Journal of Computational Design and Engineering 5 (2018) 94–103

Contents lists available at ScienceDirect

Journal of Computational Design and Engineering

journal homepage: www.elsevier.com/locate/jcde

Design and optimization of an RFID-enabled passport tracking system

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ARTICLE INFO

Article history:
Received 8 March 2017
Received in revised form 28 May 2017
Accepted 21 June 2017
Available online 22 July 2017

Keywords:
RFID
Tracking system
Multi-objective model
Fuzzy optimization
Solution method

ABSTRACT

The implementation of RFID technology has been subject to ever-increasing popularity in relation to the traceability of products as one of the most cutting edge technologies. Implementing such a technology leads to an increase in the visibility management of products. Notwithstanding this, RFID communication performance is potentially affected by interference between the RFID devices. It is also subject to additional costs in investment that should be taken into account. Consequently, seeking a cost-effective design with a desired communication performance for RFID-enabled systems has become a key factor in order to be competitive in today's markets. This study presents a cost and performance-effective design for a proposed RFID-enabled passport tracking system through the development of a multi-objective model that takes in account economic, performance and social criteria. The developed model is aimed at solving the design problem by (i) allocating the optimal numbers of related facilities that should be established and (ii) obtaining trade-offs among three objectives: minimising implementation and operational costs; minimising RFID reader interference; and maximising the social impact measured in the number of created jobs. To come closer to real design in terms of considering the uncertain parameters, the developed multi-objective model was developed in terms of a fuzzy multi-objective model (FMOM). To solve the fuzzy multi-objective optimization problem, two solution methods were used and a decision-making method was employed to select the final trade-off solution. A case study was applied to examine the applicability of the developed model and the proposed solution methods.

1. Introduction

Radio Frequency Identification (RFID) is an automatic identification technology that identifies objects within a given radio frequency range through radio waves without human intervention or data entry (Muller-Seitz, Dautzenberg, Creusen, & Stromereder, 2009). According to Mats, Peter, and Marlin (2008), chap. 1, RFID provides identification codes that can be related to human, livestock and objects for tracing purposes. Moreover, RFID can correctly present real-time information about the locations of objects. A typical RFID system consists of three main components, including an RFID reader, RFID tags and a data processing sub-system, with information being stored in the tag. This information can be read from several metres using an RFID reader, which sends it to a sub-system to be analysed and presented in a usable format. In industry, the implementation of RFID has been rapidly growing in different sectors, such as logistics and supply chain management (Mohammed, Wang, & Li, 2016; Nath, Reynolds, & Want, 2006) and object tracking (Nemmaluri, Corner, & Shenoy, 2008). However, this implementation faces several hurdles from different perspectives, such as economic challenge and the collision that may occur between RFID readers. That is, implementing a new traceability system is associated with extra cost in investment, which is seen as a barrier for many decision makers, particularly small-sized manufactures and underdeveloped countries.

Karippacheril, Diaz Rios, and Srivastava (2011), chap. 12 have argued that reducing the cost of new tracking technologies, such as having cheaper RFID tags, will lead to better supply chains. Further, reducing costs and delivering efficient performance is expected to encourage (i) decision makers to contribute to the development and implementation of tracking systems and (ii) countries like China to implement tracking systems aimed at increasing their competitiveness in global industry (Xiao-hui, Da-fang, & Dong-sheng, 2007). This has led to growing interest in seeking cost-effective designs for RFID-enabled tracking systems. The design and optimisation of such systems needs to take into account both economical and performance criteria, to obtain a cost-effective design with reasonable performance. Besides, in today's competitive economy, many parameters such as cost and potential market demand are subject

Peer review under responsibility of Society for Computational Design and Engineering.

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https://doi.org/10.1016/j.jcde.2017.06.002
2288-4300/

to uncertainty. Notwithstanding, in several cases such as encountering volatile market conditions or having capital limitations for large investments, it may be essential to consider the possibility of making variations to the network design (Davis, 1993; Fattahi, Mahootchi, & Govindan, 2015). Hence, in recent years, the problem of uncertainty has had to be taken into account regarding network design problems. A number of studies have used a fuzzy programming approach to tackle randomness in the input data of networks (Mohammed, Wang, Alyahya, & Binnette, 2017; Tseng, Jiang, & Kwon, 2015; Tseng, Konada, & Kwon, 2015).

The optimisation of an RFID-enabled system is a typical multi-objective problem associated with several variables and imprecise parameters. Specifically, multi-objective optimisation refers to an optimisation of multiple decision-making objectives concurrently, which are possibly conflicting. The multi-objective optimization approach has been used in solving various design problem (Cavaliere, Perrone, & Silvello, 2016; Qu, Liu, Duan, & Yang, 2016).

In this paper, a multi-objective optimisation model (MOOM) for tackling a design problem for a proposed RFID-enabled passport tracking network is developed. The model is aimed at minimising the implementation and operational costs, minimising the RFID reader interference and maximising the social impact measured via the number of jobs created. Furthermore, to cope with the uncertainty in critical input parameters (i.e., costs and demands), the model is developed in terms of a fuzzy multi-objective model.

The rest of this article proceeds as follows: Section 2 is dedicated to a review of the literature. Section 3 presents model development, including problem description, notation and model formulation, which is followed by an optimisation strategy being thoroughly presented in Section 4. Section 5 covers implementation and evaluation of the developed model. Finally, conclusions are drawn in Section 6.

2. Literature review

There are relatively few historical studies on the design and optimisation of RFID-enabled systems. For, most of the previous research was focused on criteria related to performance requirements, such as tag coverage and reader interference. Chen, Zhu, Hu, and Ku (2011) proposed an optimisation model used for allocating the locations of readers in an RFID-enabled network, with a multi-swarm particle swarm approach being used for optimising the model. Oztekin et al. (2010) presented a study aimed at optimising the design of an RFID-enabled network in the healthcare service sector for tracking medical assets. Kardasa, Celika, Yildiza, and Levib (2012) investigated an RFID-enabled network planning problem via the development of a multi-objective artificial bee colony algorithm that sought a trade-off among optimal tag coverage, reader interference, and load balance. Mysore, Nenavat, Unnithan, Mulukutla, and Rao (2009) proposed an algorithm for allocating the minimum number of readers required for efficient coverage when the region is an irregular shape. Ma, Hu, Zhu, and Chen (2014) presented a multi-objective artificial colony algorithm for solving an RFID-enabled network planning problem, whilst Lu and Yu (2014) formulated a k-coverage multi-dimensional optimisation model for evaluating the network performance for an RFID-enabled network. The applicability of the proposed model was demonstrated via a plant growth simulation algorithm in comparison with other algorithms. Mohammed and Wang (2017a,b) proposed a multi-objective programming model for a RFID-based meat supply chain aiming to allocate the optimal number of farms and abattoirs that should be established.

A review of the literature in this area reveals that no previous study has presented a cost-effective design for an RFID-enabled object tracking system that considers: (i) the strategic design decision regarding the numbers of related facilities that should be established; (ii) the total investment cost required for implementing the RFID; (iii) the uncertainties in the input data which have a significant impact on a network's strategic design; and (iv) the social impact as an objective.

This study contributes to the literature as follows:

- It presents the development of a FMOM to obtain an effective cost and performance design of a proposed RFID-enabled passport tracking system. This includes an allocation of the optimum number of related facilities that should be established;
- There is a trade-off among the optimisation of three of the key factors for an effective cost and performance design of an RFID-enabled system, including minimisation of the implementation and operational costs, minimization of RFID reader interference and maximisation of the social impact;
- To come closer to the real design, the developed multi-objective model also incorporates the consideration of uncertainty of input parameters in costs, demands.
- It presents an optimisation methodology that can be used for optimising a similar fuzzy multi-objective model;
- Two different solution methods used to solve the fuzzy multi-objective optimisation problem are employed, with their solution performances subsequently being compared in terms of quality. This helps in obtaining the best RFID-enabled system design and it also reflects different prospects of decision makers in different preferences;
- A real case study is used to investigate the applicability of the developed model and proposed solution methods.

To the best of our knowledge, this is the first research work applying the fuzzy multi-objective optimisation approach in an RFID-enabled system that takes into account all the three focal objectives (economical, performance and social) together.

3. Model development

3.1. Problem description

In this work, a fuzzy multi-objective model is presented for a passport tracking system consisting of a set of three stages, called office 1, office 2 and office 3. Fig. 1 depicts the structure of the concerned three-stage passport tracking network. Office 1 receives the request for new/or to renew passports from clients. It is also responsible for checking whether the required documents are correct before sending them to office 2. Office 2 is responsible for issuing the new passports and checking whether the relevant information is correct (in case of renewing a passport). After that, it sends them to office 3 to be filled in and delivered to the clients. The RFID is proposed for implementation to improve system performance in terms of information accuracy, passport tracking for security purposes and to ease their issuing and renewing processes for the clients. Accordingly, such a system is subject to extra costs in investment that need to be considered. The developed FMOM is used for obtaining a cost-effective design in relation to the numbers of stages that should be established. Also, the aim is to obtain trade-offs among the objectives previously described.

The aims of the fuzzy multi-objective model are:

- Minimise the costs required for implementing and operating the proposed RFID-enabled passport location tracking system;
- Minimise the interference that may occur among the RFID readers;
- Maximise the social impact measured via the number of jobs created.

The model is also aimed at determining a strategic design decision regarding the numbers of office 1s, 2s and 3s that should be established.

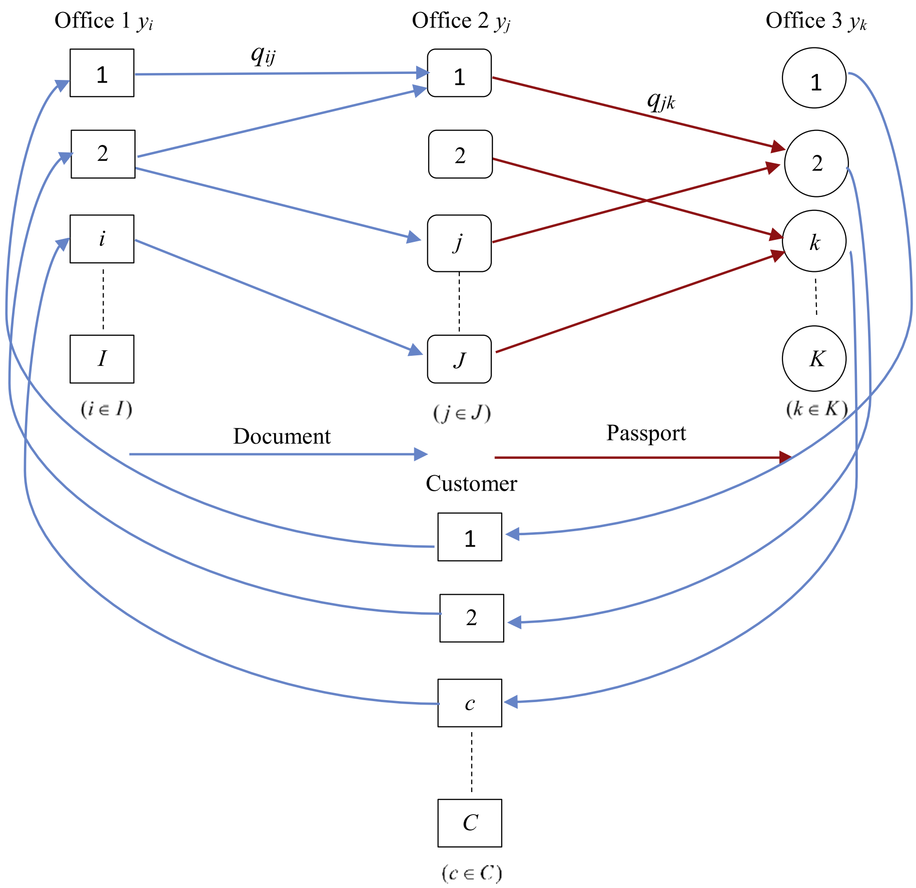

Fig. 1. Structure of the passport tracking network.

3.2. Notation

The following sets, parameters and decision variables were used in the formulation of the model:

Sets

I set of nominated office 1 $i \in I$
J set of nominated office 2 $j \in J$
K set of nominated office 3 $k \in K$
C set of customers $c \in C$

Parameters

C_{ij}^{g} RFID tag cost (GBP) per item transported from office 1 i to office 2 j
C_{i}^{r} RFID reader cost (GBP) required per office 1 i
C_{j}^{r} RFID reader cost (GBP) required per office 2 j
C_{k}^{r} RFID reader cost (GBP) required per office 3 k
C_{i}^{s} fixed cost (GBP) required for the RFID management system
C_{i}^{t} training cost (GBP) per labour at office 1 i
C_{j}^{t} training cost (GBP) per labour at office 2 j
C_{k}^{t} training cost (GBP) per labour at office 3 k
C_{i}^{l} labour cost per hour (GBP) at office 1 i
C_{j}^{l} labour cost per hour (GBP) at office 2 j
C_{k}^{l} labour cost per hour (GBP) at office 3 k
C_{ij}^{l} cost (GBP) required for labour for transporting document from office 1 i to office 2 j
C_{jk}^{l} cost (GBP) required for labour for transporting passports from office 2 j to office 3 k
R_i working rate (items) per labour at office 1 i
R_j working rate (items) per labour at office 2 j
R_k working rate (items) per labour at office 3 k
R_{ij} working rate (items) per labour required to transport document from office 1 i to office 2 j
R_{jk} working rate (items) per labour required to transport passports from office 2 j to office 3 k
H_i minimum required number of working hours (h) for labour at office 1 i
H_j minimum required number of working hours (h) for labour at office 2 j
H_k minimum required number of working hours (h) for labour at office 3 k
H_{ij} minimum required number of working hours (h) for labour transporting document from office 1 i to office 2 j
H_{jk} minimum required number of working hours (h) for labour transporting passports from office 2 j to office 3 k
C_i maximum handling capacity (items) of office 1 i
C_j maximum handling capacity (items) of office 2 j
C_k maximum handling capacity (items) of office 3 k
D_j demand (in units) of office 2 j
D_k demand (in units) of office 3 k
D_c demand (in units) of customer c
ac_i number of available career opportunities if office 1 i is opened
ac_j number of available career opportunities if office 2 j is opened
ac_k number of available career opportunities if office 3 k is opened

Decision variables

q_{ij}	quantity of units dispatched from office 1 i to office 2 j
q_{jk}	quantity of units dispatched from office 2 j to office 3 k
q_{kc}	quantity of units handed to client c from office 3 k
x_i	required number of labourers at office 1 i
x_j	required number of labourers at office 2 j
x_k	required number of labourers at office 3 k
x_{ij}	required number of labourers to transfer document from office 1 i to office 2 j
x_{jk}	required number of labourers to transfer passports from office 2 j to office 3 k
y_i	$\begin{cases} 1: & \text{if office 1 } i \text{ is opened} \\ 0: & \text{otherwise} \end{cases}$
y_j	$\begin{cases} 1: & \text{if office 2 } j \text{ is opened} \\ 0: & \text{otherwise} \end{cases}$
y_k	$\begin{cases} 1: & \text{if office 3 } k \text{ is opened} \\ 0: & \text{otherwise} \end{cases}$

3.3. Formulating the multi-objective optimisation model

The model development was based on the following assumption:

- There are no restrictions for sharing network resources, whereby any office 1 may serve any office 2 and any office 2 may serve any office 3;
- The numbers of input parameters are considered as uncertain parameters, which include costs and demand;
- Each office is equipped with an RFID reader;
- Each document is attached with an RFID tag;
- All demands from customers should be fulfilled;
- There is a certain capacity level for offices 1, 2 and 3;
- The quantity of flow of documents from customer c to office 1 i is neglected;
- Office 2 j and office 3 k *are* aware about the submitted number of documents to office 1 i and their demand is determined accordingly.

The three objectives (i.e. minimisation of implementation and operational costs, minimisation of RFID reader interference and maximisation of the social impact) are formulated as follows.

3.3.1. Objective function 1 (F_1)

Minimisation of the implementation and operational cost for the RFID-enabled passport location tracking system = RFID tag cost for each item + RFID reader cost required for office 1 i, office 2 j and office 3 k + labour costs at office 1 i, office 2 j and office 3 k + labour costs required to transport document from office 1 i to office 2 j and from office 2 j to office 3 k + training cost for labour (s) at office 1 i, office 2 j and office 3 k. Thus, minimum F_1 is formulated as follows:

$$\begin{aligned} Min\ F_1 = & \sum_{i\in I}\sum_{j\in J} C^g_{ij} q_{ij} + \sum_{i\in I} C^r_i y_i + \sum_{j\in j} C^r_j y_j + \sum_{k\in K} C^r_k y_k + C^s_i + \sum_{i\in I} C^l_i x_i H_i \\ & + \sum_{j\in J} C^l_j x_j H_j + \sum_{k\in K} C^l_k x_k H_k + \sum_{i\in I}\sum_{j\in J} C^l_{ij} x_{ij} H_{ij} + \sum_{j\in J}\sum_{k\in K} C^l_{jk} x_{jk} H_{jk} + \sum_{i\in I} C^t_i x_i \\ & + \sum_{j\in J} C^t_j x_j + \sum_{k\in K} C^t_k x_k \end{aligned} \tag{1}$$

3.3.2. Objective function 2 (F_2)

Minimisation of RFID reader interference is formulated as follows (Ma et al., 2014):

$$\begin{aligned} Min\ F_2 = & \sum_{m_i\in RS_i}\sum_{n_i\in TS_{m_i}} \left(\delta - \left(P^{m_i}_{n_\int} - \sum_{l_i\in RS}^{l_i\neq \mathrm{m}_i} P^{l_i}_{m_i} y_i\right)\right) \\ & + \sum_{m_j\in RS_j}\sum_{n_j\in TS_{mj}} \left(\delta - \left(P^{m_j}_{n_j} - \sum_{l_j\in RS}^{l_j\neq \mathrm{m}_j} P^{l_j}_{m_j} y_j\right)\right) \\ & + \sum_{m_k\in RS_k}\sum_{n_k\in TS_{m_k}} \left(\delta - \left(P^{m_k}_{n_k} - \sum_{l_k\in RS}^{l_k\neq \mathrm{m}_k} P^{l_k}_{m_k} y_k\right)\right) \end{aligned} \tag{2}$$

where $TS_{m_{i,j\ or\ k}}$ is three sets of tags in the interrogation area of reader m at Offices 1, 2 and 3, respectively. $RS_{i,\ j\ or\ k}$ is three sets of readers, which have tag n in their interrogation area at offices 1, 2 and 3, respectively. δ is the preferred power level; $P^{m_{i,j\ and\ k}}_{n_{i,j\ and\ k}}$ is the actual power level received by tag n in the interrogation area of reader m in office 1 i, office 2 j *and* office 3 k; $P^{l_{i,j\ and\ k}}_{n_{i,j\ and\ k}}$ is the received power by tag n in the interrogation area of reader l in office 1 i, office 2 j *and* office 3 k (Ma et al., 2014). It should be noted that the number of readers is equal to the number of offices that need to be established. Also, the number of tags is equal to the quantity of items transported from office 1 to office 2, where each document is attached with a tag. This objective is aimed at taking into account all the readers, excluding the best, as sources of interference.

3.3.3. Objective function 3 (F_3)

Maximisation of social impact = Career opportunities created at office 1 i + career opportunities created at office 2 j + career opportunities created at office 3 k. Thus, maximum F_3 is formulated as follows:

$$Max\ F_3 = \sum_{i\in I} ac_i y_i + \sum_{j\in j} ac_j y_j + \sum_{k\in K} ac_k y_k \tag{3}$$

It should be noted that the value of ac, i.e. the number of created careers, should be quantified by the decision makers for each potential RFID-based system. In the study, the values of ac at the three offices were quantified based on the existing passport issuing centre.

3.4. Constraints

There are a number of constraints that need to be considered and included in the optimisation. The constraints are given as:

$$\sum_{i\in I} q_{ij} \leqslant C_i\ y_i \quad \forall j \in J \tag{4}$$

$$\sum_{j\in J} q_{jk} \leqslant C_j\ y_j \quad \forall k \in K \tag{5}$$

$$\sum_{k\in K} q_{kc} \leqslant C_k\ y_k \quad \forall c \in C \tag{6}$$

$$\sum_{i\in I} q_{ij} \geqslant D_j \quad \forall j \in J \tag{7}$$

$$D_j \geqslant \sum_{k\in K} q_{jk} \quad \forall j \in J \tag{8}$$

$$\sum_{k\in K} q_{kc} \geqslant D_c \quad \forall j \in J \tag{9}$$

$$\sum_{c\in C} q_{kc} \leqslant D_k \quad \forall k \in K \tag{10}$$

$$\sum_{j\in J} q_{jk} \geqslant D_k \quad \forall k \in K \tag{11}$$

$$\sum_{i\in I} q_{ij} \leqslant x_i R_i \quad \forall \mathrm{j} \in J \tag{12}$$

$$\sum_{j\in J} q_{jk} \leqslant x_j R_j \quad \forall \mathrm{k} \in K \tag{13}$$

$$\sum_{k \in K} q_{kc} \leqslant x_k R_k \quad \forall c \in C \tag{14}$$

$$\sum_{i \in I} q_{ij} \leqslant x_{ij} R_i \quad \forall j \in J \tag{15}$$

$$\sum_{j \in J} q_{jk} \leqslant x_{jk} R_j \quad \forall k \in K \tag{16}$$

$$q_{ij}, q_{jk}, q_{kc}, x_i, x_j, x_k, x_{ij}, x_{jk} \geqslant 0, \quad \forall i, j, k; \tag{17}$$

$$y_i, y_j, y_k \in \{0, 1\}, \quad \forall i, j, k; \tag{18}$$

Eqs. (4)–(6) ensure the flow balance of the document from office 1 to office 2 and from office 2 to office 3 with respect to their capacity. Eqs. (7)–(11) ensure that all demands are satisfied. Eqs. (12)–(16) determine the required number of labourers at office 1, office 2, office 3, between office 1 and office 2 and between office 2 and office 3. Eqs. (17) and (18) limit the decision variables to being binary and non-negative.

3.5. Modelling the uncertainty

To come closer to reality, the multi-objective model needs to handle the uncertainty of some parameters, such as costs and demand. This allows the solution space to be flexible when the model contains some uncertain parameters. Consequently, the model is converted into an equivalent crisp model using the Jiménez method (Jiménez, Arenas, Bilbao, & Rodriguez, 2007). Accordingly, the equivalent crisp model can be formulated as shown below.

Minimisation of the implementation and operational costs for the RFID-enabled passport tracking system under uncertain costs is formulated as follows:

$$\begin{aligned} Min\ F_1 = & \sum_{i \in I} \sum_{j \in J} \left(\frac{C_{ij}^{gpes} + 2C_{ij}^{gmos} + C_{ij}^{gopt}}{4} \right) q_{ij} \\ & + \sum_{i \in I} \left(\frac{C_i^{rpes} + 2C_i^{rmos} + C_i^{ropt}}{4} \right) y_i \\ & + \sum_{j \in J} \left(\frac{C_j^{rpes} + 2C_j^{rmos} + C_j^{ropt}}{4} \right) y_j \\ & + \sum_{k \in K} \left(\frac{C_k^{rpes} + 2C_k^{rmos} + C_k^{ropt}}{4} \right) y_k + C_i^s \\ & + \sum_{i \in I} \left(\frac{C_i^{lpes} + 2C_i^{lmos} + C_i^{lopt}}{4} \right) x_i H_i \\ & + \sum_{j \in J} \left(\frac{C_j^{lpes} + 2C_j^{lmos} + C_j^{lopt}}{4} \right) x_j H_j \\ & + \sum_{k \in K} \left(\frac{C_k^{lpes} + 2C_k^{lmos} + C_k^{lopt}}{4} \right) x_k H_k \\ & + \sum_{i \in I} \sum_{j \in J} \left(\frac{C_{ij}^{lpes} + 2C_{ij}^{lmos} + C_{ij}^{lopt}}{4} \right) x_{ij} H_{ij} \\ & + \sum_{j \in J} \sum_{k \in K} \left(\frac{C_{jk}^{lpes} + 2C_{jk}^{lmos} + C_{jk}^{lopt}}{4} \right) x_{jk} H_{jk} \\ & + \sum_{i \in I} \left(\frac{C_i^{tpes} + 2C_i^{tmos} + C_i^{topt}}{4} \right) x_i \\ & + \sum_{j \in J} \left(\frac{C_j^{tpes} + 2C_j^{tmos} + C_j^{topt}}{4} \right) x_j \\ & + \sum_{k \in K} \left(\frac{C_k^{tpes} + 2C_k^{tmos} + C_k^{topt}}{4} \right) x_k \end{aligned} \tag{19}$$

The formulae for minimising the reader interference and maximising the social impact of the RFID-enabled passport tracking system set out in Eqs. (2) and (3), are not changed since they do not include any uncertain parameters.

$$\begin{aligned} Min\ F_2 = & \sum_{m_i \in RS_i} \sum_{n_i \in TS_{m_i}} \left(\delta - \left(P_{n \int}^{m_i} - \sum_{l_i \in RS}^{l_i \neq m_i} P_{m_i}^{l_i} y_i \right) \right) \\ & + \sum_{m_j \in RS_j} \sum_{n_j \in TS_{mj}} \left(\delta - \left(P_{n_j}^{m_j} - \sum_{l_j \in RS}^{l_j \neq m_j} P_{m_j}^{l_j} y_j \right) \right) \\ & + \sum_{m_k \in RS_k} \sum_{n_k \in TS_{m_k}} \left(\delta - \left(P_{n_k}^{m_k} - \sum_{l_k \in RS}^{l_k \neq m_k} P_{m_k}^{l_k} y_k \right) \right) \end{aligned} \tag{20}$$

$$Max\ F_3 = \sum_{i \in I} ac_i y_i + \sum_{j \in J} ac_j y_j + \sum_{k \in K} ac_k y_k \tag{21}$$

Subject to Eqs. (4)–(18). However, Eqs. (7)–(11) are reformulated to cope with the uncertain demands, as shown in Eqs. (25)–(29).

$$\sum_{i \in I} q_{ij} \leqslant C_i\ y_i \quad \forall j \in J \tag{22}$$

$$\sum_{j \in J} q_{jk} \leqslant C_j\ y_j \quad \forall k \in K \tag{23}$$

$$\sum_{k \in K} q_{kc} \leqslant C_k\ y_k \quad \forall c \in C \tag{24}$$

$$\sum_{i \in I} q_{ij} \geqslant \frac{\lambda}{2} \frac{D_{j1} + D_{j2}}{2} + \left(1 - \frac{\lambda}{2}\right) \frac{D_{j3} + D_{j4}}{2} \quad \forall j \in J \tag{25}$$

$$\frac{\lambda}{2} \frac{D_{j1} + D_{j2}}{2} + \left(1 - \frac{\lambda}{2}\right) \frac{D_{j3} + D_{j4}}{2}_j \geqslant \sum_{k \in K} q_{jk} \quad \forall j \in J \tag{26}$$

$$\sum_{k \in K} q_{kc} \geqslant \frac{\lambda}{2} \frac{D_{c1} + D_{c2}}{2} + \left(1 - \frac{\lambda}{2}\right) \frac{D_{c3} + D_{c4}}{2} \quad \forall j \in J \tag{27}$$

$$\sum_{c \in C} q_{kc} \leqslant \frac{\lambda}{2} \frac{D_{k1} + D_{k2}}{2} + \left(1 - \frac{\lambda}{2}\right) \frac{D_{k3} + D_{k4}}{2} \quad \forall k \in K \tag{28}$$

$$\sum_{j \in J} q_{jk} \geqslant \frac{\lambda}{2} \frac{D_{k1} + D_{k2}}{2} + \left(1 - \frac{\lambda}{2}\right) \frac{D_{k3} + D_{k4}}{2} \quad \forall k \in K \tag{29}$$

$$\sum_{i \in I} q_{ij} \leqslant x_i\ R_i \quad \forall j \in J \tag{30}$$

$$\sum_{j \in J} q_{jk} \leqslant x_j\ R_j \quad \forall k \in K \tag{31}$$

$$\sum_{k \in K} q_{kc} \leqslant x_k\ R_k \quad \forall c \in C \tag{32}$$

$$\sum_{i \in I} q_{ij} \leqslant x_{ij}\ R_i \quad \forall j \in J \tag{33}$$

$$\sum_{j \in J} q_{jk} \leqslant x_{jk}\ R_j \quad \forall k \in K \tag{34}$$

$$q_{ij}, q_{jk}, q_{kc}, x_i, x_j, x_k, x_{ij}, x_{ij} \geqslant 0, \quad \forall i, j, k; \tag{35}$$

$$y_i, y_j, y_k \in \{0, 1\}, \quad \forall i, j, k; \tag{36}$$

In accordance with to Jiménez's approach, it is assumed that the constraints in the model should be fulfilled using a confidence value, which is denoted as λ and this is normally determined by the decision makers. Also, mos, pes and opt are the three prominent points (the most likely, the most pessimistic and the most optimistic values), respectively (Jiménez et al., 2007).

4. Optimisation methodology

To solve the developed fuzzy tri-objective optimisation problem, the solution procedures are described as follows:

(1) Find the upper and lower bound (*U*, *L*) solution for each objective function. This can be obtained by:

Upper bound solution of objective function 1 is obtained as follows:

$$Max\ F_1(U_1) = \sum_{i\in I}\sum_{j\in J} C^g_{ij} q_{ij} + \sum_{i\in I} C^r_i y_i + \sum_{j\in j} C^r_j y_j + \sum_{k\in K} C^r_k y_k + C^s_i + \sum_{i\in I} C^l_i x_i H_i + \sum_{j\in J} C^l_j x_j H_j + \sum_{k\in K} C^l_k x_k H_k + \sum_{i\in I}\sum_{j\in J} C^l_{ij} x_{ij} H_{ij} + \sum_{j\in J}\sum_{k\in K} C^l_{jk} x_{jk} H_{jk} + \sum_{i\in I} C^t_i x_i + \sum_{j\in J} C^t_j x_j + \sum_{k\in K} C^t_k x_k \quad (37)$$

Upper bound solution of objective function 2 is obtained as follows:

$$Max\ F_2(U_2) = \sum_{m_i\in RS_i}\sum_{n_i\in TS_{m_i}} \left(\delta - \left(P^{m_i}_{n\int} - \sum_{l_i\in RS}^{l_i\neq m_i} P^{l_i}_{m_i} y_i\right)\right) + \sum_{m_j\in RS_j}\sum_{n_j\in TS_{mj}} \left(\delta - \left(P^{m_j}_{n_j} - \sum_{l_j\in RS}^{l_j\neq m_j} P^{l_j}_{m_j} y_j\right)\right) + \sum_{m_k\in RS_k}\sum_{n_k\in TS_{m_k}} \left(\delta - \left(P^{m_k}_{n_k} - \sum_{l_k\in RS}^{l_k\neq m_k} P^{l_k}_{m_k} y_k\right)\right) \quad (38)$$

Upper bound solution of objective function 3 is obtained as follows:

$$Max\ F_3(U_3) = \sum_{i\in I} ac_i y_i + \sum_{j\in j} ac_j y_j + \sum_{k\in K} ac_k y_k \quad (39)$$

Lower bound solution of objective function 1 is obtained as follows:

$$Min\ F_1(L_1) = \sum_{i\in I}\sum_{j\in J} C^g_{ij} q_{ij} + \sum_{i\in I} C^r_i y_i + \sum_{j\in j} C^r_j y_j + \sum_{k\in K} C^r_k y_k + C^s_i + \sum_{i\in I} C^l_i x_i H_i + \sum_{j\in J} C^l_j x_j H_j + \sum_{k\in K} C^l_k x_k H_k + \sum_{i\in I}\sum_{j\in J} C^l_{ij} x_{ij} H_{ij} + \sum_{j\in J}\sum_{k\in K} C^l_{jk} x_{jk} H_{jk} + \sum_{i\in I} C^t_i x_i + \sum_{j\in J} C^t_j x_j + \sum_{k\in K} C^t_k x_k \quad (40)$$

Lower bound solution of objective function 2 is obtained as follows:

$$Min\ F_2(L_2) = \sum_{m_i\in RS_i}\sum_{n_i\in TS_{m_i}} \left(\delta - \left(P^{m_i}_{n\int} - \sum_{l_i\in RS}^{l_i\neq m_i} P^{l_i}_{m_i} y_i\right)\right) + \sum_{m_j\in RS_j}\sum_{n_j\in TS_{mj}} \left(\delta - \left(P^{m_j}_{n_j} - \sum_{l_j\in RS}^{l_j\neq m_j} P^{l_j}_{m_j} y_j\right)\right) + \sum_{m_k\in RS_k}\sum_{n_k\in TS_{m_k}} \left(\delta - \left(P^{m_k}_{n_k} - \sum_{l_k\in RS}^{l_k\neq m_k} P^{l_k}_{m_k} y_k\right)\right) \quad (41)$$

Lower bound solution of objective function 3 is obtained as follows:

$$Min\ F_3(U_3) = \sum_{i\in I} ac_i y_i + \sum_{j\in j} ac_j y_j + \sum_{k\in K} ac_k y_k \quad (42)$$

(2) Find the respective satisfaction degree $\mu(x_i)$ for each objective as follows:

$$\mu_1(F_1(x)) = \begin{cases} 1 & if\ F_1(x) \geqslant U_1 \\ \frac{F_1(x)-L_1}{U_1-L_1} & if\ L_1 \leqslant F_1(x) \leqslant U_1 \\ 0 & if\ F_1(x) \leqslant L_1 \end{cases} \quad (43)$$

$$\mu_2(F_2(x)) = \begin{cases} 1 & if\ F_2(x) \geqslant U_2 \\ \frac{F_2(x)-L_2}{U_2-L_2} & if\ L_2 \leqslant F_2(x) \leqslant U_2 \\ 0 & if\ F_2(x) \leqslant L_2 \end{cases} \quad (44)$$

$$\mu_3(F_3(x)) = \begin{cases} 1 & if\ F_3(x) \geqslant U_3 \\ \frac{F_3(x)-L_3}{U_3-L_3} & if\ L_3 \leqslant F_3(x) \leqslant U_3 \\ 0 & if\ F_3(x) \leqslant L_3 \end{cases} \quad (45)$$

where Eqs. (43)–(45) indicate the satisfaction degree of the three objective functions, respectively. Further illustration of these membership functions is depicted in Fig. 2.

(3) Optimise the crisp model obtained from Section 3.5 using the proposed solution methods (Section 4.1).
(4) Select the best Pareto-optimal solution using the developed decision making algorithm (Section 4.2).

4.1. Solution approaches

4.1.1. ε-constraint

In the ε-constraint method, the fuzzy multi-objective model turns into a single-objective model by keeping the most important function as an objective function, and considering other functions as the ε-based constraints (Ehrgott, 2005). Thus, the equivalent solution formula (F) is given by:

$$Min\ F = Min\ F_1 \quad (46)$$

Subject to :

$$F_2 \leqslant \varepsilon_1 \quad (47)$$

$$[F_2]^{\min} \leqslant \varepsilon_1 \leqslant [F_2]^{\max} \quad (48)$$

$$F_3 \geqslant \varepsilon_2 \quad (49)$$

$$[F_3]^{\min} \leqslant \varepsilon_2 \leqslant [F_3]^{\max} \quad (50)$$

And Eqs. (22)–(36).

In this work, minimisation of the implementation and operational costs is kept as the objective function (Eq. (46)) and minimisation of reader interference and maximisation of social impact are shifted to constraints (Eqs. (47) and (49), respectively). Pareto solutions can be obtained by varying the ε value (Eqs. (48) and (50)). It should be noted that the selection of any objective to be an objective function or a constraint is not limited.

4.1.2. LP-metrics

In the LP-metrics method, each objective function needs to be solved individually to obtain its ideal value (F^*_1, F^*_2 and F^*_3). Subsequently, the model is solved as a single objective model using the following formula (Mohammed & Wang, 2017a,b):

$$Min\ F = \left[w_1 \frac{F_1 - F^*_1}{F^*_1} + w_2 \frac{F_2 - F^*_2}{F^*_2} + w_3 \frac{F_3 - F^*_3}{F^*_3}\right] \quad (51)$$

Subject to Eqs. (22)–(36).

4.2. The decision-making method

The next step after revealing the Pareto solutions is to determine the final trade-off solution. The final Pareto optimal solution can be determined based on the decision maker's preferences or by using a decision-making algorithm. Thus far, a number of approaches have been utilised to determine the best final solution in multi-objective problems. In this study, a decision-making method is used to select the Final Trade-off (FT) solution. The idea of this method used for selecting the best approach is based on

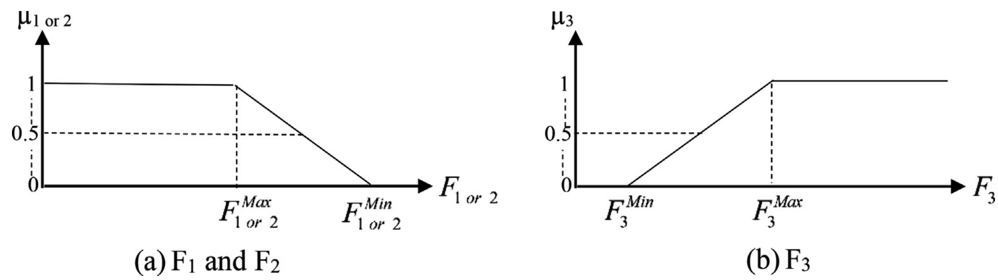

Fig. 2. Membership functions of the objectives (a) F_1 and F_2, (b) F_3.

selecting the solution approach that is closest to the ideal solution. For this technique: (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 BC value. The selection technique formula is presented as follows:

$$FT = \sum_{i=1}^{3} \frac{F_i}{F_i^*} \tag{52}$$

Fig. 3 shows a flowchart for developing and optimising the FMOM.

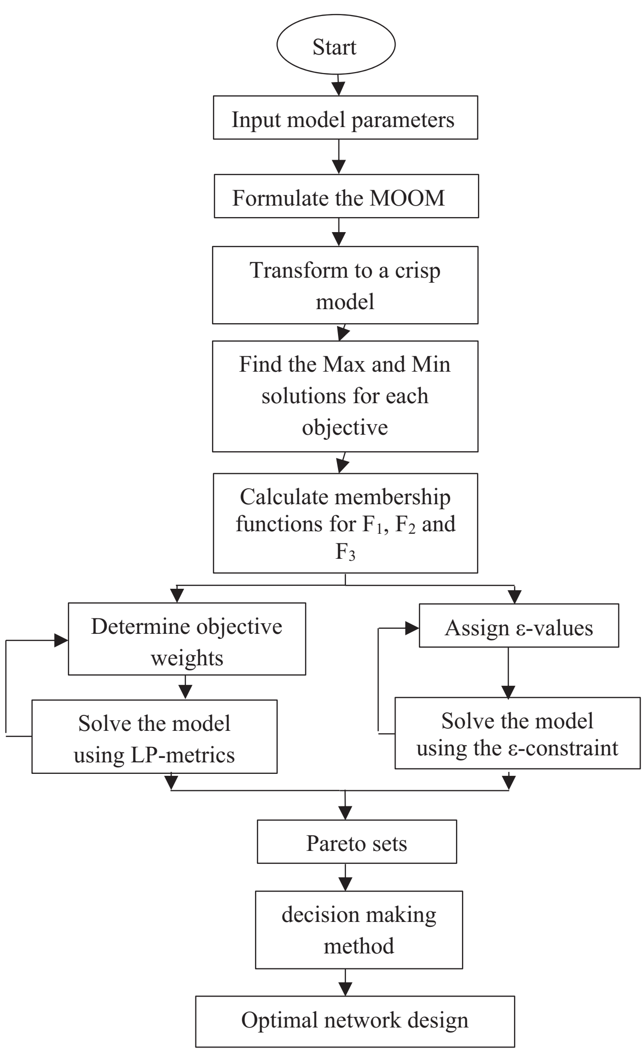

Fig. 3. Flowchart of the FMOM.

5. Application and evaluation

Conducive to the quantifying of the applicability of the developed mathematical model and the proposed optimisation methodology, a case study was applied. Table 1 shows data related to the investigated case study, which were collected from the Ministry of Interior in the KSA. The demand reported in Table 1 is the total demand over a year horizon received from costumers to renew/or issue passports. Using the case study data, the proposed optimisation methodology described in Section 4 was applied to obtain the solution of the FMOM described in Section 3.5. In this study, the model was coded and solved using LINGO[11] software on a personal laptop with Corei5 2.6gigahertz with 4 gigabytes of RAM.

5.1. Results

This section presents the computational results of the FMOM using the proposed optimisation methodology for the problem previously defined. The solution procedures of the model can be expressed as follows:

(1) Apply Eqs. (37)(42) to determine the upper and lower values for each objective function via their independent optimisation. The values are $(\{U_{F_i}, L_{F_i}\}) = (\{1419900, 498101\}, \{0.501, 0.128\}, \{58, 194\})$.
(2) Apply Eqs. (43)–(45) to determine the satisfaction degree $\mu(x_i)$ for each objective function.
(3) Optimise the FMOM model employing two methods as follows: (i) for the ε-constraint method, as illustrated in procedure 1, maximum and minimum values for each objective

Table 1
Values of the parameters.

Parameter	Value	Parameter	Value
C_{ij}^l	~(15, 18)	D_c	~(1400, 1500)
C_{jk}^l	~(15, 18)	D_j	~(1500, 1800)
C_{ij}^g	~(0.15, 0.18)	D_k	(1500, 1800)
C_{jk}^t	~(0.15, 0.18)	R_i	(43, 210)
C_i^r	~(800, 950)	R_j	(110, 174)
C_j^r	~(800, 950)	R_k	(110, 174)
C_k^r	~(800, 950)	R_{ij}	(110, 174)
C_i^t	~(800, 950)	R_{jk}	(110, 174)
C_j^t	~(800, 950)	H_i	(271, 294)
C_i^l	~(3.5, 4)	H_j	(271, 294)
C_i^l	~(3.5, 4)	H_k	(271, 294)
C_i^l	~(3.5, 4)	H_{ij}	(271, 294)
C_j^l	~(3.5, 4)	H_{jk}	(271, 294)
C_k^l	~(3.5, 4)	C_i	(1500, 1800)
		C_j	(1700, 2000)
ac_i	(7, 10)	C_k	(1700, 2000)
ac_j	(7, 10)	ac_k	(7, 10)

Table 2
ε–value assigned for objective functions two and three.

#	Assigned ε –value ε_1	ε_2
1	0.141	58
2	0.174	76
3	0.222	94
4	0.258	112
5	0.291	130
6	0.355	160
7	0.400	178
8	0.500	194

are obtained. The range between the maximum and minimum values is segmented into ten parts, the ε-points in between are assigned as ε values (See Table 2) in Eqs. (47) and (49). Then, Pareto solutions are obtained by implementing Eq. (46). The objective function related to the implementation and operational costs is minimised while the reader interference and social impact as considered as constraints. Table 3 illustrates the results for eight ε-iterations. For (ii) the LP-metrics method: each objective function is optimised independently under the problem constraints and the results are shown in Table 4. For example, optimising the second objective (F_1) independently, the solutions of the three objective functions are determined as F_1 = 498,101, F_2 = 0.137, and F_3 = 63. Illustrated in Table 4, the ideal solutions for the three objectives are in bold, these being: F_1 = 498,101; F_2 = 0.128; and F_3 = 194. Then, different combinations of weights are assigned (See Table 5) for the three objectives to obtain Pareto solutions of the FMOM. Table 6 illustrates the computation results obtained by determining eight different weights for the three objectives. These solutions are associated with the number of offices 1, 2 and 3 that should be established.

(4) Choose the best Pareto solution using the decision making method; the calculated score values of the obtained solutions are shown in Table 7.

It should be noted that the three methods were respectively implemented with eight λ levels (0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7 and 0.8). By setting these eight levels to the λ, with steps 0.1 and implementing it to the model, eight Pareto solutions were obtained. Consequently, the model should be frequently solved for each λ level.

As previously mentioned, Table 3 and 6 illustrate, respectively, the results for simultaneously optimising the three objective functions and the numbers of office 1, office 2 and office 3 that should be established. For example, solution#2 in Table 6 yields minimum implementation and operational costs equal to 517,118 GBP, minimum reader interference equals 0.138 and maximum social impact equals 76. This solution was obtained by an assignment of w_1 = 0.9, w_2 = 0.05 and w_2 = 0.05. As shown in Table 6, this solution suggests an establishment of three office 1s, three office 2s and three office 3s. It is notable in these results that trade-offs among the three objectives (e.g. minimisation of implementation and operational costs, minimisation of reader interference and maximisation of social impact) can be achieved. It should also be noted, as can be seen in Tables 3 and 6, that increasing the satisfaction level (λ-level) yields an increase in the undesired value of the first and second objective functions, while in contrast, it gives an increase in the desired value of the third objective function. This means that the decision makers will have to spend more money to cope with the uncertainties. However, decision makers can vary the importance of the three objective functions (w), ε values and the satisfaction level (λ-level), based on their preferences, to obtain another compromised solution.

To compare the three Pareto sets obtained by using two different methods, Fig. 4 illustrates Pareto fronts corresponding to the optimisation of the three objectives concurrently, using two solution methods. The two methods performed well in presenting the alternative Pareto solution. However, the results obtained by using the ε-constraint method are closer to the ideal values of the three objectives compared to those from using the LP-metrics method. As shown in Fig. 4, the objectives (i.e. implementation and operational costs, reader interference and social impact) are conflicting as it is impossible to obtain an ideal value of each objective simultaneously. In other words, the Pareto solutions cannot be improved in relation to one objective without deteriorating the performance of the others. It is worth mentioning that all Pareto-optimal solutions are feasible.

Nonetheless, after obtaining Pareto solutions, stakeholders should choose one solution to design their system. As shown in Fig. 4, the values of minimum implementation and operational costs along with those for minimum reader interference and maximum social impact are not considerably different for the two

Table 4
Solutions relating to F_1, F_2 and F_3 when optimising them independently.

Objective functions	Min F_1	Min F_2	Max F_3
F_1	**498101**	0.137	59
F_2	520090	**0.128**	63
F_3	1399053	0.499	**194**

Table 5
Assigned combination of weights relating to the LP-metrics method.

#	w_1	w_2	w_3
1	1	0	0
2	0.9	0.05	0.05
3	0.8	0.1	0.1
4	0.7	0.15	0.15
5	0.6	0.2	0.2
6	0.5	0.25	0.25
7	0.4	0.3	0.3
8	0.3	0.35	0.35

Table 3
Results related to F_1, F_2 and F_3 using the ε-constraint based on different λ values.

#	λ-level	$\mu_1(F_1)$	$\mu_2(F_2)$	$\mu_3(F_3)$	Min F_1	Min F_2	Max F_3	Open office 1	Open office 2	Open office 3
1	0.1	0.955	0.922	0.244	505,960	0.134	59	2	3	3
2	0.2	0.702	0.711	0.295	609,141	0.174	76	3	3	3
3	0.3	0.583	0.495	0.422	715,141	0.201	97	4	4	3
4	0.4	0.464	0.410	0.519	825,141	0.251	116	4	4	4
5	0.5	0.354	0.307	0.761	926,106	0.288	130	5	6	5
6	0.6	0.235	0.163	0.621	1,035,669	0.343	166	6	7	5
7	0.7	0.120	0.101	0.792	1,145,891	0.399	180	6	7	7
8	0.8	0.082	0.014	0.922	1,379,050	0.472	194	6	8	7

Table 6
Results relating to F_1, F_2 and F_3 using the LP-metrics method based on different λ values.

#	λ-level	$\mu_1(F_1)$	$\mu_2(F_2)$	$\mu_3(F_3)$	Min F_1	Min F_2	Max F_3	Open office 1	Open office 2	Open office 3
1	0.1	0.967	0.922	0.244	515,000	0.134	58	2	3	3
2	0.2	0.731	0.726	0.295	517,118	0.138	76	3	3	3
3	0.3	0.598	0.526	0.422	741,000	0.231	95	4	5	3
4	0.4	0.515	0.432	0.519	842,222	0.277	115	4	5	5
5	0.5	0.369	0.329	0.761	960,016	0.301	129	6	7	4
6	0.6	0.261	0.195	0.621	1,050,119	0.343	166	6	7	5
7	0.7	0.222	0.123	0.792	1,172,229	0.378	179	6	8	8
8	0.8	0.085	0.016	0.988	1,390,000	0.491	194	6	8	8

Table 7
Score values of Pareto solutions using the developed decision making method.

	ε-constraint method							
Solution	1	2	3	4	5	6	7	8
Score	0.27	0.25	0.22	0.2	0.19	0.27	0.27	29
	LP-metrics method							
Solution	1	2	3	4	5	6	7	8
Score	0.27	0.26	0.23	0.21	0.21	0.29	0.28	0.31

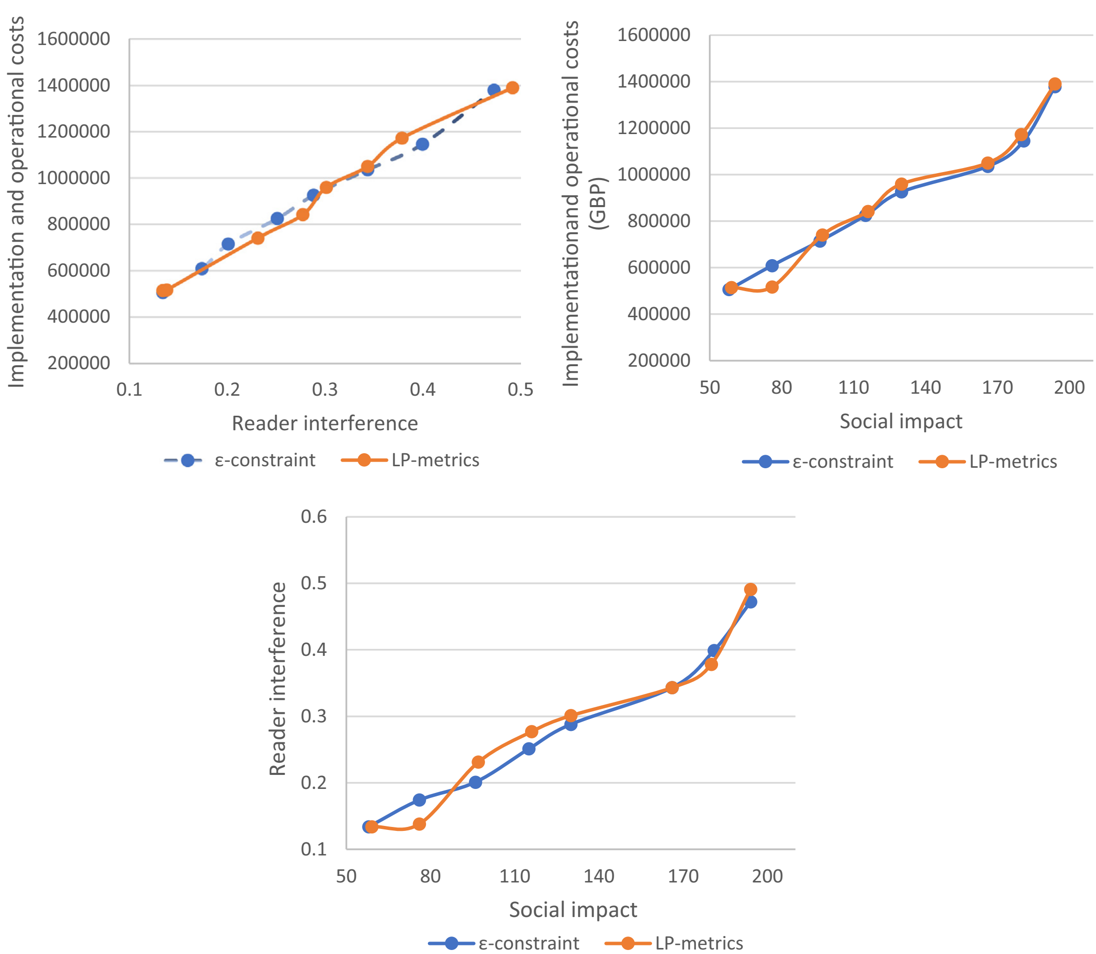

Fig. 4. Pareto fronts for the three objective functions using the two methods.

methods. This makes direct selection of the final solution a challenge. Consequently, a decision making method was employed to reveal the final solution. As revealed in Table 7, solution#5, obtained by using the ε-constraint method is the best solution, since its score is the lowest ($FT = 0.19$). This solution is obtained by an assignment of ε_1=0.291 and ε_2=0.725. This solution requires 926,106 GBP as minimum implementation and operational costs, minimum reader interference equalling 0.288 and maximum social impact equalling 130. It also needs the establishment of five office 1s, six office 2s and five office 3s.

6. Conclusions

In this study, a problem of a proposed RFID-enabled passport location tracking system was investigated using a multi-objective optimisation approach. The system consisted three stages covering office1, office 2 and office 3. The problem involved the design and optimisation of the proposed system by (i) allocating the optimal number of stages that should be opened and (2) obtaining compromised solutions among three objectives (e.g. minimisation of the implementation and operational costs, minimization of RFID reader interference and maximisation of social impact) of the proposed RFID-enabled passport location tracking system. The problem was formulated as a multi-objective model that considers the objectives previously described. Moreover, to come closer to reality, critical parameters were considered as imprecise, these being demands and costs. Accordingly, the model was developed in terms of a fuzzy multi-objective model, with a two-stage solution methodology being proposed to solve the problem. At the first stage, two solution approaches including an ε-constraint method and LP method were used for obtaining two sets of Pareto solutions. Moreover, evaluation of these two methods in solution values was presented and the results discussed. In general, they are both appropriate and efficient for solving the fuzzy multi-objective problem, hence being able to reveal trade-offs among the considered conflicting objectives. Notwithstanding this, the ε-constraint has the advantage of revealing Pareto solutions that are closer to the ideal values of the three objectives. As a second stage, a decision-making method was employed to select the final Pareto solution, which proved the greater efficiency of the ε-constraint method over the LP-metrics method. Finally, implementation within a case study verified the applicability of the developed mathematical model as well as the effectiveness of the proposed optimisation methodology in terms of: (i) presenting an optimal design for the RFID-enabled passport location tracking system; (ii) obtaining trade-offs among the three objectives; and (iii) coping with the uncertainty in the input data. Consequently, the model can be configured and utilised as a reference for the designers of similar RFID-enabled passport tracking systems.

It is certainly worth considering an investigation into the cost-effective analysis for the RFID-enabled passport tracking system and non-RFID-enabled tracking system to determine the impact in costs of the RFID implementation on the tracking system. Also, solving the developed model by deploying a meta-heuristic algorithm would be useful for handling large-sized problems in a reasonable timeframe.

Conflict of interests

We confirm that there is no conflict of interests for our submission.

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