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OPTIMISATION MODEL FOR A CHAIN LOGISTICS PROBLEM INVOLVING CHILLED FOOD UNDER CONDITIONS OF UNCERTAINTY

In the last two decades, food safety has become one of the main concerns in the area of logistics and supply chain management and also in the refrigeration or freezing of goods. Safety is a critically sensitive area in this field, as if the required safety conditions are not satisfied during the logistics process, foods will soon deteriorate and probably become unsafe for consumption by customers. Thus, the problem of ensuring the safety of chilled food has received serious attention among logistics practitioners. However, because of the complex nature of such problems, research so far has been limited to quantitative models with deterministic parameters and the robustness of the results from such models should be examined. In this paper, a robust optimisation model has been developed with the aim of optimising food safety aspects and thus minimising the logistics cost of a chilled chain system under various types of uncertainty and constraints on customers' time windows. Realizations of the model are solved by an algorithm based on artificial bee colony intelligence using MATLAB R2016a software. Finally, the results are analysed for possible real world considerations in order to propose some key practical highlights.

Keywords: *artificial intelligence, supply of chilled food, logistics, uncertainty*

1. Introduction

A chilled chain is a subject of supply chain management (SCM) in which the temperature of goods needs to be controlled throughout the logistics chain including supply, production, transportation, storage, distribution and delivery to the final customers and can be identified as a physical process in the supply and logistics of certain processed foods [17]. The management of chilled chains is a logistics procedure that involves

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maintaining ideal storage conditions for spoilable goods, such as fresh meat, fresh and frozen seafood, flowers, vegetables, from the point of origin to the point of consumption by the final consumer. According to the basic functions of logistics, chilled-chain operations can be divided into four key areas as follows: procurement (generating, processing, buying, evaluating and admission), storage (storing, loading, controlling and sorting), transmission (transport, loading, controlling and division) and consumption (final storing and sorting) [16].

The key problem here is that the goods involved in chilled chains, require precise temperature handling to remain damage free, although even without such concerns, damaged food can lead to losses in sales and reputation [6]. According to Keener [9], the monitoring of the temperature of most foods in the USA is poor and no-one knows whether food safety regulations are precisely followed. Based on his estimates, the losses due to such issues are around $2 billion per year, which includes healthcare costs. Broadly speaking, various kinds of problems result in unsafe food in chilled chains with expiration date and microbial growth being assumed to be the most important causes of such problems. The number of microorganisms in foods as a result of bacterial hazards is a major factor affecting food safety and reliability, as this measure is sensitive to changes during the transportation process. Hence, control of logistic safety is an important subject in the field of the management of chilled chains.

Optimisation theory can be applied to the issue of chilled chain logistics by developing the classical travelling salesman problem (TSP) to determine the optimal assignment of fleet vehicles to cargo goods. However, due to the complexity of models of chilled chains, the advances in quantitative research in this area are mainly based on deterministic models with few real-world constraints. Therefore, this paper presents a routing optimization (RO) model for raising the safety of chilled chains and minimizing logistical costs under uncertainty and scenario-based market demand. In addition, constraints on time windows and the fleet of vehicles available are added to the model to provide greater compatibility with real-world issues.

The paper is divided as follows. After an introduction and literature review, a mathematical model is developed, then a solution procedure is described. After that, an example is solved and computational results are obtained and analysed. Finally, in the last section, conclusions are highlighted and further developments to this study are proposed.

2. Literature review

Increasing concerns regarding food safety and quality in the area of logistics and the supply chain has encouraged the transition from SCM to FSCM (food supply chain management). In FSCM, the quality of the products provided continuously change from one step to another. These variations in product safety and quality make traditional SCM procedures, which do not take perishability into account, inappropriate [3]. Perishable products, and especially chilled goods, require special management procedures and modelling which are able to cope with challenges such as temperature control, improving quality and safety, and also waste reduction [5].

In the literature about the modelling and optimisation of the safety of chilled chains, physical loss, reliability and constraints on time windows are key issues. In addition, the basis for optimisation in logistical issues regarding chilled food chains is mainly constructed around an improved version of the TSP and vehicle routing issues from the point of view of modelling. Almonacid-Merino and Torres [1] suggested a mathematical design to measure temperature and adverse effects during the distribution of frozen foods. Koutsoumanis et al. [10] extended the shelf life decision system (SLDS) to analyse fish safety and quality. Bahk et al. [2] proposed a design for the quantitative assessment of the risk of microbes. James et al. [7] prepared a review of models of systems for supplying groceries in light of raising concerns about sustainability in supply chains. A comprehensive literature review is provided by Soysal et al. [18] on quantitative designs for the management of viable food supply chains. In terms of logistics, this involves modelling a chilled food chain.

Li et al. [12] developed an optimisation model for a chilled food chain considering the possible loss of goods. Qiu et al. [16] used the notion of cross docking in chilled food chain management and Yifeng and Ruhe [19] proposed an optimisation model for chilled food chain logistics taking into account safety and reliability. Despite the fact that research on the problem of designing logistical policies for food safety has led to improvements, uncertainty of demand is still a major consideration in the area of chilled chain logistics, as it is in a vast range of economic activities. Hence, in this work, an RO model is developed to design policies for chilled chain logistics under uncertainty of demand.

3. Description of the model

In this section, first, a procedure for measuring the reliability of safety for a chilled logistic chain is identified and then an improved mathematical model is proposed on the basis of minimising the costs of transport and losses associated with food safety issues in a chilled logistics system composed of one supply depot with a number of end customers (markets).

Generally, the concentration of microorganisms (CFU/g) is a key factor for measuring safety in a chilled logistics chain. Based on the time, temperature, tolerance (TTT) theory, the concentration of microorganisms can be accurately modelled on the basis of the model proposed by Zwietering et al. [21]. The concentration of microorganisms in a specific chilled chain is formulated by Eq. (1), which indicates that the concentration of microorganisms (n_t) mainly depends on two terms, the square of temperature variation $(T - T_{\min})^2$ and time (t). This model, presumes that before the logistics process starts, the initial concentration of microorganisms (n_0) is small. In addition, the constant b reflects the specific conditions of a system and l denotes the lag time of microorganism growth (in h).

$$n_t = n_0 \mathrm{e}^{b^2 (T - T_{\min})^2 (t - l)} \tag{1}$$

The above equation can also be extended to obtain a measure of food safety based on the concentration of microorganisms, as shown in Eq. (2). First the measure of food safety for one logistic unit (Rs) is estimated and then the measure of food safety for a chilled chain system (d) is defined by Eq. (3). In this formulation, $n_{\min}$ denotes the lowest concentration of microorganisms to cause food-borne disease (CFU/g).

$$Rs = 1 - \frac{\log n_t}{\log n_{\min}} = 1 - \frac{0.434 b^2 \left(T - T_{\min}\right)^2 t + \log n_0}{\log n_{\min}} \tag{2}$$

$$d = \frac{0.434 b^2}{\log n_{\min}} \tag{3}$$

Next, based on this theory, as used by Yifeng and Ruhe [19], this measure of food safety may be included in a model of a chilled chain system. Suppose journey k takes t_k units of time. The losses per food unit due to food safety issues for this journey may be defined by (RS_k) as given in Eq. (4), where v is defined to be the loss due to food safety issues per unit of food per unit of time (h). The total losses due to food safety issues for a chilled logistics chain (Csl) formed by one main supply depot (node 0), J demand nodes (customers, nodes 1–J) and M fleet vehicles can be derived by summing the costs over all the journeys. This is defined as in Eq. (5). In this formulation, t_{ij} is the travel time between nodes i and j plus the process time at node j. In addition, q_j^m and x_{ij}^m are defined to be the decision variables describing the amount delivered to node j by vehicle m and the indicator variable defining whether or not vehicle m is assigned to the route between i and j, respectively, i.e., $x_{ij}^m = 1$, when vehicle m travels along the route between i and j, otherwise $x_{ij}^m = 0$.

$$RS_k = vd \left(T - T_{\min}\right)^2 t_k \tag{4}$$

$$Csl = vd\left(T - T_{\min}\right)^2 \sum_{m=1}^{M}\sum_{j=0}^{J}\sum_{i=0}^{J} t_{ij}x_{ij}^{m}q_{j}^{m} \tag{5}$$

As mentioned, Eq. (5) denotes the total loss due to safety issues for a chilled logistics chain composed of j logistical units. However, all the parameters in this model are considered to be deterministic. This assumption may limit the applicability of this model to real-world problems. Thus, this work takes into account the fact that the market has uncertain demand and limited arrival time windows imposed by consumers, in order to formulate the losses due to safety issues. Based on the assumption of uncertain market demand, the unit costs of transport and losses due to safety issues are assumed to be scenario-based and subject to change. Multiple vehicles are available and the goal of the optimisation model is to determine the best vehicle routes and allocations to the consumers in a chilled food chain. To formulate the proposed model, first, the notation is presented in Section 3.1 and then the mathematical model is developed in Section 3.2.

3.1. Notation

The notation used in the mathematical model is defined below. $s \in S$, $i, j \in J$, $m \in M$ indexes for scenarios, depots, customers and vehicles.

T – temperature of goods, °C
$T_{\min}$ – temperature at which no microorganism growth occurs, °C
d – constant food security parameter of the chilled logistics chain
c^s – vehicle transport charge per unit time under scenario s
v^s – losses due to safety issues in the chilled chain per unit time under scenario s
Q_j^s – demand in market j under scenario s
L, U – lower and upper limit on demand
C_m – capacity of vehicle m
tp_j – process time at node j, h
td_{ij} – transport time between nodes i and j, h
t_{ij} – total time including transport and handling procedure
sw_j, fw_j – limited time window for customer j, h
a_j – arrival time at market j, h
n – total number of available transport vehicles
θ^s, θ_j^s – deviation for the contravention of the mean and control constraints under scenario s
λ, ω – weights for the trade-off between cost and convenience, weights of the pen-
– alties for surpluses or stock-outs per unit
q_j^m – variable describing demand in market j provided by vehicle m

x_{ij}^{m} – indicator variable describing whether or not vehicle m is used on the route between i and j

p^{s} – probability of the occurrence of scenario s

3.2. Mathematical model

Here, the RO is improved to formulate a model of a chilled logistics chain under uncertainty in all markets, considering the optimality and convenience achieved in each scenario. The RO defined for this problem is based on the model introduced by Mulvey et al. [14], which incorporates a goal programming structure with a set of scenarios with random inputs. Yu and Li [20] and Kosiński et al. [11] described a linear version of RO with fewer variables and constraints. Generally, RO is considered to be a powerful optimization procedure under uncertainty based on two types of robustness: the robustness of solutions (the solution is close to optimal in all scenarios) and the robustness of the model (the solution is close to maximum convenience in all scenarios).

In this work, the RO model is improved by combining the costs of transport from depot to markets together with the costs resulting from safety factors in the chilled logistics chain when market demands are subject to uncertainty according to various market scenarios where each scenario occurs with a specified probability. The robust model for the optimisation of a chilled logistics chain is based on the objective function (6) with its design and structural constraints given by Eqs. (7)–(18).

Minimise

$$
\begin{aligned}
&\sum_{s} p_s \left(c^s\right) \sum_{m}\sum_{j}\sum_{i} t_{ij} x_{ij}^{m} + v^s d\left(T - T_{\min}\right)^2 \sum_{m}\sum_{j}\sum_{i} t_{ij} x_{ij}^{m} \\
&+\lambda \sum_{s} p_s \left(\sum_{m}\sum_{j}\sum_{i} t_{ij} x_{ij}^{m} + v^s d\left(T - T_{\min}\right)^2 \sum_{m}\sum_{j}\sum_{i} t_{ij} x_{ij}^{m} q_j^{m} \right. \\
&\left. -\sum_{s} p_s \left(c^s \sum_{m}\sum_{j}\sum_{i} t_{ij} x_{ij}^{m} + v^s d\left(T - T_{\min}\right)^2 \sum_{m}\sum_{j}\sum_{i} t_{ij} x_{ij}^{m} q_j^{m} \right) + 2\theta^s \right) \\
&+\sum_{s}\sum_{j} w p_s \delta_j^s
\end{aligned}
\tag{6}
$$

subject to

$$
\sum_{m}\sum_{i} x_{ij}^{m} = 1;\ \forall\ j \in J\left(j \neq i\right) \tag{7}
$$

$$\sum_{m}\sum_{j} x_{ij}^{m} = 1;\ \forall\ i \in J\ \left(j \neq i\right) \tag{8}$$

$$\sum_{j} x_{ij}^{m} = \sum_{j} x_{ji}^{m};\ \forall\ \ j \in J,\ m \in M\ \left(i \in J \neq j\right) \tag{9}$$

$$\sum_{j} x_{ij}^{m} = \sum_{j} x_{ji}^{m};\forall\ i,\ j \in J,\ m \in M \tag{10}$$

$$\sum_{m}\sum_{i} x_{ij}^{m} \leq M;\ \forall\ i = 0 \tag{11}$$

$$\sum_{j} q_{j}^{m} \leq C_{m};\ \forall\ i = 0 \tag{12}$$

$$L\sum_{i} x_{ij}^{m} \leq q_{i}^{m} \leq U\sum_{i} x_{ij}^{m};\ \forall\ m \in M,\ j \in J \tag{13}$$

$$sw_{j} \leq a_{j} \leq fw_{j};\ \forall\ \ j \in J \tag{14}$$

$$x_{ij}^{m} = \sum_{m}\sum_{i} x_{0t_1}^{m} x_{t_1 i}^{m} x_{jt_2}^{m} x_{t_2 0}^{m};\ \forall\ m \in M,\ t_1, t_2 \neq 0 \neq i \neq j \in J \tag{15}$$

$$\sum_{m}\sum_{i} x_{ij}^{m} q_{j}^{m} - Q_{j}^{s} + \delta_{j}^{s};\ \forall\ s \in S,\ j \in i \tag{16}$$

$$\begin{aligned}
&c^{s}\sum_{m}\sum_{j}\sum_{i} t_{ij}x_{ij}^{m} + v^{s} d\left(T - T_{\min}\right)^{2}\sum_{m}\sum_{j}\sum_{i} t_{ij}x_{ij}^{m}q_{j}^{m} \\
&-\sum_{s} p_{s}\left(c^{s}\sum_{m}\sum_{j}\sum_{i} t_{ij}x_{ij}^{m} + v^{s} d\left(T - T_{\min}\right)^{2}\sum_{m}\sum_{j}\sum_{i} t_{ij}x_{ij}^{m}q_{j}^{m}\right) \\
&+\ \theta^{s} = 0;\ \forall\ s \in S
\end{aligned} \tag{17}$$

$$x_{ij}^{m} \in \left\{0,\ 1\right\},\ q_{j}^{m} \geq 0 \tag{18}$$

The constraints described in this model can be interpreted as follows: Constraint (7) shows that each consumer needs to be served once only by only one vehicle. Constraint (8) imposes that exactly one vehicle leaves a particular origin. Constraint (10) indicates that there is at most one vehicle travelling on the route from i to j. Constraint (11) limits the quantity of vehicles departing from the depots. Constraint (12) indicates the load capacity of each transport. Constraint (13) connects the amount of demand from a consumer satisfied by each vehicle to the number of a vehicle sent to that particular consumer zone. Constraint (14) is the time window constraint which limits the arrival time of the vehicle departing from a depot via any selected route to the consumer node at a suitable time for that consumer. Constraint (15) limits the selection of any interim vertex to one which begins from and ends at the origin. Constraint (16) is a control constraint to meet the uncertain demand for each consumer in an admissible manner according to a fulfilment level which can be justified by RO according to a trade-off between convenience and optimality. Constraint (17) indicates that a solution is robust to deviations. Constraint (18) specifies which variables are non-negative and which are binary.

4. Solution procedure

Based on the computational properties of this model, this problem is placed in the class of NP-hard problems. Heuristics are the most commonly used and suitable approaches considered for such problems in the literature. Recently, the artificial bee colony (ABC) algorithm was found to have higher efficiency than other commonly applied heuristics for the migrant salesman and fleet routing problems [12, 13]. Since this article considers an expanded version of the TSP based on the characteristics of the model, the ABC algorithm is investigated as a new and vigorous bio-inspired heuristic to solve the proposed model of a robust chilled logistics chain under uncertainty.

Based on the initial artificial bee colony algorithm introduced by Karaboga [8], the ABC model possesses the following main features: initialization, recruited bees (bees that detect and utilize the main sources of nectar and deliver it to the hive), onlooker bees (who start searching by applying data from recruited bees though waggle dances) and scout bees (who start by searching for food at random without any previous knowledge). Based on this model, food sources are interpreted as a population of possible solutions and the quantity of nectar at each source is the fitness of the related solution. Each food source is assumed to have only one recruited bee and if the quantity of nectar at a source reduces, foragers abandon this source and become scouts. Several general parameters describing the population size, maximum number of iterations (MNI) and bounds are required to be pre-set, while each of the thee mentioned bee groups evolve according to how food sources (the population of solutions) are encountered in iterative steps until the MNI is achieved.

First, in the initialization stage, after setting the general parameters, the estimated density of the food source (x_{mi}) is initialised randomly by the scouts:

$$x_{mi} = l_i + \text{rand}(0, 1)(u_i - l_i) \tag{19}$$

where x_{mi} is the solution vector, m: 1, ..., N is the generation number, and i: 1, ..., n denote the variables describing possible solution vectors. In addition, l_i and u_i are the lower and upper bounds, respectively, on the solution. Next, in the recruited bee phase, recruited bees search for new food supplies (v_{mi}) with more nectar in the vicinity of a solution that has already been found (x_{mi}). If such a new solution is fitter than the previous one, then the bee memorises this new solution and the old one is removed from its memory. The value of the new food source (v_{mi}) is generally estimated as below

$$v_{mi} = x_{mi} + \text{ rand}(-n, n)(x_{ki} - x_{mi}) \tag{20}$$

where x_{ki} is a randomly selected source and rand(–n, n) is a random number within this range. Then value of the new food source (v_{mi}) is calculated and greedy selection is applied to choose between x_{mi} and v_{mi}. The fitness value for the solution x_{mi}, $f_m(x_{mi})$, is calculated as:

$$f_m(x_{mi}) = \begin{matrix} \dfrac{1}{1 + f_m(x_{mi})} \; f_m(x_{mi}) \geq 0 \\ 1 + \left| f_m(x_{mi}) \; f_m(x_{mi}) < 0 \right| \end{matrix} \tag{21}$$

Next, in the observer bee stage, a fitness-based selection technique, such as roulette wheel selection, is used. In this study, the probability of selecting a food supply is proportional to the corresponding fitness measure. Hence, the probability with which x_m is selected (p_m) is calculated as below:

$$p_m = \frac{f_m(x_{mi})}{\sum_m^n f_m(x_{mi})} \tag{22}$$

Based on this probability distribution, one food source is chosen by an onlooker and an adjacent solution is also produced. The final choice is made according to the greedy application, as in the employed bee phase. Finally, servitor bees whose effectiveness has not improved for a pre-set number of trials become scouts and their solutions are erased from memory and new scouts start searching for new sources. These steps are repeated until the stop criteria (MCN) is satisfied.

5. Examples

In this section, two examples are described and solved using the proposed algorithm. These examples are characterized by the distance between pairs of nodes, consisting of the origin (the supply depot) and consumer nodes, the set of vehicles available (together with their load capacities) and the costs related to transport and goods losing their value. Consumer demand has limited time windows and is scenario-based. The distance matrix gives the distance between the depot and market nodes and the time needed to deliver to each node.

In this chilled chain, the measure of safety loss (d) is fixed to be 10^{-4} with the current transport temperature being 10 °C. In addition, the temperature at which no microorganism growth occurs is presumed to be 5 °C. Also, a maximum of 2 vehicles can be used for transportation with capacities of 10 and 14 tons, respectively. In addition, the average speed of both vehicles is 100 km/h. The unit costs of transportation and value loss per unit time depend on the market conditions, which can be described as “boom” in scenario 1, which occurs with a probability of 0.3, and “as expected” in scenario 2, which occurs with a probability of 0.7. The remaining parameters are specified in Tables 1 and 2.

Table 1. Distance matrix for the depot (0) and the set of market nodes [km]

	0	1	2	3	4
0	–	100	80	90	70
1	100	–	100	50	60
2	80	100	–	80	90
3	90	50	80	–	60
4	70	60	90	60	–

Table 2. Parameters describing each consumer zone and unit charges (costs) associated with the scenarios

<table>
<tr><th>Scenario</th><th>Customer zone</th><th>Demand [t]</th><th>Unit transportation cost [$/h]</th><th>Unit loss of safety cost [$/h]</th><th>Required process time [h]</th><th>Acceptable time windows [h]</th></tr>
<tr><td rowspan="4">1</td><td>1</td><td>7</td><td rowspan="4">12</td><td>11 500</td><td>0.15</td><td>(0.5, 3)</td></tr>
<tr><td>2</td><td>7</td><td>11 500</td><td>0.1</td><td>(0.5, 2)</td></tr>
<tr><td>3</td><td>6</td><td>11 500</td><td>0.1</td><td>(0.5, 3)</td></tr>
<tr><td>4</td><td>9</td><td>11 500</td><td>0.2</td><td>(0.5, 2)</td></tr>
<tr><td rowspan="4">2</td><td>1</td><td>6</td><td rowspan="4">10</td><td>10 000</td><td>0.15</td><td>(0.5, 3)</td></tr>
<tr><td>2</td><td>4</td><td>10 000</td><td>0.1</td><td>(0.5, 2)</td></tr>
<tr><td>3</td><td>5</td><td>10 000</td><td>0.1</td><td>(0.5, 3)</td></tr>
<tr><td>4</td><td>8</td><td>10 000</td><td>0.2</td><td>(0.5, 2)</td></tr>
</table>

Table 3. Computational results for case 1 ($w = 8$)

Vehicle 1						Vehicle 2					
	Depot	Markets					Depot	Markets			
	0	1	2	3	4		0	1	2	3	4
0	–	0	0	0	1	0	–	0	1	0	0
1	0	–	0	0	0	1	1	–	0	0	0
2	0	0	–	0	0	2	0	1	–	0	0
3	1	0	0	–	0	3	0	0	0	–	0
4	0	0	0	1	–	4	0	0	0	0	–
Arrivals [h]		–	–	1.5	0.7	Arrivals [h]		1.9	0.8	–	–
Quantities [t]		0	0	5.13	3.64	Quantities [t]		4.02	3.77	0	0
Unfulfilled demand in each scenario [t]						Unfulfilled demand in each scenario [t]					
S	1	–	–	0.87	5.36	*S*	1	2.98	3.23	–	–
	2	–	–	–0.13	4.36		2	1.98	0.23	–	–
Total cost [$] 842											
Transportation cost				Safety loss cost		Mean var. penalty cost			Unfulfilled demand penalty cost		
59				546		98			136		

Table 4. Computational results for case 2 ($w = 10$)

Vehicle 1						Vehicle 2					
	Depot	Markets					Depot	Markets			
	0	1	2	3	4		0	1	2	3	4
0	–	0	0	1	0	0	–	0	1	0	0
1	0	–	0	0	0	1	0	–	0	0	0
2	0	0	–	0	0	2	0	0	–	0	1
3	1	1	0	–	0	3	0	0	0	–	0
4	0	0	0	0	–	4	1	0	0	0	–
Arrivals [h]		1.5	–	0.9	–	Arrivals [h]		–	0.8	–	1.8
Quantities [t]		5.27	0	4.69	0	Quantities [t]		0	3.36	0	6.30
Unfulfilled demand in each scenario [t]						Unfulfilled demand in each scenario [t]					
S	1	1.73	–	1.31	–	*S*	1	–	3.64	–	2.7
	2	0.73	–	0.31	–		2	–	0.64	–	1.7
Total cost [$] 937											
Transportation cost			Safety loss cost			Mean var. penalty cost			Unfulfilled demand penalty cost		
57			683			111			86		

This problem is solved using the ABC algorithm by considering 300 sources of food supplies and employed bees, 300 onlooker bees with a limit of 70 which means if servitor bees cannot sufficiently increase their rate of food intake in 70 steps, then they become scouts. The algorithm runs for 500 iterations. In addition, λ is chosen to be equal to 1 and in order to analyse the robustness of the solution to variations in the costs of not meeting demand, the problem is solved for two values of ω (the unit cost for not meeting demand). For cases 1 and 2, ω is equal to 8 and 10, respectively. The problem is solved for both cases and the results obtained are presented in Tables 3 and 4.

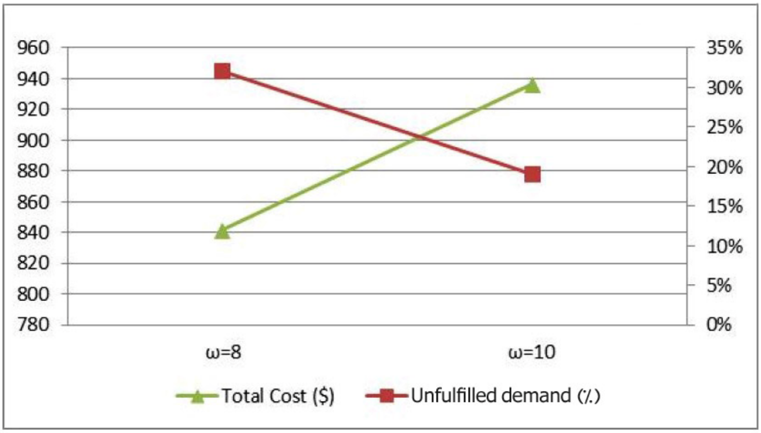

Fig. 1. Solution and robustness of the model with respect to the unit cost for unfulfilled demand, ω

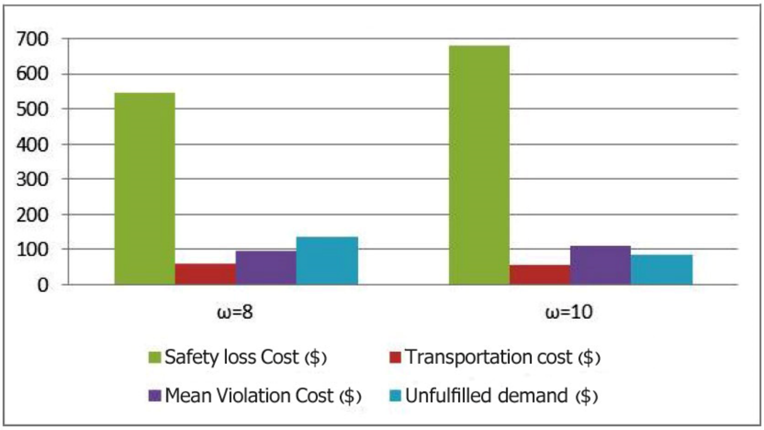

Fig. 2. Total cost breakdown with respect to the unit cost for unfulfilled demand, ω

In cases 1 and 2, two very different optimal solutions are obtained on the basis of minimizing the sum of the costs of transport, safety loss, and unfulfilled demand. In the first case ($w = 8$), according to Table 3, the optimal routes of vehicles 1 and 2 are specified as 0-4-3-0 and 0-2-1-0, respectively. This means that consumers 4 and 3 are served by vehicle 1 and customers 2 and 1 are assigned to vehicle 2. The optimal amounts supplied to each consumer are also presented in Table 3, together with the level of unfulfilled demand in each market scenario. Additionally, the arrival time of each transport to each assigned consumer region satisfies the time window restrictions. Finally, the total costs of such a solution, based on all the component costs, are calculated for the optimal solution. The best solution for the second instance ($w = 10$), is presented in Table 4. By comparing Tables 3 and 4, it is noteworthy that due to ω rising from 8 to 10, the total cost increased from \$842 to \$937. On the other hand, the level of unfulfilled demand was lower in case 2. These results are illustrated in Figs. 1 and 2. Figure 1 compares two different trends in the total cost (evidence for an effective solution) and the relative level of unfulfilled demand (evidence for a robust model). When ω was increased, the relative level of unfulfilled demand fell to 19%, as compared to 32% in case 1. On the other hand, this resulted in an increase in the total costs. Figure 2 illustrates the distribution of the component costs. The increase in the costs of safety loss is much greater than the changes in other costs. Transport costs remain nearly the same. The costs due to unfulfilled demand fall, as the relative fall in unfulfilled demand outweighs the relative increase in the costs of not meeting demand and mean violation costs increase slightly.

6. Conclusions

This article has presented a robust model for a chilled chain logistics system where customers' demands and, accordingly, revenue are uncertain and subject to change. In this optimisation problem, customer restrictions on arrival time windows are incorporated into the model based on the nature of cold chain products, in terms of time sensitivity and related safety issues. This optimisation model is used to determine the optimal transportation plan stating which vehicle is dispatched and how much is supplied to each market in order to minimise the costs of transportation and safety loss under uncertain market conditions considering the optimality and feasibility of all scenarios. In addition, two numerical examples are solved by applying the ABC algorithm using MATLAB R2016a software. Finally, the solutions indicate a trade-off between various components of the total costs and, importantly, that the costs due to safety loss are very sensitive to changes in the parameters (e.g., the unit costs related to unsatisfied demand).

This paper has extended research on modelling and optimizing chilled logistic chains and optimization by defining an RO model under uncertainty. However, this work can also be extended by, e.g., increasing the number of logistic units or using other methods of solution.

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