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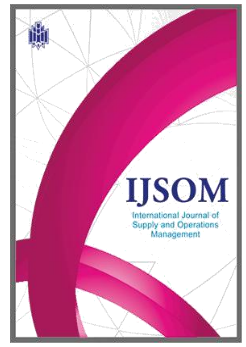

Designing a Resilient Multi-Objective Meat Supply Chain: A Robust Possibilistic Approach

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Abstract

Population growth has led to more food demand, especially meat. Designing a supply chain, especially a meat one, is complicated due to the uncertainty of food demand and the perishability of meat. To this aim, we develop a multi-objective mixed-integer linear programming model. The developed model contains four echelons, i.e., farms, slaughterhouses, retailers, and customers. The first objective function minimizes the total costs, the second objective minimizes the distribution time, and the third objective minimizes the network's non-resiliency simultaneously. An enhanced version of the augmented ε-constraint method is employed to solve the suggested model, and a set of Pareto–optimal solutions is found. This study also explores the impact of using the robust possibilistic approach in modeling a supply chain network under uncertainty. Numerical experiments demonstrate that the robust optimization approach brings significantly superior outcomes in comparison to the conventional deterministic approach, and the model provides a practical and valuable tool for real-world supply chain challenges.

Keywords: Meat Supply Chain; Resiliency; Uncertainty; Improved Augmented ε-Constraint; Multi-Objective Programming; Robust Possibilistic Approach.

1. Introduction

The food supply chain may be known as a set of facilities that harvest, produce, and distribute fruitage, verdure, Agri-based, and animal-based products. Due to population growth, the demand for food has increased, which has made the food supply chain one of the factors of economic growth. Recently, the complexity of the food supply chain has increased due to increasing information and customer expectations about food freshness(Yu & Nagurney, 2013). One of the primary complications of the food supply chain is that its quality does not remain constant, and it tends to rot over time until it perishes (Jouzdani & Govindan, 2021). Moreover, customers tend to buy fresh products. Such challenges emphasize efficient management, which is critical for food supply profitability.

Recently, resiliency has gained considerable attention since supply chains are prone to risk constantly. One can define resiliency as the capability of a network to decrease the possibility of disruptions and their results (Zhalechian et al., 2018). So many disruption risks can endanger the supply chain network’s functionality. Developing a resilient supply chain has competitive benefits for companies. Resiliency also means the capability of a supply chain network to decrease the proximity of defying unpredicted events, respond fast to disruptions, and get back to its first state after the occurrence of disruption (Bottani et al., 2019). One can apply different resilience strategies to empower the network against disruption. We adopted three resiliency measures based on the structure of the network. For this purpose, the current paper applies major resiliency features, i.e., node complexity, flow complexity, and node criticality (Zahiri et al., 2020).

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Optimal efficiency requires the simultaneous optimization of multiple objectives, which may appear to oppose each other. The meat supply chain, in particular, faces several challenges, including reducing costs while addressing the quality of products and improving network resiliency. To this aim, this paper tackles the challenges above by proposing a novel multi-objective mixed-integer linear programming model for a meat supply chain, which aims at optimizing three somewhat contradictory objective functions simultaneously, including 1) minimization of the total cost of the supply chain, 2) minimization of the distribution time, and 3) minimization of the non-resiliency of the network. This model can decide (1) the optimal flow rate of transported products in each echelon, (2) the optimum number of farms, slaughterhouses, and retailers, (3) the inventory of frozen products in retailers, and (4) critical nodes, as four main decision variables of the problem. We applied the Improved augmented ε-constraint method to solve the model. Based on this method, we generate Pareto optimal solutions to help decision-makers. An actual data set is used to prove the efficiency of the proposed model.

Several real-world assumptions have been considered and incorporated to ensure the proposed model is practical and valuable for real-world application. For instance, multi-transportation models have been considered, allowing for a more accurate representation of the actual transportation routes in the meat supply chain. Additionally, the model considers multiple manufacturing technologies with their related costs, resulting in a more realistic representation of the complexities of the meat supply chain.

Uncertainty is inevitable. To design an effective supply chain, we must consider its implications, which will help decision-makers effectively address the issues in real-world situations. We also have considered the impact of uncertainty in the proposed model. The robust possibilistic method is utilized to solve the model under uncertainty. This study examines the impact of incorporating or disregarding the robust possibilistic approach and resilience measures in modeling a supply chain network. The results reveal important insights that emphasize the practicality and usefulness of this approach, making it a valuable tool for addressing real-world supply chain challenges.

Additionally, numerical experiments conducted on an actual case study of a meat supply chain demonstrate the efficiency and effectiveness of the proposed model. This model provides a comprehensive and highly effective approach to designing an optimal meat supply chain. Incorporating robust possibilistic methods ensures that decision-makers can effectively address uncertainty in the supply chain management process.

This paper is divided into six sections: Section 2 dedicates to the review of the related literature. Section 3 provides the problem definition and the proposed model. Section 4 presents the solution approach based on the improved augmented-ε constraint and robust possibilistic method, and section 5 investigates implementation and evaluation. At last, the conclusion and future research are given in section 6.

2. Literature Review

This section reviews the most relevant articles on multi-objective optimization in food supply chains. Hasani et al. (2012) developed a multi-period, multi-product, and multi-echelon closed-loop supply chain for perishable goods under cost and demand uncertainty. To deal with parameter uncertainty, an interval-robust optimization technique is utilized. The results showed that the presence of uncertainty increases supply chain costs. The proposed model can control supply chain costs and ensure its agility. Govindan et al. (2014) proposed a multi-objective optimization model for a perishable food supply chain network considering sustainable distribution. Their study aims to minimize costs caused by greenhouse gas emissions. Because of the complicity of the proposed model, a novel hybrid metaheuristic algorithm is applied. Abtahi (2015) developed a bi-objective mathematical programming model for perishable products. The 1) objective reduces the total cost of the system, and the 2) objective reduces the difference between the highest and lowest transportation costs for distribution centers. The epsilon constraint and the NSGA-II are applied to solve the model. An & Ouyang (2016) presented a bi-level robust optimization model for a grain supply chain. The first objective maximizes profit, and the second minimizes post-harvest loss. To cope with the crop yield uncertainty, a robust program is applied. The two objectives are transformed into one, with complementarity constraints. A Lagrangian relaxation algorithm is proposed for solving the model. Case studies from Illinois and Brazil are provided to prove the applicability of the developed model. Catalá et al. (2016) developed a multi-period mixed-integer linear programming model for the Apple supply chain. The first objective maximizes the profit, and the second minimizes the shortage. To solve the multi-objective model, the lexicographic method is adopted. A case in the Argentine region is studied to show the efficiency of the model. Bai & Liu (2016) developed a new robust optimization method for designing a multi-product supply chain network under fuzzy uncertainty. The objective function minimizes the costs, while demand and cost are uncertain parameters in the model. A case study of a food processing industry is provided to demonstrate the applicability of the model. Miranda-Ackerman et al. (2017) proposed a green multi-objective supply chain network for the processed food industry. As a case study, the orange supply chain was examined to prove the applicability of the model. Genetic Algorithms and Multiple-criteria Decision Making tools are applied to solve the proposed model. Mohammed & Wang (2017) developed a multi-objective distribution planner with a fuzzy approach for a green meat supply chain, with goals of reducing overall costs, the amount of CO_2 emissions and required time to distribute the product between each echelon, and increasing the delivery rate to its maximum. Tirkolaee et al. (2017) explored the application of a robust MILP model in addressing routing challenges associated with perishable products. The model's objective was to reduce total customer service time and lower costs, considering demand uncertainty. Findings from the study demonstrated that the proposed model was effective and could be practically applied to address the issue at hand. Jouzdani et al. (2018) proposed a multi-product, multi-transportation mode supply chain under uncertainty. To show the efficiency of the model, they studied the dairy products packaging network. Sazvar et al. (2018) focused on a sustainable supply chain by developing a multi-objective linear mathematical model of a deteriorating agri-food product. The main objectives of that study were to (1) reduce overall costs, (2) reduce environmental degradation, and (3) maximize the levels of consumer health. The AUGMECON1 method was applied to resolve the suggested model. Onggo et al. (2019) studied a perishable agri-food supply chain and proposed a multi-period inventory-routing problem to reduce inventory, waste, transportation, and stock-out costs. A simheuristic algorithm is applied to solve the model. Jarernsuk & Phruksaphanrat (2019) developed a mathematical model for designing a perishable food supply chain network. The possibilistic approach is adopted to solve the model with imprecise parameters. A real case is studied which produces aromatic coconut to prove the efficiency of the model. Cheraghalipour et al. (2019) studied a two-level optimization model for the rice supply chain. The objective function minimizes the total cost. Metaheuristic, hybrid, and modified algorithms are adopted to solve the model. A real case in Iran is examined to get close to real-world use and prove the model's applicability. Shishebori & Zare (2019) proposed a multi-objective, closed-loop mushroom supply chain. The first objective minimizes the production and transportation costs, the second objective maximizes the total profit, and the third objective minimizes the total environmental impacts. The AUGMECON2 method is adopted for solving the mathematical model. A real case was studied to prove the efficiency of the proposed mathematical model. Darestani & Hemmati (2019) developed a two-objective model for a perishable supply chain under uncertainties like demand, different costs, and the capacity of distribution centers. The queue system was utilized to reduce wait time in distribution centers. The first objective reduces the total cost, and the second reduces greenhouse gas emissions. The robust method is adopted to deal with uncertainty. Imran et al. (2020) addressed a perishable food supply chain with multiple objectives. The model aims to minimize the cost of greenhouse gas emissions and maximize the priority index that ensures the social sustainability of the supply chain. The uncertainty of the costs is taken into account. Fuzzy programming was used to solve the mathematical model. Gholami-zanjani & Jabalameli (2020) proposed a two-stage scenario-based mathematical model. To cope with uncertain parameters, three resiliency approaches (readiness, flexibility, and responsiveness) are adopted. Motevalli-taher et al. (2020) studied a sustainable wheat supply chain. The proposed model aims to 1) reduce network costs, 2) reduce water consumption, and 3) increase job opportunities. The goal programming method is applied to solve the model. The demand uncertainty is considered through simulation. A case is studied to prove the model's capability. Mehrbanfar & Bozorgi-amiri (2020) developed a multi-objective model for a sustainable agriculture supply chain network with uncertain parameters. The 1) objective reduces the total costs, the 2) objective reduces the greenhouse gas emissions, and the 3) objective increases the employment rate. The AUGMECON1 method is applied to solve the model. The possibilistic programming approach is utilized to solve the model under uncertainty. The results of a real case study in Iran showed an 11.2% drop in the unemployment rate. Yakavenka et al. (2020) focused on sustainable network design for perishable supply chains. The first objective minimizes the total cost, the second minimizes the delivery time, and the third minimizes the carbon footprint. The goal programming method, minimax, and weighted sum are used to solve the model. A case of a fruit importer is studied to show the efficiency of the proposed model. Goli et al. (2020) addressed a perishable closed-loop supply chain mathematical model. The model aims to reduce costs, CO_2 emissions, and improve the social aspect of the supply chain. The model accounts for production and delivery lead times to manage perishability risks. This model's optimization is achieved by adopting a novel hybrid algorithm designed to efficiently solve the complex equations involved. Results from testing and comparing the hybrid algorithm with AUGMECON1 indicate that the former algorithm produces accurate results. Ali et al. (2021) proposed a multi-objective MINLP mathematical model for the dairy supply chain, considering perishability, and uncertainty with the aim of reducing costs and wastage. Moreover, the developed model reduces the deterioration loses, while provides the deterioration rate. Fuzzy programming approach is adopted to cope with inherent uncertainty of the supply chain. Results reflect a substantial reduction in the overall cost. Gilani & Sahebi (2021) developed a multi-objective mathematical model for designing the green pistachio supply chain network under uncertainty. The 1) objective increases profit, and the 2) objective function reduces environmental emissions. The AUGMECON1 method and the RPP-I model are adopted to solve the model with certain and uncertain parameters. A real case in Iran is studied. The results show a performance growth of 36.67%. Gholami-Zanjani et al. (2021) studied a multi-objective model for the meat supply chain. Sample average approximation and Lexicographic Weighted Tchebycheff methods are used to solve the proposed model. Different examples have been implemented to prove the applicability of the model and the solution method. Aazami et al. (2021) proposed a two-objective model for perishable products with uncertain parameters. The 1) objective maximizes the total profit, and the 2) objective minimizes the emissions. The effect of freshness and price is considered through a demand function. Three strategies are applied to encourage the customers e.g. (return of perished products, discount, and credit policies). The robust optimization method is adopted to solve the model under uncertainty. The numerical results of the case study showed a 37.5% growth in profit. Jouzdani & Govindan (2021) developed a multi-objective model for dairy products to reduce costs, power consumption, and traffic congestion associated with supply chain operations. A case is studied to prove the capability of the model. Kazemi et al. (2021) focused on a two-objective model for the rice supply chain under uncertainty. The 1) objective minimizes the total cost, and the 2) objective minimizes soil erosion. To solve the model, an extended goal programming approach is applied. Stochastic programming is adopted to deal with the uncertain parameters of the model. Afshar et al. (2022) proposed a bi-objective supply chain. The first objective reduces the expected cost, and the second objective increases the total quality of the supply chain. The result of examining a real case in the dairy industry study showed the efficiency of the model. The AUGMECON1 method is applied to solve the model. Meidute-kavaliauskiene et al. (2022) studied a multi-objective, multi-product, multi-period mathematical model for designing a perishable food supply chain network under uncertainty. The first objective reduces the total costs, the second objective reduces greenhouse gas emissions, the third objective reduces delivery time, and the fourth objective function reduces the back-order level. A hybrid approach based on Benders decomposition and Lagrangian Relaxation is adopted to solve the model. A real dataset is utilized to prove the applicability of the model. Jolai & Fathollahi-fard (2022) focused on designing a multi-objective closed-loop olive supply chain network. The 1) objective minimizes the total cost, the 2) objective minimizes pollution and carbon emissions, and the 3) objective maximizes the job opportunities. The model is solved on a small scale using the epsilon constraint method. Meta-heuristic algorithms are used to solve the model at a larger scale. A real case is studied to prove the applicability of the model. Salehi-amiri et al. (2022) studied a closed-loop avocado supply chain network with two objectives. The first objective reduced the total cost, and the second objective increased job employment. The LP -Metric method is adopted to solve the bi-objective model. A real case is studied in Puebla, Mexico, to validate the efficiency of the proposed model. The results showed that the demand has the most effect on the model. According to Table 1. Few studies considered a resilient meat supply chain under uncertainty. The contribution of this paper is compared to the discussed studies.

Assessing the impact of uncertainty in the parameters of the mathematical models will significantly impact the performance of the supply chain network and aid decision-makers in solving and dealing with real-world problems (Mohebalizadehgashti et al., 2020). To address the uncertainty of the model, we employed robust possibilistic programming (RPP-I). Numerical experiments and sensitivity analysis on a given case study are provided to prove the model's applicability and solution methodology. The literature review indicates that minimal research has considered a robust possibilistic approach in the meat industry as an uncertainty-handling method. In this study, we have developed a mixed-integer multi-objective linear programming model for a multi-product, multi-period, multi-transport, multi-echelon supply chain network design. The developed model includes four echelons, i.e., farms, slaughterhouses, retailers, and customers. This paper is the extended version of the article by Mohebalizadehgashti et al. (2020). We applied the data and case study of the primary reference of this paper to prove the capability and efficiency of the model.

In detail, the main contribution of this paper that differentiates it from the previous papers are as follows:

- Two novel objectives are added to the basic model, i.e., minimizing the delivery time and improving the resiliency of the proposed model.
- Adding many real-world assumptions, such as 1) taking into account the multi-transportation models, 2) inventory is allowed to be kept in retailers, and the cost of inventory holding is added to the model, and 3) the multi-manufacturing technologies with their related costs are considered.
- The multi-objective model is solved using the AUGMECON2 method, which can provide more efficient solutions.
- Using the robust possibilistic optimization method (RPP-I version) to cope with uncertainty in the main parameters of the model and achieve a robust solution.

Table 1. Review literature on the food supply chain

Study	Product	Problem structure	Objective function	Decision variables	Uncertainty modeling	Solution method
Hasani et al. (2012)	Perishable food	MP, MPt, CP	MC	AC, OQ, IL, Sl	Interval robust optimization	LINGO8
Govindan et al. (2014)	Perishable food	MP, MV, Mte	MC, ME	AC, OQ		Metaheuristic
Abtahi (2015)	Perishable food	SP, MV, CP	MC	AC		Epsilon constraint, NSGA-II
Catalá et al. (2016)	Apple	MP, MPt, CP	MTP, MS	IL, OQ, NF		Lexicographic
Bai & Liu (2016)	Food	SP, MPt, CP	MC	OQ	Robust optimization	
An & Ouyang (2016)	Grain	SP, CP	ML,MTP	OQ, P, AC	Robust optimization	Lagrangian relaxation algorithm
Miranda-Ackerman et al. (2017)	Juice	SP, CP	MC, ME	OQ, AC		Genetic Algorithms
Mohammed & Wang (2017)	Meat	SP, CP	MC, ME, MDR, MDT	OQ AC, NF	Fuzzy programming	LP metrics, Goal programming, Epsilon constraint
Tirkolaee et al. (2017)	Perishable product	SP,CP,MV	MC,MDT	AC,D,T		
Jouzdani et al. (2018)	Dairy	MP, MV,CP	MC	OQ, AC	Scenario-based robust optimization	
Sazvar et al. (2018)	deteriorating agri-food	MP, MPt, ICP	MC, ME, MS	OQ, IL, PF, SL, CQ		AUGMECON1
Darestani & Hemmati (2019)	Perishable food	MP, MPt, CP	MC, ME	OQ, IL, AC, DR	Robust optimization	Comprehensive criterion, Weighted sum, Torabi-Hassini
Cheraghalipour et al. (2019)	Rice	MP, MPt, CP	MC	OQ, AC		Metaheuristic & hybrid algorithm
Shishebori & Zare (2019)	Mushroom	MP, MPt, CP	MC, ME, MTP	OQ, SP		AUGMECON2
Jarernsuk & Phruksaphanrat (2019)	Coconut	MP, UCP	MTP	OQ, AC	Possibilistic Programming	
Onggo et al. (2019)	Agri-food	MP, MV, CP	MC	OQ, AC, IL, CD		Simheuristic algorithm
Gholami-zanjani & Jabalameli (2020)	Food	MP, Mte, CP	MTP	OQ, AC, IL	Robust optimization	
Motevalli-taher et al. (2020)	Wheat	MP,MPt, CP	MC, MW, MS	IL, OQ, WC, SL	Simulatio[n	Goal programming
Mehrbanfar & Bozorgi-amiri (2020)	Agri-food	MP, MPt, CP	MC, ME, MS	OQ, AC	Possibilistic Programming	AUGMECON1
Yakavenka et al. (2020)	Fruit	SP, MV, CP	MC, ME, MDT	OQ, AC		Goal programming, Weighted sum, Minimax
Imran et al. (2020)	Perishable food	MP, MPt, MV, Mte, CP	MC, ME, MPI	OQ, AC, IL	Multi-objective fuzzy programming	
Goli et al. (2020)	Perishable product	MP,MPt,MV,CP	MC,ME,MS	OQ,IL,AC	-	AUGMECON1, Hybrid approach
Gilani & Sahebi (2021)	Pistachio	MP, Mte, CP	MTP, ME	OQ, AC, IL, NF,AOC	Robust possibilistic	AUGMECON2
Ali et al. (2021)	Dairy	MP,MPt,CP	MC,ML	AC,IL,OQ,DR,NT	Fuzzy programming	LINGO 18.0
Gholami-Zanjani et al. (2021)	Meat	MP, MPt, MV, CP,RE	MI, ME	OQ, IL, AC, RP, SL		Sample average approximation, Lexicographic Weighted Tchebycheff
Aazami et al. (2021)	ready-to-eat foodstuff	MP, CP	MTP, ME	OQ, IL, AC, PF, DR, RR	Robust optimization	The weighted sum method, Epsilon constraint, AUGMECON1, Goal programming, Lexicographic
Jouzdani & Govindan (2021)	Dairy	MP, MPt, MV, CP	MC, ME, MSI	OQ, IL, AC, NF	Chance constraint programming	Revised Multi-Choice Goal programming
Kazemi et al. (2021)	Rice	SP, MPt, CP	MC , ME	OQ	Stochastic programming	Extended goal programming
Afshar et al. (2022)	Dairy	MP, MPt, CP	MC, MCS	OQ, IL, AC		AUGMECON1
Meidute-kavaliauskiene et al. (2022)	Perishable food	MP, MPt, CP	MC, ME, MDT, MBL	OQ, AC	Stochastic programming	Hybrid approach
Jolai & Fathollahi-fard (2022)	Olive	MP, CP	MC, ME, MS	OQ, IL, AC		Metaheuristic
Salehi-amiri et al. (2022)	Avocado	MP, Mte, CP	MC, MS	OQ, AC		LP -Metric
This paper	Meat	MP, MPt, MV, Mte, CP, RE	MC, MD, MDT	OQ, IL, AC	Robust possibilistic	AUGMECON2

* **CP**: capacitated; **ICP**: incapacitated; **RE:** resiliency; **MP**: multi-period; **SP**: single-period; **MPt**: multi-product; **MV**: multi-vehicle; **Mte**: multi-technology; **MC**: minimizing cost; **ME**: minimizing environmental effect; **MTP**: maximizing total profit; **MS**: maximizing social impact; **ML**: minimizing loss; **MDR**: maximizing delivery rate; **MDT**: minimizing delivery time; **MW**: minimizing the water consumption; **MPI**: maximizing profit index; **MI**: maximizing income; **MBL**: minimize back order level; **MCS**: maximizing customer satisfaction; **MPI**: maximizing priority index; **AC**: allocation coverage; **IL**: inventory level; **SL**: shortage level; **OQ**: order quantity; **NF**: number of facilities; **PF**: product flow; **AOC**: the amount of capacity; **RR**: return rate; **RP**: reorder point; **SP**: selling price; **WC**: water consumption; **CD**: customer demand; **DR:** deterioration rate; **NT**: number of trucks, **D**: distance, **T**: time.

3. Problem Definition

This study represents a multi-period, multi-product, and multi-modal transport supply chain network that simultaneously minimizes the supply chain network's cost, arrival time, and non-resiliency. Fig. 1 indicates a four-echelon meat supply chain consisting of farms, slaughterhouses, retailers, and customers. The first echelon is the farms, where animals are nurtured and sent to slaughterhouses. In slaughterhouses, animals are slaughtered and prepared as processed meat. The meat is then sent to wholesalers who sell it and deliver it to the areas of need/customers. The strategic choice of the model is to decide which farms and retailers to partner with, where to open a slaughterhouse, and what manufacturing technology to use to prepare processed meat. The sets, parameters, and decision variables of the proposed model are as follows:

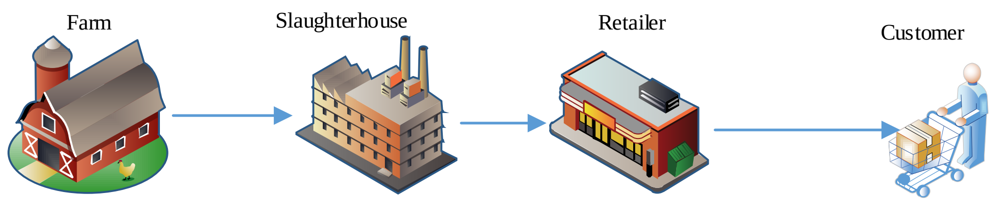

Figure 1. Meat supply chain network

Sets

i	Set of possible farm locations
j	Set of possible slaughterhouse locations
k	Set of possible retailer locations
c	Set of customers
l	Set of products *l* including livestock and meat
v	Set of transportation modes
n	Set of technology
t	Set of periods

Parameters

p_{ilt}	The cost of purchasing livestock *l* (per ton) from farm *i* in period *t*
mc_{jltn}	Manufacturing cost of livestock *l* (per ton) with technology *n* at the slaughterhouse at location *j* in period *t*
hc_{lt}	The unit cost of holding inventory of product *l* (per ton) at the end of period *t*
m_i	The fixed cost of cooperating with the farm at location *i*
w_j	The fixed cost for opening the slaughterhouse at location *j*

a_k The fixed cost for selling products via retailer at location *k*

e_{ij} The distance between the farm at location *i* and the slaughterhouse at location *j*

d_{jk} the distance between the slaughterhouse at location *j* and the retailer at location *k*

g_{kc} The distance between the retailer at location *k* and customer *c*

f_{ijltv} The unit cost of transporting livestock *l* from the farm at location *i* to the slaughterhouse at location *j* in period *t* with transport mode *v*

h_{jkltvn} The unit cost of transporting processed meat *l* with manufacturing technology *n* from the slaughterhouse at location *j* to the retailer at location *k* in period *t* with transport mode *v*

m_{kcltv} The unit cost of transporting processed meat *l* from the retailer at location *k* to customer *c* in period *t* with transport mode *v*

vl_v The velocity of transportation type *v*

de_{clt} Demand for meat *l* in period *t* (in Tons) of customer *c*

q_{il} Maximum capacity of supplying livestock *l* (in Tons) at the farm at location *i*

u_{jnl} Maximum capacity of supplying processed meat *l* (in Tons) at the slaughterhouse at location *j* with manufacturing technology n for processed meat *l* (in Tons)

o_{kl} Maximum capacity of supplying processed meat *l* (in Tons) at the retailer at location *k*

ξ Penalty factor for critical farms, slaughterhouses, retailers, and customers

β Penalty factor for the complexity of farm, slaughterhouse, retailer, and customer nodes.

α Penalty factor for the flow complexity across *f* and *a*, *a* and *r*, and *r* and *c* nodes.

$Ub_{f,t}$ The certain threshold for the sum of total inflows and outflows for farm *f* in period *t.*

$Un_{s,t}$ The certain threshold for the sum of total inflows and outflows for slaughterhouse *j* in period *t.*

$Ua_{r,t}$ The certain threshold for the sum of total inflows and outflows for retailer *r* in period *t.*

M a relatively large number

Decision Variables

XA_{ijltv} Amount of livestock *l* (in Tons) delivered to the slaughterhouse at location *j* from the farm at location *i* in period *t* with transport mode *v*

XR_{jkltvn} Amount of processed meat *l* (in Tons) with manufacturing technology n delivered to the retailer at the location *k* from the slaughterhouse at the location *j* in period *t* with transport mode *v*

XC_{kcltv} Amount of processed meat *l* (in Tons) delivered to customer *c* from the retailer at location *k* in period *t* with transport mode *v*

$In_{l,t}$ The inventory (in Tons) of processed meat *l* at the end of period *t*

S_i Equals 1 if a farm at location i is chosen; else, it equals 0.

Y_{jn} Equals 1 if the slaughterhouse at location *j* with manufacturing technology *n* is established; else, it equals 0.

Z_k Equals 1 if the retailer at location *k* is chosen; else, it equals 0.

FA_{ijt} Equals 1 if the farm at location *i* is assigned to slaughterhouse *j* in period *t;* else, it equals 0.

AR_{jkt}	Equals 1 if the slaughterhouse at location j is assigned to the retailer at location k in period t; else, it equals 0.
RC_{kct}	Equals 1 if the retailer at location k is assigned to customer c in period t; else, it equals 0.
$\acute{S}_i$	Equals 1 if the farm at location i is critical; else, it equals 0.
$\acute{Y}_{jn}$	Equals 1 if the slaughterhouse at location j with manufacturing technology n is critical; else, it equals 0.
$\acute{Z}_k$	Equals 1 if the retailer at location k is critical; else, it equals 0.

Mathematical Model

$$\min Z_1 = \sum_{i,j,l,t,v} (p_{ilt} + f_{ijltv} e_{ij}) XA_{ijltv} + \sum_{j,k,l,t,v,n} (mc_{jltn} + h_{jkltv} d_{jk}) XR_{jkltvn} + \sum_{k,c,l,t,v} m_{kcltv} g_{jc} XC_{jcltv} + \sum_{l,t} hc_{lt} In_{lt} + \sum_i m_i S_i + \sum_{j,n} w_j Y_{jn} + \sum_k a_k Z_k \tag{1}$$

$$\min Z_2 = \sum_{i,j,l,t,v} (\frac{e_{ij}}{vl_v}) XA_{ijltv} + \sum_{j,k,l,t,v,n} (\frac{d_{jk}}{vl_v}) XR_{jkltvn} + \sum_{k,c,l,t,v} (\frac{g_{kc}}{vl_v}) XC_{kcltv} \tag{2}$$

$$\min Z_3 = \underbrace{\sum_i S_i'\xi + \sum_{j,n} Y_{jn}'\xi + \sum_k Z_k'\xi}_{Node\ criticality} + \underbrace{\sum_{i,j,t} FA_{ijt}\alpha + \sum_{j,k,t} AR_{jkt}\alpha + \sum_{k,c,t} RC_{kct}\alpha}_{Flow\ complexity} + \sum_{k,c,t} \underbrace{\sum_i S_i\beta + \sum_{j,n} Y_{jn}\beta + \sum_k Z_k\beta}_{Node\ complexity} \tag{3}$$

s.t:

$$\sum_{j,l,v} XA_{ijltv} \le S_i \sum_l q_{il} \qquad \forall\, i,t \tag{4}$$

$$\sum_{k,l,v,n} XR_{jkltvn} \le \sum_{n,l} Y_{jn} u_{jnl} \qquad \forall\, j,t \tag{5}$$

$$\sum_{c,l,v} XC_{kcltv} \le Z_k \sum_l o_{kl} \qquad \forall\, k,t \tag{6}$$

$$\sum_{i,v} XA_{ijltv} \le \sum_{k,v,n} XR_{jkltvn} \qquad \forall\, j,l,t \tag{7}$$

$$\sum_{j,v,n} XR_{jkltvn} - \sum_{c,v} XC_{kcltv} + In_{l,t-1} = In_{lt} \qquad \forall\, k,l,t>1 \tag{8}$$

$$\sum_{c,v} XC_{kcltv} + In_{l,t-1} \ge de_{clt} \qquad \forall\, k,l,t>1 \tag{9}$$

$$\sum_n Y_{jn} \le 1 \qquad \forall\, j \tag{10}$$

$$\sum_{i,l,v} XA_{ijltv} \le M.FA_{ijt} \qquad \forall\, j,t \tag{11}$$

$$\sum_{j,l,v,n} XR_{jkltvn} \le M.AR_{jkt} \qquad \forall\, k,t \tag{12}$$

$$\sum_{k,l,v} XC_{kcltv} \leq M.RC_{kct} \qquad \forall\, c,t \qquad (13)$$

$$(Ub_{ft} - \sum_{j,l,v} XA_{ijltv})(1-S_i') \geq \varepsilon(1-S_f') \qquad \forall\, i,t \qquad (14)$$

$$(Un_{st} - (\sum_{i,l,v} XA_{ijltv} + \sum_{k,l,v,n} XR_{jkltvn})).(1-Y_{jn}') \geq \varepsilon(1-Y_{jn}') \qquad \forall\, j,t \qquad (15)$$

$$(Ua_{rt} - (\sum_{j,l,v,n} XR_{jkltvn} + \sum_{c,l,v} XC_{kcltv})).(1-Z_k') \geq \varepsilon(1-Z_k') \qquad \forall\, k,t \qquad (16)$$

$$S_i, Y_{jn}, Z_k, FA_{ijt,} AR_{jkt}, RC_{kct}, S_i', Y_{jn}', Z_k' \in \{0,1\} \qquad \forall\, i,j,k,t,n \qquad (17)$$

$$XA_{ijltv}, XR_{jkltvn}, XC_{kcltv} \geq 0 \qquad \forall\, i,j,k,c,l,t,v,n \qquad (18)$$

The objective function (1) tends to reduce the total costs of the network. The first part of the objective aims to reduce the purchase and transport costs of the farms. Meanwhile, the second and third parts include the transportation cost of products between the successive echelons. The rest is also related to the fixed costs of opening facilities. The second objective (2) minimizes the total distribution time in the network. The third objective (3) minimizes the non-resiliency (or maximizing resiliency) of the proposed model. The first part is related to node critically, the second part deals with flow complexity, and the third is related to node complexity. Constraints (4)-(6) ensure the capacity constraints of farms, slaughterhouses, and retailers, respectively. Constraint (7) indicates the equality of input and output of meat in slaughterhouses. Constraint (8) shows the inventory level of meat in slaughterhouses. Constraint (9) tends to satisfy customer demand. Constraint (10) ensures that only one technology type of manufacturing can be used in each slaughterhouse. Constraints (11)-(13) are allocation decision constraints, which assure that the connection between each pair of nodes is recognized as long as a flow exists in the associated links. Constraints (14)-(16) are the non-criticality state for farms, slaughterhouses, and retailers, respectively, ensuring that if the summation of outflows and inflows of a node of farms, slaughterhouses, and retailers exceeds a threshold, it is considered critical. Constraints (17) and (18) describe binary and non-negative variables.

3.1. Robust Optimization

Due to the inconsistency and instability of some critical parameters (including the demand, cost of purchase from farms, cost of sale through the retailer, cost of cooperation with farms, and cost of opening the slaughterhouse with different manufacturing technology) in the proposed model, we applied robust possibilistic approach to cope with uncertainty. Two factors play a significant role in robust decision-making, i.e., optimality robustness and feasibility robustness. The former focuses on the proximity of the value of the objective function to the optimal value, while the latter focuses on the feasibility of solving the optimization problem for (almost) all possible values of uncertain input parameters. (Pishvaee et al., 2012b). There are three robust optimization approaches, namely: 1) the hard-worst case approach, 2) the soft-worst case approach, and 3) the realistic approach. The hard worst-case ignores the possibility of infeasible answers and considers all uncertain parameters of the model with their worst-case values. This approach concentrates on feasibility robustness the most and optimality robustness the least. The soft worst-case minimizes the most unfavorable value of the objective function while not satisfying (all) their extreme worst-case constraints. At last, the third approach focuses on finding an explicit and implicit logical compromise among the robustness, cost of robustness, and other objective functions. This approach controls the scale of feasibility and optimality (Mousazadeh et al., 2018). For detailed information on robust optimization, see Pishvaee et al. (2012b). Furthermore, the recent studies by Mondal & Roy (2021) provided new insights into the adoption of robust optimization and fuzzy programing in supply chains while tackling challenges posed by real-world situations. Consider the proposed model's compact shape, excluding the second and third objective functions as follows:

$$Min\ Z = cm + dn \qquad (19)$$

$$Em \geq f$$

$Sm \leq H$

$B \leq 1$

$y \in \{0,1\}$

The parameters c, d, and f correspondingly represent the fixed opening costs, transport costs, purchase costs, and demands. As shown, E, S, and H are matrix constraint factors. Moreover, n and m represent the binary and continuous variables. B is a binary variable. We applied the expected value operator and the necessity measure to handle chance constraints, including indefinite parameters. In this paper, the trapezoidal probability distributions (see Fig. 2) are used to model uncertain parameters, which can be defined as four distinguished points, e.g., $\tilde{\xi} = (\xi_{(1)}, \xi_{(2)}, \xi_{(3)}, \xi_{(4)})$.

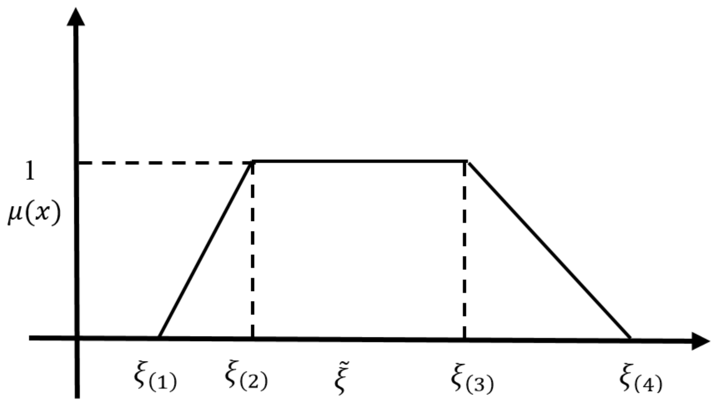

Figure 2. The trapezoidal possibility distribution of fuzzy parameter $\tilde{\xi}$

Due to the similarity of approaches, we eliminated the second and third objectives without losing the model's generality. Based on the above descriptions, the basic model of Possibilistic Chance-Constrained Programming (BPCCP) can be defined as follows:

Min E[z] = $E[\tilde{c}]m + [\tilde{d}]n$ (20)

s.t.

$Nec\{Em \geq \tilde{f}\} \geq \alpha$

$Sm \leq H$

$B \leq 1$

$y \in \{0,1\}$

$x \geq 0$

$0.5 < \alpha < 1$

And the crisp model can be modeled as follows:

Min E[z] = $E[\frac{c_{(1)}+c_{(2)}+c_{(3)}+c_{(4)}}{4}]m + [\frac{d_{(1)}+d_{(2)}+d_{(3)}+d_{(4)}}{4}]n$ (21)

s.t.

$Em \geq (1-\alpha)f_3 + \alpha f_4$

$Sm \leq H$

$B \leq 1$

$y \in \{0,1\}$

$x \geq 0$

$0.5 < \alpha < 1$

As aforementioned, the chance-constrained should be satisfied with a confidence level greater than 0.5. The confidence level is considered a parameter here. Decision-makers can select the level of confidence here. The model (21) minimizes the expected value (average) of the objective function, and the deviation of the objective function value is not considered here, which can cause a severe problem in real situations. Due to referred reasons, we applied the RPP-I model to deal with uncertainty, which is formulated as follows:

$$\text{Min E[z]} + \gamma(Z_{max} - Z_{min}) + \delta[f_{(4)} - (1-\alpha)f_{(3)} - \alpha f_{(4)}] \quad (22)$$

s.t.

$Cx \geq (1-\alpha)f_{(3)} + \alpha f_{(4)}$

$Sx \leq N$

$B \leq 1$

$y \in \{0,1\}$

$x \geq 0$

$0.5 < \alpha < 1$

Similar to the BPCCP model, the first part of the objective minimizes the expected value of the objective function. The set of two extremes, i.e., (Z_{max}, Z_{min}) is shown in the second term, which concerns the optimality robustness of the final solution by reducing the deflection from two extrema. The γ, is the impotence coefficient for the other terms of the objective. The Z_{max}, and Z_{min} are defined as follows:

$$\boldsymbol{Z_{max}} = \boldsymbol{c}_{(\boldsymbol{4})}\boldsymbol{m} + \boldsymbol{d}_{(\boldsymbol{4})}\boldsymbol{n}$$
$$\boldsymbol{Z_{min}} = \boldsymbol{c}_{(\boldsymbol{1})}\boldsymbol{m} + \boldsymbol{d}_{(\boldsymbol{1})}\boldsymbol{n} \quad (23)$$

The third term is related to the optimality robustness of the solution vector. $\delta[f_{(4)} - (1-\alpha)f_{(3)} - \alpha f_{(4)}]$ determines the confidence level of chance constraint. The δ is the penalty unit of a possible violation of the constraint. The minimum confidence level of chance constraints is a decision variable in this model. The RRP-1 model looks for a logical trade-off between the three explained parts. For more details on the Basic Possibilistic Chance-Constrained Programming (BPCCP) and the Robust Possibilistic Programming (RPP-I) model, see Pishvaee et al., (2012). Related data for solving the model using RPP-I is included in Appendix A.

4. Solution Approach

To resolve the multi-objective model, an enhanced version of the augmented ε-constraint method (AUGMECON2), by Mavrotas & Florios (2013) is applied. This method optimizes one of the (most important) objective functions and adds the other objectives to the constraints as follows:

$$\min(f_1(y) - eps * ({}^{t_2}/_{r_2} * 10^0 + \cdots + {}^{t_p}/_{r_p} * 10^{-(p-2)}) \quad (24)$$

st:

$f_k(y) + t_k = e_k$

$k = 2, 3, \ldots, p \qquad y \in T; \quad T_k \in R^+$

In which, y is the choice vector, T *is* the surface of the solution to the problem, and $f_k(x)$ is the second and third objective function of the model. Plus, eps is a very small number (between 10^{-3} and 10^{-6}), s_k is the excess variable,r_2,r_3, …, r_p are the ranges of the 2nd, 3rd, …, p^{th} objective function, e_k are the right and sight (RHS) values of the objective function. If the (*p-1*) objective function constraints are binding i.e. (S_k=0 for k=2, 3,…, p), the optimal solution is guaranteed.

5. Implementation and Evaluation

In this section, the applicability of the model is studied on a numerical example. The related data are collected from Mohebalizadehgashti et al., (2020), and the real data has been considered for other data. For instance, the distance between different facilities is calculated by Google Maps. The real locations of farms, slaughterhouses, and retailers are provided in Fig 3. Also, the other related data is provided in Table 2. to Table 4, and more complementary data are provided in Appendix A. It should be noted that the dimension of |I|, |J|, |K|, |C|, |L|, |T| equals 15, 12, 21, 20, 2, and 2 successively. The proposed mathematical model is coded and solved by GAMS 24.1.2 software using a Core i5 system with 4 GB of RAM.

Table 2. Values of parameters of the model

Parameters	Corresponding value	Parameters	Corresponding value
m_i	10,000	$q_{i1} = q_{i2}$	15 Ton
w_j	20,000	$u_{j11} = u_{j12}$	15 Ton
a_k	1,000,000	$u_{j21} = u_{j22}$	17 Ton
p_{i1t}	1,649.5	$o_{k1} = o_{k2}$	15 Ton
p_{i2t}	5574.6	$hc_{l1} = hc_{l2}$	15
m_{kcltv}	0.005	h_{jkltvn}	0.005

Table 3. shows the demand for different types of meat per ton in every period. Two kinds of products, i.e., lamb and cow, have been chosen for this study.

Table 3. The demand of each customer (zone) for either of the products in each period

ID	Demand	ID	Demand	ID	Demand	ID	Demand
1	27.316	6	0.716	11	1.594	16	0.074
2	5.369	7	0.318	12	1.331	17	0.03
3	3.838	8	1.016	13	1.317	18	0.086
4	2.332	9	0.974	14	1.299	19	0.158
5	2.172	10	1.414	15	1.049	20	0.217

Table 4. Fixed cost of opening each slaughterhouse with different technologies

ID	Technology 1	Technology 2	ID	Technology 1	Technology 2	ID	Technology 1	Technology 2
1	1,000,000	900,000	5	900,000	900,000	9	900,000	900,000
2	900,000	1,000,000	6	700,000	600,000	10	900,000	900,000
3	800,000	900,000	7	1,000,000	1,100,000	11	900,000	1,200,000
4	1,100,000	900,000	8	900,000	700,000	12	900,000	900,000

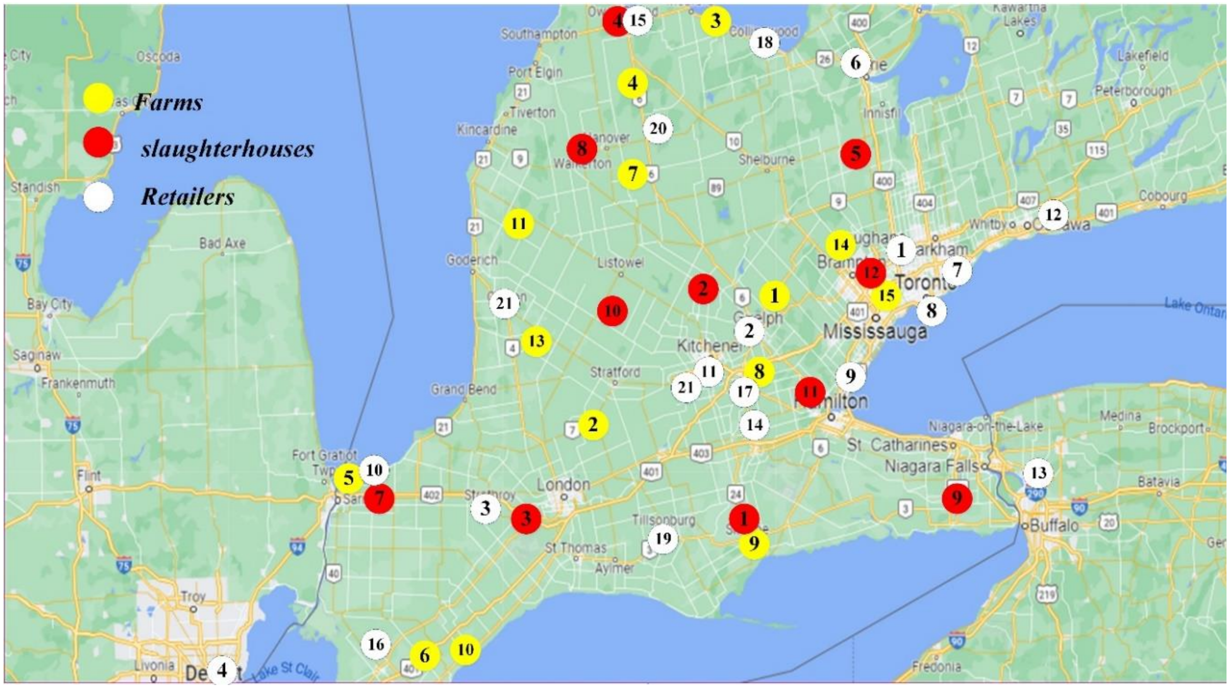

Figure 3. Location of farms, slaughterhouses, and retailers

5.1. Computational Results

To show the effect of considering uncertainty in the input data, in this section, first, the model is solved under certainty, then the RPP-I counterpart is solved, and the achieved results are analyzed and compared in detail.

Table 5. shows the achieved results of solving the deterministic (certain data) model using the AUGMECON2 method. Also, the lexicographic pay-off table method is applied to find the PIS (Positive Ideal Solution) and NIS (Nadir Ideal Solution) values of each objective function. The corresponding values of PIS and NIS and the range of each objective function are also provided in Table 5. It is worth noting that the first objective function (minimizing cost) is chosen as the primary objective, and the other objectives are considered as new constraints via the AUGMECON2 method. Accordingly, only the range of the 2nd and 3rd objectives are divided into five equal intervals, and then their relative steps (right-hand side values in the AUGMECON2 method) are calculated and provided in Table 6.

Table 5. Lexicographic pay-off table of the certain model

Objectives	Type	Obj_1	Obj_2	Obj_3
Obj_1	Minimization	8,321,454	226.7	23
Obj_2	Minimization	16,031,550	98.9	44
Obj_3	Minimization	8,621,460	178.8	23
PIS values		8,321,454	98.9	23
NIS values		16,031,550	226.7	44
Range (NIS-PIS)		7,710,096	127.8	21
Steps (5 equal Intervals)		-	31.95	5.21

Table 6. Grid points of the deterministic model

Objectives	Type	Grid points				
		1	2	3	4	5
Obj_2	*Min*	226.69	194.75	162.80	130.85	98.91
Obj_3	*Min*	44.00	38.75	33.50	28.25	23.00

Table 7. Pareto optimal solutions of the certain model

ID	Obj_1	Obj_2	Obj_3	No. of selected farms	No. of selected retailers	No. of opened slaughterhouses (Manuf. Tech.)	No. of critical farms	No. of critical slaughterhouses	No. of critical retailers	CPU time (sec)
1	8,321,484.1	226.7	23	4	4	1(1), 3 (2)	3	3	4	30
2	8,521,480.3	194.8	23	4	4	2(1), 2(2)	3	3	4	67
3	9,041,458.5	162.8	24	4	5	1(1), 3(2)	3	3	3	208
4	15,751,440.0	130.9	28	5	5	3(1), 8(2)	3	2	3	11
5	16,031,550.0	98.9	44	12	12	3(1), 9(2)	2	2	2	4

Five efficient Pareto optimal solutions are found among 25 possible combinations of right-hand side values of the second and third objective functions. These points are represented graphically in Fig 4. The results demonstrate that the model's performance varies based on these objective functions. The results of the model show that optimizing for the cost function leads to the lowest overall cost; however, this approach sacrifices time and non-resiliency. Conversely, prioritizing time optimization yields faster processing times but at a higher cost and reduced non-resiliency. Lastly, prioritizing non-resiliency optimization leads to a higher level of resiliency at a greater cost and longer processing time. These findings suggest that when seeking a balanced and effective solution, careful evaluation and optimization of each objective function is necessary, tailored to the specific needs and constraints of the project. By presenting such information, decision-makers can make more informed trade-offs between cost, time, and non-resilience. Their exact values, including the number of selected farms/opened slaughterhouses/ selected retailers and the number of critical farms/critical slaughterhouses/critical retailers are also provided in Table 7.

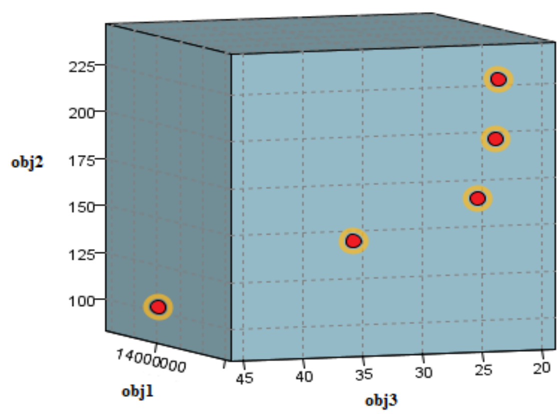

Figure 4. Pareto optimal solution

On the other hand, similar to the following steps in the abovementioned calculations, the model is solved using the RPP-I model, and the achieved results are provided in Table 8. as follows.

Table 8. Lexicographic pay-off table of the RPP-I model

Objectives	Type	Obj_1	Obj_2	Obj_3
Obj_1	Minimization	11,458,750	299.8	28.0
Obj_2	Minimization	22,018,800	130.0	45.0
Obj_3	Minimization	11,458,790	259.6	26.5
PIS values		11,458,750	130.0	26.5
NIS values		22,018,800	299.8	45.0
Range (NIS-PIS)		10,560,050	169.8	18.5
Steps (5 equal Intervals)		-	42.45	4.63

Similarly, the Pareto efficient solution (four solutions) of solving the RPP-I model using AUGMECON2 is provided in Fig 5., and Table 9. The Fig 5 displays the results of three unique objective functions with the aim of minimizing cost, time, and non-resiliency, respectively. It is evident from these findings that the performance of the model varies depending on which objective function is prioritized.

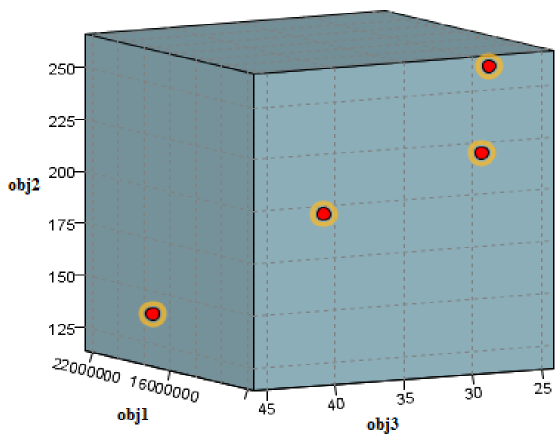

Figure 5. Pareto optimal solution

Table 9. Pareto optimal solutions of the RPP-I model

ID	Obj_1	Obj_2	Obj_3	No. of selected farms	No. of selected retailers	No. of opened slaughterhouses (Manuf. Tech.)	No. of critical farms	No. of critical slaughterhouses	No. of critical retailers	α	CPU time (sec)
1	11,458,810	257.4	27.0	5	5	1 (1), 3 (2)	4	4	4	0.709	6
2	11,997,290	215.0	27.0	5	5	2 (1), 3 (2)	4	4	4	0.573	205
3	21,537,530	172.6	29.5	6	6	7 (2)	2	3	3	0.500	66
4	21,977,550	130.9	28.0	9	15	3 (1), 9 (2)	2	2	2	0.500	5

As can be seen in Table 9., as the number of selected farms, retailers, and opened slaughterhouses increases, the value of the 1st objective function also increases. By increasing the number of active nodes and arcs, as the flow will become divided into more nodes and arcs, the number of critical nodes in all echelons decreases. Also, the achieved points of the RPP-I model (Table 9.) compared to the deterministic model (Table 7.) have a higher (worst) value in all the objective functions. The main reason is that the model adopts a more conservative approach when using the RPP-I model, which tends to have less optimality robustness while more feasibility robustness is expected (See Table 14.). These observations provide valuable insights for decision-makers when managing the trade-offs between efficiency and efficacy, aiming to determine the best course of action for the logistics supply chain.

Among the five different Pareto optimal solutions, point number 2 performs well in all three objectives, i.e., satisfies 1st objective function at around 96%, 2nd objective function at about 60%, and 3rd objective function about 98%. Detailed information on the selected solution is provided in Table 10.

Table 10. Detailed information on the selected efficient solution

Echelon	Active Nodes	Critical Nodes	% of Critical Nodes
Selected farm	5, 8, 9, 12	5, 8, 12	75%
Selected retailers	4, 9, 16, 19, 20	4, 9, 16	60%
Opened slaughterhouses	1, 6, 11 (Tech 2) 7 (Tech 1)	6, 7, 11	75%

5.2. Sensitivity Analysis

The demand parameter is the main driver in designing a supply chain network. For lower demand, fewer selected farms, retailers, and open slaughterhouses would be appropriate, but facing the higher demands would create a more expanded (sometimes more decentralized) supply chain network. The results of performing sensitivity analysis on the different values of the demand are provided in Table 11. and Fig 6.

In detail, Table 11. displays the result of changing the demand parameter on the value of objective functions, number of selected and opened facilities, number of critical facilities, and value of minimum confidence levels of minimizing each objective function. When the RPP-I model is solved under 25% of the default value of the demand, two farms and nine retailers are selected, and one slaughterhouse is opened. Though, when the model is solved with the maximum level of demand (triple the amount), fourteen farms and eighteen retailers are selected, twelve slaughterhouses are opened, and eleven farms, ten slaughterhouses, and eleven retailers are considered critical nodes. Also, in the highest level of demand, the values of α for the first objective decrease to 0.5, which is the lowest possible value, as the model tends to maintain the solution as feasible as possible. The graphical representation of the effect of changes in demand value on each objective function is provided in Fig. 6.

Table 11. Result of changes in demand

Parameter values	Obj_1	Obj_2	Obj_3	No. of selected farms	No. of selected retailers	No. of opened slaughterhouses (Manuf. Tech.)	No. of critical farms	No. of critical slaughterhouses	No. of critical retailers	α_1	α_2	α_3
0 × demand	-	-	-	-	-	-	-	-	-	-	-	-
0.25 × demand	8,215,885.6	20.3	8.5	2	9	1	1	1	1	1.00	0.5	0.5
0.5 × demand	9,313,657.0	40.2	14.5	3	13	2(2)	2	2	1	1.00	0.5	0.5
0.75 × demand	10,317,460.0	81.7	20.5	4	4	3(2)	3	3	3	1.00	0.5	0.5
1 × demand	11,458,750.0	130.0	26.5	5	5	1(1), 3(2)	5	4	4	1.00	0.5	0.5
1.25 × demand	12,875,050.0	189.1	33.0	6	6	5(2)	6	5	5	1.00	0.5	0.5
1.5 × demand	14,016,340.0	258.0	39.0	7	7	2(1), 4(2)	7	6	6	1.00	0.5	0.5
1.75 × demand	15,432,680.0	341.5	44.5	8	8	7(2)	8	6	8	0.86	0.5	0.5
2 × demand	16,945,180.0	422.0	50.0	12	16	8(2)	8	8	6	1.00	0.5	0.5
2.25 × demand	18,251,760.0	517.8	55.5	13	18	11(2)	8	8	9	0.50	0.5	0.5
2.5 × demand	19,462,210.0	622.4	60.5	13	17	1(1), 10(2)	9	9	9	0.50	0.5	0.5
2.75 × demand	20,878,450.0	717.1	66.0	14	18	1(1), 11(2)	11	10	11	0.50	0.5	0.5

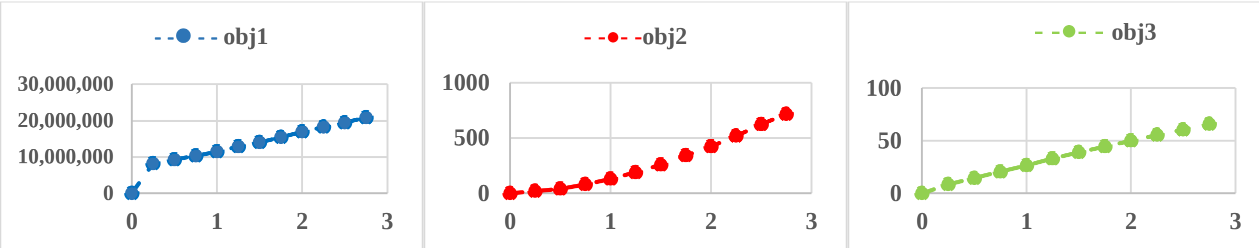

Figure 6. Sensitivity analysis on the value of demand

5.3. Managerial Insight

In this part, some managerial insights are provided. First, analyzing the degree of contrast between the 1st and 2nd objective functions would be precious. For this reason, the resilience measure is eliminated from the objective functions, and the model is transformed into a bi-objective model. The result of solving the bi-objective model under optimization of each objective function separately (as a single objective model) is provided in Table 12., in which the total costs, total delivery time, and total amount of shipped products are shown and compared. As could be seen, if one solves the model under optimization of the 1st objective functions, a drastic decrease will occur in cost-related terms, excluding the transportation costs. Indeed, when the model is solved considering the minimization of total distribution time (2nd objective), the total transportation time and total transportation cost get their minimum values.

Table 12. Solving the model under each objective functions separately

Objectives	Type	Obj_1	Obj_2	Transportation cost	Holding cost	Opening costs	Cost of working with farms	Cost of working with retailers
Obj_1	Min	8,421,464.6	250.1	112.6	0.0	3,100,000	40,000	80,000
Obj_2	Min	16,671,480.0	97.6	64.4	60.0	10,900,000	150,000	420,000

Then, to find the Pareto efficient solutions of the bi-objective model, it is solved using the AUGMECON2 method (steps are similar to previous parts), and the results are shown in Table 13. and are presented in Fig 7. The represented Pareto efficient solutions support this hypothesis that these two objective functions are in contrast to a great extent.

Table 13. Pareto optimal solutions of solving the bi-objective problem

ID	Obj_1	Obj_2	No. of selected farms	No. of opened slaughterhouses (Manuf. Tech.)	No. of selected retailers
1	8,501,465.4	178.34	4	2 (1), 2 (2)	8
2	8,751,450.5	158.15	5	1(1), 3(2)	10
3	11,421,440.0	137.95	8	6(2)	15
4	15,651,420.0	117.76	5	4(1), 8(2)	5

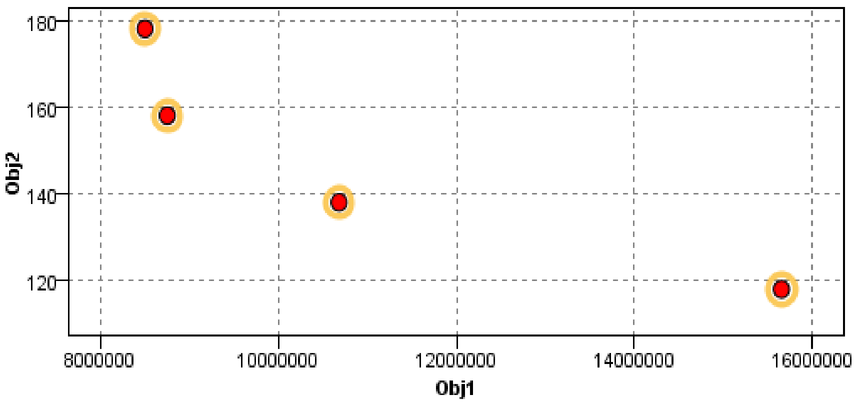

Figure 7. The Pareto optimal solutions for the bi-objective model

And last but not least, it would be essential to reflect on the effect of using the RPP-I approach for coping with uncertainty in the proposed model. For this reason, a realization method is performed in which the deterministic model and RPP-I model (including all three objectives) are solved separately, and their achieved results are tested under nominal data, including eight random nominal datasets generated via their uncertain relative ranges. The result of such realization is shown in Table 14.

As can be seen, the total average Coefficient Variation (CV) is less when using the RPP-I model. In contrast to solving the model under a certain environment, it assures more feasibility robustness. Also, the CV measure performs well in the 1st and 2nd objective functions when using the RPP-I approach. Indeed, we can observe more feasibility robustness for these two objective functions, which affects the average CV too. In fact, due to the importance of the two first objectives, one can also ignore that the deterministic model outperforms the RPP-I version in the third objective function.

Table 14. Result of solving the model under the realization

No. of realization	Deterministic			RPP-I		
	Obj_1	**Obj_2**	**Obj_3**	**Obj_1**	**Obj_2**	**Obj_3**
1	8,974,186.6	123.5	24.0	11,747,490	129.2	27.0
2	8,539,731.7	109.9	23.5	11,303,020	121.8	24.0
3	8,371,232.8	95.4	23.0	11,108,400	114.0	23.5
4	8,334,236.0	123.3	24.0	11,098,620	129.0	26.5
5	8,514,913.4	126.3	24.0	11,295,210	130.8	26.5
7	8,527,358.8	98.7	23.0	11,430,120	116.0	23.5
8	8,371,256.1	112.4	23.5	11,238,510	123.1	24.0
Average(AVE)	**8,518,987.9**	**112.79**	**23.57**	**11,317,338.6**	**123.42**	**25.00**
Standard Deviation (STD)	**218,086.1**	**12.35**	**0.45**	**221,819.8**	**6.68**	**1.58**
Coefficient of variation (CV = STD/AVE)	**0.0256**	**0.1095**	**0.0191**	**0.0196**	**0.0541**	**0.0632**
Average CV		**0.0514**			**0.0456**	

6. Conclusion

This research develops a multi-objective, multi-product, multi-period, multi-transport modal, and mixed-integer linear programming model for a meat supply chain with uncertain parameters to make a trade-off between costs, distribution time, and resiliency of the designed network. The proposed model determines the optimum flow of products across the network, the optimum quantity, and the assignment of echelons, critical nodes, and the optimum inventory level of meat in retailers in each period. A robust possibilistic approach (RPP-I) is employed to deal with uncertain parameters. Also, the AUGMECON2 method is adopted to solve the proposed multi-objective model. Finally, we provided some sensitivity analysis and managerial insights that help decision-makers to make the best decisions while dealing with real-world problems. The effect of applying or eliminating the robust possibilistic method and applying or eliminating the resilience measure is also well analyzed in the last section. The results prove that consideration of uncertainty in input parameters and adding supply chain resilience measures (as two main contributions of this paper) to the model assures the applicability of the proposed model in real-world situations to a significant extent.

Here are some potential avenues for future research. For example, introducing other objectives to the model, such as reducing emissions throughout the network or considering the sustainability impacts of activating a meat supply chain network. Moreover, considering the uncertainty of the other parameters, such as the capacity of facilities, can be investigated in future studies. Since meat is a strategic product, deploying hybrid stochastic-robust-fuzzy methods can be respected as a more efficient method to cope with other business-as-usual and exceptional risks in the network. These methods can be boosted by considering some novel resiliency measures in the model. Finally, the model can be solved via meta-heuristic algorithms for large-instance problems.

Appendix A

Table A1. Demand for each type of product in each period

Customer	Demand			
	$\xi_{(1)}$	$\xi_{(2)}$	$\xi_{(3)}$	$\xi_{(4)}$
1	25.95	27.31	31.41	32.78
2	5.10	5.37	6.17	6.44
3	3.65	3.84	4.41	4.61
4	2.22	2.33	2.68	2.80
5	2.06	2.17	2.50	2.61
6	0.68	0.72	0.82	0.86
7	0.30	0.32	0.37	0.38
8	0.97	1.02	1.17	1.22
9	0.93	0.97	1.12	1.17
10	1.34	1.41	1.63	1.70
11	1.51	1.59	1.83	1.91
12	1.26	1.33	1.53	1.60
13	1.25	1.32	1.51	1.58
14	1.23	1.30	1.49	1.56
15	1.00	1.05	1.21	1.26
16	0.07	0.07	0.09	0.09
17	0.03	0.03	0.03	0.04
18	0.08	0.09	0.10	0.10
19	0.15	0.16	0.18	0.19
20	0.21	0.21	0.25	0.26

Table A2. Fixed cost of working with farm

Farm	Cost			
	$\xi_{(1)}$	$\xi_{(2)}$	$\xi_{(3)}$	$\xi_{(4)}$
(1-15)	9,500	10,000	11,500	12,000

Table A3. Fixed cost for selling via retailer

Retailer	Cost			
	$\xi_{(1)}$	$\xi_{(2)}$	$\xi_{(3)}$	$\xi_{(4)}$
(1-21)	19,000	20,000	23,000	24,000

Table A4. Purchasing cost from farms for each type of livestock in each period

Farms	Cost							
	1	2	1	2	1	2	1	2
	$\xi_{(1)}$		$\xi_{(2)}$		$\xi_{(3)}$		$\xi_{(4)}$	
(1-15)	1,567.03	5,295.9	1,649.5	5,574.60	1896.9	6410.8	1979.4	6689.5

Table A5. Fixed opening cost for a slaughterhouse in each period using each manufacturing technology

Farms	Costs							
	1	2	1	2	1	2	1	2
	$\xi_{(1)}$		$\xi_{(2)}$		$\xi_{(3)}$		$\xi_{(4)}$	
1	950,000	855,000	1,000,000	900,000	1,150,000	1,035,000	1,200,000	1,080,000
2	855,000	950,000	900,000	1,000,000	1,035,000	1,150,000	1,080,000	1,200,000
3	760,000	855,000	800,000	900,000	920,000	1,035,000	960,000	1,080,000
4	1,045,000	855,000	1,100,000	900,000	1,265,000	1,035,000	1,320,000	1,080,000
5	855,000	855,000	900,000	900,000	1,035,000	1,035,000	1,080,000	1,080,000
6	665,000	570,000	700,000	600,000	805,000	690,000	840,000	720,000
7	950,000	1,045,000	1,000,000	1,100,000	1,150,000	1,265,000	1,200,000	1,320,000
8	855,000	665,000	900,000	700,000	1,035,000	805,000	1,080,000	840,000
9	855,000	855,000	900,000	900,000	1,035,000	1,035,000	1,080,000	1,080,000
10	855,000	855,000	900,000	900,000	1,035,000	1,035,000	1,080,000	1,080,000
11	855,000	1,140,000	900,000	1,200,000	1,035,000	1,380,000	1,080,000	1,440,000
12	855,000	855,000	900,000	900,000	1,035,000	1,035,000	1,080,000	1,080,000

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