Multi-criteria optimization for a cost-effective design of an RFID-based meat supply chain

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Abstract

Purpose – In this paper, the authors investigated a proposed RFID (radio frequency identification)-based meat supply chain to monitor quality and safety of meat products they purchase from supermarkets. The supply chain consists of farms, abattoirs and retailers. The purpose of this work presented in this paper was to determine a cost-effective trade-off decision obtained from a developed multi-criteria optimization model based on three objectives. These objectives include customer satisfaction in percentage of product quantity as requested by customers, product quality in numbers of meat products and the total implementation cost. Furthermore, this work was aimed at determining the number and locations of farms and abattoirs that should be established and quantities of products that need to be transported between entities of the proposed supply chain.

Design/methodology/approach – To this aim, a tri-criteria optimization model was developed. The considered criteria were used for minimizing the total implementation cost and maximizing customer satisfaction and product quality. In order to obtain Pareto solutions based on the developed model, four solution approaches were employed. Subsequently, a new decision-making algorithm was developed to select the superior solution approach in terms of values of the three criteria.

Findings – A case study was applied to examine the applicability of the developed model and the performance of the proposed solution approaches. The computational results proved the applicability of the developed model in obtaining a trade-off among the considered criteria and solving the RFID-based meat supply chain design problem.

Practical implications – The developed tri-criteria optimization model can be used by decision makers as an aid to design and optimize food supply chains.

Originality/value – This article presents a development of (i) a cost-effective optimization approach for a proposed RFID-based meat supply chain seeking a trade-off among three conflicting criteria; and (ii) a new decision making algorithm which can be used for any multi-criteria problem to select the best Pareto solution.

Keywords: Meat supply chain; Multi-criteria optimization; Customer satisfaction; Decision making algorithm.

1. Introduction

Meat supply chains generally constitute four different echelons which forms a network including farms, abattoirs, retailers and customers. In recent years, safety and quality of food products, which are supplied through a food supply chain network, has been one of major issues on which consumers demand more transparent information relating to food they purchase at supermarkets (Ahmed, 2008; Lever & Miele, 2012). A study by Peattie, Peattie & Jamal (2006) suggested that consumers often spend a considerable amount of time and effort seeking out fresh food by reading information such as expiry dates shown on product labels to ensure that they purchase a good quality of food products. One way to provide the prompt information on food status is to implement the RFID technology. In the past decade, implementation of RFID technology has been gaining an ever-increasing popularity as it enhances traceability of safety and quality of food products (Chrysochou et al., 2009; Manos & Manikas, 2010; Zailani et al., 2010).

Through a literature review, little research works were found for investigating the RFID-enabled supply chains seeking a compromised solution between the benefits of the RFID implementation in supply chains and its need for additional costs in relevance to the supply chain network design. In this paper, the authors examined a proposed RFID-based three-echelon meat supply chain seeking a compromised solution based on objective functions relating to the total implementation cost, customer satisfaction in percentage of satisfying customers' demand in product quantity, and product quality in numbers of meat products. To this aim, a tri-criteria mixed integer linear programming model was developed. The work also includes the determination of (i) number and locations of farms and abattoirs that should be established and (ii) quantities of livestock transported from farms to abattoirs and meat products transported from abattoirs to retailers. By solving the tri-criteria optimization problem, four solution approaches were investigated. These are compromise programming, goal programming, weighted Tchebycheff and utility function. A developed decision making algorithm was employed to select the superior solution approach based on computational results values. This approach can be used as a reference for decision makers to obtain **a cost-effective design** of food supply chains.

2. Prior studies

Multi-objective optimization refers to an optimization of multiple decision making objectives concurrently. These objectives are possibly conflicting and competing. According to a thesis work of Almaraz, 2014, in a multi-objective problem, it is impossible to obtain a single ideal solution but a trade-off among a number of objectives, since there is a contradictory among the objectives. Pareto optimal solutions are obtained based on multiple conflicting criteria. Multi-criteria optimization models were applied into supply chain network designs for solving production-distribution planning problems (Gen & Heng, 1997; Deb, 2001; Shen & Daskin, 2005; Shen & Daskin, 2005; Sabri & Beamon, 2009; Pandu, 2009; Hu & Li, 2009;). These problems can be strategic in such as the facility location-allocation problem or tactical in such as the flow of product quantities. Costs or profits are among one of other issues that may need to be considered (Jayaraman and Pirkul 2001, Syam 2002 and Syarif, Yun, and Gen 2002, Jayaraman and Ross 2003, Yan, Yu, and Cheng 2003). Altiparmak, Gen, Lin, and Paksoy (2006) proposed a genetic algorithm focusing on minimization of inbound and outbound distribution costs and maximization of customer services in terms of delivery time and capacity of distribution centers. Selim, Araz & Ozkarahan (2008) presented a multi-criteria optimization model to cope with a production-distribution planning problem in a supply chain. Fuzzy goal programming was used to incorporate decision maker's imprecise goal levels for each objective. Ferrio and Wassick (2008) formulated a mixed integer linear programming model for configuring and optimizing the design of a multi-product chemical supply chain network which consists of production sites, arbitrary numbers of distribution centers, and customers. Schütz, Tomasgard and Ahmed (2008) formulated a decision support system using a two-stage stochastic program with respect to minimizing costs of investment and operations of a supply chain. Tuzkaya and Onut (2009) studied a three-level supply chain including supplier, warehouses, and manufacturers seeking the best distribution plan of products. Li et al. (2009) developed a multi-objective optimization model to configure distribution center locations; the considered objectives were minimization of the transportation cost, transportation and production carbon emissions. Chang (2010) presented a single-objective mathematical model to optimize a multiple level supply chain network design encompassing suppliers, factories, distribution centers and retailers. The considered objective was to minimize the total cost including purchasing and transportation cost of raw materials and products, manufacturing cost of products in factories, and storage cost of products in distribution centers. Alumur et al. (2012) proposed a profit maximization modeling framework for a reverse logistics network design problem. The same method was also used by Sadjady and Davoudpour (2012) to tackle a two-level supply chain network design problem. The problem was formulated as a mono-criteria optimization model to minimize total cost, which include costs in transportation, lead-times and inventory for products and opening and operating costs for facilities. Pourrousta et al. (2012) developed a multi-objective model to minimize total cost and delivery time of products in a multi-echelon supply chain network. Liu and Papageorgiou (2014) proposed a multi-criteria optimization model for tackling a production–distribution and capacity planning problem in a supply chain using the ε-constraints and Lexicographic min–max methods.

3. Mathematical formulation

In this study, a meat supply chain comprises three echelons: farms, abattoirs and retailers, was studied. In this chain, farms supply livestock to abattoirs where slaughtered livestock as packed meat products are transported to retailers. The RFID technology was proposed for tracing safety and quality of meat products during the transportation process from farms to abattoirs and from abattoirs to retailers (Mohammed & Wang, 2015). Fig. 1 depicts the structure illustration of the investigated meat supply chain.

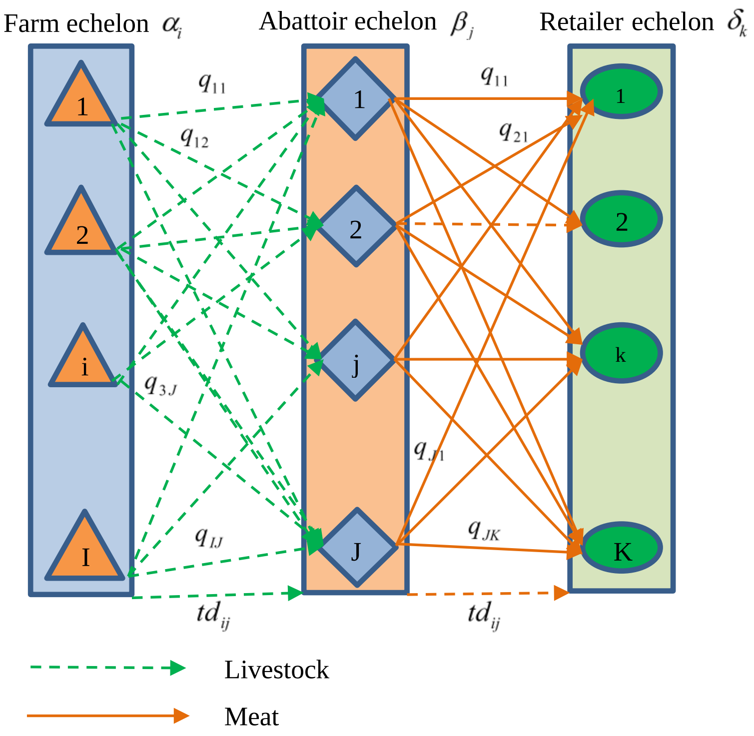


Fig. 1. The structure of the meat supply chain network.

To formulate the tri-criteria model, the following indices, parameters and decision variables are presented.

Indices

I	index used for a potential location of farm i , $1\le i \le I$
J	index used for a potential location of abattoir j , $1\le j \le J$
K	index for a fixed location of retailer k , $1\le k \le K$

Cost parameters:

C_i^{α}	cost (£) of RFID equipment and implementation required for farm i
C_j^{β}	cost (£) of RFID equipment and implementation required for abattoir j
C_i^t	RFID tag cost (£) for each item at farm i
C_j^t	RFID tag cost (£) for each item at abattoir j
TC_{ij}	unit transportation cost (£) per mile from farm i to abattoir j
TC_{jk}	unit transportation cost (£) per mile from abattoir j to retailer k
LC_i^{α}	unit labor cost (£) per hour at farm i
LC_j^{β}	unit labor cost (£) per hour at abattoir j

Parameters of capacity, demand and transportation distance:

S_{i}^{α}	maximum supply capacity (units) of farm i
S_{j}^{β}	maximum supply capacity (units) of abattoir j
W_v	transportation capacity (units) per vehicle (v)
$\mathrm{D}_{\mathrm{j}}^{\beta}$	minimum demand (in units) of abattoir j
$\mathrm{D}_{\mathrm{k}}^{\delta}$	minimum demand (in units) of retailer k
d_{ij}	travel distance (mile) from farm i to abattoir j
d_{jk}^{n}	travel distance (mile) from abattoir j to retailer k

Labor parameters:

$R_i^{l\alpha}$	working rate (items) per laborer (l) at farm i
$R_j^{l\beta}$	working rate (items) per laborer (l) at abattoir j
$N_i^{h\alpha}$	minimum required number of working hours (h) for laborer l at farm i
$N_j^{h\beta}$	minimum required number of working hours (h) for laborer l at abattoir j

Other parameters

Q_{ij}	healthiness percentage of livestock transported from farm i to abattoir j
F_{jk}	freshness percentage of meat products ~~pieces~~ transported from abattoir j to retailer k

Decision variables:

q_{ij}	quantity of units transported from farm i to abattoir j
q_{jk}	quantity of units transported from abattoir j to retailer k
x_i^{α}	number of required laborers at farm i
x_j^{β}	number of required laborers at abattoir j

Non-negative and binary decision variables:

$$y_{\mathrm{i}}^{\alpha} = \begin{cases} 1\text{: if farm } i \text{ is open} \\ 0\text{: otherwise} \end{cases}$$

$$\mathrm{y}_{\mathrm{j}}^{\beta} = \begin{cases} 1\text{: if abattoir } j \text{ is open} \\ 0\text{: otherwise} \end{cases}$$

The criteria functions are formulated as follows:

The minimum total cost F_1 = costs of RFID equipment and implementation + RFID tag cost for each item + transportations costs – labor costs saved after the RFID implementation, **i.e.,**

$$\begin{aligned} Min\ F_1 = & \sum_{i\in I} C_i^{\alpha} y_i^{\alpha} + \sum_{j\in J} C_j^{\beta} y_j^{\beta} + \sum_{i\in I} C_i^{t\alpha} q_{ij} + \sum_{j\in J} C_j^{t\beta} q_{jk} \\ & + \sum_{i\in I}\sum_{j\in J} TC_{ij} \left\lceil q_{ij} / W_v \right\rceil d_{ij} + \sum_{j\in J}\sum_{k\in K} TC_{jk} \left\lceil q_{jk} / W_v \right\rceil d_{jk} \\ & - \sum_{i\in I} LC_i^{\alpha} x_i^{\alpha} N_i^{h\alpha} - \sum_{j\in I} LC_j^{\beta} x_i^{\beta} N_j^{h\beta} \end{aligned} \tag{1}$$

The maximum customer satisfaction F_2 = the fulfilment of demand in percentage of product quantity as requested by customers, i.e.,

$$Max\ F_2 = \sum_{k=1}^{K} \left(\sum_{j=1}^{J} q_{ij} \middle/ D_k^{\delta} \right) \tag{2}$$

Maximum product quality F_3 = healthiness of livestock transported from farms to abattoirs + freshness of meat pieces transported from abattoirs to retailers, i.e.,

$$Max\ F_3 = \sum_{i=1}^{I} Q_{ij} y_i^{\alpha} + \sum_{j=1}^{J} F_{jk} y_j^{\beta} \tag{3}$$

Several constraints are grouped in different categories as follows:

Capacity constraints: show the capacity constraints of farms and abattoirs.

$$\sum_{i\in I} q_{ij} \le S_i^{\alpha}\ y_i^{\alpha} \qquad \forall\ j \in J \tag{4}$$

$$\sum_{j\in J} q_{jk} \le S_j^{\beta}\ y_j^{\beta} \qquad \forall\ k \in K \tag{5}$$

Demand constraints: ensure that the demands in quantity of products of all abattoirs and retailers are satisfied.

$$\sum_{i\in I} q_{ij} \ge D_j^{\beta} \qquad \forall\ j \in J \tag{6}$$

$$\sum_{j\in J} q_{jk} \ge D_k^{\delta} \qquad \forall\ k \in K \tag{7}$$

$$D_j^{\beta} \ge \sum_{k\in K} q_{jk} \qquad \forall\ j \in J \tag{8}$$

Working rate constraints**:** determine the required number of laborers at farms and abattoirs.

$$\sum_{j\in J} q_{ij} \le x_i^{\alpha}\ \mathrm{R}_i^{\mathrm{l}\alpha} \qquad \forall\ \mathrm{i} \in I \tag{9}$$

$$\sum_{k\in K} q_{\mathrm{jk}} \le x_{\mathrm{j}}^{\beta}\ \mathrm{R}_{\mathrm{j}}^{\mathrm{l}\beta} \qquad \forall\ \mathrm{j} \in J \tag{10}$$

Restriction constraints: restrict the decision variables to binary and non-negative.

$$q_{ij}, q_{jk}\ \ge 0,\ \forall i, j, k; \tag{11}$$

$$y_i^{\alpha}, y_j^{\beta}\ \in \{0,1\},\ \forall i, j; \tag{12}$$

Finally, $0.75 \le Q_{ij} \le 1$ and $0.75 \le F_{jk} \le 1$ constraints, which limit the healthiness percentage (Q) and the freshness percentage (F) to be between 0.75 and 1 (based on decision makers' preferences).

4. Multi-criteria optimization methodology

Multi-criteria optimization involves the simultaneous optimization of a number of decision making criteria which are conflicting and often competing. In order to solve this type of optimization problem, researchers deal with a set of solutions known as Pareto optimal solutions. Nevertheless, it can be a case that none of these Pareto solutions is better than the others considering all the criteria. Different approaches can be aided in solving such a problem. In this study, four different solution approaches were investigated aimed to obtain four sets of Pareto solutions to be selected as the best one in terms of solution quality

4.1. Compromise programming approach

The compromise programming approach is its ability to achieve efficient points in a non-convex Pareto curve (Chankong & Haimes, 1983). This method based on optimizing one criterion function and shifting the other to the constraint set to **be** restricted to an assigned value (ε). The equivalent solution formula F is presented as follows.

$$\begin{aligned} Min\ F\ =&\sum_{i\in I} C_i^{\alpha} y_i^{\alpha} + \sum_{j\in J} C_j^{\beta} y_j^{\beta} + \sum_{i\in I} C_i^{t\alpha} q_{ij} \\ &+\sum_{j\in J} C_j^{t\beta} q_{jk} + \sum_{i\in I}\sum_{j\in J} TC_{ij} \left\lceil q_{ij} / W_v \right\rceil d_{ij} + \sum_{j\in J}\sum_{k\in K} TC_{jk} \left\lceil q_{jk} / W_v \right\rceil d_{jk} \\ &-\sum_{i\in I} LC_i^{\alpha} x_i^{\alpha} N_i^{h\alpha} - \sum_{j\in I} LC_j^{\beta} x_i^{\beta} N_j^{h\beta} \end{aligned} \tag{13}$$

Additional constraints:

$$\sum_{k=1}^{K}\left(\sum_{j=1}^{J} q_{ij} \Big/ D_k^{\delta}\right) \geq \varepsilon_1 \tag{14}$$

$$\left[\sum_{k=1}^{K}\left(\sum_{j=1}^{J} q_{ij} \Big/ D_k^{\delta}\right)\right]^{\min} \leq \varepsilon_1 \leq \left[\sum_{k=1}^{K}\left(\sum_{j=1}^{J} q_{ij} \Big/ D_k^{\delta}\right)\right]^{\max} \tag{15}$$

$$\sum_{i=1}^{I} Q_{ij} y_i^{\alpha} + \sum_{j=1}^{J} F_{jk} y_j^{\beta} \geq \varepsilon_2 \tag{16}$$

$$\left[\sum_{i=1}^{I} Q_{ij} y_i^{\alpha} + \sum_{j=1}^{J} F_{jk} y_j^{\beta}\right]^{\min} \leq \varepsilon_2 \leq \left[\sum_{i=1}^{I} Q_{ij} y_i^{\alpha} + \sum_{j=1}^{J} F_{jk} y_j^{\beta}\right]^{\max} \tag{17}$$

In this paper, criterion function one is selected to be optimized based on Eq.13 and shifting criterion function two and three to be constraints (Eq. 14 and 16 respectively); An increase to the ε value (Eq.15 and 17) yields Pareto solutions.

4.2. Goal programming approach

The purpose of the goal programming approach is to find a solution that minimizes undesirable deviations between the objective functions and their corresponding goals (Charnes, Cooper & Ferguson, 1955; Colapinto, Jayaraman & Marsiglio, 2015). The solution functions are expressed as follows:

$$Min\ F \tag{18}$$

$$\frac{\varsigma^{1}}{\mathrm{G}^{1}} \leq F \tag{19}$$

$$\frac{v^{2}}{G^{2}} \leq F \tag{20}$$

$$\frac{v^{3}}{G^{3}} \leq F \tag{21}$$

The equivalent criteria functions are expressed as follows.

$$\begin{aligned}Min\ F_1 = &\sum_{i\in I} C_i^{\alpha} y_i^{\alpha} + \sum_{j\in J} C_j^{\beta} y_j^{\beta} + \sum_{i\in I} C_i^{t\alpha} q_{ij} + \sum_{j\in J} C_j^{t\beta} q_{jk} \\ &+ \sum_{i\in I}\sum_{j\in J} TC_{ij} \left\lceil q_{ij} / W_v \right\rceil d_{ij} \\ &+ \sum_{j\in J}\sum_{k\in K} TC_{jk} \left\lceil q_{jk} / W_v \right\rceil d_{jk} - \sum_{i\in I} LC_i^{\alpha} x_i^{\alpha} N_i^{h\alpha} - \sum_{j\in I} LC_j^{\beta} x_i^{\beta} N_j^{h\beta} \\ &+ \varsigma^1 - \upsilon^1 = \mathrm{G}^1\end{aligned} \tag{22}$$

$$Max\ F_2 = \sum_{k=1}^{K} \left(\sum_{j=1}^{J} q_{ij} \Big/ D_k^{\delta} \right) + \varsigma^2 - \upsilon^2 = \mathrm{G}^2 \tag{23}$$

$$Max\ F_3 = \sum_{i=1}^{I} Q_{ij} y_i^{\alpha} + \sum_{j=1}^{J} F_{jk} y_j^{\beta} + \varsigma^3 - \upsilon^3 = \mathrm{G}^3 \tag{24}$$

Where

G^1	goal of the criterion 1
G^2	goal of the criterion 2
G^3	goal of the criterion 3
ς^1	negative deviation variable of the criterion 1
ς^2	negative deviation variable of the criterion 2
ς^3	negative deviation variable of the criterion 3
υ^1	positive deviation variable of the criterion 1
υ^2	positive deviation variable of the criterion 2
υ^3	positive deviation variable of the criterion 3

Subject to an additional non-negativity restriction:

$$\varsigma,\ v\ \geq 0, \tag{25}$$

4.3. Weighted Tchebycheff approach

With this approach, the multi-objective possibilistic model can be transformed into a single-objective model *F*. The purpose of the single-objective model is to minimize the distance between the ideal objective vector *F** and the feasible objective surface (Miettinen, 1998). The solution approach function *F* can be formulated as follows:

$$Min\ F = \left(\sum_{n=1}^{3} l_n \left| F_n - F^* \right|^p \right)^{\frac{1}{p}} \tag{26}$$

Subject to constraints 4-12. Noticeably, the values of objective functions vary depending on the value of p. Usually, p is set as 1 or 2. But, other values of p can also be used. In this case study, p is set as 1.

4.4. Utility function approach

In the utility function approach, the effectiveness utility of each Pareto solution is determined by summing the scaled criteria functions. The scalar value λ for each criterion is determined by decision maker according to the importance for each criterion (Stoll, 1999). In this work, the criterion function (or utility function) U is expressed as follows:

$$U(F_1, F_2) = \left\{ \sum_{n=1}^{2} \lambda_n F_n \,\middle|\, \lambda_n < 1, \sum_{n=1}^{2} \lambda_n = 1 \right\} \tag{27}$$

4.5. Decision making algorithm

In this paper, the selection algorithm is based onto two stages; in the first stage the best trade-off solution is selected for each set of solutions. Selecting the superior approach is determined in the subsequent stage. The next two sub-sections present the two stages respectively.

4.5.1. Global criterion approach

There are several methods for selecting the most suitable solution in a multi-objective problem. In this case, the global criterion method was used for determining the best solution by minimizing the distance to the ideal objective value F_n^* (Pandu, 2009). The decision making formula is expressed as follows:

$$Min\ F = \left(\sum_{n=1}^{3} \left| F_n - F_n^* \right|^{\rho} \right)^{1/\rho}; \quad 1 \le \rho \le \infty \tag{28}$$

In this approach, the solution with the minimum distance is selected as a best solution. Generally, ρ is 1; However, other values of ρ also can be used.

4.5.2. The developed approach

The idea of the developed approach for selecting the best approach is based on selecting the solution approach that is closest to the ideal solution. In this approach, S^* represents the average superiority value for each approach; (i) determine the average mean value for the three criterion functions, (ii) sum the three average mean values, and (iii) select the approach with the lowest superiority value. The selection formula is presented as follows:

$$S^* = \sum_{n=1}^{3} \frac{F_n}{F_n^*} \tag{29}$$

Where F_i^* is the ideal value for each criterion. This value is determined by optimizing the criteria functions individually.

5. Application and comparison: South East London as a case study

A case study is presented to demonstrate the applicability of the developed tri-criteria model and compare the performance of the proposed solution approaches in terms of the criteria values. In the case study, the South-East area of London encompasses 4 farms (*I)*, 7 retailers (*K)* and 4 abattoir (*J)* suppliers. Table 1 shows the collected data which are chosen in a defined range (based on assumptions). Data, which are related to locations of farms, abattoirs and retailers, were collected from the Meat Committee in the UK (HMC, 2015). The transportation distances between supply chain facilities were estimated using Google-Maps. The demand reported in Table 1 is the total demand over a one-year period. The prices of RFID equipment and its implementation were estimated based on the marketing prices.

Table 1. Parameters used for the case study

$I = 4$
$J = 7$
$K = 4$
C_i^{α} = 4.4K-8.8K (£)
TC_{ij} = 20 (£)
C_i^t = 0.15 (£)

C_j^{β} = 1.1K-8K (£)
TC_{jk} = 20 (£)
S_i^{α} = 2.5K-4.4K
S_j^{β} = 1.2K-1.8K
D_j^{β} = 800-1.3K

D_k^{γ} = 100-800
d_{jk} = 110 – 162
W_v = 100
$R_i^{1\alpha}$ = 50
$R_j^{1\beta}$ = 50
C_j^t = 0.15 (£)

d_{ij} = 23- 400
LC_i^{α} = 6.5 (£)
LC_j^{β} = 6.5 (£)
F_{jk} = 0.75-1
Q_{ij} = 0.75-1

The tri-criteria optimization problem described in Section 3 was investigated using four different approaches. This was carried out using the LINGO^{11} software on a computer with corei5-CPU 2.60 GHz, RAM 4.00 GB.

Table 2 elucidates the values obtained using equation 1-3, respectively. Each value was optimized based on each criterion for obtaining the ideal solution. As shown in Table 2, the total cost can be minimized to £194,180 based on the criterion function one, while in this solution the criterion function two and three worsen to 75% and 8,885 items of meat products respectively. On the antithesis, if the second criterion function F_2 was only considered, customer satisfaction would increase to 100%. However, the total cost increases to £491,000. Finally, considering the third criterion F_3 individually, the objective of product quality, which increases to 13,099 items of meat product leading to an increase in the total cost of £481,390 and customer satisfaction of 99%. In this situation, the contradictory is manifested between these three criteria functions. However, moving toward an enhancement in **customer** satisfaction and product quality in supply chains requires significantly higher cost investment.

Table 2. The values of the three criteria obtained by the individual optimization.

Criterion function	**Min F_1 (£)**	**Max F_2 (%)**	**Max F_3 (Items)**
F_1	194180	0.75	8885
F_2	491000	1	13099
F_3	481390	0.99	13099

As discussed above, it can be easily noticed that there is no solution which is optimal as it is impossible to obtain an optimal solution towards the three criteria at a time. To this aim, four solution approaches were employed for seeking the Pareto sets derived from co-optimizing the three contradicting criteria by minimizing total cost F_1, maximizing **customer** satisfaction F_2 and maximizing product quality F_3.

Pareto optimal solutions can be obtained using: (i) the compromise programming approach by altering the incremental epsilon value of 526 between 8,885 to 13,099 for criterion two (Eq.15) and of **0.025** between 0.75 to 1 for criterion three (Eq.17); (ii) the goal programming approach by assigning eight different goals for the three criteria ; (iii) the weighted Tchebycheff approach using the ideal values of the three criteria functions illustrated in Table 2_were given as ideal values F_1^*, F_2^*, F_3^* for the solution function F using Eq.26; and (iv) the utility function approach using different scalar values λ.

Table 3 shows four sets of Pareto optimal solutions which were obtained using the four solution approaches. These solutions also include numbers of farms and abattoirs that should be established. Shown in Table 3, the third column shows the values of the first criterion function (F_1), obtained values of the second and third criterion functions (F_2 and F_3) in terms of percentage and items are presented in the fourth and fifth columns, respectively. The last two columns (right-end) correspond to the number of farms and abattoirs that should be established.

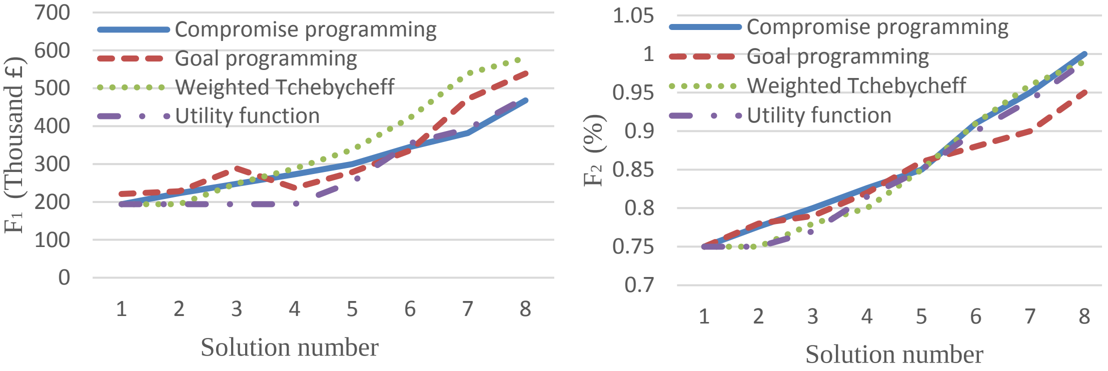
Table 3. Pareto solutions obtained by using four different approaches.

Solution approach	#	Min (F_2) (£)	Max (F_2) (%)	Max (F_3) (items)	Open farms	Open abattoirs
Compromise programming	1	194180	0.75	8885	1 0 0 1	0 1 0 1
	2	223257	0.776	9411	1 0 1 1	0 1 0 1
	3	248214	0.8	9937	1 0 1 1	0 1 0 1
	4	273171	0.826	10473	0 0 1 1	0 1 0 1
	5	300475	0.85	10989	1 0 1 1	1 0 1 1
	6	345228	0.91	11515	1 1 1 1	1 1 0 1
	7	382940	0.95	12041	1 1 1 1	1 0 1 1
	8	468475	1	13099	1 1 1 1	0 1 1 0
Goal programming	1	221655	0.75	8885	1 1 1 1	1 1 1 1
	2	228705	0.78	8913	0 1 1 1	1 1 1 0
	3	288810	0.79	9912	1 0 0 1	0 1 0 1
	4	237050	0.82	10311	1 1 1 1	1 1 1 1
	5	279835	0.86	10586	1 0 0 1	1 0 1 1
	6	336480	0.88	10642	1 1 1 1	1 1 1 1
	7	4724750	0.9	11313	1 1 1 1	1 1 0 1
	8	5391300	0.95	12141	0 0 1 1	0 1 1 0
Weighted Tchebycheff	1	194180	0.75	8885	1 0 0 1	0 1 0 1
	2	194180	0.75	8885	1 0 0 1	0 1 0 1
	3	249231	0.78	8920	1 0 1 1	1 1 1 1
	4	288557	0.8	9808	1 1 1 1	1 1 1 1
	5	338858	0.85	10414	1 1 1 1	1 1 1 1
	6	422451	0.91	11094	1 1 1 1	1 1 0 1
	7	539128	0.96	12376	1 1 1 1	1 1 1 1
	8	580471	0.99	13029	1 0 0 1	0 1 0 1
Utility function	1	194180	0.75	8885	1 0 0 1	0 1 0 1
	2	194180	0.75	8885	1 0 0 1	0 1 0 1
	3	194180	0.77	9411	0 0 1 1	0 1 0 1
	4	194180	0.815	10162	1 0 1 1	1 0 1 1
	5	253475	0.85	10876	1 1 1 1	1 1 0 1
	6	355336	0.9	11444	1 1 1 1	1 0 1 1
	7	392720	0.94	12131	1 1 1 1	0 1 1 0
	8	475660	0.99	13032	1 1 1 1	0 1 1 1

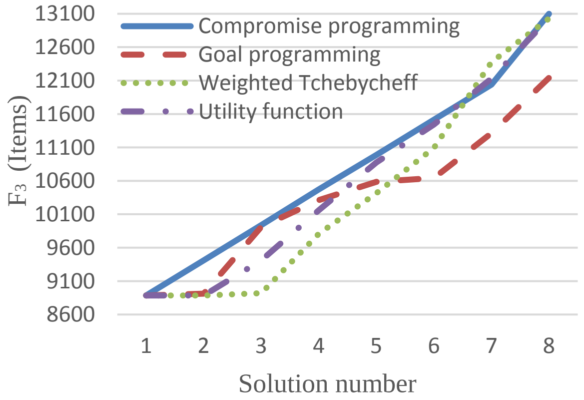
For instance, solution number 4 was obtained using the compromise programming approach by assigning $\varepsilon_1 = 0.825$ and $\varepsilon_2 = 10{,}470$; accordingly, it gives the minimum total cost of £273,171, the maximum customer satisfaction of 82.6% and the maximum product quality of 10,473 items of meat products. This solution also includes an establishment of farms three and four (0 0 1 1) and abattoirs two and four (0 1 0 1). As observed in Table 3, Pareto optimal solutions cannot be obtained according to one criterion without worsening its performance in other criteria.

5.1. Selecting the superior approach

To design the meat supply chain network, decision makers often need to find a solution based on a number of alternative possibilities using a decision making approach. Fig. 2 illustrates Pareto fronts based on optimizing the three criteria using four solution approaches.



(a) F_1 (b) F_2



(c) F_3

Fig. 2. Pareto fronts **obtained** using four solution approaches (a) F_1, (b) F_2, (c) F_3.

Fig. 2 also shows the small difference in obtained criteria values in terms of minimum total cost, maximum **customer** satisfaction and maximum product quality using the four different approaches. This leads to the difficulty in selection of the best solution. Hence, a decision making algorithm (described in sub-section 4.5.) was used. At the first stage-the global criterion approach was employed to select the best Pareto solution for each set of solutions. In this case, Pareto solutions number 3, 2, 3 and 5 (shown in Table 3) were determined as the best solutions using the four different solution approaches as described in section 4, respectively. These solutions were achieved with the minimum distances to their ideal criteria values; the values of these distances are 1.69, 1.63, 1.741 and 1.749, respectively. The developed selection technique was then applied to select the superior approach using Eq.29. Accordingly, the obtained superiority values for the compromise programming approach is 2.568, the goal programming approach is 2.637, weighted Tchebycheff approach is 2.743 and the utility function approach is 2.97. It apparently shows that the superiority of the compromise programming approach to tackles the considered tri-criteria problem as it gives the lowest value of 2.568. Its solution (number 3 in Table 3) was obtained by assigning ε_1 = 0.825 and $\boldsymbol{\varepsilon}_2$ = 9,937. Fig. 3 illustrates the optimal meat supply chain network design based on the determined solution.

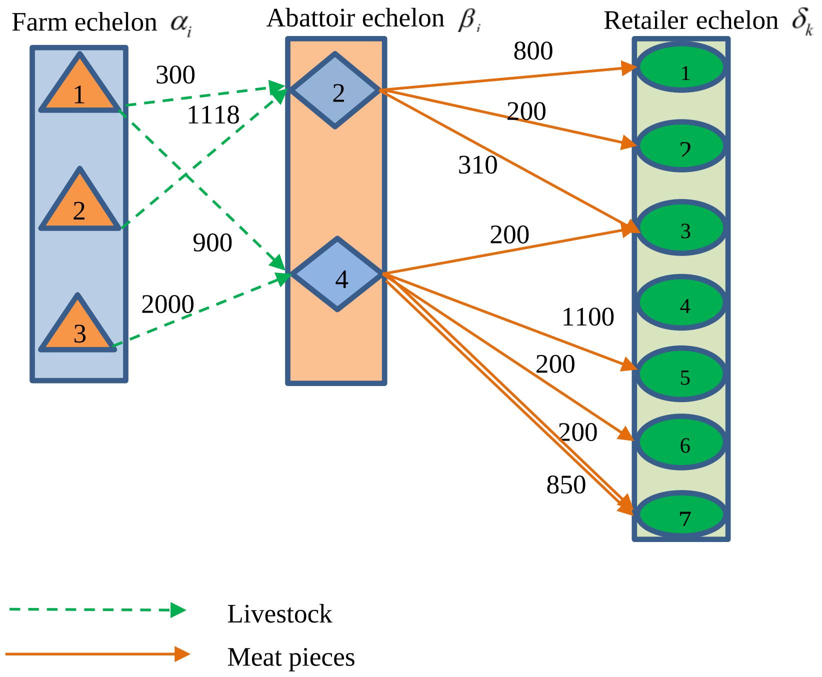


Fig. 3. The optimal meat supply chain network design.

Subsequently, three farms located in Warwickshire, Leicestershire, and the Yorkshire are determined to be established and two abattoirs located in Birmingham and Warrick. For the selected solution, the minimum total cost is £248,214, the maximum customer satisfaction is 80% and the maximum product quality is 9,937 items of meat products. The distribution plan of products was also determined; 900 livestock are to be transported from farm one (located in Warwickshire) to abattoir four (located in Warrick) and 800 items of meat products are to be transported from abattoir two (located in Birmingham) to retailer one.

6. Conclusion

In this paper, a multi-criteria mixed integer linear programming model was developed for solving an issue of a three-echelon RFID-based meat supply chain design based on three criteria: total cost of implementation, customer satisfaction (%) in a fulfillment of the demand in product quantities, and product quality in numbers of meat product. To reveal Pareto solutions based on the developed model, four solution approaches were investigated.

A numerical case study was studied for examining the applicability of the developed model using four different solution approaches. Moreover, a decision making algorithm was developed to select the best solution approach. It proved the superiority of the compromise programming approach. This study shows that the developed tri-criteria optimization model can be useful for obtaining a compromised solution between economic costs and customer satisfaction of the proposed RFID-enabled meat supply chain.

An interesting research avenue derived from this work is recommended as follows:

1. Developing a fuzzy tri-criteria programming model to cope with the uncertainty in costs, demands, healthiness percentage of livestock and freshness percentage of meat products.
2. Solving the multi-criteria optimization problem by a meta-heuristic algorithm may be useful for handling large-sized problems.

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