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Optimizing warehouse network reliability under intentional disruption by increasing network ambiguity: a multi objective optimization model

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Abstract. In today's world, intentional disruptions in networks are expanding and the impacts are seen in many parts of the world. An effective approach for reducing the impact of such disruptions is to confuse invaders. Increasing ambiguity in the network is one of the effective ways which may confuse the invaders. To attain this goal, dummy facilities are added to the network. Dummy facilities are the facilities which are exactly the same as the real ones thus making it hard for the invader to make the distinction. In this paper, a new multi-objective mathematical model is presented to suitably design a network consisting of real and dummy warehouses. One objective is to minimize the total cost and the other is set to maximize reliability. An index for assessing network reliability is also introduced and used. The model is solved using AUGMECON and NSGA-II. Results demonstrate that establishing dummy facilities in the network will increase reliability while no significant cost is imposed.

Keywords. Network reliability; warehouse location; ambiguity; intentional disruption; interdiction.

1. Introduction

In all logistic networks, warehouses are fundamental infrastructure that have significant impact on time, cost and efficiency of operations. Any disruption in warehouses may lead to great interruptions in all the other network elements operations [1]. In real world, there are two categories of disruption, one is probabilistic and the other one is not [2]. The first category of disruptions is exogenous resulting from climate changes, power failures, and so on. The latter, however, is endogenous, in the sense that disruptions are caused by actors which are usually called intentional disruption. Those problems are classified as interdiction models which are occurring rapidly all over the world and critical infrastructures or people in crowded areas are significantly affected. Attentions are increasingly paid to intentional disruptions with the aim of developing different reliability models [2–5]. A framework was developed in which the risk management strategies are described, whether disruption is endogenous or exogenous [6]. Snyder [7] was one of the leading researchers on network reliability problems. Since then, many researchers have developed different models to increase network reliability. Literature [2, 8–10] provided reviews of related fields, [8] reviewed reliability models for location problems, [9] investigated location problems under disaster events, [2] reviewed researches on supply chain disruptions and finally [10] presented a comprehensive review about network interdiction models. Most of the researchers have developed bi-level models to increase the network reliability in which the defender tries to minimize the lost or maximize reliability and the attacker invades the network to impose maximum disruption. Two major concerns are usually missing. One of them is preventing disruptions and another is considering a tradeoff between the reliability and the cost. In most of the reliability models, increasing the network reliability is the common goal. But in real world, the cost is a major concern. Simultaneous optimization of the reliability and the cost is closer to the real-world problems. Fewer researchers have paid attention to cost as the main optimization criteria.

In reliability problems, it is very important for decision makers to be able to analyze the impact of paying more cost on reliability. A bi-objective formulation is important for a decision maker who (i) has to pre-plan for various resource availabilities; given the risk of interdiction, or (ii) may wish to consider cost-to-effectiveness or risk-to-effectiveness tradeoffs that are difficult to include directly in an interdiction planning model. So, Pareto-optimal solutions are necessary.

In this paper, we propose a model in which reliability and cost are both considered as objective functions. The multi-objective model is developed to obtain solutions that well

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represent the conflicting nature of the different optimization criteria. The goal is to find a set of solutions that describe the interaction of different criteria and evaluates how improvement in one objective function impacts the value of the other objective functions. The sets are usually referred to as the Pareto-optimal set and each of its elements are Pareto optimal solution.

The first objective of the proposed model is maximizing the reliability in preventive manner. A reliability index is used and maximized that affects the ambiguity in the network and makes it difficult for interdictor to identify critical assets. The second objective function tries to minimize the total establishment and transportation cost. There are numerous variations on interdiction problems in the literature. We will thoroughly discuss about those literature gabs in the next section.

2. Literature review

To cope with intentional disruption [11] presented r-interdiction median and the r-interdiction covering models in which the most critical facilities, whose removal would expose maximum lost to network, are identified. Also extended the model which protects somehow those critical facilities by allocating fortifying resources [12]. Research work presented and extended version of interdiction median problem with fortification to simplify the solution procedure [13]. These lead to a great innovation in network reliability literature and then many other researchers paid attention to network interdiction. [2] reviewed recent related research. [14] proposed a model in which protection resources have different capacities in different time periods. Allocating protection resources as recovery strategies for disrupted facilities were developed by [15]. Disruptions sometimes lead to complete stoppage at facilities and sometimes just reduce the operation capacity of facilities. This is called partial interdiction. Many researches investigate partial interdiction in which interdicted facility lost parts of its capacity. Using two different types of fortification resources, proposed a bi-objective bi-level mathematical model to minimize the lost while interdiction is partial [16]. A hub and spoke network for food grain transportation under disruption between two Indian states was proposed [17]. Two types of reliable models by considering facility failure probability and one layer backup was developed [18]. A bi-level fortification model was presented to choose protective resources which can improve facility recovery time when the worst case disruption has been occurred [19]. A bi-level model in which the defender minimizes total demand-weighted transportation cost with the remaining facilities while the attacker tries to reach the maximum disruptions was also proposed [20].

While information plays a critical role in network reliability approaches, deciding on how information is distributed among players is very important. Many researches have assumed that the attacker has no information about protected or fortified resources. This assumption is called incomplete information. To study facility protection against intentional attacks [21] proposed a simultaneous game theory model between a defender and an attacker while attacker has no information about protection resource allocation. Meanwhile, [22] developed a multi-objective Stackelberg game between the attacker and the defender in a water supply network, in which both have incomplete information.

Incorporating the risks of disruptions in the initial design of a system is an effective approach for the networks that have not yet been established. A model designed [23] that includes hardening some of the facilities to be located. Another model proposed to design a network in which facilities can be opened in either protected or unprotected mode in which the facilities are immunized against an attacker by protection [24]. A model to simultaneously locate the facilities and design the network while dealing with risk of disruption and budget limitation was given [25].

Cost, as an important criterion in designing reliable networks, is usually considered as a constraint; but simultaneous optimizing reliability and cost has been less considered. A multi-objective optimization problem with objectives related to vulnerability and protective resources to derive the group of components that, if eliminated from the system, would cause the worsening of the global efficiency [26]. The proposed bi-objective model in which interdictor seeks to minimize both total interdiction cost and maximum flow [27]. The designed model that concurrently optimizes two objectives: (1) maximization of shortest-path length and (2) minimization of interdiction strategy cost [28]. A multi objective bi-level hub location model under intentional disruption was formulated [29]. In the model, two objective functions are considered for defender to minimize total transportation cost and minimize the maximum damage imposed to the system by the attacker. A trade-off between reliability and cost for a water distribution network, while disruption is not intentional was investigated [30].

Since the presented models are mostly NP-hard, solving them is complicated. A A taxonomy for bi-level system-interdiction and system-defense models and developed [31, 32] discussed solution techniques for all these model types and described a number of applications to infrastructure protection. Simple models can be converted into mixed-integer programs and solved by optimization software. However, for more complicated models, decomposition methods and meta-heuristics are preferred for efficiency and generalization [33]. Solution methods for stochastic network interdiction problem are investigated by [34]. A comprehensive study of the related researches is presented in table 1.

Table 1. Comparative study of relevant literature with present work

Research	Model type									Uncertainty type		
	Median	Centre	Hub Location	Covering	Fixed charge location problem	Routing	Multi-stage	Location-Allocation	Supply chain/ logistics network	Certain	Probabilistic	Fuzzy
[11]	*			*						*		
[35]	*										*	
[36]					*						*	
[37]	*										*	
[38]					*						*	
[39]	*										*	
[40]					*				*		*	
[41]						*					*	
[42]							*				*	
[43]									*		*	
[25]		*								*		
[44]		*									*	
[45]	*						*				*	
[46]									*		*	
[47]									*			*
[1]							*				*	
[48]							*	*			*	
[49]			*								*	
[50]			*								*	
[18]	*				*						*	
[51]			*							*		
[52]									*		*	
[53]									*	*		
[54]					*						*	

Table 1. continued

Research	Uncertainty on					Objective function								
	Facility failure	Demand	Routes	Supply	Costs	Minimize the operation costs	Minimize initial setup costs	Minimize transportation costs	Minimize routing costs	Minimizing risk/maximizing reliability	Maximizing profit	Minimize relocation cost	Minimize the lost	Minimize penalty costs
[11]	*							*						
[35]	*							*						
[36]	*						*	*						
[37]	*							*						
[38]	*						*	*						
[39]	*							*						
[40]	*						*	*						
[41]			*					*	*					
[42]	*								*					*
[43]		*					*	*						*
[25]	*	*	*		*	*	*	*						
[44]	*	*								*				
[45]		*				*								
[46]		*		*						*	*			
[47]			*	*		*	*	*						
[1]	*	*			*			*				*		
[48]		*					*	*						
[49]	*							*						
[50]	*	*					*	*						
[18]	*							*						
[51]								*						
[52]	*		*				*	*					*	
[53]							*	*						
[54]	*						*	*						

Table 1. continued

Research	Reliability on			Application context					
	Capacity	Facility operation	Routes/paths	Transportation network.	Health	Food	Steel	Postal network	Aeronautic network
[11]		*							
[35]		*							
[36]		*							
[37]		*			*				
[38]		*							*
[39]		*							*
[40]		*							*
[41]			*	*					
[42]		*							
[43]	*	*							
[25]		*			*				
[44]		*							*
[45]	*								
[46]		*	*			*			
[47]		*					*		
[1]	*	*			*				
[48]		*			*				
[49]		*						*	*
[50]	*	*							
[18]		*							
[51]		*							*
[52]		*	*						
[53]		*							
[54]	*	*							

Table 1. continued

Research	Solution												
	Exact						Meta-heuristic						
	Lagrangian relaxation	Implicit enumeration	Optimization software	Decomposition	Augmented ε-constraint	Shortest-path algorithm	TS	GA	Tree search	imperialist Competitive	Greedy search	Heuristic heuristic	Other
[11]			*										
[35]													*
[36]	*												
[37]									*		*		
[38]	*											*	
[39]			*										
[40]	*												
[41]						*							
[42]											*	*	
[43]			*										
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[46]			*										
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[1]					*								
[48]				*									
[49]			*										
[50]								*		*			
[18]	*												
[51]			*										
[52]				*									
[53]								*					
[54]	*												

As it can be seen in table 1, several researchers have paid attention to multi objective models in the network interdiction problems, but minimizing cost and maximizing reliability as the two objectives is missing. Besides, the need for prevention is rarely considered.

One way of making a network reliable against intentional disruption and preventing the disruptions is to deceive the attackers. A method was developed a defenderattacker network interdiction model with deception considering concealed interdiction assets and decoys used by the defender [55]. The deception has been studied by many researches. But specially, [56] demarcated two types of deception: ambiguity-increasing, and misleading.

- **Ambiguity-increasing deception** "confuses a target so that the target is unsure as to what to believe", basically to compound his uncertainty by providing too many options.
- **Misleading deception** "builds up the attractiveness of one wrong alternative" which induces the enemy to concentrate his forces on the wrong location. An example on this type is "Operation Mincemeat"; the World War II operation to divert all German attention to Sardinia away from the intended amphibious landing zone of Sicily.

To increase the network ambiguity, more deception options should be provided for attackers which will increase the costs. So, the optimum number of deceptive facilities should be obtained and established. Using dummy facilities to deceive attackers is a topic that already has been used in real world applications. For example, deceptive hosts are widely used in cyber networks to deceive hackers [57]. A method was proposed to create dummy communication in networks which makes attackers confused and increases network reliability [58]. tThe study was made about the behavior of attackers by sending false information to the control center whereas the attacker has a limited knowledge of the network [59]. Wide discussion was made about critical infrastructure protection methods by focusing on the methods of deception [60]. The surveys researches made concentrating on dummy entities in cyber networks as a method to detect and monitor advanced attacks [61].

In logistic networks [62] proposed a reliable hub location model in which dummy hubs were used to confuse attackers. They also developed deception methods in warehouse location problem in which dummy warehouses are used among real warehouses to increase ambiguity of the network [63].

In this paper a linear multi objective model is presented to increase the ambiguity of the network. To do so, several dummy warehouses are established among real ones. Dummy warehouses appear to be the same as reals, but they are much cheaper to be established. It should be noted that there are many real world cases of using dummy infrastructure like dummy airfields or dummy cities in world war II [64]. An important issue regarding the establishment of dummy facilities is the cost. Spending more money and establishing more dummy warehouses will increase the network ambiguity. But the defender must optimize the cost and the reliability of the network simultaneously. Therefore, a multi objective model is developed in which one objective function is intended to minimize the cost and another objective function is intended in maximizing reliability. In the reminder of the paper, section 3 introduces model formulation. Computational experiments are presented in sections 4 and 5 presents our conclusion.

3. Mathematical modeling

3.1 *Notation*

To increase ambiguity of the warehouse network, an appropriate number of dummy facilities should be added to the network. Also total cost, including establishing real facilities, transportation cost and the costs associated with dummy facilities and so on, should be minimized. Both reliability and cost are important for network owner and should be optimized, so a multi objective model should be developed. First, the model assumptions and notation are introduced as follows:

Assumptions:

- The network is considered with a single allocation, which means each node is allocated to only one real and one dummy other node.
- Attackers have no information about the type (either real or fake) of facilities; In other words, the attackers have incomplete information about the network.
- To make dummy warehouses like the real warehouses, dummy demand and dummy flow should be designed.

A schematic representation of the use of dummy nodes in a hypothetical network is shown in figures 1 and 2. Warehouses 1 and 2 are real and warehouses 3 and 4 are fake. In figure 1, customers are only allocated to the real warehouses, but in figure 2, they are allocated to both real and dummy warehouses.

As it can be seen in figures, before adding the dummy warehouses it is so easy for attackers to identify the real warehouses and the network is quite vulnerable. But adding the dummy warehouses in figure 2, has increased ambiguity due to increased attack options. To model the problem, different sets, parameters and variables are used that are introduced as follows.

Sets:

I: Set of demand nodes.

J: Set of candidate warehouse nodes.

Parameters:

d_{ij}: Distance between demand node i and warehouse node j.

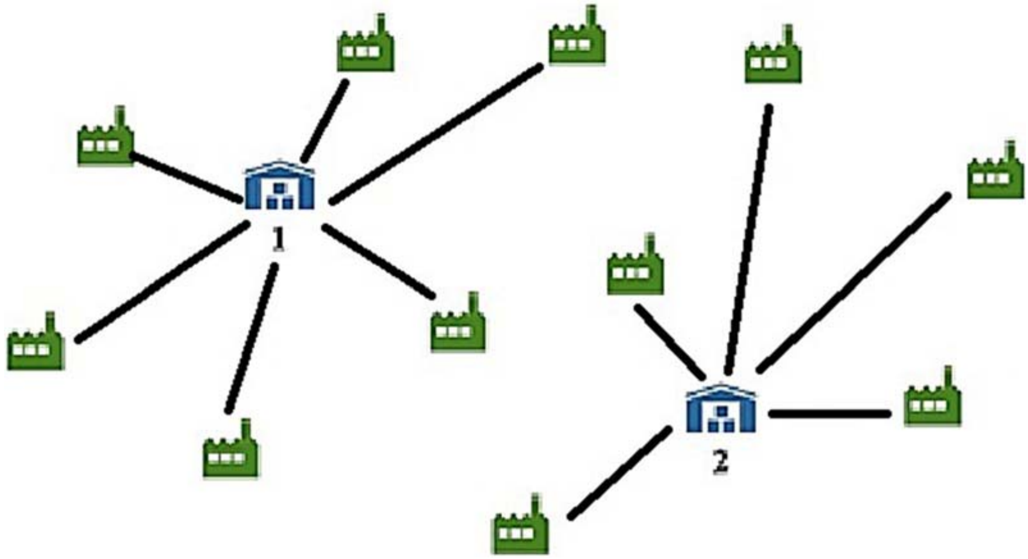

Figure 1. A warehouse network before establishing dummy warehouses.

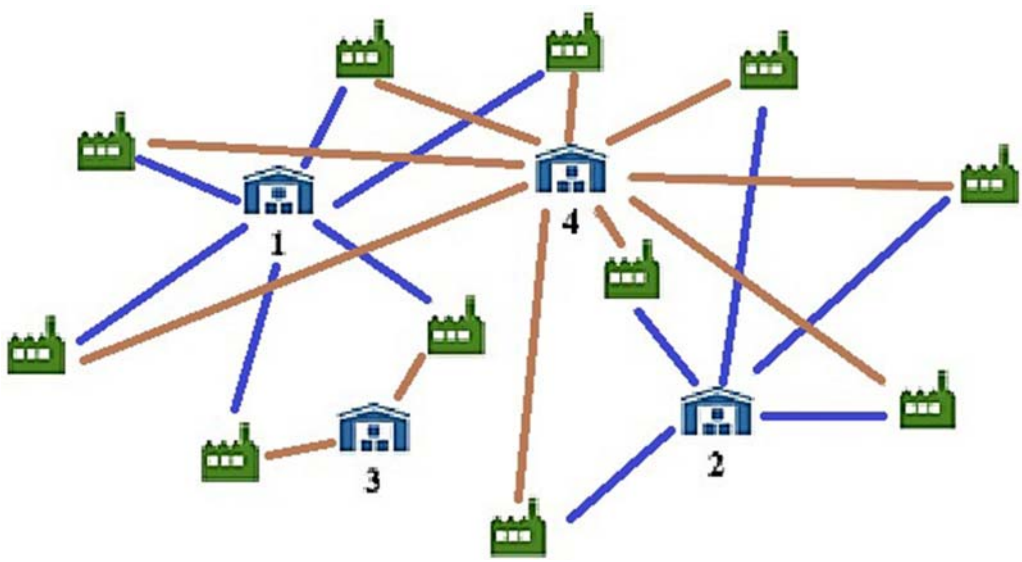

Figure 2. A warehouse network after establishing dummy warehouses.

c_{ij}: Transportation cost per unit of distance between demand node i and warehouse j.
w_i^r: Real demand of node i.
w_i^fDummy demand of node i .
Ca_j: Warehouse capacity at node j.
F_j^r: Fixed cost of establishing real warehouse at node j.
F_j^f:Fixed cost of establishing dummy warehouse at node j
Variables:
k: Total number of established warehouses (dummy and real).
R: Network Reliability index
z_j^r: Binary variable that is equal to 1 if real warehouse establishes at node j, and equal to 0 otherwise.
z_j^f: Binary variable that is equal to 1 if dummy warehouse establishes at node j, and equal to 0 otherwise.
x_{ij}^r: Binary variable which is equal to 1 if demand node i is allocated to real warehouse j, otherwise equal to 0.
x_{ij}^f: Binary variable which is equal to 1 if demand node i is allocated to dummy warehouse j, otherwise equal 0.
q_{ij}^r: Real flow between node i and warehouse j.
q_{ij}^f: Dummy flow between node i and warehouse j.

Mathematical model

Now, based on the above notations and assumptions the model is presented as follows:

$$\text{Max}\, Obj(1) = R \tag{1}$$

$$\text{Min}\, Obj(2) = \sum_{j\in J}(F_j^r z_j^r + F_j^f z_j^f) + \sum_{i\in I}\sum_{j\in J} q_{ij}^r c_{ij} d_{ij} + \sum_{i\in I}\sum_{j\in J} q_{ij}^f c_{ij} d_{ij} \tag{2}$$

$s.t:$

$$\sum_{j\in J} x_{ij}^r = 1 \quad \forall i \tag{3}$$

$$\sum_{j\in J} x_{ij}^f = 1 \quad \forall i\in I \tag{4}$$

$$x_{ij}^r \le z_j^r \quad \forall i\in I, \forall j\in J \tag{5}$$

$$x_{ij}^f \le z_j^f \quad \forall i\in I, \forall j\in J \tag{6}$$

$$q_{ij}^r \le M x_{ij}^r \quad \forall i\in I, \forall j\in J \tag{7}$$

$$q_{ij}^f \le M x_{ij}^f \quad \forall i\in I, \forall j\in J \tag{8}$$

$$\sum_{j\in J} q_{ij}^r x_{ij}^r = w_i^r \quad \forall i\in I \tag{9}$$

$$\sum_{j\in J} q_{ij}^f x_{ij}^f = w_i^f \quad \forall i\in I \tag{10}$$

$$\sum_{j\in J}(z_j^r + z_j^f) \le 1 \tag{11}$$

$$\sum_{i\in I} q_{ij}^r x_{ij}^r \le Ca_j^r \quad \forall j\in J \tag{12}$$

$$\sum_{i\in I} q_{ij}^f x_{ij}^f \le Ca_j^f \quad \forall j\in J \tag{13}$$

$$q_{ij}^r, q_{ij}^f \ge 0 \quad \forall i\in I, \forall j\in J \tag{14}$$

$$x_{ij}^r, x_{ij}^f, z_j^r, z_j^f \in \{0,1\} \quad \forall i\in I, \forall j\in J \tag{15}$$

In this model, the first objective function (1) represents the network reliability. The second objective function (2) minimizes total cost including the establishment of dummy and real warehouses and transportation costs for dummy and real flow. Constraints (3) and (4) explain that each demand node must be allocated to exactly one real and one dummy warehouse. Constraint (5) and (6) ensure that the demand node i is allocated to the node j if a real/dummy warehouse is established at this node. Constraints (7) and (8) describe mutual consistency of allocation and flow in real and dummy warehouses, i.e., if node i is allocated to real/dummy warehouse j, real/dummy flow can be established and conversely, if node i is not allocated to real/-dummy warehouse j, no real/dummy flow is allowed. Constraints (9) and (10) ensure that the sum of flow received at node i will cover the real and dummy demand at this node. Constraint (11) determines whether the real or dummy warehouse will be established at node j. Constraints (12) and (13) express capacity limitation of warehouse. Constraints (14) and (15) define the types of variables. Lemma 1 has been developed to more clearly describe the reliability introduced in the first objective function.

Lemma 1 *Objective (1) can be rewritten as* $R = \frac{\sum_{j\in J} z_j^f}{\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f}$

Proof Objective (1) is trying to maximize reliability based on cumulative failure distribution function, F, as follows [65].

$$R = 1 - Failure\,Rate \tag{16}$$

In our model, failure rate can be defined as: F= Failure rate. λ = lost when there is no dummy facilities λ' = lost when there are dummy facilities. Then we will have:

$$\text{F} = \frac{E(\lambda')}{E(\lambda)} \tag{17}$$

On the other hand:

$$E(\lambda) = N(a) \tag{18}$$

$$E(\lambda') = \sum_{i=0}^{N(a)}\left((N(a)-i)\frac{\binom{\sum_{j\in J} z_j^r}{(N(a)-i)}\binom{\sum_{j\in J} z_j^f}{i}}{\binom{\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f}{N(a)}}\right) \tag{19}$$

where N(a) is number of attacks.

Equation (19) is the expected value of a hyper-geometric distribution which can be simplified as following [66]:

$$E(\lambda') = N(a)\frac{\sum_{j\in J} z_j^r}{\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f} \tag{20}$$

So F is equal to:

$$\text{F} = \frac{E(\lambda')}{E(\lambda)} = \frac{N(a)\frac{\sum_{j\in J} z_j^r}{\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f}}{N(a)} = \frac{\sum_{j\in J} z_j^r}{\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f} \tag{21}$$

Finally, R can be obtained as:

$$R = 1 - F = 1 - \frac{\sum_{j\in J} z_j^r}{\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f} = \frac{\sum_{j\in J} z_j^f}{\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f} \tag{22}$$

So the model can be rewritten as following:

$$\text{Max } Obj(1) = \frac{\sum_{j\in J} z_j^f}{k}$$
$$\text{Min } Obj(2) = \sum_{j\in J}(F_j^r z_j^r + F_j^f z_j^f) + \sum_{i\in I}\sum_{j\in J} q_{ij}^r c_{ij} d_{ij} + \sum_{i\in I}\sum_{j\in J} q_{ij}^f c_{ij} d_{ij} \tag{23}$$

$$s.t:$$
$$\left(\sum_{j\in J} z_j^r + \sum_{j\in J} z_j^f\right) = k \tag{24}$$
$$(3) - (15)$$

k is number of total dummy and real warehouses which should be established. In this model, the first objective function (23) represents the network reliability as proved by Lemma 1. Constraint (24) ensures that the total number of established warehouses should be exactly k warehouses. With this model, a reliable warehouse network is designed in which there are some dummy warehouses beside the real ones and likewise, some dummy flows along with real flows. In the resulting network, real warehouses are hidden among dummy warehouses. If an attacker tries to attack a warehouse, (s)he may choose a dummy one; even this dummy warehouse may be more attractive for him(her) and thus, real warehouses will remain safe. Besides, since the model is optimizing costs and reliability simultaneously, network owners can manage the trade-off between cost and reliability.

4. Computational experiments

4.1 *Solution method*

There are many methods applied to solve multi objective mathematical models. Authors [67–69] performed a good survey in this topic and illustrated applying different methods. Researchers [70] used NCRO[1] and compared the results with NSGA-II algorithm for a multi objective model. Using chemical reaction optimization (CRO) algorithm achieved superior computational performance compared to other meta-heuristics [71]. A bi-objective mixed-integer programming for resilient food supply chain design is solved using an adapted ant colony optimization algorithm by [72]. Improved "max-min ant system", which is used to solve an inventory-transportation model for cost minimization of food grain supply chain [73]. Several meta-heuristic algorithms used to solve a hub interdiction problem [74]. Also, a benders' decomposition method was used by [75] to solve an arc interdiction vehicle routing problem. Finally, [77] solved a two-stage mixed integer nonlinear transportation model using two variations of PSO algorithm.

[1]Non-dominated sorting chemical reaction optimization.

To solve our presented model, two methods are used. One method is changing the model into a scenario based linear programming model and solving it by the use of general solver such as GAMS. As another method we used a NSGA II, meta-heuristic method. Those two methods and their results are presented and compared in the following subsection.

4.2 *Scenario based model*

The first objective function of the proposed model is non-linear. But k is a discrete finite variable which makes it possible to solve the model in scenarios. To do so, the model should be solved for all k values. The resulting model will be linear and hence convex, and so the global optimum solution is achievable. Since the model contains two conflicting objectives, a set of Pareto efficient solutions can be extracted. For this purpose, an improved ε-constraint method (AUGMECON) is used to solve the model [76]. Using AUGMECON one of the objective functions is kept and other objective functions are considered as constraints such that each of which is restricted by ε values. The ε values are changed from lower to upper ranges of objective functions by a specified steps. Solving the model with each new set of ε values will generate a new Pareto optimal solution for original multi-objective model. Specially, in bi-objective model, we have:

$$\begin{aligned} Max\,Obj\,(1) \\ S.T.\,Obj(2) \leq \\ \bar{e} \\ (23){-}(36) \end{aligned} \tag{25}$$

Efficient solutions of the problem are obtained by solving the model with different ε values (which is shown as $\bar{e}$ vector) in above model. Generally, applying AUGMECON to solve above bi-objective model consists of three steps which are presented below.

Step I: Constructing the pay-off table using lexicographic method

To construct the pay-off table, each objective function is optimized individually and lexicographic optimization is applied as shown in (39)–(42) and at result, the pay-off table (38) is obtained.

$$lex = \begin{pmatrix} lex_{1,1} & lex_{1,2} \\ lex_{2,1} & lex_{2,2} \end{pmatrix} \tag{26}$$

$$lex_{1,1} = Obj(1)^* : \begin{pmatrix} Max\ \text{Obj}(1) \\ s.t:\ (3)-(15), 24 \end{pmatrix} \tag{27}$$

$$lex_{2,2} = Obj(2)^* : \begin{pmatrix} Min\ \text{Obj}(2) \\ s.t:\ (3)-(15), 24 \end{pmatrix} \tag{28}$$

$$lex_{1,2} = Obj(2)^* : \begin{pmatrix} Min\ \mathrm{Obj}(2) \\ s.t:\ (3)-(15), 24 \\ Obj(1) = lex_{1,1} \end{pmatrix} \tag{29}$$

$$lex_{2,1} = Obj(1)^* : \begin{pmatrix} Max\ \mathrm{Obj}(1) \\ s.t:\ (3)-(15), 24 \\ Obj(2) = lex_{2,2} \end{pmatrix} \tag{30}$$

Step II: Defining the ε values

The decision maker should determine P grid points $e_p \in \bar{e}$ at each objective function to generate the set of ε values by (31).

$$\begin{aligned} e_p &= e_{p-1} + \frac{lex_{1,2} - lex_{2,2}}{P}, \quad p > 1 \\ e_p &= lex_{2,2}, \quad p = 1 \end{aligned} \tag{31}$$

Step III: developing optimization problems

To complete the solution procedure, a set of optimization problem with different e_p values should be developed and solved. This is presented in (32) in which δ is a tiny value and σ is a non-negative slack variable. Each optimized solution will generate a Pareto frontier efficient solution.

$$\begin{aligned} & Min\, Obj(1) + \delta.\sigma \\ s.t.\quad & Obj(2) + \sigma = e_p \\ & (23) - (36) \\ & \sigma \geq 0 \end{aligned} \tag{32}$$

4.2a *Numerical results* In this section, first, the proposed model is solved using a simple random sample data which are adapted from [77]. According to [63], fixed establishment cost of dummy warehouses and also cost of transporting dummy flows can be considered as one tenth of fixed establishment cost of real warehouses and cost of transporting real flows respectively. Datasets are attached in appendix A and the results for both objective functions regarding the different values of k (total number of warehouses, real or fake) are presented in table 2. Under Obj (1) the reliability is presented as it is obtained by lemma 1. Under Obj (2) total cost and its elements are presented. As mentioned before, the total cost is summation of transporting real flow, transporting dummy flow, establishing real warehouses and establishing dummy warehouses, which are represented in table 2.

As observed in table 1, for k = 2, one real and one dummy warehouse are recommended to be established. So the reliability index would be 0.5; as it can be seen in above table, establishing more dummy warehouses will increase the network ambiguity which will consequently increase the network reliability. For example, for k = 4 (i.e., establishing four warehouses, dummy or real), the reliability index would be 0.75. According to table 2, Pareto efficient frontier can be extracted which is depicted in figure 3. Just like the real world, achieving more reliability requires spending more money. It should be noted that the horizontal axis of figure 3 is shown for a better understanding of the failure rate (1 − R).

A great consideration of using dummy facilities is cost. Since any increase or decrease in dummy-related costs will change the results, sensitivity analysis of the model based on the costs of dummy items (specifically, F_j^f as the greatest cost) is necessary and important.

In the above numerical results (table 1), the establishment cost of a dummy warehouse, F_j^f, is relatively low compared to the establishment cost of a real warehouse, F_j^r. So, for different values of *k,* exactly one real warehouse and $k-1$ dummy warehouses are recommended to be established.

Now, let's examine F_j^f with larger values; the results for an arbitrary values of k (e.g., k = 7) are shown in table 2. As observed in table 2, by increasing F_j^f, more real warehouses are expected to be established. For example, when F_j^f is multiplied by 10, one real warehouse and three dummy warehouses are proposed to be established. But if the costs increase by 20 times, two real warehouses and four dummy warehouses are proposed to be established (table 3).

Table 2. Results for different values of k.

	Obj (1)	Obj (2)						
k	Reliability	Real transportation cost	Dummy transportation cost	Real establishment cost	Dummy establishment cost	Total cost	Real warehouses location	Dummy warehouses location
2	**0.5**	67725	10406	50000	3500	131,631	2	1
3	**0.67**	67725	7546	50000	11500	136,771	2	1, 4
4	**0.75**	67725	5958	50000	17500	141,183	2	1, 4, 3
5	**0.8**	67725	4914	50000	30000	152,639	2	1, 4, 3, 7
6	**0.83**	67725	3266	50000	36500	157,491	2	1, 4, 3, 7, 5
7	**0.86**	67725	2494	50000	45000	165,219	2	1, 4, 3, 7, 5, 6

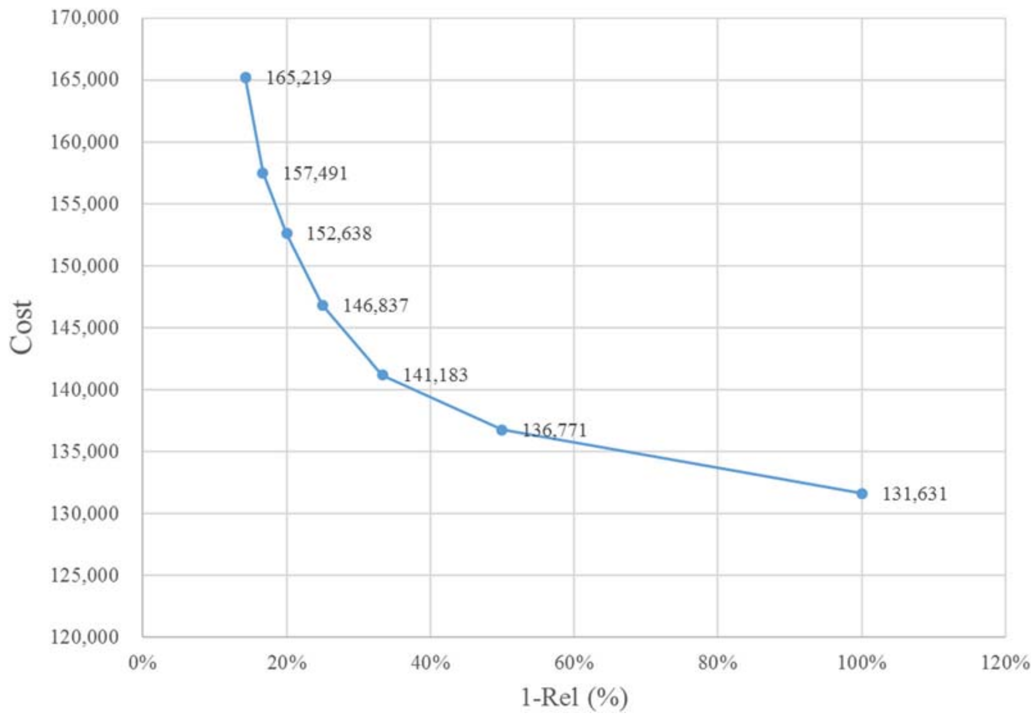

Figure 3. Pareto solution for small size data set.

Table 3. Analyzing results for larger F_j^f values.

k	Reliability	F_j^f	Number of real warehouses	Number of dummy warehouses
7	0.5	×2	1	1
7	0.67	×4	1	2
7	0.75	×10	1	3
7	0.60	×15	2	3
7	0.67	×20	2	4
7	0.71	×30	2	5

To illustrate the performance of the model, a large random dataset has been tested by the model. This data set consists of 50 nodes such that those nodes can be nominated as demand customer nodes, and real or dummy warehouses, so two 50×50 tables are constructed for costs and distances. Table 4 shows the results for different values of k.

As shown in table 4 by increasing the k values, more dummy warehouses are established which leads to more reliability. To analyze sensitivity of the model, we fixed the number of real warehouses for different values. The results are presented in figures 4 and 5.

Figures 4 and 5 represent Pareto solutions which are obtained from solving the model by using large data set. In figure 4, the number of real warehouses is fixed at 4. Since the model was defined with total 50 available nodes, there is an opportunity to consider the number of the dummy nodes in the range between 0 and 46. Therefore, reliability can be obtained in the range between 0 and 92 %. In figure 5, 8 real warehouses are considered, so the reliability can be obtained between 0 % and 84 %. If no dummy node is established, there will be no ambiguity in the network and invader can simply identify real warehouses. More dummy warehouses, on the other hand, will increase the reliability of the network.

While using dummy facilities, cost is an important concern. Establishing dummy facilities for increasing network reliability will increase the costs. It is important to note that compared to costs imposed by disruption, this increase may be neglected. It is due to the fact that the disruption costs are very high. It is considered that the cost of losing a customer due to disruption is 10 times more than the cost of serving the customer [8]. To have a clear insight on this subject, using the second dataset, a comparison between cost and reliability is presented in figure 6 which shows how much increase in reliability leads to an increase in costs. For example, to achieve 69.4 % increase in reliability, 22.5 % increase in costs is required.

As shown in figure 6, achieving more reliability requires more costs. For example, achieving 80 % reliability requires a 268 % increase in costs. Naturally, less reliability levels are cheaper. For example, to reach 50 % reliability just 49 % increase in cost will be required.

Meanwhile, having high reliability levels is not always a good decision; because high reliability levels are more suitable for critical facilities whose disruption would

Table 4. Results of large data set for different k values.

k	*R*	Number of real warehouses	Number of dummy warehouses	Location of real warehouse	Locations of dummy warehouse
1	0.00	1	0	12	–
2	0.50	1	1	12	45
3	0.67	1	2	12	45, 18
4	0.75	1	3	12	45, 18, 23
5	0.60	2	3	24	45, 18, 23
6	0.67	2	4	24	45, 18, 23, 39
7	0.71	2	5	24	45, 18, 23, 39, 11
8	0.75	2	6	24	45, 18, 23, 39, 11, 6
9	0.78	2	7	24	45, 18, 23, 39, 11, 6, 21
10	0.80	2	8	24	45, 18, 23, 39, 11, 6, 21, 49
11	0.82	2	9	24	45, 18, 23, 39, 11, 6, 21, 49, 44
12	0.83	2	10	24	45, 18, 23, 39, 11, 6, 21, 49, 44, 32
13	0.85	2	11	24	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15
14	0.86	2	12	24	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8
15	0.80	3	12	19	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8
16	0.81	3	13	19	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8, 37
17	0,82	3	14	19	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8, 37, 9
18	0,83	3	15	19	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8, 37, 9, 13
19	0.84	3	16	19	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8, 37, 9, 13, 22
20	0.85	3	17	19	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8, 37, 9, 13, 22, 27

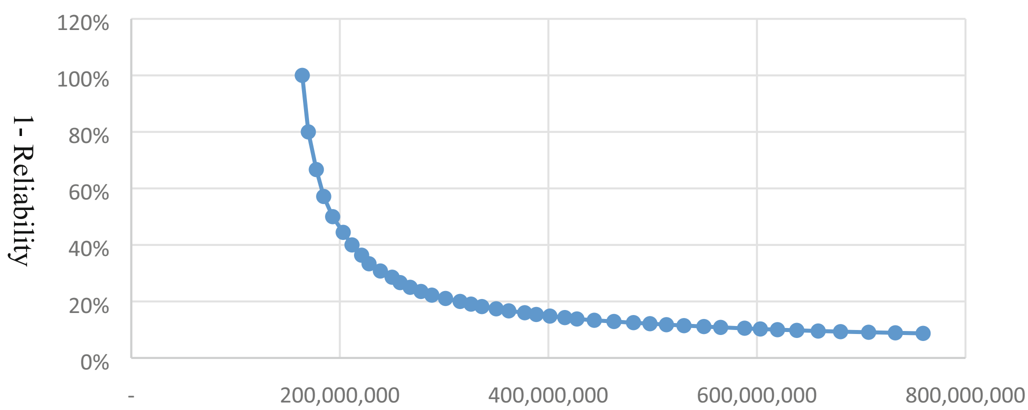

Figure 4. Pareto solution for large size example when number of real warehouses is 4.

impose significant costs. Regarding Pareto solutions, it is the decision maker that can choose the level of reliability based on the amount of its imposed costs.

4.3 *Multi-objective evolutionary algorithm*

There are several Multi-objective evolutionary (MOEA) algorithms in the literature. Since Non-dominated Sorting Genetic Algorithm II (NSGA II) in one of the best algorithms [78] in this category, we have decided to use it.

4.3a *Modules of NSGA II* **Chromosome:** A chromosome is used to represent all the variables. So real warehouses, dummy warehouses, allocation to real warehouses, allocation to dummy warehouses, real flows, dummy flows, *k* and *R* are represented by a separate variable. Representation of the chromosome is shown in figure 7.

Initial population: First, we initialize the number of generations, population and variables then the objective functions are defined. A random number is used to generate each chromosome in the population. So an $N \times V$ order matrix is defined, in which N is size of population and V is number of variables.

Evaluation of objective functions: Fitness function values are calculated based on the values of genes in chromosomes

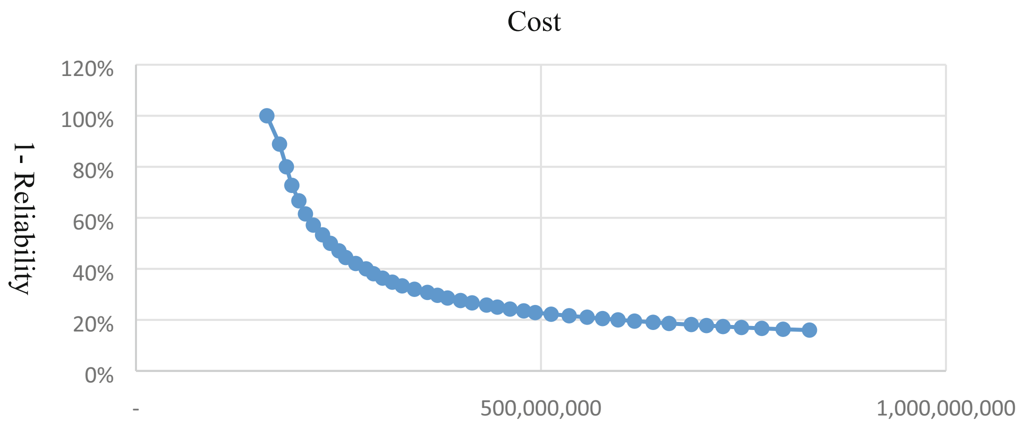

Figure 5. Pareto solution for large size example when number of real warehouses is 8.

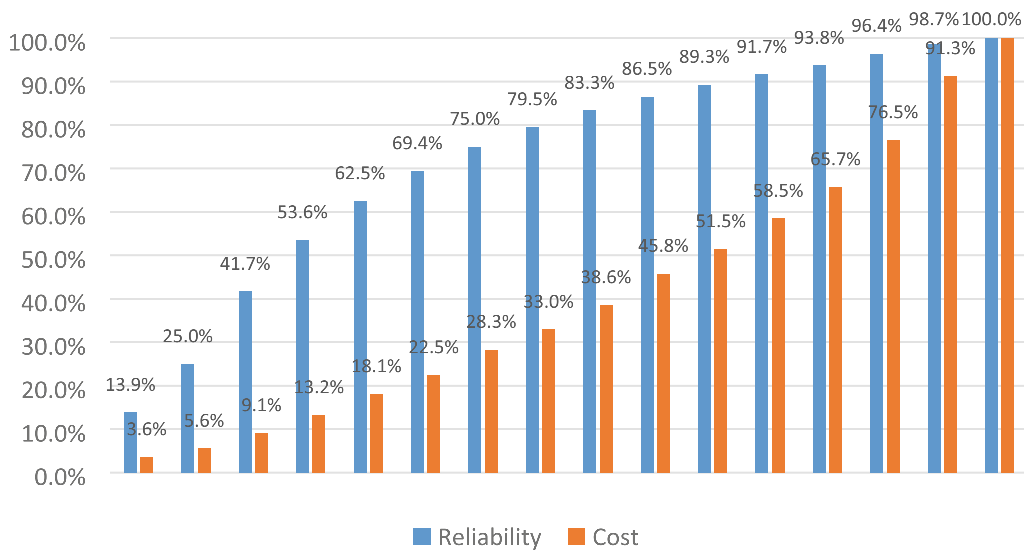

Figure 6. Comparing increase rate of reliability and cost.

Z_r1	Z_r2	…	Z_f1	Z_f2	…	X_r1	X_r2	…	X_f1	X_f2	…	q_r1	q_r2	…	q_f1	q_f2	…	k	R
Real warehouses			Dummy warehouses			Real allocation			Dummy allocation			Real demand			Dummy demand			k	R

Figure 7. Chromosome representation.

and then the values are concatenated to the columns of the matrix of size $N \times V$. So, the resultant matrix size, depends on the fitness function values, will be $N\times (V+M)$; where M is number of fitness functions.

Non-domination sorting: Non-domination sorting helps to sort the population based on non-domination property. To do so, based on fitness functions values, individuals are arranged in the ascending order. Individuals with lower rank have higher non-domination, therefore, the chromosomes that are at rank 1, are non-dominated generally.

Measurement of crowding distance: After sorting the population, chromosomes are assigned to crowding distance. The algorithm used to calculate crowding distance is presented below and n is the number of chromosomes in the ith front F_i.

```
For each individual in front Fi
    Initialize distance to be zero for all individuals in Fi(d(0)).
    For each objective function m in M
        Sort the individuals in Fi based on m
        Assign infinite distance to each individual in n as the boundary value of distance
        For each individual j in n, calculate crowding distance by
```

$$d = d(0) + \frac{m(j+1) - m(j-1)}{m_{\max} - m_{\min}}$$

Tournament selection: The algorithm which is used for tournament selection is presented below. Consider a mating pool with size z.

```
For each individual in z
    Choose n individuals in the population randomly.
    For each individual in n, show crowding distance and rank
        Select the candidate with minimum rank
        If not only one candidate has the least rank,
        Select the candidate which has maximum crowding distance
Add the selected individual to the mating pool
```

In this way a tournament selection is the one which helps to generate mating pool.

Crossover and mutation: In order to create new individuals, crossover procedure is applied which selects two individuals from the population and generates two new one by combining them. The newly generated individuals are called offsprings which contain the trait of their parents. The related probabilities for mutation and crossover are taken to be 0.1 and 0.9. Many approaches can be applied for crossover operation. We used an algorithm which is presented below.

```
For each individual i in the mating pool of size N
    Select 2 parents randomly
    For each gene g in the chromosome of size V
      Generate random number r
      If r <= 0.5
            Calculate temp = (2 x r)^(1/10)
      Else
            Calculate temp = (2 x (1-r))^(1/10)
      EndIf
      Calculate
            var = 0.5((1+temp)×g(parent1)+(1−temp)×g(parent2))
      If g is binary variable
                  If var < 0.5
                        g=0
                  Else
                        g=1
                  EndIf
      Else
                  Scale g to the range of variables
              EndIf
       Endfor
Endfor
```

Table 5. Results of large data set for different k values using NSGAII.

k	*R*	Number of real warehouses	Number of dummy warehouses	Location of real warehouse	Locations of dummy warehouse
1	0.00	1	0	12	–
2	0.50	1	1	12	45
3	0.67	1	2	12	45, 23
4	0.75	1	3	12	45, 23, 18
5	0.60	2	4	24	45, 23, 18, 39
6	0.67	2	4	24	45, 23, 18, 39
7	0.71	2	5	24	45, 23, 18, 39, 21
8	0.75	2	6	24	45, 23, 18, 39, 21, 6
9	0.78	2	7	24	45, 23, 18, 39, 21, 6, 11
10	0.80	2	8	24	45, 23, 18, 39, 21, 6, 11, 15
11	0.82	2	9	24	45, 23, 18, 39, 21, 6, 11, 15, 44
12	0.83	2	10	24	45, 23, 18, 39, 21, 6, 11, 15, 44, 49
13	0.85	2	11	24	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32
14	0.86	2	12	24	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8
15	0.80	3	12	19	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8
16	0.81	3	13	19	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8, 27
17	0,82	3	14	19	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8, 27, 9
18	0,83	3	15	19	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8, 27, 9, 13
19	0.84	3	16	19	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8, 27, 9, 13, 22
20	0.85	3	17	19	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8, 27, 9, 13, 22, 37

Table 6. Comparing results for AUGMECON and NSGA II.

	k	*R*	Number of real warehouses	Number of dummy warehouses	Location of real warehouse	Location of dummy warehouse
NSGA II results	20	0.85	3	17	19	45, 23, 18, 39, 21, 6, 11, 15, 44, 49, 32, 8, 27, 9, 13, 22, 37
AUGMECON results	20	0.85	3	17	19	45, 18, 23, 39, 11, 6, 21, 49, 44, 32, 15, 8, 37, 9, 13, 22, 27

First, crossover is operated; after that, mutation procedure is implemented. By mutation, procedure the value of a gene changes randomly. After running crossover and mutation for the generated chromosomes, fitness functions are calculated.

Generation of intermediate population: In the current generation, parents and offsprings are combined to form an intermediate population, so the new population will be greater in size than the original population. Again, non-dominated sorting is performed on the new population, because there may be potential chromosomes in both.

Generating new generation of population: To generate new population, chromosomes in original population are replaced. To do so, high rank chromosomes are added to the population to reach the population size. Based on the crowding distance, the last front is included in the population.

Termination condition: When the generation number reaches its maximum value, the search process stops.

4.3.b Computational results In this section, the proposed NSGA II algorithm is applied to solve the developed bi-objective optimization problem. The data set is the same large size data set which is used before. First, we solved the problem for different *k* values using NSGA II. The results are presented below (table 5).

Results for NSGA II are almost the same as AUGMECON but the arrangement of establishing dummy facilities differs a bit. To have an insight, the results of establishing dummy faculties when k = 20 for both solution methods are compared in table 6.

Pareto solutions for different *k* values using NSGA II are also presented and compared with the results of AUGMECON (figures 8, 9).

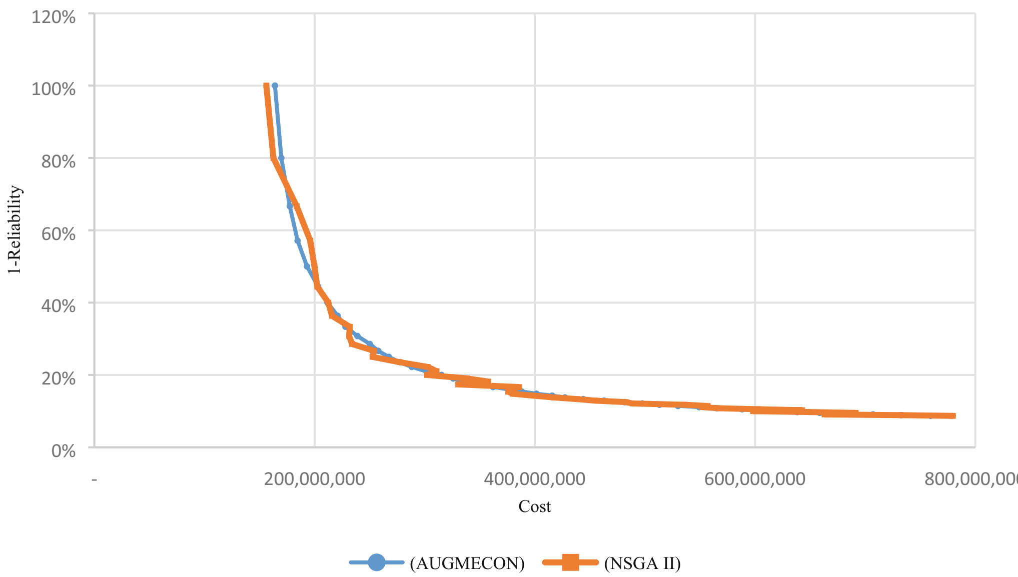

Figure 8. Comparing AUGMECON and NSGA II Pareto solutions for large size example when number of real warehouses is 4.

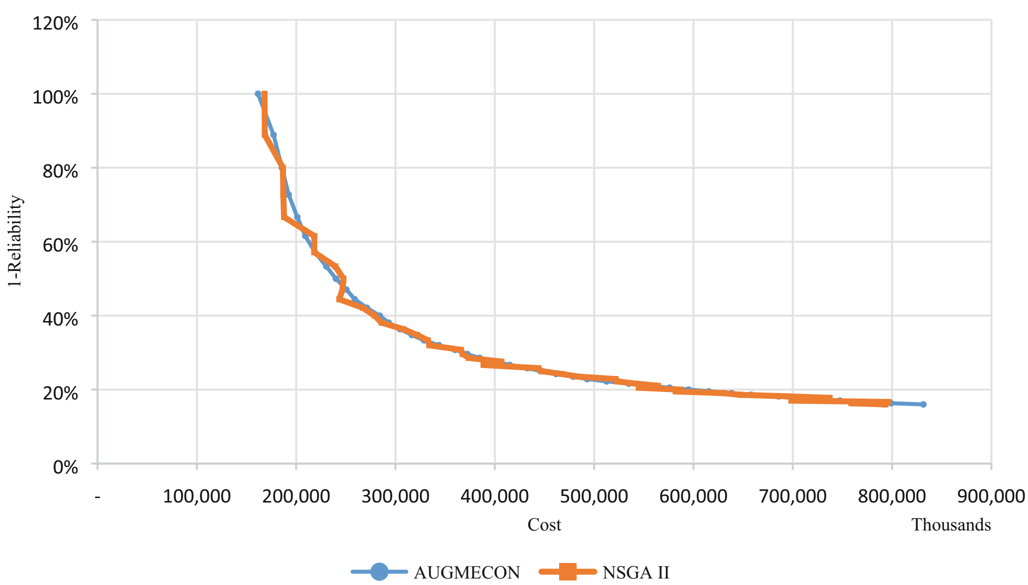

Figure 9. Comparing AUGMECON and NSGA II Pareto solutions for large size example when number of real warehouses is 8.

As it can be seen in the above figures, the NSGA II is almost performing as well as the AUGMECON and the results are almost the same. The maximum deviation between NSGAII and AUGMECON results is 5 %.

5. Conclusions

In this paper a linear multi objective mathematical model was presented to create ambiguity in warehouse location problem which makes it difficult to identify the real warehouse locations. To do so, dummy warehouses are used. Dummy warehouses are warehouses which are exactly the same as the real warehouses in shape and look but they are much cheaper in cost and easy to establish.

Using the mathematical model, a network that consists of both real and dummy warehouses is designed to minimize total cost and maximize network reliability. Those goals are quantified as the two objective function of the model. Specifically, a reliability index is proposed to assess the model performance as the second objective function. To solve the model, we used AUGMECON which is widely applied in multi-objective problems to reach Pareto solutions. The results clearly showed that establishing dummy warehouses increase reliability. The results are presented as Pareto solutions, so network owners can select optimum reliability levels depending on incurred costs. Also a NSGA II algorithm is applied to solve the model. The results are close to AUGMECON with a maximum of 5 % deviation.

As recommendations for future studies, considering variable importance values for real warehouses can be proposed as a future research. Another issue that can be addressed for future research is designing the network considering prevention radius for dummy warehouses. Because a dummy warehouse that is far away from a real warehouse would not provide much ambiguity and nearby dummy warehouses to real warehouses are more effective. Using robust optimization approaches to design the network, while there are several disruptions, scenarios are also worthy of future study.

6. Nomenclature

NP-hard	Non-deterministic Polynomial-time Hard
GA	Genetic Algorithm
TS	Tabu Search
NCRO	Non-dominated sorting Chemical Reaction Optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm II
CRO	Chemical Reaction Optimization
PSO	Particle Swarm Optimization
AUGMECON	Augmented ε-constraint Method
MOEA	Multi-Objective Evolutionary Algorithm

Appendix A. Date set 1, small size data set

	Potential locations for warehouses							
	1	2	3	4	5	6	7	Demand
Demand nodes								
1	7280	2920	8240	4420	3900	2574	6248	10000
2	2040	8510	3400	15360	7563	4228	23010	5000
3	6280	7540	2310	12300	10315	11598	12881	4000
4	5120	4110	11990	10630	14065	16506	18947	1000
5	3960	680	1670	8960	17815	6953	2501	3000
6	5500	1520	5965	6595	11066	5485	8922	6000
7	4600	821	7545	8711	4487	1410	7544	2000
Real fixed cost	3.5×10^{10}	5×10^{10}	6×10^{10}	8×10^{10}	8.5×10^{10}	9.5×10^{10}	9.9×10^{10}	
Dummy fixed cost	3.5×10^{8}	5×10^{8}.	6×10^{8}	8×10^{8}	8.5×10^{8}	9.5×10^{8}	9.9×10^{8}	

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