic planning approach based on possibility is used for the problem. This approach takes advantage of the significant advantages of both RP and FP, which clearly makes it different from other uncertainty programming approaches. In the following, the RPP-I model based on the BPCCP model is explained:

$$\begin{aligned}
&Max \;\; E[Z] - \xi\Big(Z_{(\max)} - Z_{(\min)}\Big) - \eta\left[d^4 - (1-\alpha)d^3 - \alpha d^4\right] \\
&s.t.: \\
&aX \leq (1-\alpha)d^3 + \alpha d^4 \\
&bX \leq sY \\
&Z_{(\max)} = c^4 X \\
&Z_{(\min)} = c^1 X \\
&E[Z] = pX - fY - \left[\left(\tfrac{c^1+c^2+c^3+c^4}{4}\right)\right]X \\
&Y \in \{0,1\}, X \geq 0
\end{aligned} \tag{17}$$

In Equation (17), the first term refers to the expected value of the objective function using the average values of the uncertain parameters of the model. The second term refers to the penalty cost for deviation from the expected value of the objective function (robustness). The third sentence also shows the total cost of the penalty for deviation from the demand (uncertainty parameter). Therefore, the parameter ξ is the weighting coefficient of the objective function and η is the penalty cost of not estimating the demand. Based on this, the RPP-I model will be as follows:

$$Max\ P = E[P] - \xi(P_{max} - P_{min}) - \eta \sum_{i\in I}\sum_{p\in P}\left(d^4_{ip} - \alpha d^4_{ip} - (1-\alpha)d^3_{ip}\right) \tag{18}$$

$$s.t:$$

$$\begin{aligned}
E[P] = &\sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} I_p Y_{jipv} + \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} D_p Z_{kipv} - \sum_{j\in J} f_j N_j - \sum_{j\in J} o_j N_j \\
&- \sum_{j\in J}\sum_{t\in T} g_{jt} M_{jt} - \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho^1_v + \rho^2_v + \rho^3_v + \rho^4_v}{4}\right) Y_{jipv} \\
&- \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho^1_v + \rho^2_v + \rho^3_v + \rho^4_v}{4}\right) Z_{kipv} - \sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho^1_v + \rho^2_v + \rho^3_v + \rho^4_v}{4}\right) X_{kjpv} \\
&- \sum_{j'\in J}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho^1_v + \rho^2_v + \rho^3_v + \rho^4_v}{4}\right) W_{j'jpv} + \sum_{j\in J}\sum_{t\in T}\beta_t o_j M_{jt}
\end{aligned} \tag{19}$$

$$P_{min} = \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\rho^1_v Y_{jipv} + \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\rho^1_v Z_{kipv} + \sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\rho^1_v X_{kjpv} + \sum_{j'\in J}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\rho^1_v W_{j'jpv} \tag{20}$$

$$P_{max} = \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\rho^4_v Y_{jipv} + \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\rho^4_v Z_{kipv} + \sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\rho^4_v X_{kjpv} + \sum_{j'\in J}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\rho^4_v W_{j'jpv} \tag{21}$$

$$\text{Equations (14)–(16)} \tag{22}$$

3.3. RPP-II Model

Another type of robust possibilistic programming is one in which the decision maker is not sensitive to deviations from the expected optimal value. For example, he may not care about deviations in total costs below the expected optimal value. Still, the decision maker should achieve a lower total cost than the expected optimum. In this case, the RPP-II model can be introduced. In the following, the possible robust planning of the RPP-II model based on the BPCCP model is explained:

$$
\begin{gathered}
Max\ Z = E[Z] - \xi\left(Z_{(\max)} - E[Z]\right) - \eta\left[d^4 - (1-\alpha)d^3 - \alpha d^4\right] \\
s.t.: \\
aX \leq (1-\alpha)d^3 + \alpha d^4 \\
bX \leq sYZ_{(\max)} = c^4 X \\
E[Z] = pX - fY - \left[\left(\frac{c^1+c^2+c^3+c^4}{4}\right)\right]X \\
Y \in \{0,1\},\ X \geq 0
\end{gathered} \tag{23}
$$

According to the above relationship, the RPP-II model will be as follows:

$$
Max\ P = E[P] - \xi(P_{max} - E[P]) - \eta \sum_{i \in I} \sum_{p \in P} \left(d_{ip}^4 - \alpha d_{ip}^4 - (1-\alpha) d_{ip}^3\right) \tag{24}
$$

$$s.t.:$$

$$
\begin{aligned}
E[P] = {} & \sum_{j \in J} \sum_{i \in I} \sum_{p \in P} \sum_{v \in V} I_p Y_{jipv} + \sum_{k \in K} \sum_{i \in I} \sum_{p \in P} \sum_{v \in V} D_p Z_{kipv} - \sum_{j \in J} f_j N_j - \sum_{j \in J} o_j N_j \\
& - \sum_{j \in J} \sum_{t \in T} g_{jt} M_{jt} - \sum_{j \in J} \sum_{i \in I} \sum_{p \in P} \sum_{v \in V} \left(\frac{\rho_v^1 + \rho_v^2 + \rho_v^3 + \rho_v^4}{4}\right) Y_{jipv} \\
& - \sum_{k \in K} \sum_{i \in I} \sum_{p \in P} \sum_{v \in V} \left(\frac{\rho_v^1 + \rho_v^2 + \rho_v^3 + \rho_v^4}{4}\right) Z_{kipv} - \sum_{k \in K} \sum_{j \in J} \sum_{p \in P} \sum_{v \in V} \left(\frac{\rho_v^1 + \rho_v^2 + \rho_v^3 + \rho_v^4}{4}\right) X_{kjpv} \\
& - \sum_{j' \in J} \sum_{j \in J} \sum_{p \in P} \sum_{v \in V} \left(\frac{\rho_v^1 + \rho_v^2 + \rho_v^3 + \rho_v^4}{4}\right) W_{j'jpv} + \sum_{j \in J} \sum_{t \in T} \beta_t o_j M_{jt}
\end{aligned} \tag{25}
$$

$$
P_{max} = \sum_{j \in J} \sum_{i \in I} \sum_{p \in P} \sum_{v \in V} \rho_v^4 Y_{jipv} + \sum_{k \in K} \sum_{i \in I} \sum_{p \in P} \sum_{v \in V} \rho_v^4 Z_{kipv} + \sum_{k \in K} \sum_{j \in J} \sum_{p \in P} \sum_{v \in V} \rho_v^4 X_{kjpv} + \sum_{j' \in J} \sum_{j \in J} \sum_{p \in P} \sum_{v \in V} \rho_v^4 W_{j'jpv} \tag{26}
$$

$$
\text{Equations (14)–(16)} \tag{27}
$$

3.4. RPP-III Model

Another type of robust possibilistic programming is one in which the decision maker only cares about excessive deviations from the optimal value; there is no need to calculate the expected value and the minimum expected value. In the following, the possible robust planning of the RPP-III model based on the BPCCP model is explained:

$$
\begin{aligned}
& Max\ Z = E[Z] - \xi\left(Z_{(\min)}\right) - \eta\left[d^4 - (1-\alpha)d^3 - \alpha d^4\right] \\
& s.t.: \\
& aX \leq (1-\alpha)d^3 + \alpha d^4 \\
& bX \leq sY \\
& Z_{(\min)} = c^1 X \\
& E[Z] = pX - fY - \left[\left(\frac{c^1+c^2+c^3+c^4}{4}\right)\right]X \\
& Y \in \{0,1\},\ X \geq 0
\end{aligned} \tag{28}
$$

According to the above relationship, the RPP-III model of the DCSCN based on IoT will be as follows:

$$
Max\ P = E[P] - \xi(P_{min}) - \eta \sum_{i \in I} \sum_{p \in P} \left(d_{ip}^4 - \alpha d_{ip}^4 - (1-\alpha) d_{ip}^3\right) \tag{29}
$$

$$s.t.:$$

$$
\begin{aligned}
E[P] = {} & \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} I_p Y_{jipv} + \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} D_p Z_{kipv} - \sum_{j\in J} f_j N_j - \sum_{j\in J} o_j N_j \\
& - \sum_{j\in J}\sum_{t\in T} g_{jt} M_{jt} - \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) Y_{jipv} \\
& - \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) Z_{kipv} - \sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) X_{kjpv} \\
& - \sum_{j'\in J}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V}\left(\frac{\rho_v^1+\rho_v^2+\rho_v^3+\rho_v^4}{4}\right) W_{j'jpv} + \sum_{j\in J}\sum_{t\in T} \beta_t o_j M_{jt}
\end{aligned} \tag{30}
$$

$$
P_{min} = \sum_{j\in J}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} \rho_v^1 Y_{jipv} + \sum_{k\in K}\sum_{i\in I}\sum_{p\in P}\sum_{v\in V} \rho_v^1 Z_{kipv} + \sum_{k\in K}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V} \rho_v^1 X_{kjpv} + \sum_{j'\in J}\sum_{j\in J}\sum_{p\in P}\sum_{v\in V} \rho_v^1 W_{j'jpv} \tag{31}
$$

$$
\text{Equations (14)–(16)} \tag{32}
$$

4. Solution Methods

In this section, four algorithms based on artificial intelligence, including GA, PSO, ICA, and GWO, have been introduced to solve the problem of DCSCN based on IoT. Also, the TOPSIS method is briefly explained.

4.1. GA

The GA is an optimization method inspired by living nature, which can be introduced in classifications as a numerical method, as well as a direct and random search. This algorithm is repetition-based, and its basic principles are adapted from genetics and invented by imitating several processes observed in natural evolution, and it effectively uses the old trait in a population to create new and improved solutions [29]. The GA starts by randomly generating an initial population of chromosomes while satisfying the bounds or constraints of the problem. During each generation, these chromosomes are evaluated according to the optimization goal, and the chromosomes that are considered to be a better answer to the problem in question have a greater chance of reproducing the answers to the problem [30]. To produce the next generation, new chromosomes called children are created by combining two chromosomes from the current generation using the crossover operator or by modifying the chromosome using the mutation operator.

In this article, the two-point crossover operator is used, according to Figure 3, and the single-point mutation operator, according to Figure 4, for the new generation.

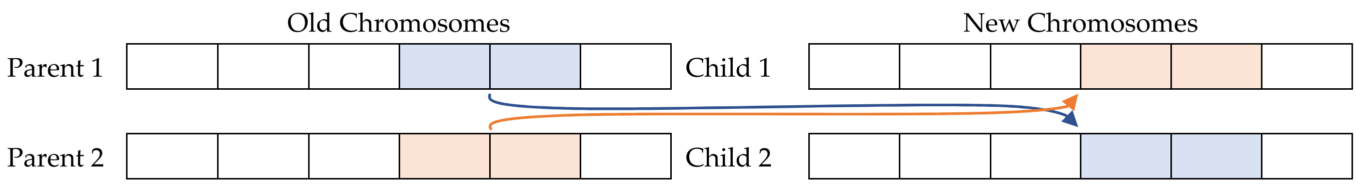

Figure 3. Two-point crossover operator.

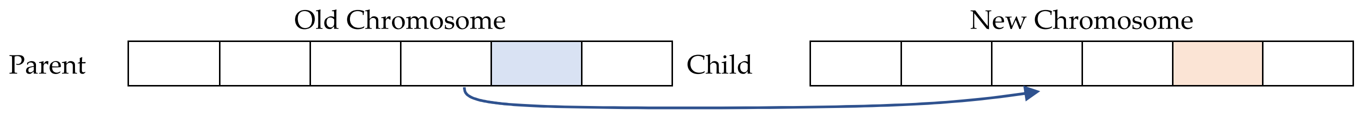

Figure 4. Single-point mutation operator.

4.2. ICA

Like other evolutionary algorithms, this algorithm also starts with some random initial population. A few of the best elements in the population (equivalent to elites in the genetic algorithm) are selected as imperialists. The rest of the population is also considered as a colony. The colonizers, depending on their power, establish with a specific process as follows: they pull towards themselves. Any empire's total power depends on its constituent parts, the imperialist country (as the core), and its colonies [31]. Mathematically, this dependence is modeled by defining imperial power as the total power of the imperialist country, plus a percentage of the average power of its colonies. The imperial competition between the early empires begins with their formation. Any empire that cannot succeed in the colonial competition and increase its power (or at least prevent its influence from decreasing), will be removed from the colonial competition scene; therefore, the survival of an empire will depend on its ability to absorb the colonies of rival empires and dominate them. As a result, in the course of imperial competition, larger empires will gradually gain power and weaker empires will be eliminated. Empires will be forced to develop their colonies to increase their power. In short, this algorithm looks at colonization as an integral part of the historical evolution and how it affects the colonizing and colonial countries as well as the whole history being used as a source of inspiration for an efficient and new algorithm in the field of evolutionary calculations. This algorithm consists of the following steps [32]:

- formation of early empires;
- the policy of attracting colonies towards imperialism;
- revolution: a sudden change in the position of a country;
- displacement of colonial and imperialist positions;
- colonial competition;
- the fall of weak empires.

4.3. PSO

The particle cumulative movement algorithm has many similarities with algorithms such as ACO or GA, but it also has serious differences, making this algorithm distinct and straightforward. As an example, this algorithm does not use operators such as intersection and mutation. As a result, this algorithm does not need to use strings of numbers and an encryption stage. Thus, it is much simpler than algorithms such as GA. This algorithm divides the solution space using a pseudo-probability function into multiple paths formed by the movement of individual particles in space. The movement of a group of particles consists of two main components, the deterministic component and the probable component. Each particle is interested in moving toward the current best solution x^* or the best solution obtained so far g^* [33].

For every particle moving through space, regardless of whether it obeys the collective intelligence or not, there are position and velocity vectors. Now, for particle i (bird), which continues to move using cumulative intelligence, if its current location vector is equal to x_i, its movement speed vector displayed as v_i can be defined according to Equation (33), as follows:

$$v_i^{t+1} = v_i^t + \alpha\epsilon_1 \odot \left[g^* - x_i^t\right] + \beta\epsilon_2 \odot \left[x_i^* - x_i^t\right] \quad (33)$$

In this equation, ϵ_1, ϵ_2 are random vectors whose values are real numbers between zero and one. Also, the symbol $\odot$ indicates the inner product between two matrices. The α and β parameters are considered learning and acceleration parameters, respectively. The initial location of the particles should be uniformly distributed throughout space, so that they can be found in most places; that is, the location of the particles should be produced with a uniform distribution. In addition, the speed of the initial change in direction should be considered equal to zero ($v_i^t = 0$). According to the velocity vector defined in Equation (33), the new location vector of each particle will also be in the form of Equation (34), as follows:

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{34}$$

In this regard, v_i can take any value in the interval $[0, v_{max}]$.

4.4. GWO

When designing the GWO, Alpha (α) is considered the most appropriate solution to mathematically model the social hierarchy of wolves. Subsequently, (β) Beta and (δ) Delta are the second and third suitable solutions. The remaining candidate solutions are assumed to be Omega (X). To hunt, gray wolves must find and surround prey. Therefore, the following equations update the positions of wolves around the prey [34]:

$$\vec{D} = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)| \tag{35}$$

$$\vec{X}(t+1) = \vec{X}(t) - \vec{A}.\vec{D} \tag{36}$$

In the above equation, $\vec{C}$ and $\vec{A}$ are coefficient vectors; $\vec{X}_p$ is the position vector of prey; and $\vec{X}$ is the position vector of gray wolves. It is a balancing act between siege and hunting. Therefore, the search radius must be optimized during the process; for this purpose, the equations related to the two coefficients used in the above relationships are as follows:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{37}$$

$$\vec{C} = 2\vec{r_2} \tag{38}$$

The above equations enable the gray wolves to update their position around the prey, which is why the following equations are used for hunting:

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_1.\vec{X}_\delta - \vec{X}\right| \tag{39}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta \tag{40}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{41}$$

4.5. Initial Solution

In this paper, four algorithms are used to solve sample problems of different sizes. The most critical issue in using algorithms based on artificial intelligence is designing an initial solution (initial chromosome) to solve the problem. In this paper, the initial solution is considered in Figure 5.

Section 1		Section 2		Section 3		Section 4	
$v(\|J\| + \|I\|)$		$v(\|K\| + \|I\|)$		$v(\|J\| + \|J\|)$		$v(\|K\| + \|J\|)$	
$j_1, \ldots, j_J$	$i_1, \ldots, i_I$	$k_1, \ldots, k_K$	$i_1, \ldots, i_I$	$j_1, \ldots, j_J$	$j_1, \ldots, j_J$	$k_1, \ldots, k_K$	$j_1, \ldots, j_J$
Random key		Random key		Random key		Random key	

Figure 5. Initial solution for DCSCN.

An initial solution to the random data problem between 0 and 1 of length $2|K| + 4|J| + 2|I|$ is to decode the above solution; Algorithm 1 is performed for Sections 1–4.

Algorithm 1. Decoding on initial solution for any two-echelon supply chain

Input : $Set\ of\ I, J, V,\ dem_{ip},\ Cap_{jp}, Tr_{jiv}, Cv_v$
Output : X_{ijpv}, Z_j
For $t = 1\ to\ P$ ***do***
Select $a\ node\ on\ d = argmax\{v(j+i), \forall i \in I, j \in J\}$
Select $a\ vehicle\ on\ v^* = random\ selcetion\ between\ v \in V$
If $d \leq |J|$
$j^* = d,$ ***Select*** $a\ node\ on\ i^* = min\{Tr_{j^*iv^*}, \forall\ i \in I\ and\ v(|J|+i) \neq 0\}$
$X_{j^*i^*pv^*} = \min(Cv_{v^*}, Cap_{j^*p}, Dem_{i^*p})$
If $Cv_{v^*} = 0$ ***then*** $selecta\ vehicle\ on\ v^* = random\ selcetion\ between\ v \in V$
If $Cap_{j^*p} = 0$ ***then*** $v(j^*) = 0\ and\ Tr_{j^*iv^*} = \infty$
If $Dem_{i^*p} = 0$ ***then*** $v(|J|+i^*) = 0\ and\ Tr_{ji^*v^*} = \infty$
End if
If $d > |J|$
$i^* = d - |J|,$ ***Select*** $a\ node\ on\ j^* = min\{Tr_{ji^*v^*}, \forall\ j \in J\ and\ v(j) \neq 0\}$
$X_{j^*i^*pv^*} = \min(Cv_{v^*}, Cap_{j^*p}, Dem_{i^*p})$
If $Cv_{v^*} = 0$ ***then*** $select\ a\ vehicle\ on\ v^* = random\ selcetion\ between\ v \in V$
If $Cap_{j^*p} = 0$ ***then*** $v(j^*) = 0\ and\ Tr_{j^*iv^*} = \infty$
If $Dem_{i^*p} = 0$ ***then*** $v(|J|+i^*) = 0\ and\ Tr_{ji^*v^*} = \infty$
End if
End for

4.6. TOPSIS Method

The technique for order of preference by similarity to ideal solution (TOPSIS) method is a multi-criteria decision-making (MCDM) technique for ranking and selecting alternatives based on their closeness to an ideal solution.

Key steps in the TOPSIS method:

1. Construct the Decision Matrix:
   - ✓ List the alternatives (options) and criteria.
   - ✓ Populate the matrix with values representing the performance of each alternative for each criterion.
2. Normalize the Decision Matrix:
   - ✓ Scale the values in the matrix to ensure comparability across criteria. The common formula for normalization is as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{42}$$

where r_{ij} is the normalized value for the *i*-th alternative and *j*-th criterion.

3. Weight the Normalized Matrix:
   - ✓ Multiply the normalized values by their respective criteria weights:

$$v_{ij} = w_j.r_{ij} \tag{43}$$

where w_j is the weight of the *j*-th criterion.

4. Determine the Ideal and Negative-Ideal Solutions:
   - ✓ Ideal solution (A^+): The best value for each criterion (e.g., maximum for benefit criteria, minimum for cost criteria).
   - ✓ Negative-ideal solution (A^-): The worst value for each criterion (e.g., minimum for benefit criteria, maximum for cost criteria).
5. Calculate the Separation Measures:
   - ✓ Compute the Euclidean distance of each alternative from the ideal and negative-ideal solutions, as follows:

$$S_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^+\right)^2} S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_{ij} - v_j^-\right)^2} \quad (44)$$

6. *Calculate the Relative Closeness (C)**:
   - ✓ Compute the closeness coefficient for each alternative as follows:

$$C_i^* = \frac{S_i^-}{S_i^{\mp} + S_i^-} \quad (45)$$

   - ✓ This value ranges between 0 and 1. A higher C_i^* indicates that the alternative is closer to the ideal solution.
7. Rank the Alternatives:
   - ✓ Rank the alternatives based on their C_i^* values in descending order. The highest value represents the best alternative.

5. Results

After introducing algorithms based on artificial intelligence to solve the problem of the DCSCN based on the IoT, it has been analyzed and has solved various sample problems in this section. At first, GAMS 23.5.2 software (Baron solver) was used to validate the mathematical model, and a small-size sample problem was solved. The sensitivity analysis of the mathematical model using different uncertainty control methods is also performed in a small size with GAMS software. In the following, algorithms based on artificial intelligence such as GA, PSO, ICA, and GWO are used to solve different large-size sample problems. Finally, the solution methods have been prioritized based on the proximity indicators to the total DCSCN profit and CPU time.

5.1. Mathematical Model Validation

In this section, the validation of the mathematical model of the DCSCN based on the IoT is discussed first. Hence, a sample problem is considered, including three production centers, three distribution centers, four customers, three types of IoT tools, two types of vehicles and two types of products. Due to a lack of access to real world data, random data based on uniform distribution were used. Table 2 shows the random data considered based on the uniform distribution function for the DCSCN based on the IoT.

Table 2. Problem data based on uniform distribution function.

Parameter	Value	Parameter	Value
λ_{ip}	0.3	χ_{ip}	$\sim U$ [1000, 1200] ton
λ'_{ip}	0.2	o_j	$\sim U$ [3 8] $
γ_i	0.5	g_{jt}	$\sim U$ [1000, 2000] $
γ'_i	0.4	β_t	0.7
f_j	$\sim U$ [10, 000, 12, 000] $	ϖ_{jp}	$\sim U$ [500, 800] ton
$\tilde{d}_{ip}$	$d_{ip}^1 \sim U[100, 150]$ ton; $d_{ip}^2 \sim U[150, 200]$ ton; $d_{ip}^3 \sim U[200, 250]$ ton; $d_{ip}^4 \sim U[250, 300]$ ton		
$\tilde{\rho}_v$	$\rho_v^1 \sim U[1, 3]$ $; $\rho_v^2 \sim U[3, 5]$ $; $\rho_v^3 \sim U[5, 7]$ $; $\rho_v^4 \sim U[7, 10]$ $		

Due to the non-linearity of the mathematical model presented in this research, the Baron solver was used in GAMS 23.5.2 software to solve the problem. Also, the indeterminacy of the mathematical model led to the use of the following four methods of BPCCP, RPP-I, RPP-II, and RPP-III to control the demand and transportation cost parameters. After solving the mathematical model based on the four mentioned control methods, the optimal value of the objective function (total DCSCN profit) is presented in Table 3.

Table 3. The total profit obtained with different uncertainty control methods.

Model	Profit	IoT Deployment Costs	Savings Due to the Deployment of the IoT
BPCCP	53,912.35	2348.68	3268.98
RPP-I	46,358.15	2548.92	3518.25
RPP-II	48,354.68	2348.68	3268.98
RPP-III	44,938.49	2548.92	3518.25

The results of Table 3 show that the profit obtained using the BPCCP method is higher than that of other RPP methods, because in the RPP methods, the penalty cost of facing a lack of demand also exists in the objective function of the problem and leads to an increase in total costs. Solving the mathematical model in a small size also shows that the savings due to deploying IoT tools in distribution centers are higher than the cost of deploying equipment.

In the BPCCP model, out of three distribution centers, two distribution centers, numbers 1 and 2, were selected, based on cost and income balance. IoT tool #2 was selected for distribution center #1 and IoT tool #3 was selected for distribution center #2. In the following, the decision-making variables in the BPCCP model have been investigated. The most important issue in the DCSCN is to achieve the exact amount of customer demand as well as the selling price of the product in the direct and indirect channels. Table 4 shows the actual demand of customers as well as the price of the product in the direct and indirect channels.

Table 4. Actual customer demand along with their selling prices in direct and indirect channels.

Chanel	Product	Customer				Selling Price
		1	2	3	4	
Direct	1	227.82	224.96	235.09	229.39	134.56
	2	243.85	229.82	238.11	236.58	137.17
Indirect	1	211.6	208.73	218.86	213.17	157.74
	2	227.22	213.19	221.48	219.95	160.92

The results of Table 3 show that due to the price elasticity of the substitute product, the actual demand in the direct and indirect channels is different. As can be seen, the average total customer demand in the direct channel is higher than the average customer demand in the indirect channel. Meanwhile, the average price was also higher due to the high demand for direct channels compared to indirect channels. The average price in the direct channel is USD 235.83; in the indirect channel, it is USD 219.41. Figure 6 shows the amount of transferred product numbers 1 and 2 between different echelons of the supply chain network.

Figure 6 shows that distribution center number 3 was not selected, and therefore, no products were transferred through this center. Also, both centers Nos. 1 and 2 are equipped with IoT tools. Equipping these two centers with IoT tools has increased the total supply chain costs by USD 2348.68 and decreased operational costs by USD 3268.98.

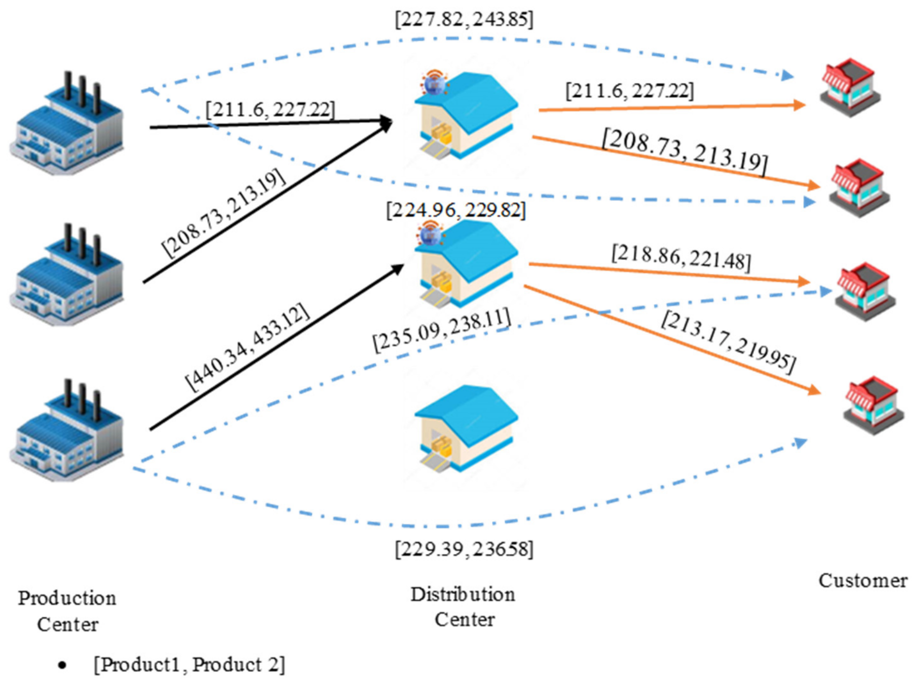

Figure 6. Amount of product transferred between supply chain network echelons.

5.2. Sensitivity Analysis

In this section, the effect of changing the different problem parameters on the profitability of the DCSCN is investigated. These parameters include the change in the uncertainty rate, the change in the price elasticity of the substitute product, the price elasticity based on demand, and the profitability factor of using the IoT.

Sensitivity analysis shows how fluctuations in the uncertainty rate impact profitability, demonstrating the model's robustness and adaptability. It highlights profit resilience under varying conditions, identifies critical thresholds for risk management, and justifies IoT integration by linking real-time adjustments to enhanced performance. This analysis builds confidence in the model's viability for optimizing dual-channel supply chains in dynamic and uncertain environments.

Demand and transportation cost parameters are presented with uncertainty in the form of trapezoidal fuzzy numbers. Therefore, BPCCP, RPP-I, RPP-II, and RPP-III models were used to control uncertain parameters. To investigate the effect of the uncertainty rate on profit, a sensitivity analysis was performed with different models, and the value of the uncertainty rate was considered to be between 0.1 and 0.9. Therefore, Table 5 shows the effect of the uncertainty rate on the total DCSCN profit.

Table 5. The effect of uncertainty rate on the total profit.

α	Profit			
	BPCCP	**RPP-I**	**RPP-II**	**RPP-III**
0.1	58,655.2	51,475.7	56,038.5	50,428.7
0.2	57,369.5	50,141.0	53,745.0	49,715.7
0.3	55,975.8	48,672.4	52,448.7	47,854.3
0.4	54,638.1	47,458.7	50,185.9	46,526.7
0.5	53,912.4	46,358.2	48,354.7	44,938.5
0.6	52,564.5	45,176.7	46,758.7	43,475.5
0.7	51,468.7	44,395.4	45,258.3	41,987.7
0.8	50,035.4	42,975.6	43,935.7	40,254.2
0.9	48,756.7	41,544.7	42,419.9	38,876.3

The results of Table 4 show that with the increase in the uncertainty rate, the costs of the supply chain network increase, and this problem leads to a decrease in total profit. The reason for the increase in total costs is the direct impact of the uncertainty rate on the actual demand and pricing. So, with the increase in the uncertainty rate, the demand of direct and indirect channels increases and the price of products decreases to some extent. An increase in product transportation costs due to increased demand leads to an increase in total costs. On the other hand, by examining different methods, it can be seen that with the increase in the uncertainty rate, the cost increase in the RPP-III method is more than RPP-I and RPP-II. This issue has led to a decrease in the total DCSCN profit in the RPP-III model compared to other models. The standard deviation of this model is lower than that of other control models.

Table 6 also shows the total DCSCN profit for different values of the substitute product's price elasticity parameter.

Table 6. Effect of substitute product price elasticity on the total DCSCN profit.

λ_{ip}	λ'_{ip}	**Profit**	λ_{ip}	λ'_{ip}	**Profit**
0.1	0.2	43,254.1	0.3	0.1	48,132.7
0.2	0.2	46,935.6	0.3	0.2	53,912.4
0.3	0.2	53,912.4	0.3	0.3	57,935.5
0.4	0.2	69,145.7	0.3	0.4	64,525.9
0.5	0.2	96,584.4	0.3	0.5	84,596.1

The results of Table 6 show that with the increase in the price elasticity of the substitute product in the direct and indirect channels, the amount of demand and the sales price in this channel have increased compared to other channels, leading to an increase in the sales amount of the products. However, it can be seen that with the increase in the price elasticity of the alternative product in the direct channel due to eliminating intermediaries, the profitability is higher compared to the indirect channel.

In another analysis and in Table 7, the impact of price elasticity based on demand on the total DCSCN profit is examined.

Table 7. The effect of price elasticity based on demand on the total DCSCN profit.

γ_i	γ'_i	**Profit**	γ_i	γ'_i	**Profit**
0.3	0.4	40,248.7	0.4	0.3	46,144.7
0.4	0.4	44,250	0.4	0.4	48,636.3
0.5	0.4	53,912.4	0.4	0.5	53,912.4
0.6	0.4	69,248.7	0.4	0.6	63,415.6
0.7	0.4	88,144.3	0.4	0.7	78,155.3

By examining the results of Table 6, it can be seen that with the increase in the price elasticity based on demand in the direct and indirect channels, the amount of demand and sales price in this channel have increased compared to other channels and have led to an increase in product sales. However, it can be seen that with the increase in product price elasticity based on demand in the direct channel due to the elimination of intermediaries, profitability is higher compared to the indirect channel.

Examining the output variables of the problem in a small sample showed that using IoT tools in the DCSCN reduced operating costs in distribution centers. This section investigates the impact of the energy-saving coefficient on the total DCSCN profit. The savings factor is actually the reduction in costs related to workforce and energy in the construction of distribution centers. This value is considered equal to 0.7 in the main model. Table 8 shows the total DCSCN profit for energy-saving coefficient changes.

Table 8. The effect of the energy-saving coefficient on the total DCSCN profit.

β_t	Profit	Changes %
0.5	51,247.7	−4.94%
0.6	52,864.7	−1.94%
0.7	53,912.4	0
0.8	55,487.6	+2.92%
0.9	57,365.5	+6.40%

The results of Table 7 show that the profitability factor of the IoT increases, and the total DCSCN profit increases. For example, with an increase of 0.2 in this coefficient, the total DCSCN profit has increased by 6.4%.

After checking the validity of the mathematical model and analyzing its sensitivity with different parameters, some sample problems were solved in large sizes. Since the presented mathematical model is a non-linear and NP-hard model, algorithms based on artificial intelligence such as GA, PSO, ICA, and GWO were used to solve the problem in large sizes. In the following, the initial parameters of these algorithms are fine-tuned using the Taguchi method.

5.3. Parameter Tuning of Algorithms Based on Artificial Intelligence

The Taguchi method is one of the methods first used to solve the algorithm parameters in the literature. In this method, three levels are considered for each factor (parameter), and achieving the best combination of these three levels can improve the efficiency of that algorithm in searching the solution space.

To tune the algorithms' parameters with the Taguchi method, the ratio of the mean square of the squares is used with the help of a logarithmic scale because the results behave more linearly with the help of the S/N ratio. According to the maximization of the objective function, the most suitable S/N ratio for the mathematical model is "small is better ratio". This ratio is used if we want to minimize the response variable as much as possible. Equation (46) shows this ratio, as follows:

$$\frac{S}{N} = -10\log_{10}(MSD) = -10\log_{10}\left[\frac{\sum y^2}{n}\right] \tag{46}$$

After each experiment, the RPD is used to reduce the calculation error. Equation (47) shows the calculation formula of the RPD.

$$RPD = \frac{Best\ solution - solution_i}{Best\ solution} \tag{47}$$

In the above relationship, the best value of the objective function obtained among all experiments is known as the *Best solution* and the objective function value of each experiment is known as the $solution_i$. The levels defined for the parameters of the problem and the best levels obtained from the analysis of experiments are shown in Table 9.

Table 9. Value of defined parameters for each level.

Algorithm	Factor	L1	L2	L3	Optimum L	Optimum Value
GA	Max it	100	200	300	3	300
	N pop	100	150	200	3	200
	Pc	0.7	0.8	0.9	2	0.8
	Pm	0.05	0.07	0.09	2	0.07
PSO	Max it	100	200	300	3	300
	N particle	100	150	200	1	100
	C1	1	1.5	2	2	2
	C2	1	1.5	2	2	1.5

Table 9. *Cont.*

Algorithm	Factor	L1	L2	L3	Optimum L	Optimum Value
ICA	Max it	100	200	300	3	300
	N coun	100	150	200	3	200
	N imp	50	75	100	2	75
	Rev Rate	0.2	0.3	0.5	3	0.5
	Def Rate	0.2	0.3	0.5	3	0.5
GWO	Max it	100	200	300	3	300
	N wolf	100	150	200	1	100
	A	1	2	3	1	1

5.4. Solving Large-Size Sample Problems with Algorithms Based on Artificial Intelligence

The NP-hardness of the problem investigated in this research, as well as the lengthening of the time to solve large-size sample problems with GAMS, has led to the use of algorithms based on artificial intelligence in this section to solve the problem in large sizes. Therefore, 15 sample problems in different sizes are designed according to Table 10.

Table 10. The size of sample problems in large sizes.

Sample Problem	Production Center	Distribution Center	Customer	Product	IoT Tool	Vehicle
1	3	3	4	3	3	2
2	4	4	10	3	3	3
3	6	6	13	3	3	3
4	6	6	15	4	3	4
5	8	8	18	4	4	4
6	8	8	22	4	4	4
7	10	10	26	5	4	5
8	10	10	30	5	4	5
9	12	12	34	5	5	5
10	15	15	38	6	5	6
11	15	15	42	6	5	6
12	18	18	45	6	5	6
13	22	22	48	8	6	7
14	25	25	52	8	6	7
15	30	30	55	8	6	7

After solving the sample problems in a large size with algorithms based on artificial intelligence, the average solution (total DCSCN profit) obtained in three repetitions and also the average CPU time obtained from solving sample problems are shown in Table 11.

Table 11. Average indices obtained in different sample problems.

Sample Problem	Profit				CPU-Time			
	GA	PSO	ICA	GWO	GA	PSO	ICA	GWO
1	79,650.60	79,639.00	79,660.20	80,556.60	27.690	29.880	31.480	34.800
2	99,856.4	100,950.9	102,002.9	101,574.6	30.670	32.570	34.390	37.430
3	116,939.1	117,646.8	117,482.0	116,686.5	34.290	36.940	38.750	42.850
4	118,151.7	119,124.6	118,776.7	118,200.8	39.480	41.300	43.930	47.310
5	119,964.9	121,535.0	119,844.7	121,300.5	46.840	49.970	51.420	56.110
6	122,163.9	123,206.1	121,223.9	122,263.6	57.340	60.150	63.300	68.140
7	123,903.2	122,520.2	123,888.6	122,793.2	69.210	72.820	75.980	81.900
8	138,784.1	139,017.1	139,244.0	141,191.2	82.490	86.320	90.310	96.920
9	151,493.6	151,051.5	154,198.1	152,883.1	97.280	101.61	105.29	111.24
10	157,172.0	157,752.9	160,455.4	158,980.2	115.68	121.07	127.32	135.57
11	162,307.1	162,448.0	163,267.6	162,244.0	135.24	140.42	145.04	155.71

Table 11. *Cont.*

Sample Problem	Profit				CPU-Time			
	GA	PSO	ICA	GWO	GA	PSO	ICA	GWO
12	166,885.1	166,203.7	168,067.6	168,197.9	158.76	164.85	173.39	183.09
13	176,545.9	175,576.3	174,043.7	175,191.0	190.67	199.42	205.69	219.88
14	198,116.8	198,531.1	197,181.4	198,878.2	230.17	240.17	246.00	265.53
15	203,774.9	204,417.6	205,754.7	205,568.9	281.09	293.43	302.05	318.14
Mean	142,380.6	142,641.4	143,006.1	143,100.7	106.46	111.39	115.62	123.64

The results of solving the sample problem in a large size show that the GWO has achieved the highest efficiency in terms of being close to the optimal solution (total cost). The next priorities are the ICA, PSO, and GA. Also, the results show that the CPU time to solve the mathematical model in large sizes with the GA is shorter than the PSO, ICA, and GWO. Figure 7 shows the average total DCSCN profit and CPU time in large sizes with algorithms based on artificial intelligence.

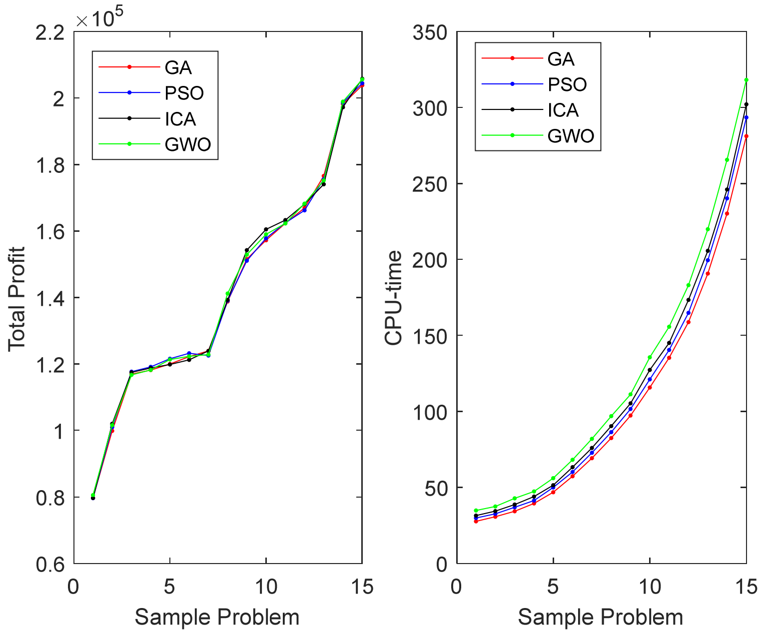

Figure 7. Average profit and CPU time to solve sample problems in large sizes.

Figure 7 shows that the solution time has increased exponentially with the increase in the problem size. This issue is proof of the NP-hardness of the DCSCN based on IoT, since the algorithms in different indices have obtained different results. In the following, the significant difference in the averages of each index between the algorithms was investigated, and this was achieved through the *t*-test at the 95% confidence level. Table 12 shows the results of the *t*-test at the 95% confidence level for a significant comparison of the difference in the averages of the total DCSCN profit and CPU time between different solution methods.

The results of Table 11 show that there is no significant difference between the profit among the solution methods. This issue is obtained through the *p*-value being higher than the value of 0.05. Also, based on the results obtained, it can be seen that due to the high values of *p*-value above 0.05, there is no significant difference between the CPU time of the solution methods. Therefore, to rank algorithms based on artificial intelligence to solve the problem of the DCSCV based on IoT, the TOPSIS method with a weight of 0.5 for each index was used.

Table 13 shows each algorithm’s utility weight based on the proximity indicators to the total DCSCN profit and time.

Table 12. The results of the *t*-test statistical test at the 95% confidence level to compare the significance of the difference in indicators.

Index	Algorithm	Mean Difference	Lower Bound	Upper Bound	T Value	*p* Value
Profit	GA-PSO	261	−26,222	26,743	0.02	0.984
	GA-ICA	625	−25,944	27,195	0.05	0.962
	GA-GWO	720	−25,864	27,304	0.06	0.956
	PSO-ICA	365	−26,134	26,863	0.03	0.978
	PSO-GWO	495	−26,054	26,973	0.04	0.972
	ICA-GWO	95	−26,505	26,695	0.01	0.994
CPU time	GA-PSO	4.9	−55.0	64.9	0.17	0.867
	GA-ICA	9.2	−51.6	69.9	0.31	0.759
	GA-GWO	17.2	−45.5	79.9	0.56	0.579
	PSO-ICA	4.2	−57.5	66.2	0.14	0.89
	PSO-GWO	12.2	−51.6	76	0.39	0.697
	ICA-GWO	8	−56.6	72.6	0.25	0.801

Table 13. Summary of TOPSIS ranking method results.

Index	GA	PSO	ICA	GWO
Profit	1,422,380.63	142,641.38	143,006.10	143,100.68
CPU time	106.46	111.39	115.62	123.64
Utility Weight	0.967	0.712	0.467	0.033
Rank	1	2	3	4

Contrary to the high efficiency of the gray wolf algorithm in achieving a near-optimal solution, in the general summary, the GA was recognized as a more efficient algorithm than the other algorithms used in problem-solving.

6. Managerial Insights

The findings from this research provide the following actionable insights for managers aiming to optimize their dual-channel supply chain operations using IoT under uncertainty:

➢ Strategic IoT Integration

Managers should prioritize integrating IoT technologies into their supply chain networks to enhance visibility, improve real-time decision-making, and respond proactively to disruptions. IoT can significantly improve operational efficiency, particularly in demand forecasting and inventory management.

➢ Profit-Driven Infrastructure Investments

Equipping distribution centers with IoT devices should be evaluated as a strategic investment rather than a cost. Managers can use cost-benefit analyses to determine where IoT deployment will yield the highest returns, particularly in centers that handle high-demand variability or perishable goods.

➢ Optimized Dual-Channel Pricing Strategies

In this research, the importance of leveraging IoT data for dynamic pricing across direct and indirect channels is highlighted. Managers should adopt flexible pricing models that consider real-time demand signals and customer preferences, enabling them to capture maximum market share while maintaining profitability.

➢ Location-Based Decision-Making

The strategic placement of distribution centers, informed by IoT-driven insights, is crucial for minimizing transportation costs and enhancing service levels. When making location decisions, managers should consider factors such as proximity to demand clusters, transportation networks, and regional uncertainties.

- Uncertainty Mitigation and Risk Management

IoT can act as a critical tool for reducing the impact of uncertainties in the supply chain. Managers should use IoT-generated predictive analytics to anticipate disruptions, optimize safety stock levels, and develop contingency plans that ensure the continuity of operations.

- Balancing IoT Implementation Costs and Benefits

While IoT implementation requires significant upfront investment, managers must assess its long-term value in terms of increased efficiency, reduced waste, and higher profitability. A phased approach to IoT adoption, starting with high-impact areas, can provide measurable returns without overburdening budgets.

- Sustainability and Circular Supply Chains

IoT technologies also offer managers the opportunity to align their supply chains with sustainability goals. Real-time tracking and analytics can support circular economy initiatives, such as efficient resource utilization and waste reduction.

- Enhanced Customer Experience

The use of IoT for tracking and monitoring can improve transparency and reliability across the supply chain, leading to higher customer satisfaction. Managers can leverage this capability to build stronger relationships with customers and gain a competitive advantage.

- Collaborative Ecosystems

IoT adoption benefits from collaboration among supply chain stakeholders, including suppliers, logistics providers, and retailers. Managers should foster partnerships and shared data ecosystems to unlock the full potential of IoT in supply chain optimization.

- Scalability for Future Growth

IoT-driven supply chains offer scalability and adaptability to changing market conditions. Managers should design IoT implementations with scalability in mind, ensuring that infrastructure and processes can accommodate growth and evolving technology trends.

7. Conclusions

In this paper, a mathematical model was presented of a DCSCN based on IoT under uncertainty, and its solution was presented using algorithms based on artificial intelligence such as GA, PSO, ICA, and GWO. The main purpose is to present a strategic decision model regarding the location of distribution centers and equipping/not these centers with IoT tools in the first stage and tactical decision-making such as determining the actual demand in direct and indirect channels and pricing products in each channel. For this, a supply chain consisting of production centers, distribution centers, and customers was considered to make appropriate decisions to increase the total DCSCN profit.

Due to the uncertainty of demand and transportation costs, four different models were used to control them. In these models, we can refer to pessimistic FP, including the BPCCP model, and robust possibilistic programming, including RPP-I, RPP-II, and RPP-III models. In the analysis of a sample problem in a small size, it was observed that although the RPP-III method is less profitable than other models, it is possible in the DCSCN, but it has a lower standard deviation and higher reliability.

Examining the changes in the uncertainty rate on the BPCCP model also showed that the amount of demand has increased with the increase in the uncertainty rate. This issue has led to decreased income and, as a result, the total DCSCN profit. Among other RPP models, the RPP-III model obtained the lowest profit among the methods. On the other hand, by examining the parameters of price elasticity of the substitute product and elasticity of the product price based on demand, it was observed that with the increase in these two parameters, the amount of actual demand and the price of the product increased, and this also led to an increase in total DCSCN profit. With a more detailed examination of the problem, it was also observed that the increase in the price elasticity parameters of the alternative product and the elasticity of the product price based on demand in the direct channel has led to more profitability due to the elimination of costs related to the distribution center.

By analyzing the mathematical model in the conditions of use and non-use of IoT, it was also observed that deploying IoT equipment in distribution centers has in fixed costs. Profitability has also occurred due to the reduction in operating costs. The investigation of this issue showed that by increasing the profitability factor of the IoT in the supply chain by 0.2, the total DCSCN profit increased by 6.5%.

By solving 15 sample problems of a large size with algorithms based on artificial intelligence, it was observed that in terms of total DCSCN profit, the GWO has the best performance. In contrast, in terms of CPU time, the GA is more efficient than other algorithms. To achieve a more definitive result, the t-test statistical test was used at the 95% confidence level, and the results showed that there is no significant difference between the total DCSCN profit and the CPU time between different solution methods. Therefore, by ranking the algorithms with the TOPSIS method, the GA was ranked as the most efficient algorithm, followed by PSO, ICA, and GWO. The TOPSIS method was chosen due to its use and validity in similar articles and a review of the literature on the subject.

The integration of the Internet of Things (IoT) into supply chain networks has revolutionized how organizations manage their operations, particularly in uncertain environments. Despite the numerous advantages IoT offers, such as real-time data monitoring, enhanced visibility, and predictive analytics, significant challenges impede its full potential. Addressing these limitations is crucial for ensuring IoT-driven supply chain systems are resilient, efficient, and sustainable. Additionally, modern supply chains' dynamic and complex nature opens avenues for future research to further refine and optimize IoT applications. Below, the key limitations and prospective research directions are outlined to guide advancements in this domain.

Some of the limitations of this research include the following:

✓ Data Security and Privacy Issues

Despite its potential, IoT faces significant privacy data security and privacy challenges. The vast amount of sensitive data generated by IoT devices increases the risk of cyberattacks, which can compromise the integrity of supply chain networks. Future frameworks must address these vulnerabilities to ensure safe data transmission and storage.

✓ High Implementation Costs

Implementing IoT solutions requires substantial infrastructure, technology, and skilled personnel investment. Many small and medium-sized enterprises (SMEs) struggle to afford these initial costs, limiting widespread adoption.

✓ Scalability Concerns

IoT applications often perform well in isolated pilot projects but encounter scalability issues when expanded to entire supply chain networks. Interoperability between IoT devices and legacy systems remains a significant hurdle, impeding full-scale deployment.

✓ Regulatory and Standardization Challenges

The lack of global standards for IoT integration in supply chains leads to regional inconsistencies and compatibility issues. This limitation restricts the seamless flow of goods and data in multinational supply chain networks.

✓ Environmental Concerns

IoT devices' production, operation, and disposal contribute to environmental challenges, including electronic waste and energy consumption. Sustainable practices are necessary to mitigate these impacts.

Some of the future research directions of this study include the following:

✓ Advanced Data Security Frameworks

Future research should focus on developing robust cybersecurity protocols, including blockchain integration and advanced encryption techniques, to protect IoT data in supply chains.

✓ Interoperability Standards

The creation of universal standards for IoT device interoperability is critical for achieving seamless integration in complex, multinational supply chain networks. Researchers should collaborate with regulatory bodies to establish and promote these standards.

✓ AI-Driven Predictive Analytics

Future studies could investigate the combination of IoT data with artificial intelligence (AI) for predictive analytics. This approach can enhance the ability to foresee disruptions and optimize decisions in uncertain conditions.

✓ Digital Twin Technology Integration

Digital twins—virtual replicas of physical supply chains—can complement IoT by simulating and predicting real-time scenarios. Future research should explore how IoT and digital twin technology can work synergistically to address uncertainty.

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