

1 **Design and optimization of an RFID-enabled automated warehousing system under**
2 **uncertainties: a multi-criterion fuzzy programming approach**

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21 **Abstract**

22 In this paper, we investigated the design and optimization of a proposed RFID-enabled
23 automated warehousing system in terms of the optimal number of storage racks and collection
24 points that should be established in an efficient and cost-effective approach. To this aim, a
25 fuzzy tri-criterion programming model was developed and used for obtaining trade-off
26 decisions by measuring three conflicting objectives. These are minimization of the warehouse
27 total cost, maximization of the warehouse capacity utilization and minimization of the travel
28 time of products from storage racks to collection points. To reveal the alternative Pareto-
29 optimal solutions using the developed model, a new approach was developed and compared
30 with a recently developed fuzzy approach so-called SO (Selim and Ozkarahan). A decision
31 making algorithm was used to select the best Pareto-optimal solution and the applicability of
32 the developed model was examined using a case-study. Research findings demonstrate that the
33 developed model is capable of generating an optimal solution as an aid for the design of the
34 proposed RFID-enabled automated warehousing system.

35 **Keywords:** Automated warehouse; RFID; Design; Fuzzy approach; Multi-criterion optimization.

36 **1. Introduction**

37 Warehouses are one of main components consisting of an entire supply chain network in which
38 a warehouse receives and stores merchandising products that are often transported from
39 suppliers to retailers. Hence, accuracy of transportation time plays an important role on the
40 entire supply chain network, which traditionally relies on a well-organized warehouse
41 management (Choi et al., 2013; Yeung et al., 2011). For the last decade, it has been seen a
42 growing trend in application and implementation of automated warehouses aiming to improve
43 the warehouse efficiency and capacity utilization, and reduce the material-handling time of
44 warehouses. On the other hand, automation of warehouses is subject to additional costs that

45 need to be considered; this led to research interests in optimization of automated warehouse
46 designs by enhancing efficiency and reducing unnecessary costs.

47 There are relatively a few studies in optimization of automated warehouse designs in several
48 aspects—such as costs and capacity utilization. Lu et al. (2006) reviewed some fundamental
49 issues, methodologies, applications and potentials of applying Radio Frequency Identification
50 (RFID) techniques in manufacturing sectors. Van Der Berg (1999) presented a review on
51 approaches and techniques applied for the warehouse management planning and control. Ma
52 et al. (2015) formulated an automated warehouse as a constrained multi-objective model aimed
53 at minimizing the scheduling quality effect and the travel distance. Huang et al. (2015)
54 proposed a nonlinear mixed integer program under probabilistic constraints for site selection
55 and space determination of a warehouse. The purpose of this work was to minimize the total
56 cost of inbound and outbound transportation and the total cost of warehouse operations in a
57 two-stage network. Lerher et al. (2013) developed a multi-objective model for analyzing the
58 design of an automated warehouse towards the optimization of the travel time of product, the
59 total cost of the automated warehouse and quality in the number of material handling devices.
60 Lerher et al. (2010) also investigated the design and optimization of the automated storage and
61 retrieval system aiming to minimize the initial investment and annual operating cost of the
62 system using the genetic algorithm. Wang et al. (2010) presented a study of an RFID-based
63 automated warehousing mechanism in order to address the tighter inventory control, shorter
64 response time and greater variety of stock keeping units (SKUs), which are the most important
65 challenges for designing future generation warehouses. Lu et al. (2006) presented a five-step
66 deployment process aimed at developing a holistic approach for implementing RFID in
67 manufacturing enterprises. Lerher et al. (2007) proposed a mono-objective optimization
68 approach for seeking the cost-effective design of an automated warehouse. Ashayeri et al.
69 (1987) developed a design model of an automated storage and retrieval system incorporating

70 the main influential parameters to minimize costs in investment and operation. Karasawa et al.
71 (1980) developed a nonlinear mixed integer model aimed at minimizing the cost for an
72 automated warehouse system.

73 A review of the literature reveals that there were no previous studies in applying the fuzzy
74 multi-criterion optimization approach in the context of the warehouse design (Lerher et al.,
75 2013), in particular for the Radio Frequency Identification (RFID)-enabled automated
76 warehousing system. This paper addresses a contribution in developing a fuzzy tri-criterion
77 optimization model based on a proposed RFID-enabled automated warehousing system
78 incorporating the uncertainty in varying demand, costs and items locations. The developed
79 model aims at simultaneously optimizing a number of conflicting criteria including
80 minimization of the total cost, maximization of the warehouse capacity utilization and
81 minimization of travel time of products. In other words, it aims at obtaining a trade-off that can
82 concurrently maximizes the degree of satisfaction and minimize the degree of dissatisfaction
83 at a time for the problem under investigation.

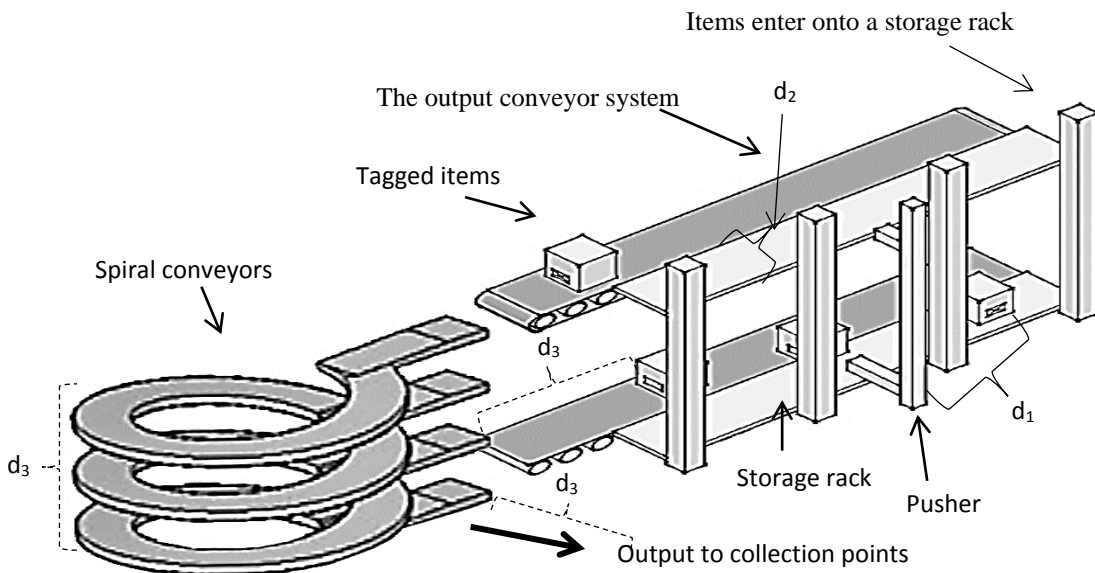
84 The remaining part of the paper proceeds as follows: In section 2, the problem description and
85 the model formulation are presented. In section 3, the optimization methodology is described.
86 In section 4, it demonstrates the application and evaluation of the developed multi-criterion
87 model using a case study. In section 5, conclusions are drawn.

88 **2. Problem description and model formulation**

89 Figure 1 illustrates the structure of the proposed RFID-enabled automated storage and retrieval
90 racks (AS/RR) used for this study (Wang et al., 2010). The module comprises of two types of
91 powered conveyors aligned next to one another; these are input conveyors (storage racks) and
92 output conveyors. The entire operation of each conveyor system is controlled by a
93 programmable logic controller that communicates with mounted sensors via a local area

94 network. Within the RFID-inventory management system, a chosen SKU can be released by
95 the mechanical control system based on a number of assignment policies or rules. These rules
96 include for example the rule of being nearest to a collection point and/or a modular arm which
97 is free or adjacent to the chosen SKU.

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100 Fig. 1. Structure of the proposed RFID-enabled AS/RR.

101 One of the main issues to be addressed in designing the proposed RFID-enabled automated
102 warehouse include allocating the optimum number of racks and collection points with respect
103 to three criterion functions: (1) minimization of total cost, (2) maximization of capacity
104 utilization of the warehouse and (3) minimization of travel time of products from storage racks
105 to collection points.

106 2.1. Notations

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

Sets:

I	set of nominated storage racks $i \in I$
J	set of nominated collection points $j \in J$
K	set of fixed departure gates $k \in K$

Given parameters:

C_i^r	fixed cost required for establishing an RFID-enabled rack i
C_j^c	fixed cost required for establishing a collection point j
C_i^t	unit RFID tag cost per item at rack i
C_{jk}^T	unit transportation cost per meter from collection point j to departure point k
C_j^l	unit labor cost per hour at collection point j
R_j^l	working rate (items) per laborer at collection point j
N_j^h	minimum required number of working hours for laborers l at collection point j
W	transportation capacity (units) per forklift
S_i^r	maximum supply capacity (units) of rack i
S_j^c	maximum supply capacity (units) of collection point j
D_j	demand (units) of collection point j
d_1	travel distance needed (m) for a pusher from its location to a selected item
d_2	travel distance (m) of a selected item from its position at a storage rack to an output conveyor
d_3	travel distance (m) of a selected item from its position at an output conveyor to a collection point

d_{jk}	travel distance (m) of a selected item from collection point j to departure gate k
S_p	speed (m/s) of the moving-pusher along d_i
S_{pp}	speed (m/s) of the moving-pusher to push a selected item onto an output conveyer.
S_c	speed (m/s) of the output conveyor and the spiral conveyor.

Decision variables

q_{ij}	quantity in units ordered from rack i to collection point j
q_{jk}	quantity in units dispatched from collection point j to departure gate k
x_j	required number of laborers at collection point j
y_i	$\left\{ \begin{array}{l} 1: \text{if rack } i \text{ is opened} \\ 0: \text{otherwise} \end{array} \right.$
y_j	$\left\{ \begin{array}{l} 1: \text{if collection point } j \text{ is opened} \\ 0: \text{otherwise} \end{array} \right.$

109 2.2 Formulation of the multi-criterion optimization problem

110 The three criteria, which include minimization of total cost, maximization of capacity
 111 utilization and minimization of travel time, are formulated as follows:

112 Criterion function 1 (F_1)

113 In this case, the total cost of establishing the RFID-enabled automated warehouse includes the
 114 costs of establishing RFID-enabled racks, collection points, RFID tags, transportation of
 115 products and labors in the warehouse. Thus, minimization of the total cost F_1 can be expressed
 116 below:

$$\begin{aligned}
\text{Min } F_1 = & \sum_{i \in I} C_i^r y_i + \sum_{j \in J} C_j^c y_j + \sum_{i \in I} \sum_{j \in J} C_i^l q_{ij} + \sum_{j \in J} \sum_{k \in K} C_{ij}^T \left[q_{jk} / W_f \right] d_{jk} \\
& + \sum_{j \in J} C_j^l x_j N_j^h
\end{aligned} \tag{1}$$

117 Criterion function 2 (F₂)

118 The capacity utilization is defined as the used capacity divided by the actual capacity. Thus,
119 maximization of capacity utilization F₂ is expressed as follows:

$$\text{Max } F_2 = \left(\sum_{i \in I} \frac{[(C_a) - (C_u)]^2}{\sum i} \right)^{\frac{1}{2}} \tag{2}$$

120 Where $C_a = \sum_{i \in I} \sum_{j \in J} \frac{q_{ij}}{S_i^r}$ and $C_u = \frac{\sum_{i \in I} \sum_{j \in J} q_{ij}}{\sum_{i \in I} S_i^r}$, which refer to the actual (a) and used (u) capacity

121 (C).

122 Criterion function 3 (F₃)

123 Travel time (tt) of an in-store item includes, tt of a pusher from its location to an item, tt of an
124 item from its location at the storage rack to an output conveyer and tt of an item onto a conveyer
125 system to the collection point. Thus, minimization of travel time F₃ is expressed as follows:

$$\text{Min } F_3 = \sum_{i \in I} \sum_{j \in J} \left(\frac{d_1}{S_p} + \frac{d_2}{S_{pp}} + \frac{d_3}{S_c} \right) q_{ij} \tag{3}$$

126 2.3 Constraints

127 The above model was developed under the following constraints:

$$\sum_{i \in I} q_{ij} \leq S_i^r y_i \quad \forall j \in J \tag{4}$$

$$\sum_{j \in J} q_{jk} \leq S_j^c y_j \quad \forall k \in K \quad (5)$$

$$\sum_{i \in I} q_{ij} \geq D_j \quad \forall j \in J \quad (6)$$

$$D_j \geq \sum_{k \in K} q_{jk} \quad \forall j \in J \quad (7)$$

$$\sum_{j \in J} q_{ij} \leq x_j R_j^1 \quad \forall i \in I \quad (8)$$

$$q_{ij}, q_{jk} \geq 0, \quad \forall i, j, k; \quad (9)$$

$$y_i, y_j \in \{0, 1\}, \quad \forall i, j; \quad (10)$$

128 Equations 4 and 5 refer to the flow balance of a product travelling from a storage rack to a
 129 collection point and from a collection point to a departure gate. Equations 6 and 7 refer to
 130 demands in quantity to be satisfied. Equation 8 determines the required number of labors at a
 131 collection point. Equations 9 and 10 limit the decision variables to binary and non-negative.

132 3. The proposed optimization methodology

133 3.1 Solution procedures

134 To reveal the alternative Pareto-optimal solutions using the developed model, the following
 135 procedures were used:

136 (1) Convert the developed model into an equivalent crisp model (shown in section 3.2).

137 (2) Find the upper and lower bound (U, L) solution for each criterion function. This can be
 138 obtained as follows:

139 For upper bound solutions:

$$\begin{aligned}
Max F_1(U_1) = & \sum_{i \in I} C_i^r y_i + \sum_{j \in J} C_j^c y_j + \sum_{i \in I} \sum_{j \in J} C_i^t q_{ij} + \sum_{j \in J} \sum_{k \in K} C_{ij}^T \left[q_{jk} / W_f \right] d_{jk} \\
& + \sum_{j \in J} C_j^l x_j N_j^h
\end{aligned} \tag{11}$$

$$Max F_2(U_2) = \left(\sum_{i \in I} \frac{[(C_a) - (C_u)]^2}{\sum i} \right)^{\frac{1}{2}} \tag{12}$$

$$Max F_3(U_3) = \sum_{i \in I} \sum_{j \in J} \left(\frac{d_1}{S_p} + \frac{d_2}{S_{pp}} + \frac{d_3}{S_c} \right) q_{ij} \tag{13}$$

140 For lower bound solutions:

$$\begin{aligned}
Min F_1(L_1) = & \sum_{i \in I} C_i^r y_i + \sum_{j \in J} C_j^c y_j + \sum_{i \in I} \sum_{j \in J} C_i^t q_{ij} + \sum_{j \in J} \sum_{k \in K} C_{ij}^T \left[q_{jk} / W_f \right] d_{jk} \\
& + \sum_{j \in J} C_j^l x_j N_j^h
\end{aligned} \tag{14}$$

$$Min F_2(L_2) = \left(\sum_{i \in I} \frac{[(C_a) - (C_u)]^2}{\sum i} \right)^{\frac{1}{2}} \tag{15}$$

$$Min F_3(L_3) = \sum_{i \in I} \sum_{j \in J} \left(\frac{d_1}{S_p} + \frac{d_2}{S_{pp}} + \frac{d_3}{S_c} \right) q_{ij} \tag{16}$$

141 (3) Find the respective satisfaction degree $\mu(x_i)$ for each criterion as follows:

$$\mu_1(F_1(x)) = \begin{cases} 1 & \text{if } F_1(x) \geq U_1 \\ \frac{F_1(x) - L_1}{U_1 - L_1} & \text{if } L_1 \leq F_1(x) \leq U_1 \\ 0 & \text{if } F_1(x) \leq L_1 \end{cases} \tag{17}$$

$$\mu_2(F_2(x)) = \begin{cases} 1 & \text{if } F_2(x) \geq U_2 \\ \frac{F_2(x) - L_2}{U_2 - L_2} & \text{if } L_2 \leq F_2(x) \leq U_2 \\ 0 & \text{if } F_2(x) \leq L_2 \end{cases} \quad (18)$$

$$\mu_3(F_3(x)) = \begin{cases} 1 & \text{if } F_3(x) \geq U_3 \\ \frac{F_3(x) - L_3}{U_3 - L_3} & \text{if } L_3 \leq F_3(x) \leq U_3 \\ 0 & \text{if } F_3(x) \leq L_3 \end{cases} \quad (19)$$

142 (4) Transform the crisp model obtained from section 3.2 to a single criterion function using
143 the proposed solution approaches (shown in section 3.3).

144 (5) Vary the weight combination set consistently for the three criteria to reveal Pareto-
145 optimal solutions. Usually, the weight combination set is allocated by decision makers
146 based on the importance of each objective.

147 (6) Select the best Pareto-optimal solution using the proposed decision making algorithm.

148 3.2 Formulating the uncertainty

149 To incorporate the uncertainty in varying demand, costs and items locations, the developed tri-
150 criterion model is converted into an equivalent crisp model using the Jiménez method (Jiménez
151 et al., 2007). Accordingly, the equivalent crisp model can be formulated as follows:

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$$\begin{aligned} \text{Min } F_1 = & \sum_{i \in I} \left(\frac{C_i^{rpes} + 2C_i^{rmos} + C_i^{ropt}}{4} \right) y_i + \sum_{j \in J} \left(\frac{C_j^{cpes} + 2C_j^{cmos} + C_j^{copt}}{4} \right) y_j \\ & + \sum_{i \in I} \sum_{j \in J} \left(\frac{C_i^{lpes} + 2C_i^{lmos} + C_i^{lopt}}{4} \right) q_{ij} + \sum_{j \in J} \sum_{k \in K} \left(\frac{C_{ij}^{Tpes} + 2C_{ij}^{Tmos} + C_{ij}^{Topt}}{4} \right) \lceil q_{jk} / W_f \rceil d_{jk} \\ & + \sum_{j \in J} \left(\frac{C_j^{lpes} + 2C_j^{lmos} + C_j^{lopt}}{4} \right) x_j N_j^h \end{aligned} \quad (20)$$

$$Max F_2 = \left(\sum_{i \in I} \frac{[(C_a) - (C_u)]^2}{\sum i} \right)^{\frac{1}{2}} \quad (21)$$

$$Min F_3 = \sum_{i \in I} \sum_{j \in J} \left(\frac{d_1^{pes} + 2d_1^{mos} + d_1^{opt}}{4S_p} + \frac{d_2^{pes} + 2d_2^{mos} + d_2^{opt}}{4S_{pp}} + \frac{d_3^{pes} + 2d_3^{mos} + d_3^{opt}}{4S_c} \right) q_{ij} \quad (22)$$

153 Subject to:

$$\sum_{i \in I} q_{ij} \leq S_i y_i \quad \forall j \in J \quad (23)$$

$$\sum_{j \in J} q_{jk} \leq S_j y_j \quad \forall k \in K \quad (24)$$

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

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

$$\sum_{j \in J} q_{ij} \leq x_j \frac{\lambda}{2} \frac{x_{j1} + x_{j2}}{2} + \left(1 - \frac{\lambda}{2}\right) \frac{x_{j3} + x_{j4}}{2} R_j^1 \quad \forall i \in I \quad (27)$$

$$q_{ij}, q_{jk} \geq 0, \quad \forall i, j, k; \quad (28)$$

$$y_i, y_j \in \{0, 1\}, \quad \forall i, j; \quad (29)$$

154 According to Jiménez's approach, it is supposed that the constraints in the model should be
 155 satisfied with a confidence value which is denoted as λ and it is normally determined by
 156 decision makers. Also, mos, pes and opt are the three prominent points (the most likely, the
 157 most pessimistic and the most optimistic values), respectively (Jiménez et al., 2007).

158 3.3 Optimization approaches

159 3.3.1 The developed approach

160 With the developed approach the multi-criterion model can be transformed into a single-
 161 criterion model which is formulated by optimizing each criterion individually. This single-
 162 criterion model aims to minimize the scalarized differences between each criterion and its
 163 optimal value. Undesired deviations are proposed to be subtracted from the single criterion
 164 function with the aim to achieve more accurate criterion values. These values are close enough
 165 to Pareto-optimal solutions which lead to a clear insight of a compromised solution between
 166 conflicting criteria for decision makers.

167 The solution function (F) is formulated as follows:

$$\text{Min } F = \left(\sum_{n=1}^3 \sum_{f=1}^3 \vartheta_n \mu_f(x) \right) - F_d, \quad \sum_{n=1}^3 \vartheta_n = 1 \quad (30)$$

168 Set $\vartheta_n^* = \frac{\vartheta_n F_n^*}{F_n^* - F_n}$, then

$$F_d = \vartheta_1^* F_1 + \vartheta_2^* F_2 + \vartheta_3^* F_3 = \frac{\vartheta_1 F_1^*}{F_1^* - F_1} F_1 + \frac{\vartheta_2 F_2^*}{F_2^* - F_2} F_2 + \frac{\vartheta_3 F_3^*}{F_3^* - F_3} F_3 \quad (31)$$

169 Based on the aforementioned procedures, the above criterion function can be expressed further
 170 as follows.

$$\text{Min } F = (\vartheta_1 \mu_1 - \vartheta_2 \mu_2 - \vartheta_3 \mu_3) - \left(\frac{\vartheta_1 F_1^*}{F_1^* - F_1} F_1 + \frac{\vartheta_2 F_2^*}{F_2^* - F_2} F_2 + \frac{\vartheta_3 F_3^*}{F_3^* - F_3} F_3 \right) \quad (32)$$

171 Subject to equations 4-10.

172 3.3.2 The SO approach

173 In this approach, the auxiliary crisp model in section 3.2 is converted to a mono-criterion
 174 function using the following solution formula (Selim and Ozkarahan, 2008):

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$$\text{Max } \lambda(x) = \gamma \lambda_o + (1-\gamma) \sum_{f \in F} \theta_f \lambda_f \quad (33)$$

176 Subject to:

177

$$\lambda_o + \lambda_f \leq \mu(x), \quad f=1,2,3 \quad (34)$$

$$x \in F(x), \quad \lambda_o \text{ and } \lambda \in [0, 1] \quad (35)$$

178 In which, the value of variable $\lambda_o = \min \mu\{\mu(x)\}$, which indicates the minimum satisfaction
179 degree for each criterion function. Also, λ_f refers the difference between the satisfaction degree
180 of each criterion and minimum satisfaction degree of criteria ($\lambda_f = \mu(x) - \lambda_o$).

181 3.4 The decision making algorithm

182 The next step after revealing the Pareto solutions is to determine the best trade-off solution.
183 The best Pareto optimal solution can be determined based on decision maker's preferences or
184 by using a decision making algorithm, although there are a number of approaches which can
185 be utilized to determine the best solution in multi-criterion problems. In this study, the
186 technique namely TOPSIS (order preference by similarity to ideal solution) was employed for
187 revealing the best trade-off solution. This approach can be used for selecting a solution nearest
188 to the ideal solution, but also the farthest from the negative ideal solution (Ramesh et al., 2012).

189 Assume $PR = \{PR_{op} | o = 1, 2, \dots, x \text{ (number of pareto solutions)}; p = 1, 2, \dots, y \text{ (number of criteria)}\}$
190 refers the $x * y$ decision matrix, where PR is the performance rating of alternative Pareto
191 solutions with respect to criterion function values. Thus, the normalized selection formula is
192 presented as follows:

$$NPR = \frac{PR_{op}}{\sum_{p=1}^o PR_{ap}} \quad (36)$$

193 The amount of decision information can be measured by the entropy value as:

$$E_p = \frac{-1}{\ln x} \sum_{o=1}^x PR_{op} \ln(PR_{op}) \quad (37)$$

194 The degree of divergence D_p of the average intrinsic information under $p = 1, 2, 3, 4$ can be
 195 calculated as follows:

$$D_p = 1 - E_p \quad (38)$$

196 The weight for each criterion function value is given by:

$$w_p = \frac{D_p}{\sum_{k=1}^y D_k} \quad (39)$$

197 Thus, the criterion weighted normalized value is given by:

$$v_{op} = w_o PR_{op} \quad (40)$$

198 Where, w_o refers to a weight in alternatives which are normally assigned by the decision
 199 makers.

200 The positive ideal solution (AT⁺) and the negative ideal solution (AT⁻) are taken to generate
 201 an overall performance matrix for each Pareto solution. These values can be expressed as
 202 below:

$$\begin{aligned} AT^+ &= (\max(v_{o1}) \quad \max(v_{o2}) \quad \max(v_{oy})) = (v_1^+, v_2^+, \dots, v_y^+) \\ AT^- &= (\min(v_{o1}) \quad \min(v_{o2}) \quad \min(v_{oy})) = (v_1^-, v_2^-, \dots, v_y^-) \end{aligned} \quad (41)$$

A distance between alternative solutions can be measured by the n-dimensional Euclidean distance. Thus, the distance of each alternative from the positive and negative ideal solutions is given as:

$$D_p^+ = \sqrt{\left\{ \sum_{o=1}^y (v_{op} - v_o^+)^2 \right\}} , \quad p = 1, 2, \dots, x \quad (42)$$

$$D_p^- = \sqrt{\left\{ \sum_{o=1}^y (v_{op} - v_o^-)^2 \right\}} , \quad p = 1, 2, \dots, x \quad (43)$$

203 The relative closeness to each of values of alternative solutions to the value of the ideal solution
 204 is expressed as follows:

$$rc_p = \frac{D_p^-}{D_p^+ + D_p^-}, \quad p = 1, 2, \dots, x \quad (44)$$

205 Where $D_p^- \geq 0$ and $D_p^+ \geq 0$, then, clearly, $rc_p \in [1, 0]$

206 The trade-off solution can be selected with the maximum rc_p or rc_p listed in descending order.

207 Fig. 2 shows a flowchart of the proposed optimization methodology.

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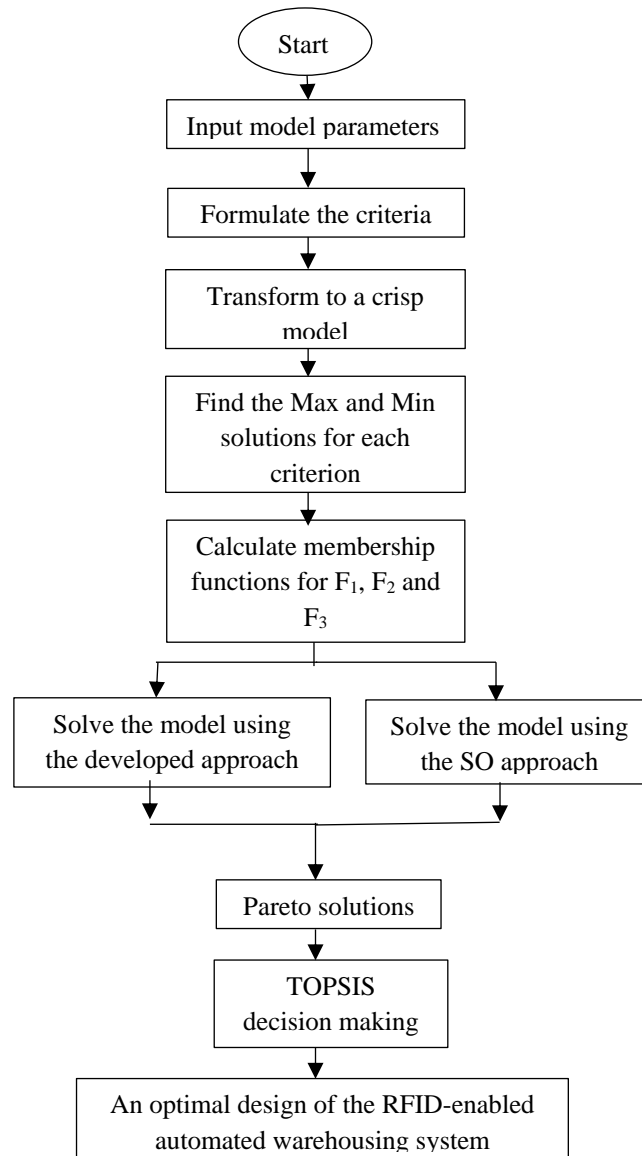


Fig. 2. Flowchart of the optimization methodology.

230 4. Application and evaluation

231 In this section, a case study was used for examining the applicability of the developed tri-
232 criterion model and evaluating the performance of the proposed optimization methodology. A
233 range of application data is presented in Table 1. It is assumed that (1) width, length and height
234 of each rack are $W = 0.3$ m, $L = 18$ m and $H = 5$ m, (2) the distance between the start of a spiral
235 conveyer to the end of a collection points is 2 m and (3) the pusher is located at the center of
236 each rack. All these parameters are taken from a real-world automated warehouse design; the

237 prices of RFID equipment and its implementation were estimated based on the marketing
 238 prices. The optimizer of the developed tri-criterion model is LINGO¹¹. All computational
 239 experiments were conducted on a laptop with a 2.60 GHz CPU and a 4 G memory.

240 Table 1. Application data used for the case study.

$I = 12$	$C_i^t = 0.25 \text{ £}$	$d_{jk} = 20-45 \text{ m}$	$d_1 = 0.1 - 4 \text{ m}$
$J = 15$	$C_{jk}^T = 0.4 - 0.7 \text{ £}$	$S_c = 35 \text{ m/s}$	$d_2 = 0.3 \text{ m}$
$K = 2$	$R_j^l = 100$	$W = 48$	$d_3 = 7 - 23 \text{ m}$
$C_j^l = 6.5 - 9 \text{ £}$	$S_i = 25-35\text{K£}$	$D_j = 6\text{K} - 9\text{K}$	$S_p = 1 \text{ m/s}$
$C_i^r = 60-90 \text{ K£}$	$S_j = 20-29\text{K£}$	$C_j^c = 15-18\text{K£}$	$S_{pp} = 0.8 \text{ m/s}$

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242 4.1 Results and discussions

243 This section presents the results which were obtained based on the developed fuzzy tri-criterion
 244 model using the proposed fuzzy solution approaches for the problem previously defined. The
 245 solution steps of the developed model are described as follows:

- 246 1) Obtain the upper and lower values for each criterion function by solving them
 247 individually. The results are $(\{U_{F_i}, L_{F_i}\}) = (\{504, 1,230\}, \{0.66, 0.94\}, \{4.27, 12.25\})$.
- 248 2) Find the respective satisfaction degree $\mu(x_i)$ for each criterion function. The satisfaction
 249 degrees are reported in Table 2.

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254 Table 2. Result of satisfaction degree of each criterion function.

$\mu(x_1)$	0.95	0.93	0.85	0.81	0.7	0.623	0.6	0.55
$\mu(x_2)$	0.7	0.78	0.83	0.88	0.92	0.97	0.98	0.99
$\mu(x_3)$	0.97	0.96	0.93	0.90	0.85	0.84	0.81	0.76

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256 3) Convert the multi-objective crisp model to a single criterion model using (i) the
 257 developed approach by assigning weight values shown in Table 3 and (ii) the SO
 258 approach by assigning the value of γ which is set as 0.33 by the decision makers who
 259 consider a balance in importance of each of the three criteria. The two approaches are
 260 compared by assigning different λ levels. Table 4 shows the computational results
 261 obtained using the two approaches. Accordingly, Table 5 shows the corresponding
 262 optimum numbers of storage racks and collection points that should be established. Fig.
 263 3 illustrates Pareto optimal fronts among the three criterion functions obtained by using
 264 the two approaches.

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276 Table 3. Assignment of weight values for obtaining Pareto solutions using two approaches.

#	Criteria weights		
	g_1, θ_1	g_2, θ_2	g_3, θ_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

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288 Table 4. The results obtained by assigning the varying λ values to each of the three criterion

289 functions.

378 non-zero elements, 64 constraints, 129 total variables, 68 integer variables

#	λ -level	Developed approach				SO approach			
		Min F ₁ (K£)	Max F ₂ (%)	Min F ₃ (h)	Run time (s)	Min F ₁ (K£)	Max F ₂ (%)	Min F ₃ (h)	Run time (s)
1	0.3	504	0.66	4.29	2	504	0.66	4.29	2
2	0.4	595	0.71	5.31	2	595	0.71	5.31	3
3	0.5	678	0.78	6.51	2	681	0.78	6.58	2
4	0.6	795	0.84	7.75	1	790	0.84	7.69	3
5	0.7	894	0.89	8.92	3	913	0.89	9.12	4
6	0.8	978	0.92	10.18	4	1053	0.93	11.91	3
7	0.9	1064	0.93	11.97	4	969	0.92	10.33	4
8	1	-	-	-	-	1096	0.94	12.19	4

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299 Table 5. The optimal numbers of storage racks and collection points that should be established.

#	Developed approach		SO approach	
	Opened storage	Opened collection	Opened storage	Opened collection
	racks	points	racks	points
1	6	9	6	9
2	6	9	6	9
3	7	8	7	8
4	9	11	9	11
5	10	12	10	13
6	11	13	12	14
7	11	13	11	13
8	-	-	12	15

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301 4) Select the best solution using the TOPSIS method, the scored values of Pareto-optimal
302 solutions are reported in Table 6.

303 Table 6. Pareto-optimal solutions ranked based on scores using the TOPSIS method.

Developed approach								
Solution	1	2	3	4	5	6	7	8
Score	0.245	0.234	0.266	0.245	0.2544	0.279	0.273	-
SO approach								
Solution	1	2	3	4	5	6	7	8
Score	0.245	0.234	0.266	0.245	0.2544	0.267	0.273	0.243

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305 As mentioned above, Table 4 and 5 show the obtained two sets of Pareto-optimal solutions,
306 respectively, which were obtained based on the three criterion functions to determine the

307 numbers of storage racks and collection points that should be established. For instance, solution
308 1 shown in Table 4 is obtained using the developed approach under an assignment of
309 $\mathcal{G}_1=1, \mathcal{G}_2=0$ and $\mathcal{G}_3=0$, it gives the minimum total cost of 504 K£, the maximum capacity
310 utilization of 66% and the minimum travel time for all the requested products of 4.29 h. The
311 result shown in Table 5, the solution consists of six storage racks and nine collection points
312 and these trade-off results are obtained based on the three criteria towards the minimization of
313 total cost, the maximization of capacity utilization and the minimization of travel time.
314 Nevertheless, as shown in Fig. 3, with the Pareto optimal method, it cannot generate a better
315 overall result by gaining one best result based on one criterion function without worsening the
316 results in the other criterion functions, although all Pareto-optimal solutions are feasible. It
317 proves the confliction among the three criteria. For instance, an increase in the desired value
318 of criterion two (e.g. maximization of capacity utilization) leads to an increase in the undesired
319 value of criterion one (e.g. minimization of total cost).

320 It can be noted in Table 4 that by increasing the satisfaction level λ , it leads to an increase in
321 the undesired value of the first and third criterion functions (e.g. minimization of total cost and
322 minimization of travel time, respectively). Although it yields an increase in the desired value
323 of the second criterion function (e.g. maximization of capacity utilization). In this case,
324 decision makers have to spend more money to cope with the uncertainties. However, decision
325 makers can vary weight the importance (\mathcal{G}_n , or Θ_f) of each of the three criterion functions and
326 the satisfaction level λ based on their preferences in order to obtain another compromised
327 solution.

328 Through a comparison of the two sets of Pareto-optimal solutions shown in Table 4, the values
329 obtained based on the three criterion functions using the developed approach are more balanced
330 than those (of solutions 6-8) using the SO approach. The optimization run time of using the

331 developed approach for the eight iterations was slightly faster than the SO method. It also
332 indicates that there is no feasible solution obtained using the developed approach when the
333 weight for the first criterion (minimization of total cost) is set less than 0.4. This implies that
334 decision makers cannot ignore the importance of cost as it yields an inapplicable warehouse
335 design. In other words, with the developed approach it gives a more realistic and balanced
336 solution.

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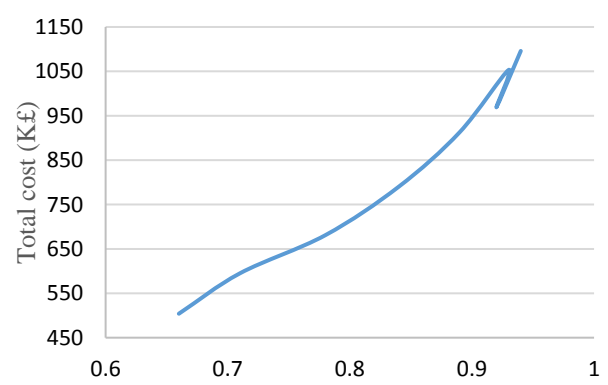
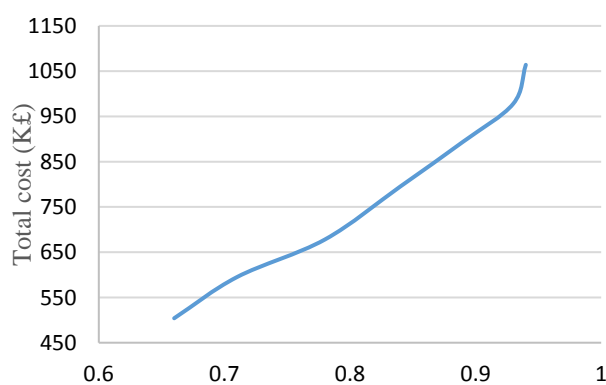
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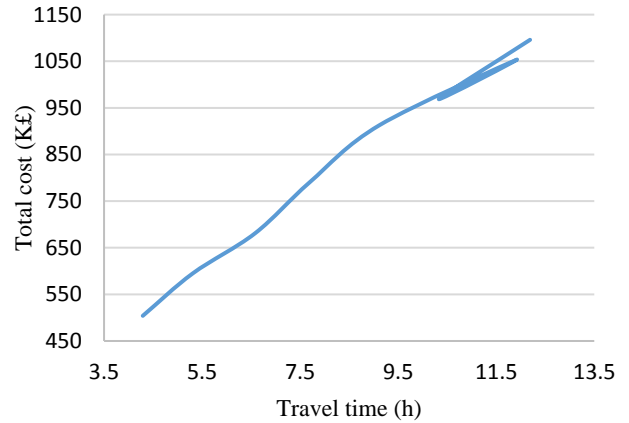
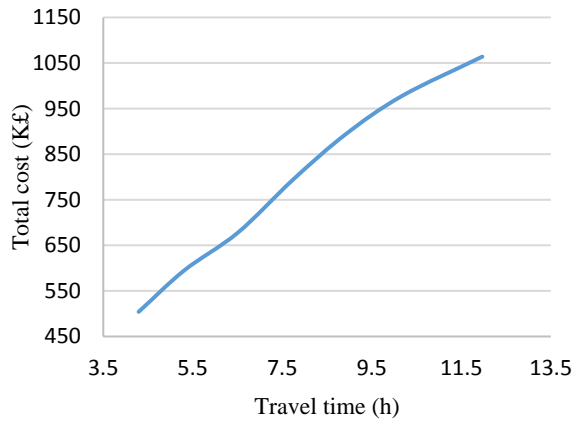
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Using the developed approach

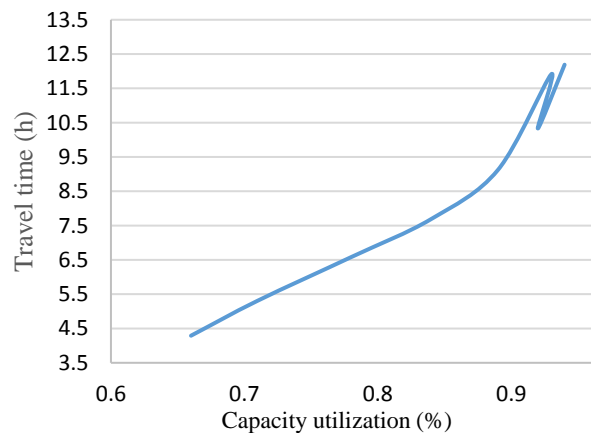
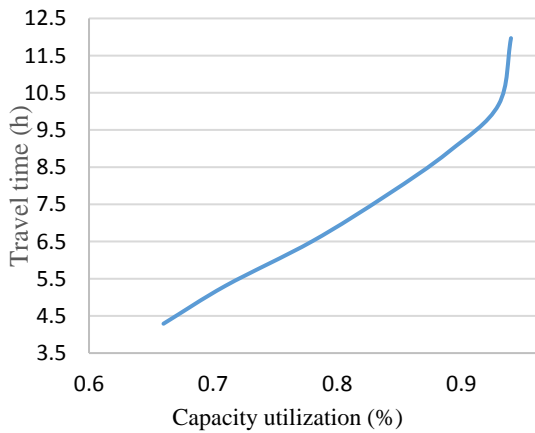
Using the SO approach

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Using the developed approach

Using the SO approach

364 Fig. 3. Pareto optimal fronts among the three criterion functions obtained by the two
365 approaches.

366 After obtaining a set of Pareto-optimal solutions, decision makers may determine a solution
367 depending on their preferences or using a decision making algorithm. In this work, the TOPSIS
368 method was employed to select the best solution. As shown in Table 6, solution 6 is chosen as
369 the best solution as its score is the highest ($rc_p = 0.279$) with the total cost of £ 978K, 92%

370 capacity utilization and the travel time of 10.18 h. Also, it requires an establishment of eleven
371 storage racks to supply products to thirteen collection points.

372 **5. Conclusions**

373 In this research, a design of the proposed RFID-enabled automated warehousing system was
374 studied using the multi-objective optimization approach. The work was involved in
375 optimization of the design in terms of (1) allocating the optimal number of storage racks and
376 collection points that should be established and (2) obtaining a trade-off decision between the
377 negative impact of costs and the positive impact of maximization of the warehouse capacity
378 utilization and minimization of travel time of products travelling from storage racks to
379 collection points. To this aim, a tri-criterion programming model was developed and the model
380 was also converted to be a fuzzy programming model for incorporating parameters in varying
381 which include demands, costs and random locations of items in a warehouse. A two-stage
382 solution methodology was proposed to solve the fuzzy multi-criterion optimization problem.
383 At the first stage, the developed approach and the SO approach were used for obtaining two
384 Pareto-optimal sets. The results, which were obtained using the two different approaches, are
385 compared and it shows that both approaches are appropriate and efficient for the fuzzy multi-
386 criterion model; for revealing a trade-off decision among the considered criteria. Nevertheless,
387 the developed approach has more advantages, which includes (1) the solutions gained using
388 this approach are more balanced than using the SO approach (2) with the developed approach,
389 the run time (s) is slightly faster than using the SO approach and (3) it gives more realistic
390 solutions for an applicable warehouse design. In the second stage, the TOPSIS method was
391 employed to reveal the best Pareto solution. Finally, implementation of a case study
392 demonstrates the applicability of the developed model and the effectiveness of the proposed
393 optimization methodology which can be useful as an aid for optimizing the design of the RFID-
394 enabled automated warehousing system.

395 An interesting research study derived from this work may be a comparison between the RFID-
396 enabled automated warehousing system and the non-RFID-enabled automated warehousing
397 system in terms of these three criteria (e.g. minimization of total cost, maximization of capacity
398 utilization and minimization of travel time). It was also suggested to compare the developed
399 solution approach with the other available approaches such as e-constraint and augmented e-
400 constraint. Finally, by optimizing the developed model by a meta-heuristic algorithm may be
401 useful for handling the large-sized problems in a reasonable time.

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