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Designing a green meat supply chain network: A multi-objective approach

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ABSTRACT

Traditional logistics management has not focused on environmental concerns when designing and optimizing food supply chain networks. However, the protection of the environment is one of the main factors that should be considered based on environmental protection regulations of countries. In this paper, environmental concerns are considered in formulating a mathematical model to design and configure a multi-period, multi-product, multi-echelon green meat supply chain network. We develop a multi-objective mixed-integer linear programming formulation to optimize three objectives simultaneously: minimization of the total cost, minimization of the total CO_2 emissions released from transportation, and maximization of the total capacity utilization of facilities. To demonstrate the efficiency of the proposed optimization model, we design a green meat supply chain network for Southern Ontario, Canada. A solution approach based on augmented ε-constraint method is employed to solve the proposed model. As a result, a set of Pareto-optimal solutions is obtained. The set of Pareto-optimal solutions gives decision-makers the opportunity to make a trade-off between economic, environmental, and capacity utilization objectives. Our example shows that it is possible to keep emissions reasonably low without incurring high total costs. Finally, the impacts of uncertainty on the proposed model are investigated using several decision trees. Optimization of a food supply chain, particularly a meat supply chain, based on multiple objectives under uncertainty using decision trees is a new approach in the literature.

1. Introduction

In recent decades, rapid population growth has led to a significant increase in food demand. Food industry is one of the main important industries in Canada. In 2014, the food and beverage industry was the second largest manufacturing industry in Canada with the shipment worth of $105.5 billion. The meat industry is the largest Canadian food processing industry. In 2014, 25% of all shipments, which is equal to $26.3 billion, accounted for the meat industry (Agriculture and Agri-food Canada, 2017).

To handle the high food demand, food supply chain management plays a vital role. In order to be effective, a strong food supply chain network (FSCN) needs to have a cost-effective design that helps make strategic and tactical decisions about the locations and allocation of relevant facilities in the network, as well as the optimal quantities of products that are transported in each echelon of the network.

Defining an adequate capacity level helps organizations meet customer demand with the right quantity of product at the right time (Adland et al., 2018). Maximizing the capacity utilization of facilities is an important factor that significantly increases the logistic network efficiency while decreasing the total costs for facilities (Jakubovskis, 2017). Capacity utilization is especially important in the North American meat industry, given the shortage of skilled labor (Lewis and Peters, 2011; Kay, 2018). Which is why meat-processing companies in North America are constantly improving their capacity utilization. For example, Maple Leaf Foods (a Canadian meat- and food-processing firm) announced the closure of its 42,000-square foot plant and its plans to consolidate operations at two other plants, with capacity to spare (Leshchenko, 2012).

Environmental concerns are other factors that should be taken into account in the design and configuration of FSCs. One reason to consider them is different environmental protection regulations that have been introduced by governments. These regulations have forced companies to redesign their supply chain networks. Furthermore, different international agreements have been signed between countries to address environmental issues. For instance, the United Nations Framework Convention on Climate Change (UNFCCC) was established in 1992 as a global treaty to reduce greenhouse gas (GHG) emissions. In Canada, this agreement has been enforced since 1994. Every year, Canada prepares a comprehensive report including estimations of different emissions such as carbon dioxide (CO_2) and nitrous oxide (N_2O) in various sectors of the economy, specifically agriculture, energy, waste, and land use.

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Canada also has a comprehensive plan to reduce GHG, which is called the Pan-Canadian Framework on Clean Growth and Climate Change. According to Environment and Climate Change Canada, 2018), Canada's GHG emissions decreased from 732 megatons of carbon dioxide equivalent in 2005 to 704 megatons of carbon dioxide equivalent in 2016. Canada's lowest level of emissions was in 2009 with 682 megatons of carbon dioxide equivalent. Alberta and Ontario (two provinces in Canada) had the highest level of total emissions in 2005. The emissions were 231 and 205 megatons of carbon dioxide equivalent, respectively. In 2016, Ontario's emissions decreased by 22%, reaching 161 megatons of carbon dioxide equivalent, while Alberta's emissions increased by 14%, reaching 263 megatons of carbon dioxide equivalent. The other Canadian provinces, including: Quebec, British Columbia, New Brunswick, Nova Scotia, and Prince Edward Island, decreased their total emissions between 2005 and 2016 by 11%, 5.1%, 24%, 33%, and 10%, respectively (Environment and Climate Change Canada, 2018). CO_2 is the largest emission contributing to Canada's total emissions. Specifically, 79% of the total emissions in 2016 were CO_2 (Environment and Climate Change Canada, 2018). These statistics underscore the importance of minimizing total CO_2 emissions as an objective in addition to considering other objectives.

In addition to the importance of food supply chain management, capacity utilization, and environmental concerns, it is vital to address uncertainty. Since uncertainty is inescapable in the real world, considering its impact helps decision-makers to effectively tackle real-world problems (Chopra and Meindl, 2015; Mogre and D'Amico, 2016). In the meat sector, various uncertainties exist that should be taken into account for a more comprehensive analysis. For example, according to a report by the Ontario Ministry of Agriculture, Food, and Rural Affairs (Ontario Ministry of AgricultureFood and Rural Affairs, 2018), the average price of livestock has fluctuated remarkably during the last couple of years (e.g., an increase of 27% in lamb prices from 2013 to 2014). We take into account such uncertainty, along with other fluctuations (i.e., changes in demand), and their effects on the total cost of the network are investigated in the second part of this paper.

This research is inspired by a meat-processing firm in Ontario, Canada. Given the existing customers, the main goal of our research is to assist the meat-processing firm in deciding which farms and retailers should be selected to work with, and where abattoirs should be opened. It is also important to determine the flow of commodities between each echelon of the network. There are several challenges to achieve the defined goals. These include: (1) considering several important objective functions simultaneously, (2) applying an appropriate solution approach that can generate Pareto-optimal solutions, (3) addressing uncertain parameters, such as price fluctuations, and investigating their impact on the total cost of the network, and (4) gathering and employing real data to show the efficiency of the proposed model.

In this paper, we consider several aspects in an integrated manner to simultaneously consider three conflicting objectives: minimizing total transportation costs and fixed costs, minimizing total CO_2 emissions released from transportation, and maximizing total capacity utilization in each echelon of the network. The combination of these objectives has not been used in previous research papers on the meat industry. Our proposed model is able to determine (1) the optimal quantities of products to be transported in every echelon of the network, (2) the optimal number and location of farms, abattoirs, and retailers, and (3) how they are connected with each other. The main research contributions of this article are summarized as follows:

- Developing a new multi-period, multi-product, multi-echelon, and multi-objective mixed-integer linear programming optimization model to design a meat supply chain network in Southern Ontario, Canada. In this model, we consider (a) both economic and environmental goals, (b) final customers as a key factor in the supply chain network, (c) distances between the real locations of the network's facilities using Google Maps.
- Employing real data to analyze a green meat supply chain network in Ontario, Canada.
- Developing a solution approach based on augmented ε-constraint technique. Based on the developed solution method, we generate Pareto-optimal solutions for decision-makers to consider the trade-off between economic, environmental, and capacity objectives.
- Taking into account the effects of uncertainty in the proposed network based on several decision trees.

To the best of our knowledge, this paper is the first attempt that simultaneously considers the aforementioned objectives in a multi-product and multi-period model for a multi-echelon green meat logistics network with application in Ontario.

The outline of this article is as follows: the related literature is reviewed in Section 2. Section 3 provides the problem description with the related assumptions. Section 4 presents the proposed multi-objective mixed-integer linear programming (MILP) model. The solution approach based on augmented ε-constraint method is presented in Section 5. Section 6 shows how the proposed mathematical model is employed to design a green meat supply chain network in Southern Ontario, Canada. Section 7 introduces and applies decision trees to consider the impacts of uncertainty on the proposed model. Finally, conclusions and future research are discussed in Section 8.

2. Literature review

In this section, we have reviewed existing papers related to multi-objective optimization in FSCs, optimization under uncertainty in supply chains, and green supply chain networks' optimization, in order to better situate our work within the literature.

2.1. Multi-objective optimization in FSCs

There are some studies that have applied multi-objective optimization to FSC network design. These objectives have focused on different concerns such as maximization of quality and the safety of products (James et al., 2006; Ahumada and Villalobos, 2009; Akkerman et al., 2010; Rong et al., 2011; Soysal et al., 2012; Rijpkema et al., 2016), or minimization of the total network cost (Villegas et al., 2006; Bhattacharya and Bandyopadhyay, 2010; Cheshmehgaz et al., 2013; Mogale et al., 2018). Paksoy et al. (2012) proposed a multi-objective linear programming formulation to minimize the total transportation cost between different echelons of the supply chain network for vegetable oils. Teimoury et al. (2013) examined the food and vegetable supply chain in Tehran. They proposed a multi-objective formulation, and a solution approach based on simulation.

García-Flores et al. (2014) focused on the meat industry in Northern Australia, and formulated a mathematical model to obtain the optimal quantity of products to be transported in different echelons of the network. Mohammed and Wang (2015) proposed a multi-objective mathematical model with the aim of maximizing the integrity of Halal meat, minimizing the whole investment expenditure, and maximizing the return of investments (ROI) in a meat supply chain. They employed a Petri-net model, which is a graphical simulation model, to show how their proposed network behave. Mohammed and Wang (2016) proposed a mixed-integer linear programming formulation to deal with four objectives simultaneously: minimizing total cost, and maximizing profits, freshness, and consumer satisfaction.

Mohammed and Wang (2017a) provided a multi-objective model for minimizing the total transportation cost, the number of vehicles in transportation, and the delivery time, in the meat supply chain network. They used three solution approaches, including weighted Tchebycheff, ε-constraint, and LP-metrics techniques, to solve their multi-objective model. Then, they showed that the ε-constraint method outperformed the other two techniques. Mohammed and Wang (2017b) developed a multi-objective formulation in a three-echelon meat logistics network. These objectives included: minimizing the whole cost including transportation costs and implementation costs, maximizing product quality, and maximizing customer satisfaction. Four techniques were applied for solving the model: goal programming, compromise programming, utility function, and weighted Tchebycheff method. The results showed that the compromise programming approach outperformed the other three approaches.

2.2. Optimization under uncertainty in supply chains

We reviewed several papers that have utilized multi-objective models in different kinds of supply chain networks. However, the reviewed papers did not consider uncertainty in their models. Decision-making in the real world takes place in an environment with uncertain parameters such as customer's demands and purchasing cost. Therefore, taking the effects of uncertainty into account in optimization models helps decision-makers to tackle real-world problems. Several studies have been conducted which analyzed the impact of uncertainty in various supply chain networks. These studies used a variety of approaches to deal with uncertainty. These approaches included: fuzzy programming (e.g., Liang, 2006; Torabi and Hassini, 2008; Özceylan and Paksoy, 2013, 2014; Gholamian et al., 2015; Moheb-Alizadeh et al., 2011; Amin and Zhang, 2012), stochastic programming (e.g., Santoso et al., 2005; Feitó-Cespón et al., 2017; Jeihoonian et al., 2017), robust optimization (e.g., Mudchanatongsuk et al., 2008; Chung et al., 2011; Jabbarzadeh et al., 2014), scenario-based analysis, and decision tree methods (e.g., Canbolat et al., 2007; Amin and Zhang, 2013; Amin et al., 2017). To be more concise, in the rest of this subsection, we focus on the most relevant studies which address uncertainty in their analyses.

Liang (2006) developed a fuzzy based linear programming formulation under uncertainty to minimize the total delivery time and the total distribution cost of food and drinks in Taiwan. Mirzapour Al-E-Hashem et al. (2011) investigated the supply chain of wood and paper in Iran by developing a multi-product, multi-period, and multi-objective mixed-integer non-linear programming formulation considering two conflicting objectives. The objectives were maximization of customer satisfaction and minimization of total cost. Demand and cost parameters are the sources of uncertainty in their proposed model. They employed LP-metrics method as a solution method to solve their proposed model. Mirakhorli (2014) investigated a closed-loop logistics network of bread in Iran by proposing a fuzzy multi-objective linear programming formulation. Demand and return are two main uncertain parameters in this study. The goal was to minimize the total cost and the total transportation time concurrently. He utilized a genetic algorithm to solve the proposed mathematical model. Yang et al. (2015) studied a dairy supply chain formulating a two-stage multi-objective mathematical model, which was solved by a genetic algorithm and a biogeography-based optimization algorithm. Demand and transportation costs were two sources of uncertainty in their proposed model.

Azadeh et al. (2017) presented a mixed-integer non-linear programming formulation to investigate the crude oil supply chain in Iran under uncertainty of production capacity, cost, and the consumption rate of petroleum goods produced from crude oil. They employed three solution methods: evolutionary algorithm, genetic algorithm, and particle swarm technique. The obtained results showed that the evolutionary algorithm outperformed the other two solution methods. Mohammed et al. (2017) formulated a multi-objective model to optimize four conflicting objectives: the minimization of the total cost, maximization of the integrity of Halal meat products, maximization of the ROI, and maximization of capacity utilization for Halal meat logistics under uncertainty. They employed the modified weighted-sum and ε-constraint techniques to solve the proposed model. Rahimi et al. (2018) made a trade-off between the present and future profits by introducing a bi-objective and multi-period mixed-integer programming model under uncertainty of demand, selling price, and purchasing cost. They employed LP-metrics method to convert the multi-objective to a single goal model. The effectiveness of their proposed model was shown in a real case study with a well-known food distributer in Iran. Yu et al. (2018) introduced a bi-objective optimization model to investigate fresh agri-product under uncertainty of information. Two main objectives in their proposed model were maximization of customer satisfaction and minimization of total cost. Two-phase method was used in their paper as a solution method.

From the existing methods for handling uncertainty, we use the decision tree method because it provides decision-makers with the ability to analyze different scenarios. Although scenario-based methods are not usually suitable for handling a remarkably large number of scenarios, for computational reasons, their relative simplicity and flexibility allow for more tractable models and easier implementation (Snyder, 2006; Govindan et al., 2017).

2.3. Green supply chain network optimization

In recent decades, environmental issues have become one the biggest challenges in designing a supply chain network. Green supply chain management is defined as integrating environmental factors into traditional supply chain management (Srivastava, 2007), which has mainly focused on the financial aspects of supply chain management such as overall network cost. Environmental factors are equally as important as the economic aspects of supply chain networks (Mohammed and Wang, 2017c).

Overall, the studies discussed above have made notable contributions towards developing optimization models under uncertainty in various supply chain networks. However, they have not taken environmental concerns like greenhouse gas emissions. A few studies have integrated these two factors in designing green logistics networks. Soysal et al. (2012) provided a review of sustainable food supply chain management (SFSCM).

Chaabane et al. (2012) provided a mixed-integer linear programming formulation to minimize total logistics costs and greenhouse gas (GHG) emissions in a closed-loop supply chain, including five layers of the supply chain: suppliers, plants, distribution centers, customers, and recycling centers. However, uncertainty was not included in their proposed model.

Soysal et al. (2014) developed a multi-objective linear programming (MOLP) model considering transportation emissions. The goals of their study are to minimize the total logistics costs and the total quantity of CO_2 emissions in a beef supply chain network. They employed ε-constraint method to solve their presented model. However, they did not consider multiple products, they only focused on beef. In addition, the uncertainty effects were not analyzed. Furthermore, customers, which are an important factor to take into consideration, were not addressed.

Bortolini et al. (2016) focused on fresh food supply chain networks and developed a multi-objective mathematical formulation with the aim of minimizing operating costs, CO_2 emissions, and the delivery time of products. However, they did not take uncertainty into account in the model. Mohammed and Wang (2017c) introduced a fuzzy multi-objective programming model to optimize four conflicting objectives in the meat supply chain network: minimizing the whole cost, minimizing the CO_2 emissions, minimizing the distribution time of the products in each echelon of the network, and maximizing the average delivery rate. Then, they utilized three techniques: goal programming, ε-constraint, and LP-metrics, to solve the proposed model. They showed that ε-constraint method has a better performance than the other two solution approaches. However, this study did not consider multiple products, and their proposed model is not multi-period. In addition, they did not incorporate customers into their supply chain network, they only focused on farms, abattoirs, and retailers. Babbar and Amin (2018) developed a two-phase model including a quality function deployment (QFD) and a multi-objective model in the beverage industry. The goal of the first phase was supplier selection, while the second phase focused on determining the order quantity using weighted-sum, ε-constraint, and distance techniques. Five objectives were considered in the second phase of their study: minimizing the total cost, minimizing the defect rate, minimizing the carbon emission, maximizing the weight of suppliers, and maximizing on-time delivery. Mohebalizadeh and Hafezalkotob (2018) developed a sustainable supply chain network in a fuzzy environment by introducing a multi-objective mixed-integer linear programming model, which minimizes total cost, energy consumption, and delivery time while maximizes number of jobs. Then, they utilized weighted metric methods and modified fuzzy parametric programming (MFPP) as two solution methods to solve the multi-objective problem.

Table 1 provides a summary of related papers that have considered environmental concerns in logistics mathematical models. The research gaps can be identified according to the information in this table. Based on Table 1, very few studies have considered environmental concerns in the meat industry. It is apparent that the existing papers have not created a comprehensive supply chain network including final customers - which are the main part of a meat supply chain network. Furthermore, they did not simultaneously consider multiple products and multiple periods in their models. Considering multiple products in the network design helps to create a comprehensive and cost-effective supply chain network. According to Table 1, just a few papers have captured uncertainty in the models. This paper's primary research contributions, and the features that differentiate our research from other studies, are displayed in the last row of Table 1.

MOLP: multi-objective linear programming; MILP: mixed-integer linear programming; MIGP: mixed-integer goal programming; MOFP: multi-objective fuzzy programming; MOOM: multi-objective optimization model; MOP-NL: non-linear multi-objective programming; ILP: integer linear programming; LP: linear programming; GP: goal programming; Sim: simulation.

3. Problem statement

In Canada, red meat consists of pork, lamb and mutton, goat, beef and veal, horse, bison, and venison while white meat includes: chicken, rabbit, turkey, and duck. Ontario farm animals are slaughtered and processed in two types of inspected plants: federal or provincial. Specifically, the meat that is sold outside of the province is slaughtered in a federal plant, while the meat that is sold within the province is slaughtered in a provincially licensed meat plant.

The Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA) is responsible for inspecting provincial meat plants. There are two types of meat plants within this category: abattoirs (slaughter plants) and freestanding meat plants. The first type of meat plant (abattoirs) slaughters animals. These plants may or may not process the meat further, while the second type of meat plant only performs the additional processing such as cutting and boning. There are different livestock meat associations in Canada, such as: Canadian Pork Council (CPC), Canadian Meat Goat Association (CMGA), and Canadian Cattlemen's Association (CCA). In Ontario, Beef Farmers of Ontario is the provincial member association that connects beef producers to CCA. This corporation provides different services to beef farmers, such as verifying the cattle age, registering livestock brands on behalf of the OMAFRA, and tracking cattle information, such as vaccinations.

The Canadian Food Inspection Agency (CFIA) regulates the transportation of live animals from farms to abattoirs. CFIA requires that animals have approved tags before leaving farms. This is the main requirement for livestock producers (farms) that helps to identify animals and trace them. Some requirements are imposed on abattoirs by CFIA, such as “abattoir operators must be able to identify the carcasses of livestock in the abattoir; they must also record the identification numbers of the approved and revoked tags of any animals that are slaughtered”. The animals' food, water, and rest time during transportation are important issues that must be considered by the person who transports them. These time requirements vary for different species of animals. For example, according to the Health of Animals Regulations Part XII: Transportation of Animals-Regulatory Amendment, which is enforced by CFIA, the maximum time interval for pigs without feed, water, and rest is 28 h. According to CFIA, after the maximum time interval has occurred all animals should rest for at least 8 h with access to food and water.

Fig. 1 demonstrates a four-echelon meat supply chain network including farms, abattoirs, retailers, and customers. In this network, farms, which have different types of animals, are responsible for supplying livestock to abattoirs, where livestock is slaughtered and packed as processed meat. Afterwards, meat is transported to the large-scale retailers who are responsible for selling and transporting it to the demand zones (called customers). Based on our observation, the primary goal is to help the meat-processing firm in deciding which farms and retailers should be selected to work with, and where abattoirs should be opened. The following assumptions are made to deal with this problem:

- Demand of customers is known in advance and must be satisfied.
- Maximum capacities of farms, abattoirs, and retailers are known.
- We assume that all parameters, including the purchasing cost of livestock, are known in advance. However, since the value of some parameters are often subject to uncertainty, we will investigate the impact of the uncertainty of those parameters on the total cost of the supply chain network using decision trees.
- No inventory of meat is allowed in abattoirs or retailers.
- Road transportation mode is selected to transport the products between the chosen facilities in the network.
- 53-foot tri-axle combination freight livestock trailers are used to transport livestock from farms to abattoirs.
- 53-foot reefer trailers are used to transport meat products from abattoirs to retailers, and from retailers to customers.
- Since the demand is generated by end buyers, including the shoppers and restaurants residing in cities, each city is considered as a demand zone (i.e., a customer) by the firm. This is because the firm controls its supply chain, starting with purchasing livestock from farms to selling meats to cities (its customers) through large-scale retailers. Therefore, the demand in each period is large enough to justify the use of 53-foot reefer trailers for the transportation of meats to customers.
- Livestock is slaughtered in provincial meat plants located in Southern Ontario.
- There is a fixed-cost for working with a farm. This cost can take different forms. Although there are various regulations in the Canadian meat industry and the quality of meats is inspected by the Canadian Food Inspection Agency [1], there are some meat-processing firms that have a more rigorous monitoring process (e.g., Olymel[2]). One of the major requirements of this fixed cost is to continuously monitor the quality of livestock, regardless of the quantity purchased, over the planning horizon.
- There is a fixed-cost for selling products through each retailer. This upfront payment is a fixed fee paid by the firm over a specific period of time in order to obtain access to space at the retailer. In the literature, this is also known as slotting fee (Marx and Shaffer, 2007). Based on our observations from the meat market in Ontario, the firm must incur this fixed cost in order to offer its products for sale.

Both strategic and tactical decisions should be made in this problem.

[1] http://www.inspection.gc.ca/eng/1297964599443/1297965645317.
[2] http://www.olymel.ca/en/.

The strategic decisions are employed to determine the locations and allocation of farms, abattoirs, and retailers, while the tactical decisions are made to determine the quantities of the products that are transported in the proposed meat supply chain network. The outcome of this research answers the following important questions that can assist decision-makers with selecting a cost-effective supply chain network while considering environmental concerns.

(1) Which farms should be selected?
(2) Where should abattoirs be located?
(3) Which retailers should be selected for selling the meat products?
(4) How many products are transported between the selected facilities in the proposed network?

4. Optimization model

In this section, a multi-objective mixed-integer linear programming (MILP) model is proposed to optimize the three conflicting objectives in the green meat logistics network. The details of the MILP model are as follows:

Sets.

F: set of potential farm locations $(1 \ldots f \ldots F)$
A: set of potential abattoir locations $(1 \ldots a \ldots A)$
R: set of potential retailer locations $(1 \ldots r \ldots R)$
C: set of customers $(1 \ldots c \ldots C)$
J: set of products j including livestock and meat $(1 \ldots j \ldots J)$
T: set of time periods $(1 \ldots t \ldots T)$

Parameters.

p_{fjt}: purchasing cost per ton of livestock j from farm f in period t
n_f: fixed-cost of working with farm f
b_a: fixed-cost for opening abattoir a
e_r: fixed-cost for selling products via retailer r
de_{fa}: transportation distance (mile) from farm f to abattoir a
ge_{ar}: transportation distance (mile) from abattoir a to retailer r
he_{rc}: transportation distance (mile) from retailer r to customer c
kc_{fajt}: unit transportation cost per mile for livestock j from farm f to abattoir a in period t
lc_{arjt}: unit transportation cost per mile for processed meat j from abattoir a to retailer r in period t
mc_{rcjt}: unit transportation cost per mile for meat j from retailer r to customer c in period t
d_{cjt}: demand (ton) of customer c for meat j in period t
x_{fj}: maximum supply capacity (ton) of farm f for livestock j
o_{aj}: maximum supply capacity (ton) of abattoir a for processed meat j
u_{rj}: maximum supply capacity (ton) of retailer r for meat j
α: CO_2 emission factor per ton and per mile
w_j: weight (ton) of product j including livestock and meat

Decision Variables.

QU_{fajt}: quantity of livestock j (ton) transported from farm f to abattoir a in period t
QN_{arjt}: quantity of processed meat j (ton) transported from abattoir a to retailer r in period t
QA_{rcjt}: quantity of meat j (ton) transported from retailer r to customer c in period t
Z_f: binary variable, equals to 1 if farm f is selected, 0 otherwise
I_a: binary variable, equals to 1 if abattoir a is open, 0 otherwise
Y_r: binary variable, equals to 1 if retailer r is selected, 0 otherwise

Objective Functions

$$Min\ Z_1 = \sum_f \sum_a \sum_j \sum_t (p_{fjt} + kc_{fajt}*de_{fa})*QU_{fajt} + \sum_a \sum_r \sum_j \sum_t lc_{arjt}*ge_{ar} *QN_{arjt} + \sum_r \sum_c \sum_j \sum_t mc_{rcjt}*he_{rc}*QA_{rcjt} + \sum_f n_f *Z_f + \sum_a b_a*I_a + \sum_r e_r*Y_r \tag{1}$$

$$Min\ Z_2 = \alpha\Big(\sum_f \sum_a \sum_j \sum_t w_j*de_{fa}*QU_{fajt} + \sum_a \sum_r \sum_j \sum_t w_j *ge_{ar}*QN_{arjt} + \sum_r \sum_c \sum_j \sum_t w_j*he_{rc}*QA_{rcjt}\Big) \tag{2}$$

$$Max\ Z_3 = \sum_f \sum_a \sum_j \sum_t QU_{fajt}/x_{fj} + \sum_a \sum_r \sum_j \sum_t QN_{arjt}/o_{aj} + \sum_r \sum_c \sum_j \sum_t QA_{rcjt}/u_{rj} \tag{3}$$

s.t.

$$\sum_a \sum_j QU_{fajt} \le Z_f. \sum_j x_{fj} \qquad \forall\ f, t \tag{4}$$

$$\sum_r \sum_j QN_{arjt} \le I_a. \sum_j o_{aj} \qquad \forall\ a, t \tag{5}$$

$$\sum_c \sum_j QA_{rcjt} \le Y_r . \sum_j u_{rj} \qquad \forall\ r, t \tag{6}$$

$$\sum_f QU_{fajt} \ge \sum_r QN_{arjt} \qquad \forall\ a, j, t \tag{7}$$

$$\sum_a QN_{arjt} \ge \sum_c QA_{rcjt} \qquad \forall\ r, j, t \tag{8}$$

$$\sum_r QA_{rcjt} = d_{cjt} \qquad \forall\ c, j, t \tag{9}$$

$$Z_f,\ I_a,\ Y_r \in \{0,1\} \qquad \forall\ f, a, r \tag{10}$$

$$QU_{fajt},\ QN_{arjt},\ QA_{rcjt} \ge 0 \qquad \forall\ f, a, r, c, j, t \tag{11}$$

The first objective (Z_1) minimizes the total transportation cost and the fixed costs. The first part is related to the purchasing cost and transportation cost of livestock that are sent from farms to abattoirs. The second and third parts of the objective function consider the transportation cost of sending meat from abattoirs to retailers and from retailers to customers, respectively. The other parts are related to the fixed costs associated with farms, abattoirs, and retailers. The second objective function (Z_2) minimizes CO_2 emissions released from transportation. The last objective function (Z_3) maximizes capacity utilization of facilities. The first term of Z_3 considers capacity utilization of farms while the second and third terms take into account the capacity utilization of abattoirs, and retailers, respectively. Constraints (4), (5), and (6) satisfy capacity limitations of farms, abattoirs, and retailers, respectively. Constraints (7) and (8) state that input meat and output meat should be equal in each abattoir and each retailer, respectively (for each product in each time period). Constraint (9) satisfies customer demand for each product. Lastly, Constraints (10) and (11) define binary variables and non-negative variables.

5. Solution approach

Different solution methods have been developed in the literature to solve multi-objective problems (Paksoy et al., 2012; Bortolini et al., 2016; Moheb-Alizadeh and Handfield, 2017). In this paper, augmented ε-constraint method, which is an improved version of traditional ε-constraint technique, is employed to convert the presented multi-objective model into a single one. The traditional ε-constraint method, which was introduced by Chankong and Haimes (1983), optimizes one

Table 1
Review of the literature considering environmental concerns in logistics models.

Studies	Model Type	Uncertainty	Multi-Product	Multi-Period	Type of Products	Real Location
Neto et al. (2008)	MOLP		✓		Pulp, Paper	
Pati et al. (2008)	MIGP		✓		Paper	
Akkerman et al. (2009)	MILP			✓	Meals	
Van Der Vorst et al. (2009)	Sim			✓	Pineapples	
Oglethorpe (2010)	GP				Pork	
Bauer et al. (2010)	MILP			✓		✓
Paksoy et al. (2010)	MOLP		✓			
Harris et al. (2011)	Sim			✓	Automotive	✓
Paksoy et al. (2011)	LP		✓			
Bektaş and Laporte (2011)	ILP			✓		
Wang et al. (2011)	MOP-NL		✓			✓
Chaabane et al. (2011)	MOLP		✓		Steel	
Ubeda et al. (2011)	MILP			✓	Food	✓
Chaabane et al. (2012)	MILP		✓	✓	Aluminum	
Elhedhli and Merrick (2012)	MIP-NL					
Abdallah et al. (2012)	MILP		✓			
Mallidis et al. (2012)	MILP		✓			✓
Pishvaee and Razmi (2012)	MOFP	✓			Needle, Syringe	
Ruiz-Femenia et al. (2013)	MILP	✓	✓	✓	Petrochemical	✓
Harris et al. (2014)	MIP					
Soysal et al. (2014)	MOLP			✓	Beef	✓
Validi et al. (2014)	MOO				Milk	✓
Bing et al. (2014)	MILP		✓		Plastic waste	✓
Bortolini et al. (2016)	MOLP		✓		Fruit, Vegetable	✓
Talaei et al. (2016)	MILP	✓	✓		Copiers industries	
Banasik et al. (2017)	MILP		✓	✓	Bread	
Jindal and Sangwan (2017)	MILP	✓	✓			
Keshavarz Ghorabaee et al. (2017)	MOOM	✓	✓	✓	Home appliances	✓
Mohammed and Wang (2017c)	MOLP	✓			Meat	✓
Nurjanni et al. (2017)	MILP					✓
Babbar and Amin (2018)	MILP		✓	✓	Beverages	
Pourjavad and Mayorga (2018)	MILP	✓		✓		
Mohebalizadeh et al. (2018)	MILP		✓	✓	Meat	✓
Current Study	MILP	✓	✓	✓	Meat	✓

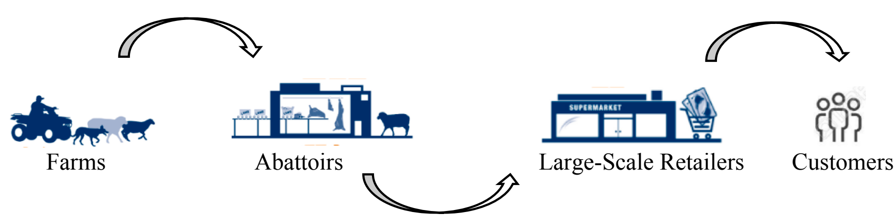

Fig. 1. A four-echelon meat supply chain network.

objective function when the rest of the objective functions are considered as constraints with proper upper or lower bounds. These bounds, which are altered to obtain the Pareto solutions, are different levels of ε. This method was widely employed in the literature (Amin and Zhang, 2013; Soysal et al., 2014; Mohammed et al., 2017). However, augmented ε-constraint method, which was introduced by Mavrotas (2009), has attracted the attention of researchers in recent years because of its advantages. For instance, this method can guarantee the efficiency of the Pareto-optimal solutions. In addition, this method can reduce the computational time when researchers need to solve problems with more than two objective functions (Mavrotas, 2009). Some studies have applied the improved version of the traditional ε-constraint method (Ahmadi et al., 2012; Mavrotas and Florios, 2013; Ramos et al., 2014; Felfel et al., 2016; Moheb-Alizadeh and Handfield, 2019). The augmented ε-constraint method is utilized to solve a multi-objective model through the following steps (Mavrotas, 2009):

- Step 1: Choosing one objective function as the main objective. In this work, we consider the cost objective, Z_1, as the main objective function.
- Step 2: Generating a payoff table to find the range of the objectives that are transferred into constraints. To meet this goal, the maximum and minimum values of every objective should be calculated. The emission objective, Z_2, as well as the capacity objective, Z_3, are transferred into constraints. Then, the range of each objective is obtained by calculating the global optimal solution of each objective and replacing the obtained value in the rest of the objective functions. In this way, we will have three values, which help us to determine the maximum and minimum values of each objective.
- Step 3: Dividing the range of each objective to q equal intervals, which leads to having ν ($|\nu| = q + 1$) grid points for each objective function. Each grid point provides a sub-problem that needs to be solved. The result is one Pareto–optimal solution for each sub-problem.
- Step 4: Changing the form of the proposed model as follows:

$Min\ Z_1$

s.t.

$$Z_2 \leq Z_{2(\min)} + \nu.\ \Delta\varepsilon_{z_2}$$

$$Z_3 \geq Z_{3(\min)} + \nu.\ \Delta\varepsilon_{z_3}$$

where $\nu = 0, 1, 2, \ldots, q$,

$$\Delta\varepsilon_{z_2} = \left(\frac{Z_{2(max)} - Z_{2(min)}}{q}\right),\ \Delta\varepsilon_{z_3} = \left(\frac{Z_{3(\max)} - Z_{3(\min)}}{q}\right).$$

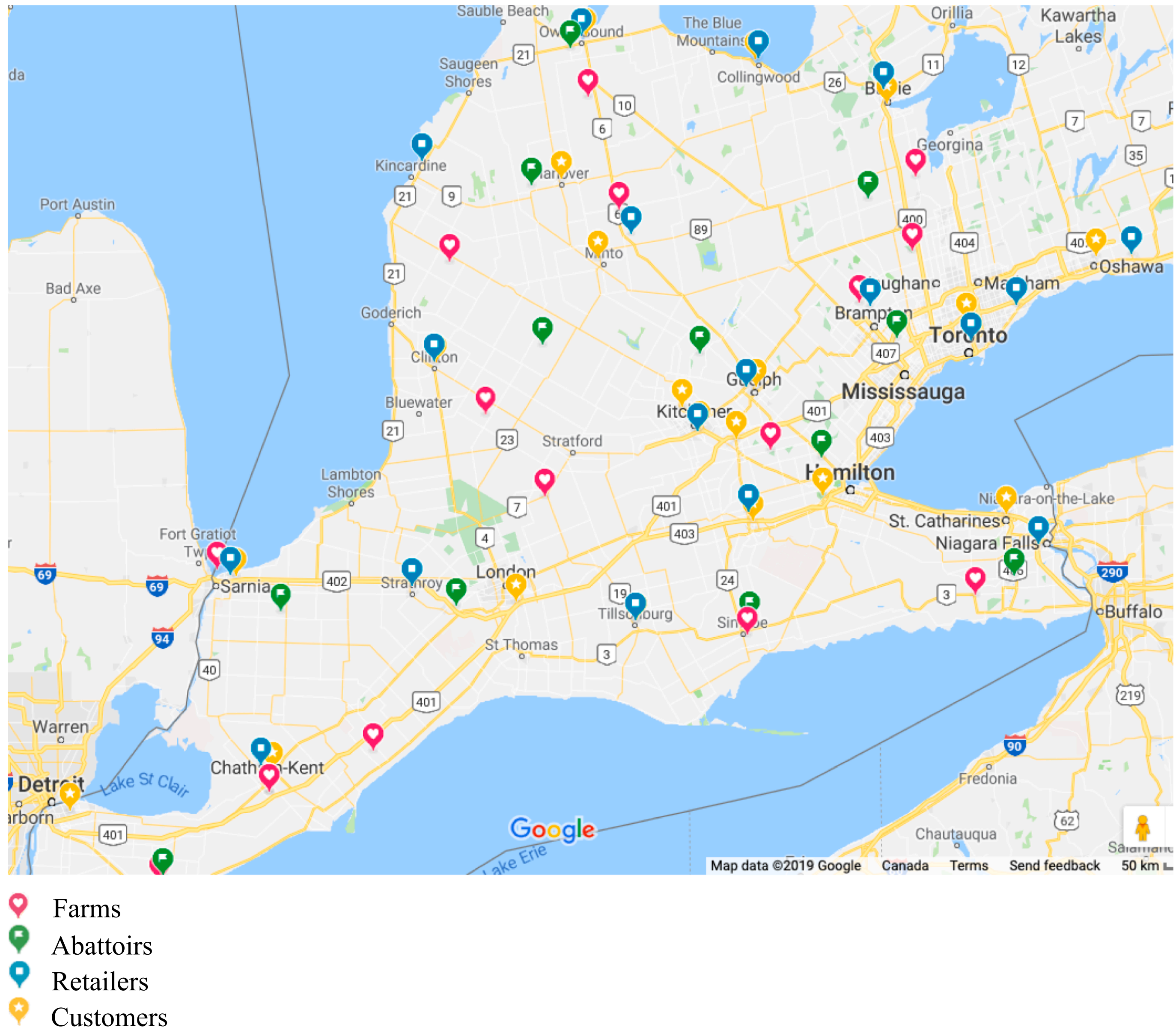

Fig. 2. Locations of the facilities and customers.

Table 2
Values of the parameters defined to solve the mathematical model.

$F = 15$	$kc_{fajt} = lc_{arjt} = mc_{rcjt} = 0.005$	$d_{131t} = d_{132t} = 1.317$ ton
$A = 12$	$d_{11t} = d_{12t} = 27.316$ ton	$d_{141t} = d_{142t} = 1.299$ ton
$R = 21$	$d_{21t} = d_{22t} = 5.369$ ton	$d_{151t} = d_{152t} = 1.049$ ton
$C = 20$	$d_{31t} = d_{32t} = 3.838$ ton	$d_{161t} = d_{162t} = 0.074$ ton
$J = 2$	$d_{41t} = d_{42t} = 2.332$ ton	$d_{171t} = d_{172t} = 0.030$ ton
$n_f = 10{,}000$	$d_{51t} = d_{52t} = 2.172$ ton	$d_{181t} = d_{182t} = 0.086$ ton
$e_r = 20{,}000$	$d_{61t} = d_{62t} = 0.716$ ton	$d_{191t} = d_{192t} = 0.158$ ton
$\alpha = 222$ g per ton-mile	$d_{71t} = d_{72t} = 0.318$ ton	$d_{201t} = d_{202t} = 0.217$ ton
$w_1 = 0.635$ ton	$d_{81t} = d_{82t} = 1.016$ ton	$x_{f1} = x_{f2} = 15$ ton
$w_2 = 0.041$ ton	$d_{91t} = d_{92t} = 0.974$ ton	$o_{a1} = o_{a2} = 15$ ton
$b_a = 1{,}000{,}000$	$d_{101t} = d_{102t} = 1.414$ ton	$u_{r1} = u_{r2} = 15$ ton
p_{f1t} = \$1,649.5 per ton	$d_{111t} = d_{112t} = 1.594$ ton	
p_{f2t} = \$5,574.6 per ton	$d_{121t} = d_{122t} = 1.331$ ton	

- **Step 5:** Transforming the objective function constraints of the above model to equalities by adding proper slack or surplus variables in order to guarantee the efficiency of the obtained solutions. In addition, the slack and surplus variables are added to the main objective. Furthermore, the other constraints are considered in this step. Therefore, we will have:

Table 3
Pay-off table to show the range of.Z_2 and Z_3

Objective function	Z_2 (kg)	Z_3 (ton)
Minimize Z_1	1421	63.14
Minimize Z_2	1016	63.14
Maximize Z_3	21,358	183.04

$$Min\ (Z_1 + \beta.\ (S_1 + S_2)) \tag{12}$$

s.t.

(4) – (11)

$$Z_2 + S_1 = Z_{2(\min)} + v.\ \Delta\varepsilon_{z_2} \qquad v = 0,1,2,\ \ldots, q \tag{13}$$

$$Z_3 - S_2 = Z_{3(\min)} + v.\ \Delta\varepsilon_{z_3} \qquad v = 0,\ 1,\ 2,\ \ldots,\ q \tag{14}$$

where β is a very small number usually between 10^{-3} and 10^{-6}.

Table 4
Pareto-optimal solutions.

v	Cost ($)	Emission (kg)	Capacity (ton)
0	11,560,470	1016	63.144
1	5,578,361	3559	78.132
2	5,979,292	6101	93.12
3	6,370,222	8644	108.108
4	6,771,153	11,187	123.096
5	8,003,629	13,730	138.084
6	10,929,190	16,273	153.072
7	13,003,220	18,815	168.06
8	15,077,240	21,358	183.048

However, β does not have any impact on the value of the main objective function (Mota et al., 2015). The values of S_1 and S_2 should be equal to zero or very close to zero in order to have an efficient Pareto optimal solution (Felfel et al., 2016).

It should be noted that there is no single solution that simultaneously optimizes the three aforementioned objectives. Therefore, trade-offs between different objectives are considered based on the set of Pareto-optimal solutions, which are calculated by applying the augmented ε-constraint technique. The optimality of the Pareto solution is guaranteed when there is no feasible solution that can improve some objectives without deteriorating the rest of the objectives at the same time (Coello and Romero, 2003).

6. Application of the model

In this part, the efficiency of the proposed mathematical model is investigated by applying the proposed optimization model to design and optimize a green meat supply chain network in Southern Ontario, Canada. The locations of different facilities have been shown in Fig. 2. There are 15 potential farms, 12 provincially licensed meat plants, and 21 retailers. Table A1 (in Appendix A) provides a list of facilities and their locations. Furthermore, 20 cities in Southern Ontario are selected as customers: Toronto, Hamilton, London, Kitchener, Windsor, Sarnia, Owen Sound, Chatham-Kent, Brantford, Barrie, Oshawa, Niagara, Guelph, Cambridge, Waterloo, Hanover, Clinton, Minto, Tillsonburg, and Collingwood. Google Maps is used to calculate the real distances between different locations. Two products, including cow and lamb, have been chosen for this application. The weights of the products are considered according to the information provided by OMAFRA.

The purchasing cost of livestock from farms is based on the average prices that Ontario livestock farmers received for slaughter of different types of meat in 2017. Interested readers may refer to Statistics Canada, 2017. The demand of each customer for each product is assumed to be 0.01 of the population of the city, which is based on the 2016 Census data, provided by Statistics Canada 2017). The Canadian dollar is considered as the common currency. As we assumed before, the heavy-duty vehicles, which are tri-axle combination freight livestock trailers and reefer trailers made in 2017, are used to transport livestock and meat products, respectively, between different locations. The maximum transportation capacity of trailers to transport livestock is equal to 55,000 lbs. or 24,500 kg. This type of trailer is classified under Class 8 heavy-duty vehicles. It should be noted that every vehicle has a CO_2 emissions rate that must not exceed the pre-defined CO_2 emissions standard. In this research, the amount of CO_2 emissions standard, α, is determined based on the Heavy-duty Vehicle and Engine Greenhouse Gas Emission regulations under the Canadian Environmental Protection Act, 1999 issued on April 14, 2012, and amended 2015-07-16. Based on the above regulation, α is equal to 222 g per ton-mile for vehicles that transport livestock. Moreover, the maximum transportation capacity of a reefer trailer is 44,000 lbs. or 20,000 kg. Therefore, this type of trailer is classified under Class 8 heavy-duty vehicles. Hence, the same CO_2 emissions standard rate, $\alpha = 222$ g per ton-mile, is used for this type of trailer. Table 2 provides the values for the parameters that have been utilized in this application.

The augmented ε-constraint method is coded using LINGO 17 software on a 1.8 GHz laptop computer to solve the mathematical model. The generated pay-off information to obtain the range of the objectives, Z_2 and Z_3, is provided in Table 3. Based on Table 3, $Z_{2(\min)}$ is equal to 1016 kg while $Z_{2(\max)}$ is equal to 21,358 kg. Therefore, the range of this objective function is between 1016 kg and 21,358 kg. The same process is done for Z_3. The next step is to divide the range of Z_2 and Z_3 to q equal intervals. In this paper, q is equal to 8. Therefore, we will have 9 grid points, which means that 9 Pareto-optimal solutions will be generated. It should be noted that the larger number of q can generate denser efficient solutions with larger computational time (Mavrotas, 2009). In the next stage, we modify the form of the proposed mathematical model, as was explained in Steps 4 and 5 in Section 4.

Table 4 shows the set of Pareto-optimal solutions obtained from solving the proposed model by the augmented ε-constraint method using LINGO 17. This set provides a chance for decision-makers to make trade-offs between different objective functions and to choose the

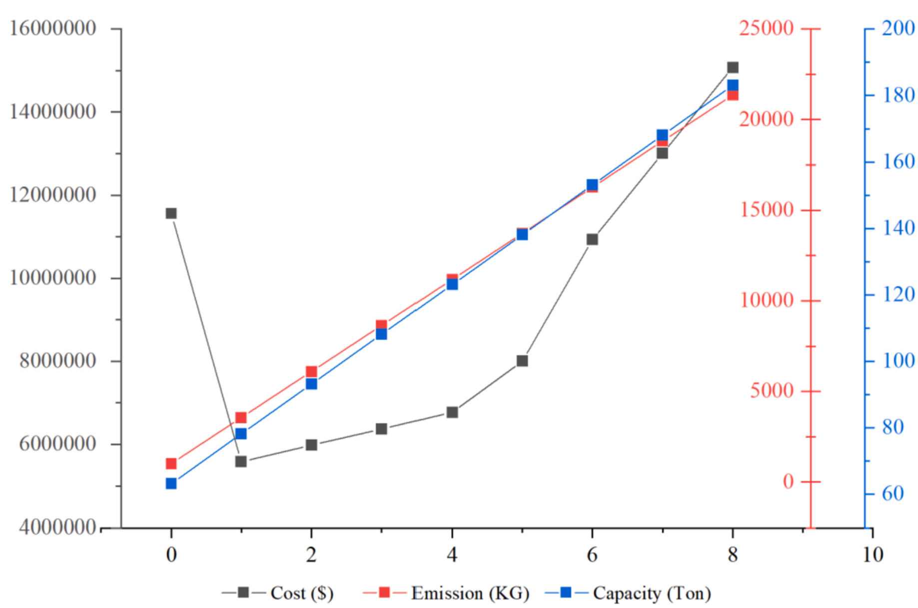

Fig. 3. Pareto-optimal solutions for the multi-objective functions.

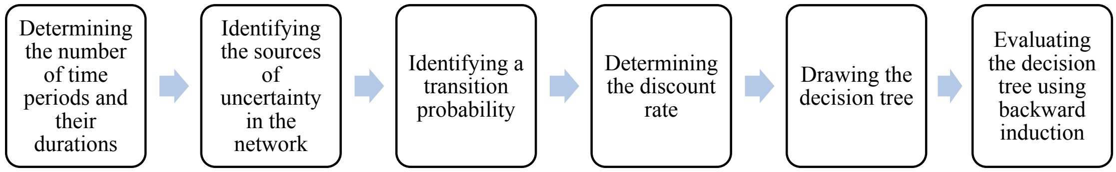

Fig. 4. A schematic illustration of the decision tree approach.

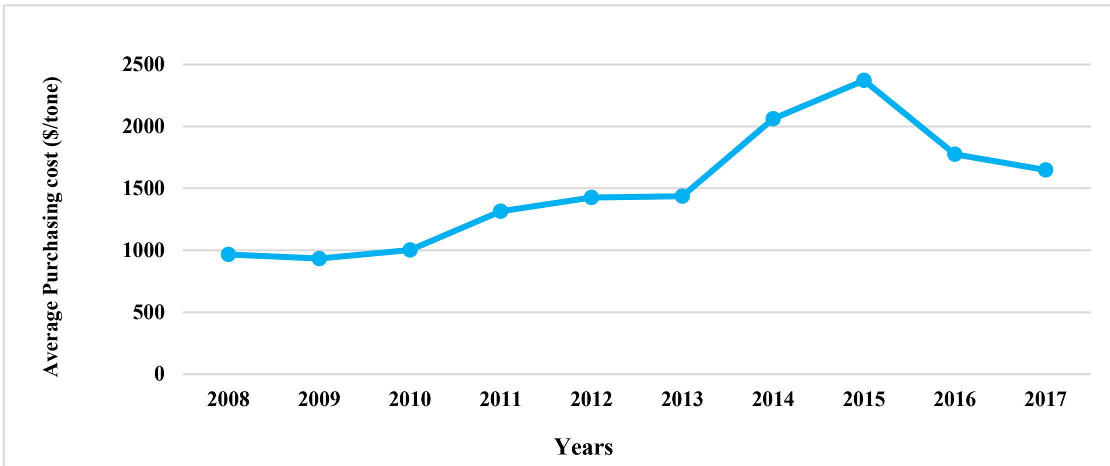

Fig. 5. Average purchasing cost of livestock from farmers by slaughterers for cows (Ontario Ministry of AgricultureFood and Rural Affairs, 2018).

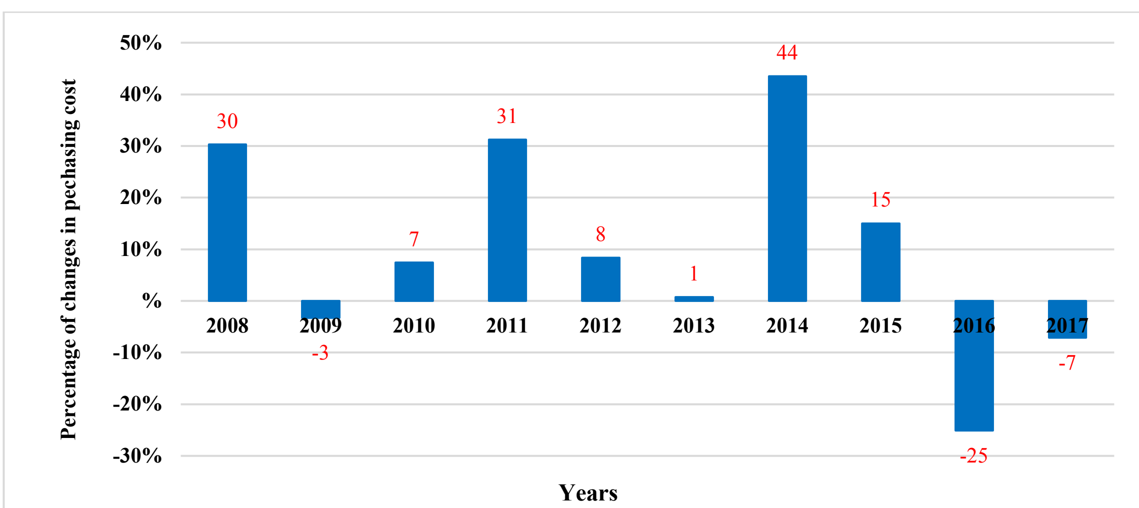

Fig. 6. Percentage of purchasing cost change for cows (Ontario Ministry of AgricultureFood and Rural Affairs, 2018).

preferred solution. Based on the results in Table 4, the emission objective has its minimum value when $v = 0$; the cost objective has the minimum value when $v = 1$, while the capacity utilization objective has its maximum value when $v = 8$. Particularly, the results indicate that improving the capacity objective by approximately 190% deteriorates the environmental objective by 2002%; and improving the capacity objective by approximately 134% deteriorates the economic objective by 170%. Fig. 3 illustrates a comparison between the three objectives in terms of obtained Pareto-optimal solutions. As Fig. 3 shows, all the objectives have a growing trend when v is increased. The model is solved in 10.34 s when $v = 0$ while the computational time is 27 s when $v = 8$. There are 5164 variables including 48 integer variables, 467 constraints, and 40,014 non-zero elements for both values of v.

Considering Step 4 of the solution method, one can see that the total cost is minimized subject to different constraints, including a maximum emission level and a minimum utilization value (constraints (13) and (14)). As illustrated in Fig. 3, by increasing the value of v, both the emission level and the capacity utilization will grow. This is because more emissions are allowed and the minimum capacity utilization is lifted. However, it is not easy to comment on the behavior of the total cost, since an increment in the value of v effects both the maximum emission level and the minimum utilization value simultaneously, i.e., it loosens constraint (13) while it tightens constraint (14). Such evidence is observable from Fig. 3, the incremental value of v does not favor the total cost when $v \geq 1$, while this behavior is different at $v = 0$.

7. Investigating the impact of uncertainty

The proposed mathematical model in Section 4 is a multi-period model that does not capture a consideration of uncertainty. However,

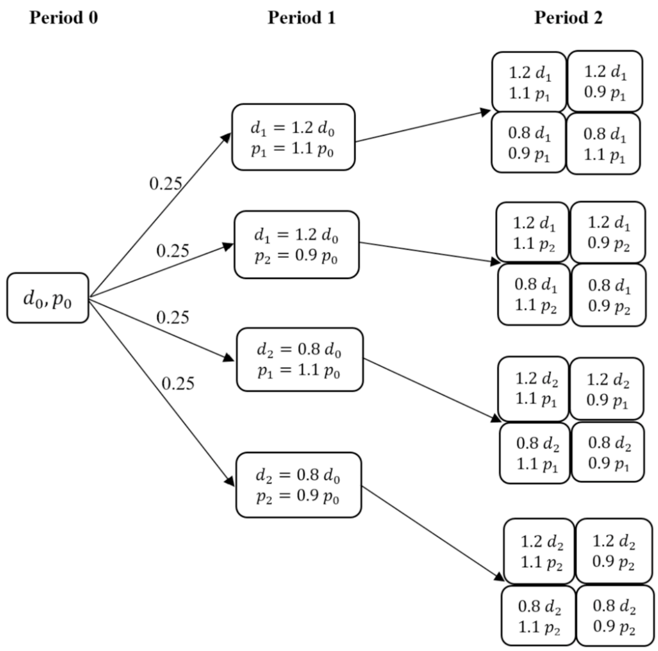

Fig. 7. Decision tree (first product).

Table 5
Cost in period 2 ($v = 3$).

Node	Cost ($)
$1.2\ d_1,\ 1.1\ p_1$	5,901,661
$1.2\ d_1,\ 0.9\ p_1$	5,825,623
$0.8\ d_1,\ 0.9\ p_1$	4,915,857
$0.8\ d_1,\ 1.1\ p_1$	5,011,947
$1.2\ d_1,\ 1.1\ p_2$	5,825,623
$0.8\ d_1,\ 1.1\ p_2$	4,915,857
$0.8\ d_1,\ 0.9\ p_2$	4,837,237
$1.2\ d_1,\ 0.9\ p_2$	5,763,410
$1.2\ d_2,\ 1.1\ p_1$	5,011,947
$1.2\ d_2,\ 0.9\ p_1$	4,915,857
$0.8\ d_2,\ 1.1\ p_1$	4,105,433
$0.8\ d_2,\ 0.9\ p_1$	3,992,346
$1.2\ d_2,\ 1.1\ p_2$	4,915,857
$1.2\ d_2,\ 0.9\ p_2$	4,837,237
$0.8\ d_2,\ 1.1\ p_2$	3,992,346
$0.8\ d_2,\ 0.9\ p_2$	3,899,819

when tackling real-world problems, we need to consider uncertain parameters. In this section, the multi-period model is converted to a single period model in order to consider uncertainty of financial factors in different periods. Then, a solution approach, which is called decision tree, is employed to investigate the effects of uncertainty in the mathematical model. Different studies employed the decision tree method to analyze uncertainty (Nepal and Yadav, 2015; Chopra and Meindl, 2015; Mogre and D'Amico, 2016; Abdi and Labib, 2017; Amin et al., 2017). The decision tree method gives a chance to decision makers to consider different scenarios along with their probabilities in designing supply chain networks. Fig. 4 shows the steps of the decision tree method, which is explained as follows:

1. Determining the number of time periods in the future and the duration of each period. Three periods (Period 0, Period 1, and Period 2) are considered here. The duration of each period is one year.
2. Identifying the sources of uncertainty in the network. The purchasing cost of livestock from farms and customer demand are two sources of uncertainty in this study.
3. Identifying a transition probability, which is the probability of moving forward from Period h to Period $h + 1$. Different transition probabilities are taken into account to see how this factor can affect the proposed model.
4. Determining the discount rate, *dr*, which is the rate of return of money in the future in each period. This rate helps to obtain the present value of future cash flow using the discount factor, *df*, which is obtained through the following formula:

$$df = \frac{1}{1 + dr}$$

5. Drawing the decision tree for predefined periods considering multiple nodes in each period. Each node consists of a combination of the values for uncertain parameters. Nodes are connected by arrows from Period h to Period $h + 1$. The transition probabilities are written on top of each arrow.
6. Evaluating the decision tree starting from the last period and moving back to the first period.

First, a single period multi-objective mixed-integer linear programming model is solved by employing the augmented ε-constraint method. As a result, Pareto-optimal solutions are generated. Then, the solution of $v = 3$ is chosen as the best solution considering the trade-offs between the three objectives. In the next step, the model is solved by the augmented ε-constraint method for each node of Period 2 while $v = 3$. This process helps to obtain the total cost for each node of the last period. Then, the expected cost of each node of Period 2, G, is calculated. Following this step, the total cost moved from Period 2 to Period 1, K, is calculated considering the discount factor. It should be noted that the total cost for each node of Period 1, C, needs to be obtained using the augmented ε-constraint technique to solve the single period and multi-objective mixed-integer linear programming model. The whole cost of Period 1 is obtained through the summation of K and L. The same process is utilized to obtain the whole cost of Period 0, which is called the Present Value of Total Cost (PVTC).

Different scenarios, which are considered for each product, are defined to investigate the effects of uncertainty. They are as follows:

a. Changes in demand and purchasing cost of livestock from farms.
b. Changes in transition probabilities
c. Changes in rate of return.

7.1. First product (cow)

According to the Ontario Ministry of Agriculture, Food and Rural Affairs (2018), the average purchasing cost of livestock has increased

Table 6
Total cost in Period 1.

Node	G = Expected cost in Period 2	K = Cost from Period 2 in Period 1 = $(G/[1 + dr])$	L = Cost of Period 1	$K + L$ = Total cost of Period 1
$1.2\ d_0,\ 1.1\ p_0$	5,413,772	4,921,611	4,940,993	9,862,604
$1.2\ d_0,\ 0.9\ p_0$	5,335,532	4,850,483	4,857,803	9,708,286
$0.8\ d_0,\ 1.1\ p_0$	4,506,396	4,096,723	4,979,181	9,075,904
$0.8\ d_0,\ 0.9\ p_0$	4,411,315	4,010,286	4,889,048	8,899,334

Table 7
Total cost in Period 0.

Node	M = Expected cost in Period 1	Q = Cost from Period 1 in Period 0 = (M/[1 + dr])	S = Cost of Period 0	Q + S = Total cost of Period 0
d_0, p_0	9,386,532	8,533,211	4,916,741	13,449,952

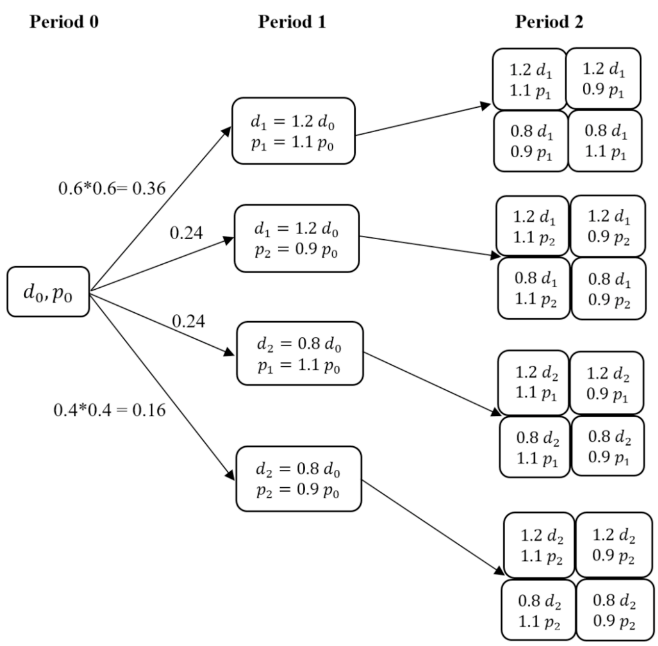

Fig. 8. Decision tree considering the new transition probabilities.

significantly from 2008 to 2017. Fig. 5 shows this growing trend. Fig. 6 illustrates the purchasing cost change percentage for cows based on Fig. 5. According to Fig. 6, the average change in the purchasing cost percentage for cows is 10%.

7.1.1. Changes in demand and purchasing cost of livestock from farms

In this subsection, the effects of uncertain parameters, which are the purchasing costs of livestock from Ontario farmers and customer demand, are investigated on the single period model. It is assumed that the demand increases or decreases by 20% with the probability of 0.5 for the first product (cow) for all customers. As was explained in the previous subsection, the purchasing costs of livestock increase or decrease by 10% with the probability of 0.5. The discount rate, *dr*, is considered 0.1 for each year.

Fig. 7 shows the decision tree including nodes with different values of demand and purchasing cost, and the transition probabilities, which are 0.5*0.5 = 0.25 for each arrow. Table 5 includes the obtained cost values for each node of Period 2. These results were obtained through employing the augmented ε-constraint technique for solving the single period and multi-objective mixed-integer linear programming model for each node of Period 2 while $v = 3$.

Table 6 contains the total cost in Period 1. For example, the expected cost in Period 2, $g = 0.25 \times$ (5,901,661 + 5,825,623 + 4,915,857 + 5,011,947) = 5,413,772. The cost from Period 2 moved to Period 1, K = 5,413,772/1.1 = 4,921,611. Then, the value of L is obtained through using the augmented ε-constraint technique to solve the single period multi-objective mixed-integer linear programming model for each node of Period 1. Therefore, the total cost of Period 1 is the summation of K and L, which is equal to 9,862,604. Similar calculations are used to obtain the total cost in Period 0 (see Table 7). Finally, Present Value of Total Cost (PVTC) = 4,916,741 (cost of Period 0) + 8,533,211 (cost moved from Period 1 to Period 0) = 13,449,952. The PVTC values help decision-makers to choose the best option (least cost) considering uncertainty when they are going to design different supply chain networks.

7.1.2. Changes in transition probabilities

In this subsection, the probabilities of increase or decrease in demand and purchasing cost are changed to see how the probabilities can affect the model. The probability of increase in uncertain parameters is considered 0.6, while the probability of decrease is assumed 0.4. Fig. 8 illustrates the decision tree considering the new transition probabilities. Tables 8 and 9 include the obtained results. The new PVTC is 13,619,768, which shows that changing one unit of transition probability can increase the PVTC by 1,698,161 because (13,619,768-13,449,952)/(0.6–0.5) = 1,698,161. The main reason for the above increment is the increase in the expected cost in Period 2, G. This leads to increase in the total cost of Period 1, $K + L$, and following that, the expected cost in Period 1, M.

7.1.3. Changes in rate of return

In this subsection, the discount rate, *dr*, is changed from 0.1 to 0.15. The other parameters remain the same, which means that the demand increased or decreased by 20% while the purchasing cost increased or decreased by 10% with the transition probability of 0.5. The new PVTC is 12,909,953, which shows that increasing the rate from 0.1 to 0.15 diminishes the PVTC by 539,999 because (12,909,953 - 13,449,952)/(0.15–0.1) = −539,999. The main reason for the above decrease is because the cost from Period 2 in Period 1, K, is diminished. This leads to decrease the total cost of Period 1, $K + L$, and following that, the expected cost in Period 1, M.

7.2. Second product (lamb)

According to the Ontario Ministry of Agriculture, Food and Rural Affairs (2018), the average purchasing cost of livestock has increased from $3380.6 per ton in 2008 to $5574.6 per ton in 2017. Fig. 9 shows this growing trend. Fig. 10 illustrates the purchasing cost percentage changes for lamb based on Fig. 9. According to Fig. 10, the average change in the purchasing cost percentage for cows is 6%.

Table 8
Total cost in Period 1.

Node	G = Expected cost in Period 2	K = Cost from Period 2 in Period 1 = (G/[1 + dr])	L = Cost of Period 1	K + L = Total cost of Period 1
1.2 d_0, 1.1 p_0	5,512,152	5,011,047	4,940,993	9,952,040
1.2 d_0, 0.9 p_0	5,434,206	4,940,188	4,857,803	9,797,991
0.8 d_0, 1.1 p_0	4,608,186	4,189,260	4,979,181	9,168,441
0.8 d_0, 0.9 p_0	4,512,779	4,102,527	4,889,048	8,991,575

Table 9
Total cost in Period 0.

Node	M = Expected cost in Period 1	Q = Cost from Period 1 in Period 0 = (M/[1 + dr])	S = Cost of Period 0	Q + S = Total cost of Period 0
d_0, p_0	9,573,330	8,703,027	4,916,741	13,619,768

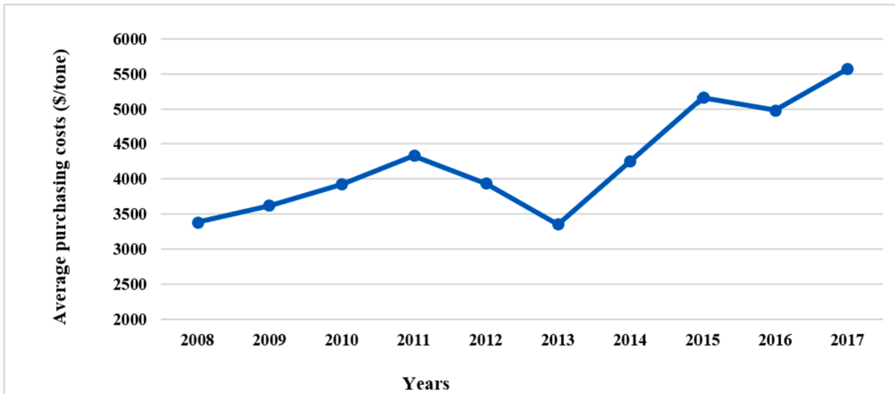

Fig. 9. Average purchasing cost of livestock from farmers by slaughterers for lamb (Ontario Ministry of AgricultureFood and Rural Affairs, 2018).

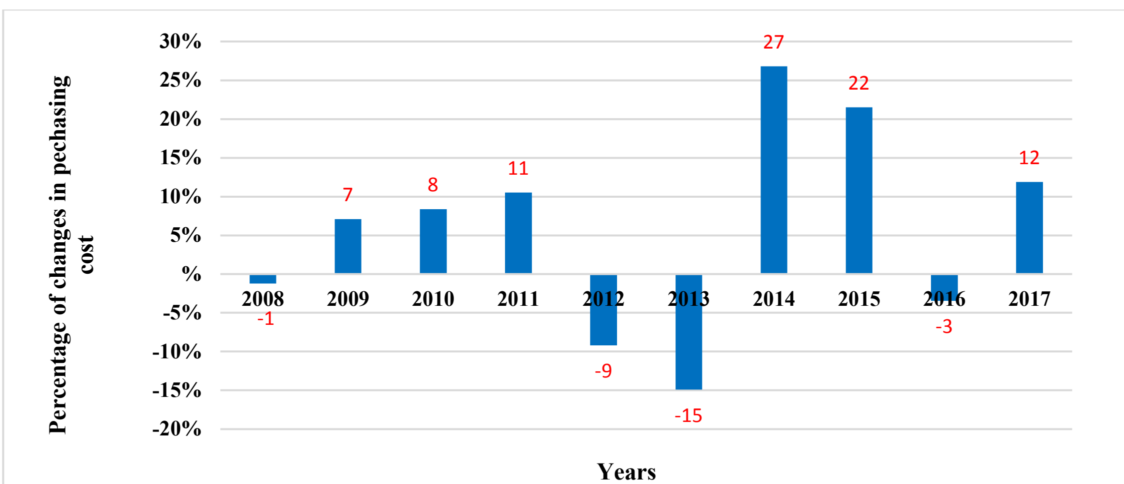

Fig. 10. Percentage of purchasing cost changes for lamb (Ontario Ministry of AgricultureFood and Rural Affairs, 2018).

7.2.1. Changes in demand and purchasing cost of livestock from farms

In this subsection, the effects of changing the uncertain parameters are investigated on the single period model for the second product, lamb. Like the first product, it is expected that the demand of lamb increases or decreases by 20% with the probability of 0.5. As it was explained in the previous subsection, the purchasing cost of livestock increases or decreases by 6% with the probability of 0.5. The discount rate, dr, remains the same, 0.1 for each year. Fig. 11 shows the decision tree. Transition probabilities are defined for each arrow as $0.5 \times 0.5 = 0.25$. Table 10 includes the calculated cost values for each node of Period 2. Like the first product, these results were acquired through employing the augmented ε-constraint method for solving the single period multi-objective mixed-integer linear programming model for each node of Period 2 while $v = 3$. Tables 11 and 12 contain the total cost in Period 1 and Period 0, respectively. The PVTC in this case is equal to 13,449,896, which is very close to the PVTC of the first product (13,449,952).

7.2.2. Changes in transition probabilities

In this part, the probability of increase in uncertain parameters is changed from 0.5 to 0.6 while the probability of decline is changed from 0.5 to 0.4. Fig. 12 displays the decision tree.

The new PVTC in this case is 13,629,095. Based on this calculation, changing one unit of transition probability can increase the PVTC by 1,791,989 because (13,629,095- 13,449,896)/(0.6–0.5) = 1,791,989. Like the first product, the main reason for the above increment is because the expected cost in Period 2, G, is increased. This leads to increase the total cost of Period 1, $K + L$, and following that, the expected cost in Period 1, M.

7.2.3. Changes in rate of return

In this subsection, the discount rate, dr, is changed from 0.1 to 0.15. The other parameters remain the same. The new PVTC is 12,909,900, which shows that increasing the discount rate from 0.1 to 0.15 diminishes the PVTC by 539,999 because (12,909,900–13,449,896)/(0.15–0.1) = −539,996. The main reason for the above decrease is because the cost from Period 2 in Period 1, K, is diminished. This leads to decrease the total cost of Period 1, $K + L$, and following that, the expected cost in Period 1, M.

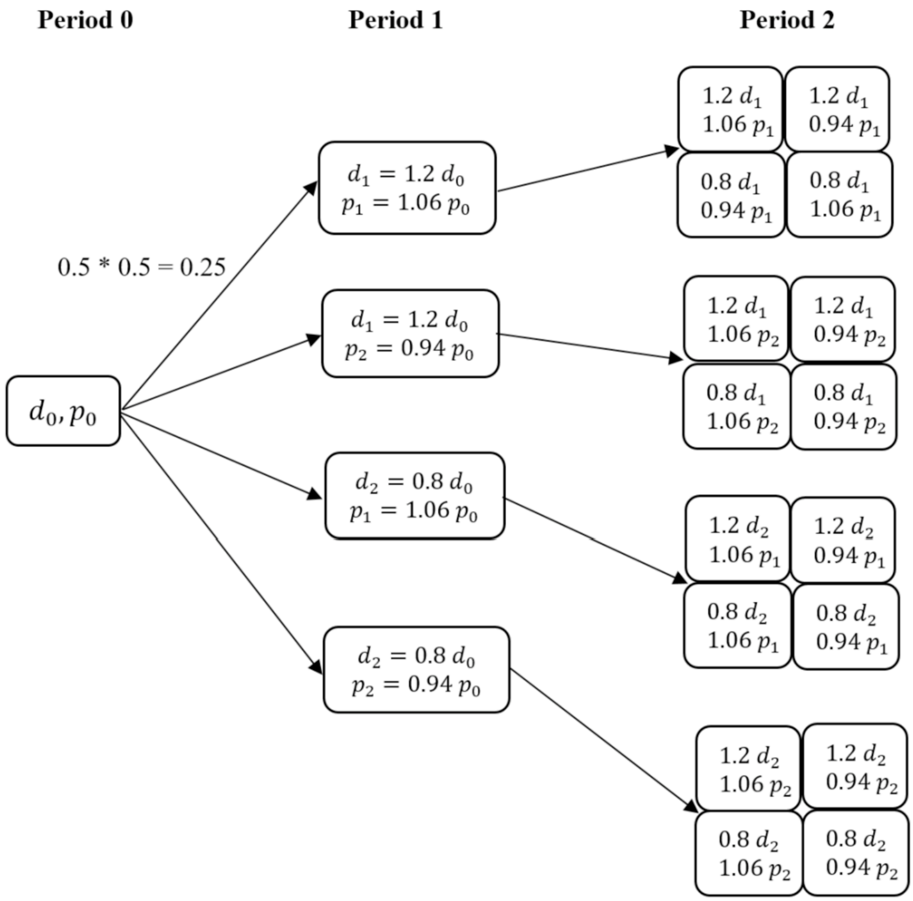

Fig. 11. Decision tree (second product).

Table 10
Cost in period 2 ($\nu = 3$).

Node	Cost ($)
$1.2\ d_1,\ 1.06\ p_1$	5,972,146
$1.2\ d_1,\ 0.94\ p_1$	5,918,419
$0.8\ d_1,\ 0.94\ p_1$	4,910,920
$0.8\ d_1,\ 1.06\ p_1$	4,946,735
$1.2\ d_1,\ 1.06\ p_2$	5,918,419
$0.8\ d_1,\ 1.06\ p_2$	4,910,920
$0.8\ d_1,\ 0.94\ p_2$	4,879,160
$1.2\ d_1,\ 0.94\ p_2$	5,870,774
$1.2\ d_2,\ 1.06\ p_1$	4,946,735
$1.2\ d_2,\ 0.94\ p_1$	4,910,920
$0.8\ d_2,\ 1.06\ p_1$	3,946,295
$0.8\ d_2,\ 0.94\ p_1$	3,922,421
$1.2\ d_2,\ 1.06\ p_2$	4,910,920
$1.2\ d_2,\ 0.94\ p_2$	4,879,160
$0.8\ d_2,\ 1.06\ p_2$	3,922,421
$0.8\ d_2,\ 0.94\ p_2$	3,901,249

8. Conclusions

In this study, a multi-product, multi-period, and multi-objective mixed-integer linear programming model has been developed to design and optimize a multi-echelon supply chain network including multiple farms, abattoirs, retailers, and customers. One of the main contributions of this paper is to consider a comprehensive network in the meat industry, which includes different elements such as customers. The other contribution of this paper is its consideration of both economic and environmental objectives in the proposed model. Three important objectives have been investigated simultaneously in this paper. They include minimizing total transportation cost and fixed costs, minimizing total CO_2 emissions released from transportation, and maximizing total capacity utilization in each echelon of the network.

The proposed model in this paper can determine the optimal number of products to be transported in each echelon of the network, and the optimal number and allocation of farms, abattoirs, and retailers. The augmented ε-constraint method has been employed to solve the proposed model. Then, the model has been applied to design a real green meat supply chain network in Southern Ontario, Canada, taking into account the real data, including distances between different

Table 11
Total cost in Period 1.

Node	G = Expected cost in Period 2	K = Cost from Period 2 in Period 1 = $(G/[1 + dr])$	L = Cost of Period 1	$K + L$ = Total cost of Period 1
$1.2\ d_0,\ 1.06\ p_0$	5,437,055	4,942,777	4,961,787	9,904,564
$1.2\ d_0,\ 0.94\ p_0$	5,394,818	4,904,380	4,919,553	9,823,933
$0.8\ d_0,\ 1.06\ p_0$	4,431,593	4,028,721	4,906,846	8,935,567
$0.8\ d_0,\ 0.94\ p_0$	4,403,438	4,003,125	4,878,692	8,881,817

Table 12
Total cost in Period 0.

Node	M = Expected cost in Period 1	Q = Cost from Period 1 in Period 0 = $(M/[1 + dr])$	S = Cost of Period 0	$Q + S$ = Total cost of Period 0
d_0, p_0	9,386,470	8,533,155	4,916,741	13,449,896

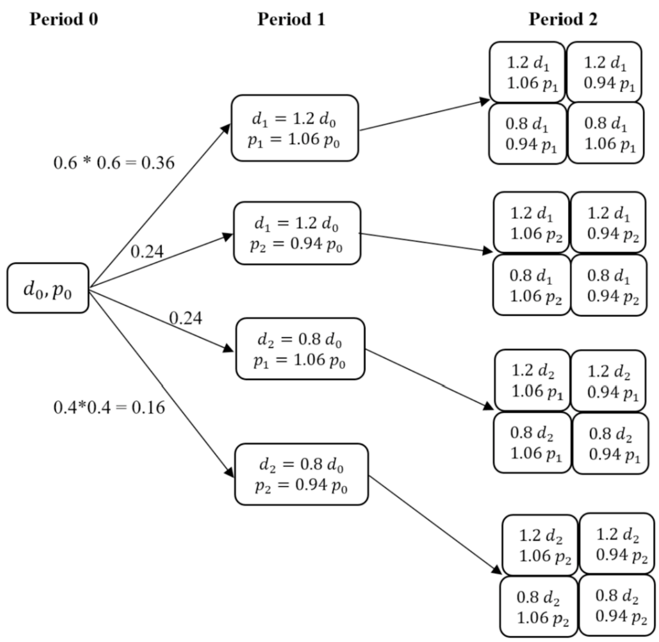

Fig. 12. Decision tree considering new transition probabilities.

facilities of the network using Google Maps.

By applying the augmented ε-constraint method, we generated several Pareto-optimal solutions that can be selected by managers based on their preferences. This set of Pareto-optimal solutions gives decision-makers the opportunity to make a trade-off between economic, environmental, and capacity utilization objectives. For example, it is possible to keep emissions reasonably low without incurring high total costs (e.g., $v = 1$ in Fig. 3). However, if supply chain managers only make decisions based on minimizing the environmental consequences or maximizing the capacity utilization of facilities, they might encounter significantly higher total costs (e.g., see $v = 0$ or $v = 8$ in Fig. 3).

In the second part of this research, the effects of uncertain parameters, which are customer demand and the purchasing costs of livestock from Ontario farmers, have been considered on the single period model employing several decision trees. This method helps decision-makers to choose the best network design option by comparing the Present Value of Total Cost (PVTC).

Through our illustrative example, we observed that a change in transition probability influences PVTC. However, this impact was not very significant in case of both products (i.e., 1.26% in the first product and 1.33% in the second product). Thus, it illustrates that PVTC is not very sensitive to transition probabilities and managers will have a good estimate of PVTC even without having accurate transition probabilities. Furthermore, unsurprisingly, the discount rate has a significant impact on PVTC since a larger discount rate will decrease PVTC. The impact was approximately the same for both products (almost 4%) when the discount rate was increased from 0.1 to 0.15. Thus, it is important for managers to have a good estimate of the discount rate before making decisions according to PVTC.

There are three research limitations worth mentioning for our study. Firstly, in our study, it is assumed that the transportation cost between facilities only depends on the distance. However, it is important to note that the transportation cost between any two points can be influenced by a variety of factors, such as the origin of movement. Secondly, only one type of trailer is assumed to be used for the movement of livestock from farms to abattoirs. Although 53-foot tri-axle combination freight livestock trailers are one of the most common trailers, a variety of other options (e.g., 24-foot cattle trailer) for the transportation of livestock from farms could also be considered. Lastly, in our study, no inventory of meat is allowed to be kept at a retailer from one period to the next. Since we based this assumption on our observation for fresh meats, our model cannot be applied directly to frozen meats which can be carried for multiple periods.

Some future research directions for this work are as follows: considering the inventory of meat in retailers for frozen meats; adding more objectives to the proposed model such as minimizing the delivery time of meat products where this would have a direct impact on the meat quality; and simultaneously investigating the impacts of uncertain parameters on both products.

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Appendix A. Additional information about facilities and their locations

Table A.1Names and locations of farms, abattoirs, and retailers

Item	Farms (cities)	Abattoirs (cities)	Large-Scale Retailers (cities)
1	Wishing Well Sanctuary (Bradford)	Townsend Butchers Inc. (Simcoe)	Walmart (Vaughan)
2	Cedar Row Farm Sanctuary (Lakeside)	ENS Poultry Inc (Elora)	No-frills (Guelph)
3	Beaver Creek Farm (Stevensville)	Mount Brydges Abattoir Ltd. (Mount Brydges)	Food basic (Strathroy)
4	DragonFly Farm Store (Chatsworth)	Country Meadow Meats (Owen Sound)	Walmart (Windsor)
5	Children's Animal Farm (sarina)	Beeton Meats (Beeton)	Beef way (Tiverton)
6	Buis Beef (Chatham)	Gord's Abattoir Ltd. (Leamington)	Metro (Barrie)
7	All Sorts Acre Farm (Ayton)	Weiland Meats Market (Petrolia)	Food basic (Scarborough)
8	Fairchild Farm (Hamilton)	Walkerton Meat Market (Walkerton)	Food basic (Toronto)
9	Meadow Lynn Farms (Simcoe)	Niagara Sausage & Meat Products Limited (Welland)	Walmart (Hamilton)
10	Clear Creek Farms (Highgate)	Atwood Heritage Processing Inc. (Atwood)	Walmart (Sarnia)
11	Meeting Place Organic Farm (Ashfield-Colborne-Wawanosh)	Millgrove Packers Limited (Waterdown)	No Frills (Kitchener)

12	Memoory Cattle Farms (Leamington)	Off the Bone Meat Products Ltd. (Mississauga)	Loblaws (Bowmanville)
13	DJ Farms (Staffa)		Walmart (Niagara Falls)
14	Armstrong Manor Farm (Caledon)		Food basic (Brantford)
15	Beretta Farms, (Etobicoke)		Metro (Owen Sound)
16			Real Canadian Superstore (Chatham)
17			Freshco (Cambridge)
18			Loblaws (Collingwood)
19			Metro (Tillsonburg)
20			No Frills (Mount Forest)
21			Foodland (Clinton)

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