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Inventory Routing Problem in Supply Chain of Perishable Products under Cost Uncertainty

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Abstract: This paper presents a multi-objective, multi-period inventory routing problem in the supply chain of perishable products under uncertain costs. In addition to traditional objectives of cost and greenhouse gas (GHG) emission minimization, a novel objective of priority index maximization has been introduced in the model. The priority index quantifies the qualitative social aspects, such as coordination, trust, behavior, and long-term relationships among the stakeholders. In a multi-echelon supply chain, the performance of distributor/retailer is affected by the performance of supplier/distributor. The priority index measures the relative performance index of each player within the supply chain. The maximization of priority index ensures the achievement of social sustainability in the supply chain. Moreover, to model cost uncertainty, a time series integrated regression fuzzy method is developed. This research comprises of three phases. In the first phase, a mixed-integer multi-objective mathematical model while considering the cost uncertainty has been formulated. In order to determine the parameters for priority index objective function, a two-phase fuzzy inference process is used and the rest of the objectives (cost and GHG) have been modeled mathematically. The second phase involves the development of solution methodology. In this phase, to solve the mathematical model, a modified interactive multi-objective fuzzy programming has been employed that incorporates experts' preferences for objective satisfaction based on their experiences. Finally, in the third phase, a case study of the supply chain of surgical instruments is presented as an example. The results of the case provide optimal flow of products from suppliers to hospitals and the optimal sequence of the visits of different vehicle types that minimize total cost, GHG emissions, and maximizes the priority index.

Keywords: inventory routing problem; time series predicted uncertain costs; time series integrated regression fuzzy; priority index; fuzzy-inference system (FIS); modified interactive multi-objective fuzzy programming

1. Introduction

Designing supply chain networks with the consideration of quantitative objectives such as cost, profit, and time have been excessively reported in the literature [1–4]. However, quantitative objectives rarely ensure robustness in supply chains over time under uncertainty due to the unavoidable social behavior of supply chain partners in value chains. Variations and fluctuations due to uncertain changes in the social behaviors of partners affect the overall operational performance of the supply chain. Therefore, there is a need to integrate qualitative and quantitative factors to investigate and optimize the performance of the overall supply chain. This research is an attempt to integrate the qualitative and quantitative performance measures for the design and optimization of supply chain networks under cost uncertainty. Cost is a major performance indicator for any supply chain. Supply chain cost includes production, logistics, and inventory holding cost.

In multi-period supply chain models, cost uncertainty results in demand and supply unbalance that leads to overall profit reduction. Traditional literature in supply chain considers cost uncertainty and cost reduction as major concerns of supply chain managers and investors. The supply chain process is a multi-period process, and in each period, the cost of commodities or processes does not remain same and linked with each other. Hence, dealing with the cost of each period in an isolated manner does not help in making effective decisions. Therefore, in this research, a time series forecasting method (time series integrated regression fuzzy) is developed for addressing the future cost uncertainty while considering past data. As a result, more rationalized and realistic decisions could be made which are based on past events. In addition to this, one of the major characteristics of research is its area of scope. Research is considered more effective if it is capable to deal with maximum possible scenarios. Keeping this fact in mind, this research has considered the aspect of a multi-product. The proposed model can provide promising decisions for both single product and multi-product problems efficiently.

The environment is adversely affected due to transportation and production activities. Emission of greenhouse gases (GHG) such as carbon dioxide and nitrogen dioxide have a negative impact on human health and ecosystem [5,6]. While designing a supply chain network, consideration for reducing GHG emissions ensures sustainability. Environmental impact can be reduced by using environmentally friendly vehicles for transportation purposes. The optimal selection and routing of electric or fuel vehicles, substantially reduce the GHG emissions. In the proposed optimization model, the selection of different vehicles having different electric and fuel consumption rates will affect GHG emissions, total cost, and priority index.

Cost and environmental factors are easier to model by using mathematical modeling. However, considering only cost and GHG minimization does not guarantee supply chain sustainability. Social factors such as coordination, trust, behavior, and long-term relationship also affect the overall performance of the supply chain. In order to quantify these qualitative factors, a novel objective of priority index maximization is introduced. Each partner in a supply chain evaluates subsequent partners on the basis of the aforementioned social factors and assigns a numeric number that determines the priority index. Later on, the priority index is used as an objective function in a multi-objective optimization model that needs to be maximized. Priority index maximization means distributors/customers with the highest priority index are served by manufacturers/distributors on a priority basis.

In this research paper, a multi-objective, multi-period, vehicle routing supply chain problem considering cost, GHG emission, and priority index is proposed. All desired objectives of GHG emission, cost, and priority index (player's qualitative characteristics) have been developed. Figure 1 shows the procedure for developing the objectives of cost, GHG, and priority index. Priority index is a novel objective considered in the proposed optimization model. Fuzzy inference system is employed to model qualitative characteristics. A rule-based fuzzy inference system (FIS) converts these qualitative attributes into numbers, which is termed as priority index. The optimization of multi-objective models considering qualitative characteristics (priority index) along with GHG emissions and cost uncertainty has been rarely reported in the previous literature. As these objectives are conflicting in nature, a multi-objective optimization method has been employed to achieve efficient solutions. The model assumptions are shown in Figure 2.

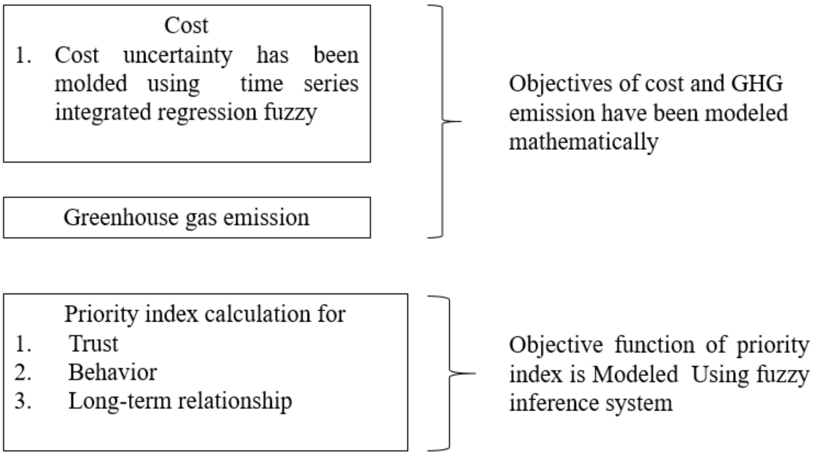

Figure 1. Procedure for objective function development.

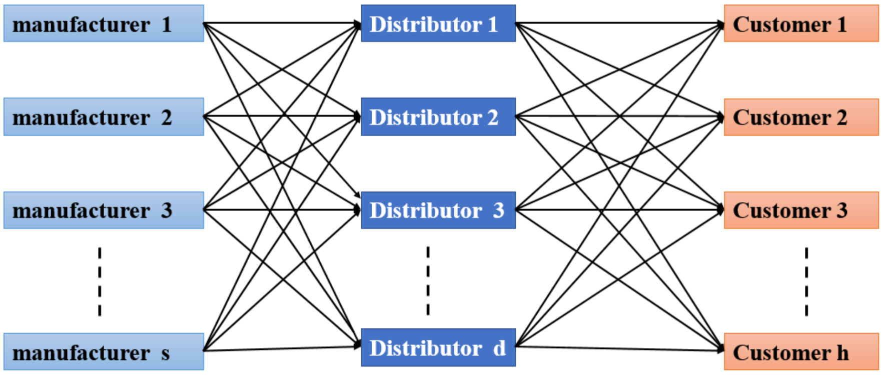

Figure 2. Supply Chain network design Model Assumptions.

There are three phases of this research and each phase has theoretical and practical novelty. In the first phase, a fuzzy inference system is used to assign priority index to each player. Priority index converts the qualitative social factors into quantitative form which is used as a parameter for priority index maximization objective. In the second phase, time series integrated regression fuzzy approach is developed for incorporating uncertain predicted cost for future time periods which is used in cost objective function. After that, a multi-objective and multi-period optimization model involving the objectives of cost, greenhouse gas emission, and priority index has been formulated. In the third phase, modified interactive multi-objective fuzzy programming is used to solve the model, which has the capability of achieving the desired level of satisfaction for all objectives. In the traditional interactive multi-objective fuzzy programming approach, opinions of all experts are considered same irrespective of their experience. However, in the proposed approach, the opinions of experts are given relative importance on the basis of their experience. Finally, a numerical example is presented for the elaboration and real-time implementation of the model.

The rest of the paper is organized as follows: Section 2 presents a literature review. Section 3 includes mathematical modeling, followed by solution methodology in Section 4. Section 5 is about results and discussion and finally, conclusions are presented in the Section 6.

2. Literature Review

The supply chain of materials and products for retail stores have been excessively reported in the literature addressing the logistics, production, and inventory problems. However, perishable products have not been given attention previously. The supply chain of perishable items is more complex than non-perishable items because of their limited shelf life. In addition, perishable items require special vehicles for transportation to avoid quality losses. Perishable items include food, vegetable, fruits, medicine, and unsterilized surgical instruments. Chung and Kwon [7] studied an integrated supply chain management model for perishable pharmaceutical items. La Scalia et al. [8] focused on the food supply chain model considering the shelf life of products on smart logistic units for efficient and effective management. Hiassat et al. [9] emphasized the perishable food supply chain for solving inventory routing location-allocation model optimization. Dellino et al. [10] studied the multi-objective perishable packed food supply chain considering sales and freshness rate.

In addition to food supply chain. Perishable items such as surgical supplies have also been reported in the literature. Tipu and Fantazy [11] proposed a model to compare the surgical instruments supply chain strategies such as flexibility in the context of small and medium enterprises (SMEs). Farrokhi et al. [12] focused on lean approach to maintain the supply chain of medical supplies. Smith et al. [13] improved the surgical supply chain by introducing the concept of data standardization of medical products, such as medicines, surgical instruments, and other equipment. Hansen and Grunow [14] developed a two-stage stochastic model for surgery medicine supply chain planning, considering a shorter product life cycle, introduction of a new medicine, and its authorization in the market.

Kumar et al. [15] investigated cost reduction in medical supplies (surgical instruments, surgical equipment, and medical machines) with the consideration of their quality during supply. Hasani et al. [16] focused multi-product, multi-period and multi-echelon global supply chain of medical devices under uncertain environment. Hosseini-Motlagh et al. [17] studied the uncertain blood supply chain with the objectives of cost minimization and substitution levels to provide safer blood transfusion services.

Multi-period supply chain models should consider the uncertainty because input parameters keep on changing with the passage of time. Many researchers have considered uncertainty in their models. Imran et al. [18] addressed a multi-objective and multi-period supply chain model for the medicine supply chain with the conflicting objectives of cost, time, and quality. Pasandideh et al. [19] considered a bi-objective optimization problem for multi-periods and multi-products in three echelon supply chain networks under an uncertain environment. Authors considered cost, demand, production time, and setup time as uncertain and uncertainty was molded with random variable with fixed lower and upper bound for all time periods. Akbari and Karimi [20] addressed a multi-period supply chain network problem within process uncertainty for which the cost remained the same in all time periods. Jana et al. [21] presented an integrated-inventory model for supply chain in an uncertain environment with conditionally perishable delays [22].

Ramezani et al. [23] studied a multi-period, multi-product, multi-echelon and close loop supply chain model in which researchers considered demand along with return rate as an uncertain parameter but the cost remained deterministic in all time periods. Zahiri et al. [24] focused on organ transplant centers and their allocation in the optimal location in an uncertain environment of demand and cost in multi-period. In this model uncertainty in cost over time always fluctuated among fixed boundaries however in reality bound of uncertainty varies over time. Recent innovations in the field of technology and research and development have resulted in complex supply chain networks. In order to evaluate to performance of modern supply chain networks, one has to consider many conflicting performance measures at a time.

The evolution and analysis of supply chain networks on the basis of multi-objectives is becoming more popular because of increased computational power. Yuce et al. [25] considered the multi-objective supply chain problem and optimized it using adaptive neighborhood search and site abandonment strategy and optimized the cost and lead time. Moghaddam [26] developed a supplier selection model in reverse logistics system with the objectives of total profit, while considering total defective parts, late delivered parts, and economic risk factors. Ghorbani et al. [27] focused on the multi-objective problem with the objectives of recycling cost, rate of waste generated by reactors, and material recovery time for recyclable products. Heidari-Fathian and Pasandideh [28] proposed a multi-objective model for organ transplant transportation network design with the consideration of cost, lead time, and waiting time in queue. Sweetapple et al. [29] investigated the objectives of GHG emission, effluent quality, and operational cost. Mousazadeh et al. [30] focused a multi-objective problem of the pharmaceutical supply chain which minimized the total cost and backorders using bi-objective mixed-integer linear programming.

In this research, not only the traditional objectives such as cost and GHG emission are considered it also introduced a novel objective of priority index which evaluates qualitative attributes of players in the supply chain quantitatively. Fuzzy inference system is used for modeling the objective of priority index. Though Taylan et al. [31] used fuzzy inferences system for project selection and risk assessment but they just assigned priority ranks to each project, however, in this case, authors not only prioritize the distributors and hospitals, but also set maximization of prioritization as the third objective of supply chain model. In addition, the introduction of decision variables for serving the preferred distributors and customers distinguishes the proposed model from previous ones. To the best of our knowledge, the combination of predicted and uncertain costs, GHG emission, and priority index has not been addressed in the literature of perishable supply chain.

The proposed model is a multi-objective and multi-period optimization model. To solve this multi-objective supply chain problem a modified interactive fuzzy programming is introduced which specifies the satisfaction level of each objective. Although Paksoy et al. [32] used this method to solve supply chain problems but in their case expert opinion was considered without giving importance to experience. The proposed technique has the power of decision making with the consideration of expert experience. Table 1 shows the comparison of the proposed research with existing literature and it can be seen that the combination of cost, greenhouse gas emissions, and priority index using interactive multi-objective programming is not addressed so far.

Table 1. Comparison of proposed research with existing literature.

Author	Periods		Objectives	Research Methodology
	Single	Multi		
Kumar, Ozdamar and Ning Zhang [15]		✓	Cost, quality	Statistical model
Franca et al. [33]	✓		Profit and quality	Heuristic method
Mirzapour Al-E-Hashem et al. [34]		✓	Cost and customer satisfaction	LP metric method
Farrokhi, Gunther, Williams and Blackmore [12]		✓	Risk, quality, and risk	Lean methodology
Zahiri, Tavakkoli-Moghaddam and Pishvaee [24]	✓		Cost	Possibilistic programming
Taylan et al. [31]	✓		Risk	Fuzzy AHP and TOPSIS
Sweetapple, Fu and Butler [29]	✓		GHG, cost, and quality	NSGA-II
Akbari and Karimi [20]		✓	Cost	Robust programming
Mousazadeh et al. [30]		✓	Cost, unfilled demand	Robust possibility programming
Pasandideh, Niaki and Asadi [19]	✓		Inventory cost	NSGA-II and NRGA
Hansen and Grunow [14]	✓		Cost	Linear programming
Unger and Landis [35]	✓		Environmental, economic, and health	Statistical model
Zhalechian et al. [36]	✓		Economic, environment, and social	Stochastic possibilistic programing
Shabani and Sowlati [37]		✓	Profit	Stochastic robust programming
Mohammed et al. [38]		✓	Cost	Robust programming
Govindan and Fattahi [39]		✓	Mean risk	Linear programming
Quddus et al. [40]	✓		Cost	Linear programming
Roy et al. [41]		✓	Cost	Analytical model
Proposed model		✓	Priority index, cost, and GHG	interactive multi-objective fuzzy programming

3. Formulation of Mathematical Model

3.1. Problem Description

In traditional multi-period models, the cost does not remain the same in all periods. It fluctuates with the passage of time, caused by uncertain changes in production and supply chain costs. The change in cost cannot be modeled with the consideration of uncertainty in cost only. However, for accurate prediction, there must be an integrated time series model that can predict the cost for future periods based on past data. In addition to this, incorporation of the qualitative behavior of suppliers, distributors, and customers affects the overall performance of supply chain. Misalignment among cost, environmental factors such as GHG emission, and prioritization of customers based on qualitative factors such as trust, behavior cause poor performance of the overall supply chain. To obtain useful insights about a supply chain system correct assessment mechanism of the aforementioned objective parameters is of the highest importance. Since the optimal tradeoff among these objectives ensures the sustainability and robustness in supply chain.

Consider a set of selling periods "t" in which a set of suppliers "m" supplies set of products "p" to set of distributors "d". The distributors "d" supply the products "p" to customers "r". The following decisions are to be made in this centralized supply chain model in each period for achieving the objectives of cost, GHG emission, and priority index.

- What amount of products do the manufacturers produce?
- What amount of products is supplied from suppliers (manufacturer) to the distributors?
- What amount of products do distributors supply to the customers?
- What is the inventory level of supplier (manufacturer) and distributor?
- Which type and how many vehicles (electric, fuel) are required to supply products from suppliers/distributors to the distributors/customers?
- How can we incorporate qualitative social behavior of supply chain partners in improving and optimizing the overall performance of supply chain?
- In what sequence selected vehicles will supply products from suppliers/distributors to the distributors/customers.

Decision-makers are more concerned about the fluctuation in supply cost in the future, the uncertain qualitative factors, and environmental concerns. Therefore, they are in the endeavor of achieving a tradeoff of these three objectives.

The assumptions of the model are outlined in this section.

- A logistics company has different types of vehicles and provides services in all periods.
- Suppliers and distributors can use a heterogeneous fleet of vehicles with different cost, capacity, and technology.
- Both supplier and distributor have storage equipment which emits GHGs.
- The safety stock of manufacturers and distributors is known.
- Cost in the next period depends upon the previous period.
- The demand of products for the current time period is known, while for the future, forecasted demand is used.

3.2. Notation

3.2.1. Sets

m	Suppliers	$m = 1, 2, 3, \ldots, M$
d	Distributors	$d = 1, 2, 3, \ldots, D$
d	customers	$h = 1, 2, 3, \ldots, H$
p	product	$p = 1, 2, 3, \ldots, P$
u	vehicle type	$u = 1, 2, 3, \ldots, U$
k	vehicle technology	$k = 1, 2, 3, \ldots, K$
t	time period	$t = 1, 2, 3, \ldots, T$
s	set of machines	$s = 1, 2, 3, \ldots, S$
i	sequence subscript	$i = 1, 2, 3, \ldots, N$
e	employee type	$e = 1, 2{,}3, \ldots, E$
q	objective	$q = 1, 2{,}3, \ldots, Q$

3.2.2. Parameters

η_{mp}	capacity of supplier (manufacturer) "m" for the inventory of the product "p"
η_{dp}	capacity of distributor "d" for the inventory of the product "p"
A_{pmt}	ordering cost of raw material of product "p" by manufacturer "m" in time period "t"
A_{pdt}	ordering cost of raw material of product "p" by distributor "d" in time period "t"
H_{pmt}	inventory holding cost of product "p" for the supplier "m" in period "t"
φ_{pmt}	holding time of product "p" by supplier "m" in time period "t"
φ_{pdt}	holding time of product "p" at distributor center "d" in time period "t"
H_{pdt}	inventory holding cost of product "p" for distributor "d" in time period "t"
ζ_{pmd}^{ukt}	transportation cost in supplying product "p" by supplier "m" to distributor "d" with vehicle type "u" having technology "k" in time period "t"
ζ_{pdh}^{ukt}	transportation cost in supplying product "p" by distributor "d" to customer "h" with vehicle type "u" having technology "k" in time period "t"
γ_u	fuel consumption rate (liter/kilometer) of vehicle with fuel technology
p_u	electricity consumption rate (watt/kilometer) of vehicle with electric technology
ε_{md}	distance between supplier "m" and distributor "d"
ε_{dh}	distance between distributor "d" and customer "h"
z_{uk}	loading capacity of vehicle type "u" with technology "k"
D_{pht}	expected demand of the product "p" from hospital "h" in time period "t"
G_{uk}	GHG emission produced per kilometer by vehicle type "u" with technology "k"
ρ_{md}	priority index value assigned by manufacturer "m" to distributor "d"
ρ_{dh}	priority index value assigned by distributor "d" to customer "h"
MC_{pmd}^{t}	manufacturing cost of product "p" supplied by the supplier "m" to the distributor "d" in time period "t"
C_{pmd}^{t}	total cost incurred by supplier "m" to supply product "p" to distributor in time period "t"
C_{phd}^{t}	total cost incurred by distributor "d" to supply product "p" to customer in time period "t"
P_{rm}	power of machine "r" being operated by supplier "m"
P_{hpm}	power of holding equipment "h" of product "p" in supplier "m" facility
P_{hpd}	power of holding equipment "h" of product "p" at distribution center "d"
χ_{pm}	production capacity of supplier "m" in for product "p"
J_{pmt}	minimum order quantity of product "p" can supply in each period "t"
τ_{prm}	processing time of product "p" on machine "r" by supplier "m"

U_t cost of electricity (per kilowatt-hour) in time period "t"
α_{pmt} number of orders of product "p" placed by manufacturer "m" in time period "t"
α_{pdt} number of orders of product "p" placed by distributor "d" in time period "t"
W_{edt} wages of employee type "e" in distributor center "d" in time period "t"
L_{edt} number of employee type "e" at distribution center "d" in time period "t"
FC_{pmd}^{ukt} fixed cost of hiring a vehicle type "u" with technology "k" to supply product "p" by supplier "m" to distributor "d" in period "t"
FC_{pdh}^{ukt} fixed cost of hiring a vehicle type "u" with technology "k" to supply product "p" by distributor "d" to hospital "h" in period "t"
μ_{pm} maximum order of products "p" that supplier "m" can supply to a distributor
σ_{pm} safety stock level of manufacturer "m" for product "p"
σ_{pd} safety stock level of distributor "d" for product "p"
ρ_u power consumption rate of electric vehicles (watts/kilometers)
φ_{pm} storage capacity of devices with supplier "m" for storing product ""
φ_{pd} storage capacity of devices with distributor "d" for storing product "p"
SC_{pmt} setup cost of product "p" for each manufacturer "m" in time period "t"
ω_p mass of product "p"
ν_{pt} raw material price (per kilogram) for product "p" in time period "t"
$\delta_{t,t+1}^{U}$ predicted change in cost of electricity between time period "t" and "$t+1$"
$\delta_{t,t+1}^{v}$ predicted change in cost of raw material between time period "t" and "$t+1$"
$\delta_{t,t+1}^{o}$ predicted change in cost of diesel oil between time period "t" and "$t+1$"
$\nabla_{t,t+1}^{w}$ percentage wage increment between time "t" and "$t+1$"
β regression coefficient
Δ_U fuzzy deviational variable for change in change of cost of electricity between consecutive time periods.
Δ_{PM} fuzzy deviational variable for change in change of cost of raw material between consecutive time periods
Δ_{OP} fuzzy deviational variable for change in change of cost of oil between consecutive time periods
α_{pdt} number of orders of product "p" placed by distributor "d" in time period "t"
W_{edt} wages of employee type "e" in distributor center "d" in time period "t"
L_{edt} number of employee type "e" at distribution center "d" in time period "t"

3.2.3. Variables

Continuous Variables

q_{pmt} quantity of product "p" produced by manufacturer "m" in time period "t"
Q_{pmd}^{ukt} quantity of product "p" supplied by supplier "m" to distributor "d" in time period "t" with vehicle type "u" having technology "k"
I_{pmt} ending inventory level of product "p" with supplier "m" in time period "t"
n_{pmd}^{ukt} required number of vehicle type "k" with "u" technology in period "t" for supplying product "p" from manufacturer "m" to distributor "d"
Q_{pdh}^{ukt} quantity of product "p" supplied by distributor "d" to customer "h" in time period "t" with vehicle type "u" having technology "k"
I_{pdt} ending inventory level of product "p" with distributor "d" in time period "t"
n_{pdh}^{ukt} required number of vehicle type "k" with "u" technology in time period "t" for supplying product "p" from distributor "d" to customer "h"

Binary Decision Variables

X_{pmd}^{ukt}	"1" if supplier "m" is selected for supplying product "p" to distributor "d" in time period "t" with vehicle type "u" having technology "k" 0 otherwise
X_{pmd}^{ukt}	"1" if distributor "d" is selected for supplying product "p" to customer "h" in time period "t" with vehicle type "u" having technology "k" 0 otherwise
Y_{pmdi}^{ukt}	1 if vehicle type "u" with technology "k" carrying product "p" departed from supplier "m" visits distributor "j" in sequence "i" in time period "t" 0 otherwise
Y_{pdhi}^{ukt}	1 if vehicle type "u" with technology "k" carrying product "p" departed from distribution "d" visits customer "h" in sequence "i" in time period "t" 0 otherwise

3.3. Formulation of Objective Functions

There are three objectives in this paper, namely: cost, GHG emission, and priority index. Details of each objective along with its mathematical model are given below:

3.3.1. Cost

This is a centralized supply chain model where the total cost is the sum of all costs associated with different parties in the supply chain.

$$\text{Total cost} = \text{suppliers}' \text{ cost} + \text{distributors}' \text{ cost} + \text{customers}' \text{ cost} \tag{1}$$

$$\text{Suppliers}' \text{ total cost} = \text{manufacturing cost} + \text{inventory holding cost} + \text{transportation cost} \tag{2}$$

$$\text{Distributors}' \text{ total cost} = \text{logistic cost} + \text{inventory holding cost} + \text{ordering cost} \tag{3}$$

a. Total cost of suppliers

$$TC_{pmd}^{t} = MC_{pmd}^{t} + H_{pmt} + \zeta_{pmd}^{ukt} \tag{4}$$

$$MC_{pmd}^{t} = \frac{U_t}{60000} \times \left(\sum_{r=1}^{R} P_{rm} \times \tau_{prm} \right) + \left(\omega_p \times v_{pt} \right) \tag{5}$$

Equation (5) shows the manufacturing and raw material costs. As the costs of electricity and raw material do not remain same in all the time periods, the situation can be modeled by using the proposed time series integrated regression fuzzy approach.

$$\delta_{t,t+1}^{U} = \beta_0 + \beta_1 t^n + \beta_2 t^{n-1} + \ldots + \beta_n t^0 \tag{6}$$

Equation (6) is a polynomial regression equation of order "n" which depicts the change in the cost of electricity. Similarly, a polynomial regression equation is generated for raw material and energy prediction. Hence, Equation (5) can be rewritten as Equation (7).

$$MC_{pmd}^{t} = \left(\sum_{r=1}^{R} P_{rm} \times \rho_{prm} \right) \times \frac{U_1}{60000} \left(\prod_{t=1}^{T} (1 + \delta_{t,t+1}^{U}) \right) + \omega_p v_{p1} \left(\prod_{t=1}^{T} (1 + \delta_{t,t+1}^{RM}) \right) \tag{7}$$

Equation (7) is a time series equation which predicts the future manufacturing cost of product "p" supplied by supplier "m" to distributor "d" in the time period "t". This series equation shows the trend of the cost of electricity and raw material which is either increasing or decreasing. However, the cost of electricity fluctuates each year, therefore, the change in cost is considered uncertain. So, "$\delta_{t,t+1}^{U}$" and "$\delta_{t,t+1}^{v}$" are considered as fuzzy variables and finally de-fuzzified formulation of Equation (7) is obtained as follows:

$$MC_{pmd}^{t} = \left(\sum_{r=1}^{R} P_{rm} \times \rho_{prm} \right) \frac{U_1}{60000} \left(\prod_{t=1}^{T} (1 + \delta_{t,t+1}^{U} + \tfrac{\Delta_{U1} - \Delta_{U2}}{3}) \right) + \omega_p v_{p1} \left(\prod_{t=1}^{T} (1 + \delta_{t,t+1}^{RM} + \tfrac{\Delta_{RM1} - \Delta_{RM2}}{3}) \right) \tag{8}$$

Equation (8) is the time series integrated regression fuzzy equation for future uncertain manufacturing cost prediction which considers both trend and uncertainty aspects. The trend is greatly influenced by political, environmental, social, and government policies. To hold the perishable products, the suppliers have to maintain a specific temperature using refrigerators. So, holding cost is computed using Equation (9)

$$H_{pmt} = \left(P_{hpm} \times \varphi_{pmt}\right)\left(\frac{U_1}{60000}\right)\left(\prod_{t=1}^{T}(1 + \delta_{t,t+1}^{U} + \frac{\Delta_{U1} - \Delta_{U2}}{3})\right) \tag{9}$$

As there are two types of vehicle technologies, the cost calculation methods for both are also different. Equation (10) shows the cost calculation of both types of transportation.

$$\zeta_{pmd}^{ukt} = \left\{ \begin{array}{ll} \left(\frac{\gamma_u}{\varepsilon_{md}} \times\right) OP_1\left(1 + \delta_{t,t+1}^{op} + \frac{\Delta_{OP1} - \Delta_{OP2}}{3}\right) & if\ k = 1 \\ \left(\frac{P_u}{\varepsilon_{md}} \times\right)\left(\frac{U_1}{60000}\right)\left(1 + \delta_{t,t+1}^{U} + \frac{\Delta_{U1} - \Delta_{U2}}{3}\right) & if\ k = 2 \end{array} \right\} \tag{10}$$

Combining Equations (8)–(10), final Equation (11) is formulated as:

$$\begin{aligned} TC_{pmd}^{t} = & \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\left\{\left(\sum_{r=1}^{R} P_r \times \tau_{prm}\right)\frac{U_1}{60000}\left(\prod_{t=1}^{T}(1 + \delta_{t,t+1}^{U} + \frac{\Delta_1 - \Delta_2}{3})\right) + \omega_p v_{p1}\left(\prod_{t=1}^{T}(1 + \delta_{t,t+1}^{RM} + \frac{\Delta_1 - \Delta_2}{3})\right)\right\} \times q_{pmd}^{ukt} \\ & + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} FC_{pmd}^{ukt} \times X_{pmd}^{ukt} + \left\{\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(\frac{\zeta_{pmd}^{ukt}}{Zuk}\right) \times Q_{pmd}^{ukt}\right\} \\ & + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(P_{hpm} \times \varphi_{pmt}\right)\left(\frac{U_1}{60000}\right)\left(\prod_{t=1}^{T}(1 + \delta_{t,t+1}^{U} + \frac{\Delta_1 - \Delta_2}{3})\right) \times I_{pmt} \end{aligned} \tag{11}$$

b. Total cost of distributors

The total cost of distributors consists of ordering cost, holding cost, and transportation cost.

$$TC_{pdh}^{t} = A_{pmd}^{t} + H_{pdt} + \zeta_{pdh}^{ukt} \tag{12}$$

$$\text{Ordering cost} = (\text{cost of employees involved in purchasing}) + (\text{inhouse quality inspection cost}) \tag{13}$$

There are two types of employees directly affecting the ordering cost. Firstly, the executive employees involved in preparing a requisition or purchase order, and finance managers who issue payment to the suppliers. Secondly, the cost of labor associated with the inspection of raw materials.

$$A_{pmt} = \left(\frac{\text{Annual cost of employee}}{\text{Number of orders per anum}} \times \text{Total number of employess}\right) \tag{14}$$

$$A_{pmt} = \frac{1}{\alpha_{mt}}(W_{edt} \times L_{edt}) \tag{15}$$

$$A_{pmt} = \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{t=1}^{T}\frac{1}{\alpha_{mt}}(W_{edt} \times L_{edt}) \tag{16}$$

Equation (16) shows the ordering cost in the time period "t". In traditional multi-period models, the cost is assumed to be fixed. However, if salary incremental policy is considered, labor cost follows the increasing trend. Equation (17) is valid when the salary increment remains constant in all periods for all types of employees.

$$A_{pdt} = \sum_{p=1}^{P}\sum_{j=1}^{J}\sum_{d=1}^{D}\sum_{t=1}^{T}\frac{1}{\alpha_{pdt}}(W_{edt} \times L_{edt}) \times (1 + \delta_{t,t+1}^{w})^{t} \tag{17}$$

Equation (18) shows the holding cost of inventory by distribution centers.

$$H_{pdt} = \left(P_{hpd} \times \varphi_{pdt}\right)\left(\frac{U_1}{60000}\right)\left(\prod_{t=1}^{T}(1 + \delta^{U}_{t,t+1} + \frac{\Delta_{U1} - \Delta_{U2}}{3})\right) \tag{18}$$

The transportation cost is computed using Equation (19).

$$\zeta^{ukt}_{pdh} = \begin{Bmatrix} \left(\frac{\gamma_u}{\varepsilon_{dh}}\right)OP_1\left(1 + \delta^{op}_{t,t+1} + \frac{\Delta_{OP1}-\Delta_{OP2}}{3}\right) & if\ k = 1 \\ \left(\frac{P_u}{\varepsilon_{dh}}\right)\left(\frac{U_1}{60000}\right)\left(1 + \delta^{U}_{t,t+1} + \frac{\Delta_{OP1}-\Delta_{OP2}}{3}\right) & if\ k = 2 \end{Bmatrix} \tag{19}$$

Combining Equations (17)–(19), the total cost function of distributor is obtained as under:

$$\begin{aligned} TC^{t}_{pdh} = & \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(\frac{\zeta^{ukt}_{pdh}}{z_{uk}}\right) \times Q_{pdhtuk} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} FC^{ukt}_{pdh} \times X^{ukt}_{pdh} \\ & + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} \zeta^{ukt}_{pdh} \times n^{ukt}_{pdh} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T}\left(P_{hpd} \times \tau_{pdt}\right)\left(\frac{U_1}{60000}\right)\left(\prod_{t=1}^{T}(1 + \delta^{U}_{t,t+1} + \frac{\Delta_{U1}-\Delta_{U2}}{3})\right) \times I_{pmt} \\ & + \sum_{p=1}^{P}\sum_{e=1}^{E}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} \frac{1}{\alpha_{pdt}}(W_{edt} \times L_{edt}) \times (1 + \delta^{w}_{t,t+1})^{t} \times X^{ukt}_{pmd} \end{aligned} \tag{20}$$

By combining Equations (11) and (20), Equation (21) is obtained which represents the total cost of centralized supply chain.

$$\begin{aligned} & Minimize\ TC \\ & = \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\begin{Bmatrix} \left(\sum_{r=1}^{R} P_r \times \tau_{prm}\right)\frac{U_1}{60000}\left(\prod_{t=1}^{T}(1 + \delta^{U}_{t,t+1} + \frac{\Delta_1-\Delta_2}{3})\right) \\ +\omega_p v_{p1}\left(\prod_{t=1}^{T}(1 + \delta^{v}_{t,t+1} + \frac{\Delta_1-\Delta_2}{3})\right) \end{Bmatrix} \times q^{ukt}_{pmd} \\ & + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} FC^{ukt}_{pmd} \times X^{ukt}_{pmd} + \left\{\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(\frac{\zeta^{ukt}_{pmd}}{z_{uk}}\right) \times Q^{ukt}_{pmd}\right\} \\ & + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{t=1}^{T}\left(P_{hpm} \times \varphi_{pmt}\right)\left(\frac{U_1}{60000}\right)\left(\prod_{t=1}^{T}(1 + \delta^{U}_{t,t+1} + \frac{\Delta_1-\Delta_2}{3})\right) \times I_{pmt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} \zeta^{ukt}_{pmd} \times n^{ukt}_{pmd} \\ & \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\left(\frac{\zeta^{ukt}_{pdh}}{z_{uk}}\right) \times Q^{ukt}_{pmd} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} FC^{ukt}_{pdh} \times X^{ukt}_{pdh} \\ & + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} \zeta^{ukt}_{pdh} \times n^{ukt}_{pdh} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{t=1}^{T}\left(P_{hpd} \times \varphi_{pdt}\right)\left(\frac{U_1}{60000}\right)\left(\prod_{t=1}^{T}(1 + \delta^{U}_{t,t+1} + \frac{\Delta_{U1}-\Delta_{U2}}{3})\right) \times I_{pmt} \\ & + \sum_{p=1}^{P}\sum_{e=1}^{E}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} \frac{1}{\alpha_{pdt}}(W_{edt} \times L_{edt}) \times (1 + \delta^{w}_{t,t+1})^{t} \times X^{ukt}_{pmd} \end{aligned} \tag{21}$$

3.3.2. Greenhouse Emission

The second objective of this optimization model is GHG emission, which is produced by vehicles during supply of products from suppliers to distributors and distributors to hospitals. Equation (22) shows the total GHG emission in all time periods.

$$Minimize\quad GE = \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} G_{uk} \times \varepsilon_{md} \times n^{ukt}_{pmd} + \sum_{p=1}^{P}\sum_{d=1}^{D}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T} G_{uk} \times \varepsilon_{dh} \times n^{ukt}_{pdh} \tag{22}$$

3.3.3. Priority Index

The sustainability of suppliers and customers is the core requirement of modern businesses. To ensure the suitability, satisfaction and preferences of potential consumers and suppliers is desirable. In this research, an objective is proposed which evaluates the customers and suppliers by using qualitative variables, simultaneously. A rule-based fuzzy inference system is then employed to model the qualitative variables quantitatively.

Fuzzy Inference System (FIS)

Fuzzy inference system is a process of converting a crisp model into a fuzzy model, and then evaluating fuzzy model with a set of logical rules, and finally decoding the fuzzy model into the crisp model. There are two types of approaches used for FIS systems namely: Sugeno and Mamdani. It is very difficult to define rules in linguistic terms in the Sugeno model, however, in the Mamdani approach, the linguistic information can be modeled easily based on the knowledge of experts. The FIS system proposed by Mamdani [42] consists of four steps. The steps are presented in Figure 3.

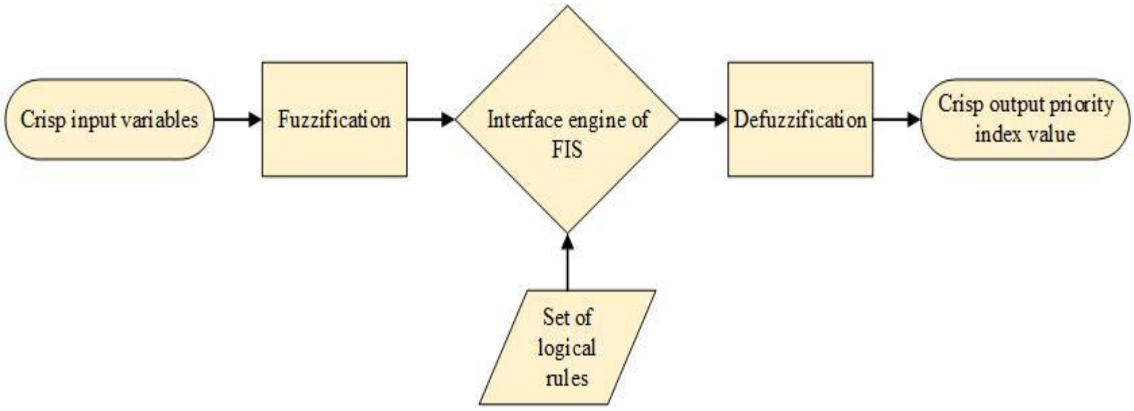

Figure 3. Fuzzy inference system.

The development of a fuzzy inference system consists of four steps:

1. Determining fuzzy membership function and fuzzification of inputs.
2. Defining the set of logical rules based on expert opinions.
3. Evaluating the set of rules on fuzzified inputs using inference engine.
4. De-fuzzifing the fuzzy model into to crisp model.

$$Maximize\ \ PI = \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\rho_{mdt}\times Y_{pmd}^{ukt} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K}\sum_{t=1}^{T}\rho_{dht}\times Y_{pdh}^{ukt} \quad (23)$$

Subject to

$$\sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K} Q_{pmd}^{ukt} \le \chi_{pm} \qquad \forall_i \in \{p,m,t\} \quad (24)$$

$$Q_{pmd}^{ukt} \le J_{pm}\times X_{pmd}^{ukt} \qquad \forall_i \in \{m,d,u,k,t\} \quad (25)$$

$$I_{pmt} = \sum_{p=1}^{P} q_{pmt} - \sum_{d=1}^{D}\sum_{u=1}^{U}\sum_{k=1}^{K} Q_{pmd}^{ukt} \qquad \forall_i \in \{m,t\} \quad (26)$$

$$I_{pmt} \le \eta_{pmt} \qquad \forall_i \in \{p,m,t\} \quad (27)$$

$$I_{pmt} \ge \sigma_{pmt}\times q_{pmt} \qquad \forall_i \in \{p,m,t\} \quad (28)$$

$$\sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{u=1}^{U}\sum_{k=1}^{K} Q_{pmd}^{ukt} - \sum_{p=1}^{P}\sum_{h=1}^{H}\sum_{u=1}^{U}\sum_{k=1}^{K} Q_{pdh}^{ukt} \ge I_{pdt} \qquad \forall_i \in \{p,d,t\} \quad (29)$$

$$I_{pdt} \le \eta_{pdt} \qquad \forall_i \in \{p,d,t\} \quad (30)$$

$$I_{pdt} \geq \sigma_{pdt} \times \sum_{m=1}^{M} \sum_{u=1}^{U} \sum_{k=1}^{K} Q_{pmd}^{ukt} \qquad \forall_i \in \{p, d, t\} \tag{31}$$

$$\sum_{d=1}^{D} \sum_{u=1}^{U} \sum_{k=1}^{K} Q_{pdh}^{ukt} = ED_{pht} \qquad \forall_i \in \{p, h, t\} \tag{32}$$

$$\sum_{d=1}^{D} Y_{pmdi}^{ukt} = X_{pmd}^{ukt} \qquad \forall_i \in \{p, m, i, u, k, t\} \tag{33}$$

$$\sum_{i=1}^{N} Y_{pmdi}^{ukt} = X_{pmd}^{ukt} \qquad \forall_i \in \{p, m, d, u, k, t\} \tag{34}$$

$$\sum_{h=1}^{H} Y_{pdhiukt} = X_{pdhukt} \qquad \forall_i \in \{p, d, i, u, k, t\} \tag{35}$$

$$\sum_{i=1}^{N} Y_{pdhi}^{ukt} = X_{pdh}^{ukt} \qquad \forall_i \in \{p, d, h, u, k, t\} \tag{36}$$

$$n_{pmd}^{ukt} \times z_{uk} = Q_{pmd}^{ukt} \qquad \forall_i \in \{p, m, d, u, k, t\} \tag{37}$$

$$n_{pdh}^{ukt} \times z_{uk} = Q_{pdh}^{ukt} \qquad \forall_i \in \{p, d, h, u, k, t\} \tag{38}$$

$$\left\{q_{pmt}, Q_{pmd}^{ukt}, I_{pmt}, Q_{pdh}^{ukt}, I_{pdt}, n_{pmd}^{ukt}, n_{pdh}^{ukt}\right\} \geq 0 \tag{39}$$

$$\left\{Y_{pmdi}^{ukt}, Y_{pdhi}^{ukt}, X_{pmd}^{ukt}, X_{pdhukt}\right\} \in (0, 1) \tag{40}$$

Equation (24) shows the production capacity constraints of suppliers. Constraints in Equation (25) restrict the model for not supplying the products from supplier to manufacture more than maximum allowed quantity. Ending inventory level of each manufacturer and holding capacity is given in Equations (26) and (27). Safety stock of manufacturer is provided in Equation (28). Inventory of the distributors and holding capacity of each distributor are shown in Equations (29) and (30). Equation (31) shows the safety stock of distributors. Constraints in Equation (32) represent the demand generated from each customer during each time period. Equation (33) restricts that vehicle type "u" with technology "k" moves from supplier to distributor for which supplier is elected. If a supplier is selected for multiple distributors, then the sequence of visiting or priority of supplying orders to distributors is decided with constraints in Equation (34). Similarly, constraints in Equations (35) and (36) are vehicle routing constraints among distributors and customers. Required number of selected vehicles between manufacturers and distributors are provided by Equation (37). The constraint in Equation (38) computes the required types of vehicles between distributors and customers. The non-negativity constraint for all variables is given in Equation (39). Equation (40) represents the binary variables in the model.

4. Solution Methodology

To solve this model, a modified, interactive multi-objective fuzzy programming approach is proposed, for which the details are provided below:

4.1. Modified Interactive Multi-Objective Fuzzy Programming

Fuzzy interactive multi-objective programming was introduced by Zimmermann [43]. This approach prioritizes each objective on a set of human expert opinions, and the opinion of each expert is equally weighted. However, the worth of an expert's opinion depends on his/her skill, experience, and knowledge, therefore, the weight of prioritization must consider this factor. The proposed modified interactive multi-objective fuzzy programming involves expert opinion weight and function prioritization on the basis of expert experience, skill and, knowledge. The procedure of the proposed approach consists of the following steps:

Step-1: first, get alpha extreme solutions by solving each objective individually. Once the objective value of each objective is achieved, then set one of the objectives as equality constraints and re-optimize other objectives. Repeat this process for all objectives and obtain the maximum and minimum value of each objective.

Step-2: formulate fuzzy membership functions for all objectives using the maximum and minimum values obtained in the previous step. Equation (41) shows the generic membership function.

$$\mu_q = \left\{ \begin{array}{cc} 0 & f \geq f_q^{\alpha-lb} \\ \frac{f_q^{\alpha-ub}-f}{f_q^{\alpha-ub}-f_q^{\alpha-lb}} & f_q^{\alpha-lb} < f < f_q^{\alpha-ub} \\ 1 & f \leq f_q^{\alpha-ub} \end{array} \right\} \tag{41}$$

$f_q^{\alpha-lb}$ and $f_q^{\alpha-ub}$ are the extreme function values of function "q".

Step-3: the last step in this approach is the conversion of multi-objective model into a single objective. In this approach, fuzzy linguistic weight method is adopted. In the fuzzy linguistic method, the importance of the objectives is then measured in terms of the linguistic variables. The most important objective may get a value of ~1, and the least important will get ~0. Table 2 shows the scale of the linguistic variables. The panel of the decision-makers usually rates the weights of the objectives. Previous researchers used this method of weighing. In their method, the opinion of each expert is valued equally; however, experts might have different skills and experiences so giving them the same value may not be effective for decision-making of critical situations. Based on the experience and number of experts, an aggregate fuzzy number is computed as follows.

$$IE_i = \frac{E_i}{\sum\limits_{i=1}^{I} E_1} \tag{42}$$

Table 2. Fuzzy numbers scale for the importance of objectives.

Priority of Objective	Fuzzy Numbers
Least important	(0.0,0.1,0.2)
Less important	(0.2,0.3,0.4)
Important	(0.4,0.5,0.6)
More important	(0.6,0.7,0.8)
Most important	(0.8,0.9,1.0)

Equation (42) computes the importance of the opinion of expert "i" relative to all the experts. Finally, Equation (43) gives the aggregate fuzzy number on the basis of the importance of expert opinions.

$$AFN_o = \frac{\sum\limits_{i=1}^{I} w_{0i} \times IE_i}{I} \tag{43}$$

The normalized weight of each objective can be calculated by using Equation (44).

$$NFW_q = \frac{AFN_q}{\sum\limits_{q=1}^{Q} AFN_q} \quad (44)$$

If there is a set of objectives then $AFN_0 \in (0,1)$ so, the final single function is formed that can be seen in Equation (45).

$$F = \sum_{q=1}^{Q} NFW_q \times \mu_q \quad (45)$$

Subject to
Model constraints in Equations (24)–(40).

4.2. Numerical Example: Case Study of Supply Chain of Surgical Instruments

This section provides a case study of a group of surgical instrument manufacturing industries and their supply chain. The data used in this case study has been collected through time and motion study and process mapping of production and supply chain. In addition, the procurement and finance department of surgical manufacturing industry assisted in acquiring data related to material, machine, and labor costs. Also, the feedback of production, supply chain, finance, and procurement managers is used for the data validation.

Problem Statement

Consider a group of surgical instruments manufacturing company which has two plants for manufacturing of surgical instruments. The manufacturing process plan and required power of each machine is given in Table 3. To manufacturer a scissor AISI 304 is used and its current cost is 2.20 $/kg. The cost of electricity in the base period is 0.17 $/kilowatt-hour.

Table 3. Manufacturing process plan of scissor along with the power of machines.

Machine #	Process	Process Time (Minutes)	Power of Machine (Watt)
1	Drop Forging	1.2	900.00
2	Milling	2.0	1500.0
3	Drilling	2.4	1800.0
4	CNC Milling	1.5	1125.0
5	Carbide coating	1.0	40,000
6	Grinding	2.4	3000.0
7	Polishing	1.5	13,000
8	Electroplating	3.5	45,000
9	Electroscopic inspection	4.4	3300.0
10	Acid Etching	0.5	375.00
11	Laser Etching	1.3	975.00

The manufacturers are using the same production systems and supply sterilized surgical instruments to distribution centers. There are three distribution centers located near these plants. The distance between manufacturers and distributors are given in Table 4.

Table 4. Distance between manufacturers and distributors (km).

	$d = 1$	$d = 2$	$d = 3$
$m = 1$	120.00	109.00	78.00
$m = 2$	90.00	54.00	140.00

Three types of vehicles are being used with two types of technology: electricity and fuel technology. Table 5 shows the power and fuel consumption of each vehicle type.

Table 5. Power consumption of each vehicle type and technology and fixed cost of hiring.

	$k = 1$		$k = 2$	
	Power Consumption (W/km)	**Fixed Cost ($)**	**Fuel Consumption (L/km)**	**Fixed Cost ($)**
$u = 1$	20,000.00	100	0.06	120
$u = 2$	22,000.00	140	0.07	160
$u = 3$	24,000.00	150	0.08	210

Distributors place an order to selected manufacturers in each period and bears the ordering cots. Ordering cost is composed of wages of labor involved in procurement. There are two types of employees directly affecting the ordering cost namely: executives and quality inspectors. Table 6 shows the number of each employee type and their annual wages, along with the percentage increment in their salaries per annum.

Table 6. Labor type, number, cost, and, wage increment at each distribution center.

	$d = 1$		$d = 2$		$d = 3$	
Employee Type	$e = 1$	$e = 2$	$e = 1$	$e = 2$	$e = 1$	$e = 2$
Number of employees	8	7	5	4	3	9
Annual wage ($)	8400	3600	9000	4000	9300	3750
Annual salary increment	13%	13%	15%	15%	15%	15%

The manufacturer supplies the product to the distributors and also store some products as an inventory. To store the inventory of sterilized products manufacturer, use a refrigerator of 745.7 horsepower which has a capacity to store 5000 products. Similarly, distribution centers use refrigerators of 1342.26 horsepower with a capacity to store 10,000 sterilized scissors. Distributors supply products to the hospitals with the help of vehicles which have been discussed previously. The distance among distributors and hospitals is given in Table 7.

Table 7. Distance between distributors and hospitals.

	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$d = 1$	40	60	90	38	85	102
$d = 2$	36	78	100	45	78	98
$d = 3$	74	67	89	90	110	104

The capacities of vehicles supplying products among manufacturers, distributors, and hospitals are given in Table 8. The annual forecasted demand of products for each hospital during each period is shown in Table 9. As both manufacturers and distributors hold some inventory, the safety stock level of each manufacture and distributor is given in Table 10.

Table 8. The capacity of each vehicle type and technology.

	$u = 1$	$u = 2$	$u = 3$
$k = 1$	3000	5500	8000
$k = 2$	5000	6000	7000

Table 9. Annual forecasted demand (units) of each hospital in each time period.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
$h = 1$	40,000	30,000	50,000	38,000	50,900
$h = 2$	20,000	28,000	50,000	36,500	41,000
$h = 3$	34,000	40,000	45,000	49,000	48,000
$h = 4$	68,000	44,000	37,000	65,900	54,000
$h = 5$	37,500	56,000	65,000	47,650	28,000
$h = 6$	59,000	58,000	36,000	47,600	40,000

Table 10. Safety stock of each manufacturer and distributor.

	$m = 1$	$m = 2$	$d = 1$	$d = 2$	$d = 3$
Safety stock	5%	4%	3%	2%	4%

The manufacturers have prioritized the distributors using fuzzy inference FIS on the basis of qualitative factors such as trust, behavior, and long-term relationship. Similarly, distributors have also prioritized the hospitals. Table 11 shows the priority index of each distributor evaluated by each manufacturer (supplier), while Table 12 shows the priority index table developed by each distributor for each hospital.

Table 11. Priority index of each distributor by each manufacturer.

	$d = 1$	$d = 2$	$d = 3$
$m = 1$	0.67	0.72	0.58
$m = 2$	0.53	0.81	0.72

Table 12. Priority index of each hospital by each distributor.

	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$d = 1$	0.52	0.52	0.64	0.65	0.55	0.57
$d = 2$	0.55	0.57	0.58	0.54	0.67	0.55
$d = 3$	0.76	0.69	0.59	0.58	0.60	0.80

All parties involved in this supply chain are interested in minimizing cost, GHG emissions while maximizing the service of the customers on the basis of priority index. Small, medium, and large electric vehicles have 0.12 kg/km, 0.37 kg/km, and 0.4 kg/km GHG emission while fuel vehicles emit 0.603 kg/km, 0.598 kg/km, and 0.87 kg/km, respectively. All the supply chain partners also want to consider the fluctuations in cost over time to achieve these objectives. Keeping in view these objectives, top management is interested in determining the optimal production quantity in each manufacturing plant, optimal quantity supplied from manufacturer, distributors, and hospital, ending inventory of manufacturer and distributor, and number of vehicles for supplying the quantity of products between manufacturers, distributors, and hospital. Since the costs of raw material, electricity, and oil varies over time, the change in cost is highly uncertain. To model this, an integrated fuzzy polynomial regression model is proposed. Equation (46) shows the regression model for the change in the cost of raw material with the adjusted R-square value of 0.69.

$$\delta_{t,t+1}^{RM} = -2.89 \times 10^{-8} \times t^5 + 4.88 \times 10^{-6} \times t^4 - 0.0002923 \times t^3 + 0.007282 \times t^2 - 0.06626 \times t + 0.1293 \quad (46)$$

The cost variation in each period is uncertain therefore values of uncertain variables are needed to model the predicted uncertain change. Table 13 shows the deviational parameters in the change of raw material AISI 304 steel over time.

Table 13. Deviational parameters for the cost of AISI 304 steel.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$
Δ_{RM1}	−0.03	−0.33	−0.27	0.10	−0.23	−0.37
Δ_{RM2}	0.20	−0.11	0.16	0.31	0.245	0.26

Equation (47) shows the polynomial regression for the cost of electricity with adjusted R-square value of 0.799.

$$\delta^{U}_{t,t+1} = -0.0005032 \times t^2 + 0.01796 \times t - 0.01934 \tag{47}$$

The deviational variables for the change in the cost of electricity over the time are presented in Table 14.

$$\delta^{op}_{t,t+1} = -1.88 \times 10^{-7} \times t^4 + 2.27 \times 10^{-5} \times t^3 - 0.00086 \times t^2 + 0.01057 \times t - 0.02926 \tag{48}$$

Table 14. Deviational parameters for the cost of electricity.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Δ_{U1}	−0.17	−0.15	−0.10	−0.07	−0.04
Δ_{U2}	0.95	0.47	0.20	0.10	0.04

Polynomial regression for change in oil price is provided by Equation (48). The adjusted R square for this equation is 0.772. The deviational variable for change in oil price is provided in Table 15.

Table 15. Deviational variables for change in future purchasing price of diesel oil.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
Δ_{OP1}	−0.05	−0.05	−0.11	−0.08	−0.03
Δ_{OP2}	−0.01	0.05	0.05	0.08	0.05

5. Results and Discussion

For solving, expert opinions are required to convert the proposed multi-objective model into a single objective by assigning priority weights to each objective. Table 16 shows the weights assigned by experts along with their experience.

Table 16. Weight determination of each objective.

Expert	Experience	Experience Weight	Preferences of the Decision-Makers		
			Cost	GHG Emission	Customer Priority
1	5	0.092593	More important	Important	Important
2	20	0.37037	More important	More Important	Important
3	10	0.185185	Most important	Important	Most Important
4	12	0.22222	important	Important	Important
5	7	0.12963	More Important	More important	Important
Total	54	1	$AFN_{cost} = 0.256$	$AFN_{time} = 0.115$	$AFN_{quality} = 0.1144$

By using Equation (44), normalized fuzzy weights of cost, GHG emission, and priority index are 0.53, 0.24, and 0.23, respectively. To convert multi-objective model into a single objective all objectives should be either of minimization or maximization but in this case, cost and GHG emission required to be minimized while the priority index is maximized. Therefore, to convert the priority index objective function into a minimization problem, the priority index objective is reformulated as under:

$$Minimize \quad PI = \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{u=1}^{U}\sum_{k=1}^{K}(1-\rho_{mdt})\times 100\times Y_{pmdtuk} + \sum_{p=1}^{P}\sum_{m=1}^{M}\sum_{d=1}^{D}\sum_{t=1}^{T}\sum_{u=1}^{U}\sum_{k=1}^{K}(1-\rho_{dht})\times 100\times Y_{pdhtuk} \quad (49)$$

The numerical example consists of 5975 variables, 1490 inequality constraints and 1480 equality constraints. The optimal solution of numerical example is obtained in 22.69 s by solving the modified multi-objective interactive fuzzy programming in MATLAB R2017a on personal computer with 8 GB RAM and 3.40 GHz processor.

To get robust results, the priority index is treated as a percentage in numerical example. Table 17 shows the pay-off table for all objectives. Using the pay-off values table and Equation (41) satisfaction level of each objective can be computed. For example, the satisfaction level of cost function is as under:

$$\mu_{\text{cost}} = \left\{ \begin{array}{cc} 0 & f > 256672058.78 \\ \frac{365192261.76 - f}{365192261.76 - 256672058.78} & 256672058.78 < f < 365192261.76 \\ 1 & f < 365192261.76 \end{array} \right\} \quad (50)$$

Table 17. Pay-off values of all objectives.

	Cost ($)	GE (Kg)	PI
Cost ($)	256,672,058.78	9084.46	304.200
GE (Kg)	365,192,261.76	3486.28	272.730
PI	256,672,058.78	3486.28	1391.00

Similarly, the satisfaction level of each objective can also be computed as shown in Table 18. After combining all functions and normalized fuzzy weights the following single objective is obtained in Equation (51).

$$Minimize \quad f = 0.53\times\mu_{\text{cost}} + 0.24\times\mu_{GE} + 0.23\times\mu_{PI} \quad (51)$$

Subject to constraints in Equations (24)–(40).

Table 18. Optimal values of all objectives and satisfaction level of each objective.

	Cost ($)	GE (kg)	PI
Objective value	523,833,812.35	15,416.95	2974.92
Satisfaction level%	93.37	60.97	39.64

The quantity of products produced by each manufacturer during each period is given in Table 19 and inventory levels are provided in Table 20. The inventory levels at each distribution center are given in Table 21.

Table 19. Quantity produced by selected supplier/manufacturer in each period of time.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
$m = 1$	165,499	87,626	132,739	129,141	104,705
$m = 2$	238,542	238,542	238,542	238,542	238,542

Table 20. Inventory level at each manufacturing plant in each time period.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
$m = 1$	8275	4381	6637	6457	5235
$m = 2$	9542	9542	9542	9542	9542

Table 21. Inventory level at each distribution center in each time period.

	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$
$d = 1$	0.00	0.00	0.00	0.00	0.00
$d = 2$	7724.49	6244.90	7102.04	7033.67	6569.39
$d = 3$	0.00	0.00	0.00	0.00	0.00

As it is clear from Table 21 that only one distributor "$d = 2$" is supplying the surgical instruments to the hospital to fulfill their demand. Therefore, the quantity of surgical instruments supplied by selected manufacturers to distributor "$d = 2$" with vehicle type "u" and technology "k" in time period $t = 1$ is given in Table 22. Decisions for the rest of the periods are provided in Table A1 of the Appendix A. Table 23 shows the required number of vehicle types for supplying surgical instruments from manufacturers to distributor $d = 2$ in time period $t = 1$. Data for the rest of the periods are given in Table A2 of the Appendix A.

Table 22. Quantity of surgical instruments supplied by manufacturers to distributor "$d = 2$" in period $t = 1$.

		$d = 2$					
		$u = 1$		$u = 2$		$u = 3$	
		$k = 1$	$k = 2$	$k = 1$	$k = 2$	$k = 1$	$k = 2$
$t = 1$	$m = 1$	35,400	36,500	13,424	35,400	36,500	0
	$m = 2$	37,000	38,500	39,000	37,000	38,500	39,000

Table 23. Required number of each vehicle between manufacturers and distributor in period $t = 1$.

		$d = 2$					
		$u = 1$		$u = 2$		$u = 3$	
		$k = 1$	$k = 2$	$k = 1$	$k = 2$	$k = 1$	$k = 2$
$t = 1$	$m = 1$	7	6	3	7	6	0
	$m = 2$	6	5	8	6	5	8

During optimization, only distributor $d = 2$ is selected so Table 24 shows the quantity of surgical instruments supplied each distributor to each hospital in time period $t = 1$ and details for rest of time periods can be found in Table A3 of the Appendix A.

Table 24. Quantity of surgical instruments supplied by distributor $d = 2$ to all hospitals in period $t = 1$.

			$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$t = 1$	$u = 1$	$k = 1$	0	0	0	0	20,500	0
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	37,000	37,000	37,000	37,000	0	37,000
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	33,000	23,000	17,000	31,000	37,000	32,000
		$k = 2$	0	0	0	0		0

The required number of vehicles for supplying surgical instruments from distributors to all hospitals in time period $t = 1$ is shown in Table 25. See Table A4 in the Appendix A for other time periods.

Table 25. Required number of each vehicle between distributor “d = 2” and hospitals during time period t = 1.

			h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
t = 1	u = 1	k = 1	0	0	0	0	3	0
		k = 2	0	0	0	0	0	0
	u = 2	k = 1	6	6	6	6	0	6
		k = 2	0	0	0	0	0	0
	u = 3	k = 1	6	4	3	3	6	5
		k = 2	0	0	0	0	0	0

As only distributor “d = 2” is providing products to hospitals so all vehicles from all manufacturers supply products to distributor “d = 2”. However, distributor “d = 2” will supply the products to hospitals on the basis of their priority index. The sequence of fulfilling the customer’s orders by distributor “d = 2” is given in Table 24. Per the objective of the priority index, the hospitals at top priority must be served on the basis of the priority index. We introduced a binary decision variable for deciding the sequence of visiting to assigned hospitals. It is a multi-dimensional matrix based on the number of distributors, hospitals, vehicle type and technology, and periods. Therefore, authors have coded binary data into numbers. If one considers “t = 1”, “u = 3” and “k = 1” from Table 26 it can be concluded that distributor “d = 2” will use vehicle type “u” with technology “k” to supply products to hospital “h = 5” first shipment and in second shipment it will go hospital “h = 2” and then hospital “h = 1” and so on. Table 24 shows the sequence of the visit of vehicles from distributors to hospitals in period t = 1. However, details for the next time periods are in Table A5 in the Appendix A.

Table 26. Sequence of supplying instruments to hospitals with selected vehicles in period t = 1.

			h = 1	h = 2	h = 3	h = 4	h = 5	h = 6
t = 1	u = 1	k = 1	0	0	0	0	1	0
		k = 2	0	0	0	0	0	0
	u = 2	k = 1	4	5	2	3	0	1
		k = 2	0	0	0	0	0	0
	u = 3	k = 1	3	5	6	2	1	4
		k = 2	0	0	0	0	0	0

The satisfaction level measures the closeness of the objective function value. In case of minimization problem if objective function approaches to lower bound then the solution is said to be 100% satisficed. In the case of maximization problems if optimal solution approaches the upper bound then the satisfaction level is 100%. As cost, GHG emissions were conflicting objective so the satisfaction level of each objective is shown in Figure 4.

5.1. Managerial Insights

This research is useful for supply chain managers, procurement managers, and production managers for strategic decision making. In reality, manufacturers prefer to supply the products to customers on the basis of various qualitative criteria. This research approach not only prioritizes the customers but also introduces a multi-objective method to optimize the supply chain process with reduced costs and low GHG emissions. The supply chain is a multi-period process and in each period the cost of supply chain may not be the same because of various factors such as government rules and regulation, political, geographical, and environmental factors. Consideration of uncertainty and prediction of cost for future periods makes it more realistic and flexible for real-time decision making. Stability and profitability are the major benefits of this proposed research.

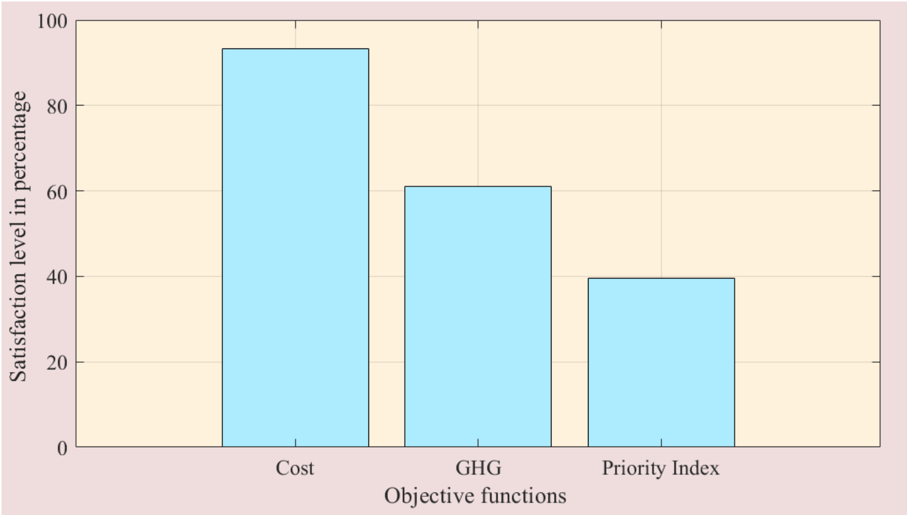

Figure 4. Satisfaction level of each objective.

a. Stability

The traditional supply chain model for multi-period considered the uncertainty in cost but uncertainty in cost is influenced by various unpredicted factors. Therefore, this research not only considers the uncertainty but also the forecasted change in uncertain cost. The planning and design of supply chain systems with the consideration of predicted uncertain cost make this model more stable and capable to deal with the cost influencing unpredicted events in future periods of time.

b. Profitability

Profit is the function of cost and it is affected by change in manufacturing cost. In supply chain, usually, there is a contract among the parties for fixed sales prices. However, the manufacturing cost of the product does not remain same in each period resulting in fluctuation in profit. Therefore, modeling and designing supply chain systems with predicted uncertain cost can reduce this fluctuation and managers can make decisions with high accuracy.

5.2. Scalability and Generalization

The proposed research is useful in decision making for complex supply chain network design with robust results. This study has been conducted for the supply chain of surgical instruments. However, the mathematical model developed in Section 3 is a generic model and can be used for the supply chain of perishable items such as food and medicine supply chain. As, the nature of the problem is a multi-objective, so the optimal trade-off of conflicting objectives such as cost, greenhouse gas emission, and priority index has been obtained by optimizing the satisfaction level of each objective. The proposed modified interactive multi-objective fuzzy programming enables users to prioritize the objectives based on their importance.

5.3. Limitation of Proposed Research

This research is limited to the supply chain of perishable commodities such as food, medicine, and surgical instruments. The nature of the model is static because it involves the deterministic parameters in multi-periods. However, inventory routing problems can be modeled in a dynamic pattern with stochastic parameters.

6. Conclusions

This research addressed the multi-objective, multi-period inventory routing problem in the supply chain of perishable items with the consideration of cost, GHG emission, and priority index. Priority index is a novel objective that measures qualitative social factors such as trust, behavior, and long-term relationship of supply chain partners. In a traditional multi-period model, the cost of uncertainty has been modeled either using random variables or fuzzy number that does not provide any information about the dependency of future cost value on present value. In order to include, the uncertainty and time series behavior of cost, a time series integrated regression fuzzy model is introduced for modeling the parameters for cost objective function for multi-periods. To reduce the environmental impact, an objective of GHG emission has been optimized for the selection of appropriate sources of transportation which emits minimum GHG. To model the objective of priority index (PI) a fuzzy inference system (FIS) is employed which converts the qualitative variables into quantitative variables. This multi-objective model is a mixed-integer linear programming model (MILP). Consideration of priority index and time series predicted uncertain cost along with GHG emissions in a multi-objective optimization model differentiates this model from the existing ones. Priority index converted the qualitative factors into quantitative form. In addition to these theoretical contributions, the development of the modified interactive multi-objective fuzzy programming technique, incorporating expert opinion along with their practical experience, highlights the methodological innovations for desired optimal results. A case study of surgical instrument supply chain is used for real-life application of the proposed model. The solution of numerical example provided the decision of optimal production, optimal inventory levels at manufacturers and distributors, optimal quantity supplied from manufacturers to distributors, and distributors to hospitals. Satisfaction level of cost, GHG, and priority index was 93.37%, 60.97%, and 39.64%, respectively. The satisfaction level shows the optimality of an objective defined by the expert. It also provided the required number of vehicle types and priority of shipments by manufacturers to distributors and distributors to hospitals. The proposed model can be generalized for the implementation of the food supply chain as well where deterioration requires special vehicles for transportation. Future research work includes the dynamic vehicle routing problem integrated with the production planning of manufacturing systems under an uncertain environment of change in technology.

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Appendix A

Table A1. Quantity of surgical instruments supplied by manufacturers to distributor "d = 2" in periods t = 2–5.

		$d = 2$					
		$u = 1$		$u = 2$		$u = 3$	
		$k = 1$	$k = 2$	$k = 1$	$k = 2$	$k = 1$	$k = 2$
$t = 2$	$m = 1$	10,245	36,500	0	0	36,500	0
	$m = 2$	37,000	38,500	39,000	37,000	38,500	39,000
$t = 3$	$m = 1$	35,400	36,500	0	17,702	36,500	0
	$m = 2$	37,000	38,500	39,000	37,000	38,500	39,000
$t = 4$	$m = 1$	35,400	36,500	0	14,284	36,500	0
	$m = 2$	37,000	38,500	39,000	37,000	38,500	39,000
$t = 5$	$m = 1$	26,469	36,500	0	0	36,500	0
	$m = 2$	37,000	38,500	39,000	37,000	38,500	39,000

Table A2. Required number of each vehicle between manufacturers and distributor in period t = 2–5.

		$d = 2$					
		$u = 1$		$u = 2$		$u = 3$	
		$k = 1$	$k = 2$	$k = 1$	$k = 2$	$k = 1$	$k = 2$
$t = 1$	$m = 1$	7	6	3	7	6	0
	$m = 2$	6	5	8	6	5	8
$t = 2$	$m = 1$	2	6	0	0	6	0
	$m = 2$	6	5	8	6	5	8
$t = 3$	$m = 1$	7	6	0	4	6	0
	$m = 2$	6	5	8	6	5	8
$t = 4$	$m = 1$	7	6	0	3	6	0
	$m = 2$	6	5	8	6	5	8
$t = 5$	$m = 1$	5	6	0	0	6	0
	$m = 2$	6	5	8	6	5	8

Table A3. Quantity of surgical instruments supplied by distributor d = 2 to all hospitals in period t = 2–5.

			$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$t = 2$	$u = 1$	$k = 1$	37,000	37,000	37,000	37,000	37,000	37,000
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	3000	21,000	0	17,000	19,000	11,000
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	13,000	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 3$	$u = 1$	$k = 1$	37,000	37,000	37,000	37,000	37,000	37,000
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	23,000	18,000	18,000	20,000	18,000	29,000
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 4$	$u = 1$	$k = 1$	37,000	37,000	37,000	35,900	37,000	37,000
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	21,000	29,500	32,000	0	10,650	30,600
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 5$	$u = 1$	$k = 1$	37,000	37,000	37,000	37,000	37,000	37,000
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	13,900	24,000	11,000	17,000	11,000	23,000
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0

Table A4. Required number of each vehicle between distributor "d = 2" and hospitals in period t = 2–5.

			$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$t = 2$	$u = 1$	$k = 1$	6	6	6	6	6	6
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	1	4	0	3	3	2
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	2	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 3$	$u = 1$	$k = 1$	6	6	6	6	6	6
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	4	3	3	3	3	5
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 4$	$u = 1$	$k = 1$	6	6	6	6	6	6
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	4	5	5	0	2	5
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 5$	$u = 1$	$k = 1$	6	6	6	6	6	6
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	2	4	2	3	2	4
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0

Table A5. Sequence of supplying instruments to hospitals with selected vehicles in period t = 1.

			$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$t = 2$	$u = 1$	$k = 1$	4	3	5	6	2	1
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	5	3	0	2	4	1
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	1	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 3$	$u = 1$	$k = 1$	5	6	3	4	2	1
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	1	2	4	3	5	6
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0
$t = 4$	$u = 1$	$k = 1$	3	2	4	5	6	1
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	5	3	4	0	2	1
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0

Table A5. *Cont.*

			$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$	$h = 6$
$t = 5$	$u = 1$	$k = 1$	3	2	5	6	1	4
		$k = 2$	0	0	0	0	0	0
	$u = 2$	$k = 1$	4	3	2	6	5	1
		$k = 2$	0	0	0	0	0	0
	$u = 3$	$k = 1$	0	0	0	0	0	0
		$k = 2$	0	0	0	0	0	0

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