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A Bi-Objective Mathematical Model to Design a Fiber Optic Network Under Uncertainty Environment: A Case Study in Iran

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Abstract

In today's world, advances in technology communications and the digital economy have dramatically contributed to the increase in the use of information technology services. For this purpose, an utterly competitive environment has been created for companies active in information technology. On the other hand, the increase may be accompanied by problems such as reduced service quality and dissatisfaction. One of the services to which the government pays special attention is the Internet service, which can be provided through various platforms. Fiber Optic Technology owing to its cost-effectiveness, high capacity as well as high reliability, has attained much attention. In this sense, this paper proposes an optimization model to design a Fiber Optic Network with a two-connected topology. The concerned model is formulated in the form of two objectives encompassing minimizing network design costs and minimizing unreliability. The cost of creating a fiber optic route between two vertices is considered to be imbued with uncertain. A Fuzzy Mathematical Programming approach has been exploited to withstand the uncertainty in the proposed model. Given that the proposed model is computationally difficult, NSGA-II and MOPSO algorithms have been devised to solve it. Eventually, using the real data of the Telecommunication Infrastructure Company, the validation of the presented algorithms has been corroborated. The Results show that MOPSO fulfills better than NSGA-II in terms of intensification and diversification, and vice versa.

Keywords: Fiber optic technology, Fuzzy mathematical programming, NSGA-II, MOPSO, IT.

1 | Introduction

Recently, Fiber Optic Technology (FOT) is one of the most important parts of modern information technology. The reasons for using FOT can be introduced as its cost-effectiveness, high reliability, and high capacity (Koh and Lee, 1995). The FOT can transmit thousands of telephone conversations and data at high speeds over multiple fibers compared to similar technologies such as copper Technology (Cardwell et al., 1989; Koh and Lee, 1995). On the other hand, if the fiber connection is disconnected, the services provided will be severely damaged, and the connection may be disconnected altogether (Cardwell et al., 1989). Due to the advantages, disadvantages, and

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characteristics of FOT, designing and planning of FOT must be considered (Monma and Shallcross, 1989). One of the earliest studies is that of Cardwell et al. (1988), who used the effect of FOT on the design of the telephone network. Recently, the development of FOT for communication networks, medical applications, and other applications represents a unique confluence of the physics, electronics, and mechanical engineering disciplines (Tubert-Brohman et al., 2013). One of the most important applications of Information Technology (IT) is the telecommunication network. The development of the digital economy and the high penetration rate of mobile phones and people's lifestyles have made governments' approach to the information and communication technology industry a driver of economic progress. The Digital economy can increase productivity, transparency, and less corruption in countries, promote innovation and creativity, reduce inequality, improve the quality of government services, reduce bureaucracy, and improve public welfare. Due to the competitive environment and response to customer demand, governments have been forced to optimally utilize their capacity.

IT industry in countries offers various services such as "provide Internet bandwidth", "provide transmission cloud bandwidth", "provide internal Internet exchange point (IXP) bandwidth" and "International capacity transit" (Büyüközkan and şakir Ersoy, 2009). The services procured are provided through platforms such as radio communication. Owing to weaknesses, instance service delivery limitations, and high maintenance costs of service provider equipment in radio communication and satellite communication, FOT is known as a secure way of communication. On the other hand, hazards such as natural disasters (floods and earthquakes) will threaten the reliability and survivability of fiber optic paths. Based on previous research performed, it can be understood that survivability against failures is of great importance in FOT (Cardwell et al., 1989; Koh and Lee, 1995; Monma and Shallcross, 1989). To guide the proposed research, the below questions are asked:

- How can a fiber optic network be designed and programmed to consider the design of DMUs?
- Given the complexity of network models, how can the proposed model be solved?
- Given the necessity of designing a network with high reliability and savings, how can the balance between goals be managed?

The remainder of this study can be defined as follows: In the next section, important research in the field of IT is reviewed. In Section 3, the designing and planning of the fiber optic network are considered. In Section 4, we utilize multi-objective algorithms to solve the proposed fiber optic network. Section 5 presents fuzzy mathematical programming to overcome the uncertainty of the proposed model. Section 6 provides a case study, and related computational results are presented in Section 7. Ultimately, Sections 8 and 9 provide managerial implications and concluding remarks, respectively.

2. Literature review

A Network Design Problem (NDP) has been used in various scopes, such as telecommunications, electricity distribution, and gas pipelines (Dengiz et al., 1997). Several types of research have been performed to design a network with connectivity constraints (Cardwell et al., 1989; Chudley and Greeno, 2020; Monma and Shallcross, 1989). Based on the widespread ability of FOT in various scopes, the Designing of Fiber Optic Network (DFON) was considered one of the attractive topics.

In the DFON, the connection between the two nodes is considered an indicator of network security and survivability. Therefore, Two-Connected topology (TCT) has been used in the DFON, and the connection between nodes is made by fiber cable. To increase survivability and reliability in the DFON, it is necessary to establish a minimum of two fiber connections between nodes (Koh and Lee, 1995). Therefore, due to the importance of reliability and survivability of the DFON, TCT is performed to ensure an acceptable level of reliability in the DFON.

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In the real case, it is difficult to make strategic decisions, because there isn't enough historical information. Even with historical details, it sometimes seems impossible to determine the distribution of inputs and parameters (Dehghani et al., 2018). One of the parameters that are very important in DFON is the cost of establishing the connection, because it depends on many elements, including geographical situation. On the other hand, due to the lack of sufficient information in this scope, determining the distribution of the cost parameter seems difficult. Therefore, when the parameters are in an uncertain environment, and their distribution is not easy to recognize, fuzzy mathematical programming methods are recommended (Dehghani et al., 2018).

DFON problem is one of the NP-hard problems, so the complexity of the DFON has also been proven (Koh and Lee, 1995). Therefore, according to the complexity of the DFON problem, heuristic and meta-heuristic algorithms are developed to solve these problems. Many algorithms have been proposed for DFON Problems, in the proposed research by Koh and Lee (1995), The Tabu Search algorithm, which is one of the iterative algorithms, has been used to solve DFON problems. In some studies, population-based algorithms have been used to solve the DFON problem, one of the most popular of which is the Genetic Algorithm (Dengiz et al., 1997). In some researches, we encounter with multi-objective models. In this case, multi-objective optimization such as NSGA-II can be used (Deb et al., 2002). Yazar et al. (2016) proposed the DFON to deal with two main problems: The green field design (area with no Internet access) and copper field re-design (area with limited access to copper networks). In the green field design problem, DFON with the lowest cost and high bandwidth Internet access are considered. In the re-design of the copper field application, the goal is to improve the network connection status by reinforcing the network with fiber optical wires. Angilella et al. (2018) developed the DFON for the "fiber to home" problem, which aim is to minimize the cost of the network. Angilella (2018) presented the DFON for the "fiber to home" problem according to economic objectives. Based on the complexity of the proposed model, a hybrid approach has been used to solve it. Rabbani et al. (2018) suggested an integrated mathematical model, which consists of a three-level network of fiber-optic by considering the backbone network and local access networks simultaneously. The target of the presented model located the location of the central hubs and concentrators, and communication of main hubs, so that network cost is minimized. Owing to the complexity of the proposed model, two meta-heuristic methods have been applied to solve it. Wu et al. (2020) presented the DFON and traffic grooming problem arising in optical telecommunication networks. In their study, the aim is to install a minimum number of connections between the nodes and routes of the demand for the light paths. Based on the complexity of the proposed model Tabu Search algorithm is used to discover the optimal value of decision variables. Table 1 shows a summary of the literature review.

Table 1. Summary of literature review.

No	Author	Objective function	complexity reduction	Uncertainty	method of problem solving
1	Yazar et al. (2016)	1. Minimizing cost 2. Achieve high bandwidth Internet access	-	-	Metaheuristic algorithm
2	Angilella, Chardy, and Ben-Ameur (2018)	Minimizing the cost of network	-	-	Metaheuristic algorithm
3	Angilella (2018)	Minimizing the cost of network	-	-	hybrid approach

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4	Rabbani, Ravanbakhsh, and Taheri (2018)	1. Minimizing the cost of network 2. Optimal routing	-	-	Metaheuristic algorithm
5	Wu, Lü, and Glover (2020)	1. Minimizing the number of connections 2. Optimal routing	-	-	Metaheuristic algorithm
6	Present research (2022)	1. Minimizing the cost of network 2. Maximizing the survivability	*	*	Metaheuristic algorithm

In this study, DFON in uncertain conditions for the IT industry in Iran has been considered. In the proposed DFON, the first objective function is to minimize network costs. The second objective function maximizes survival and reliability in the DFON, which due to its relevance to governance issues, is of great significance. In the proposed DFON, due to the uncertainty of connection costs, fuzzy mathematical programming is proposed to overcome the uncertainty of the presented model. Due to the high complexity and multi-objective proposed model, NSGA-II and MOPSO algorithms have been used to solve it. Finally, the proposed DFON is validated with real data from the Infrastructure Communications Company, and based on the Taguchi method, the presented algorithms are compared.

According to Table 1 and the research reviewed in this study, the important contributions and novelties gained from the literature are introduced as follows:

- Designing and planning DFON for the IT industry in Iran under reliability and survivability.
- Based on the uncertainty conditions in the proposed model, fuzzy mathematical programming has been developed.
- Owing to the high complexity and multi-objective proposed model, NSGA-II and MOPSO algorithms have been implemented.
- The proposed metaheuristic algorithms have been compared with the Taguchi method, and hyperparameters are determined.
- Finally, the DFON has been validated according to real data from Infrastructure Communications Company.

3. Problem description

This study has been considered to DFON that the purpose of designing the proposed network is to establish communication between different cities in Iran. In the proposed network, services such as the Internet and mobile phones, which have already been provided through other platforms, can be procured through fiber optics. The advantages of DFON consist of its high speed and capacity compared to other platforms, but on the other hand, it suffers from disadvantages such as vulnerability to natural disasters. One of the ways to deal with the weakness of DFON is to increase the reliability

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and survivability of the proposed DFON. In this study, TCT has been applied to overcome the weakness of DFON. The proposed DFON according to TCT is schematically shown in Figure 1.

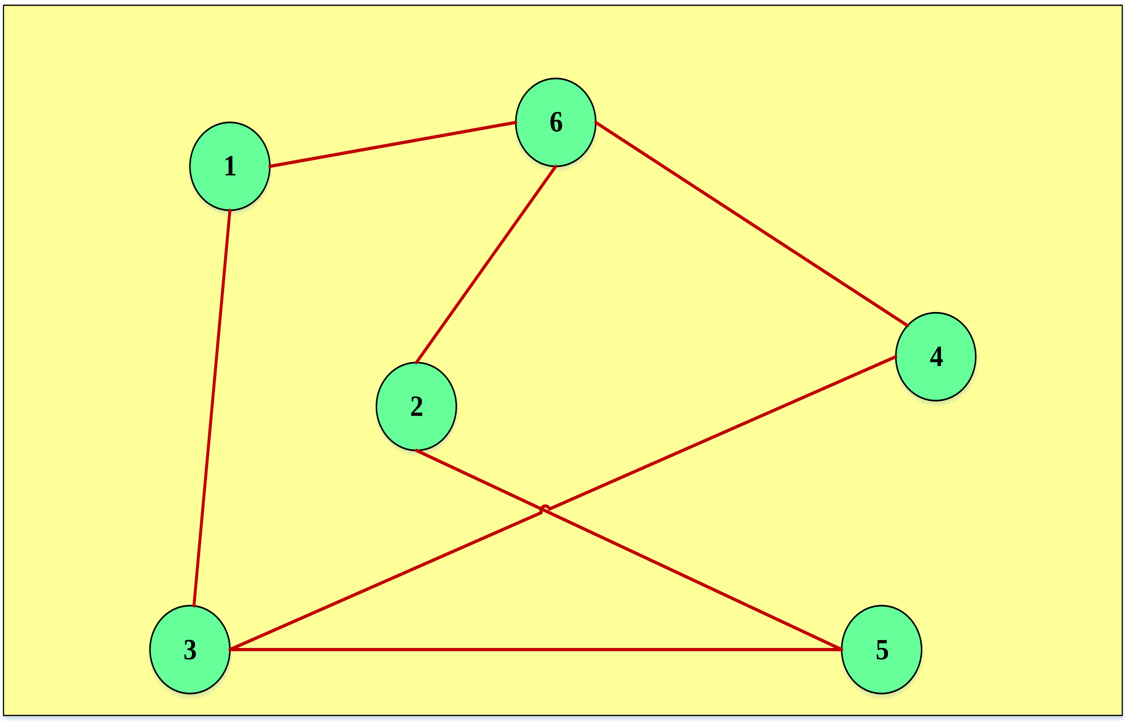

Figure 1. Schematic of the proposed DFON with two-connectivity.

According to Figure 1, we define $G(V, E)$ to introduce Vertices and Edges. It is clear that connectivity in DFON is established, and we can determine the adjacency matrix as follows:

$$AM = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 \end{pmatrix}$$

The order of *AM* matrix is 6, which means that it represents the number of routes (length=1) between two vertices. Similarly, the relationship between the number of routes and the power of *AM* matrix is defined as Equation (1):

$$\begin{array}{ll} AM^1 & \text{Number of routes (length=1) between two vertices} \\ AM^2 & \text{Number of routes (length=2) between two vertices} \\ AM^3 & \text{Number of routes (length=3) between two vertices} \\ AM^4 & \text{Number of routes (length=4) between two vertices} \\ AM^5 & \text{Number of routes (length=5) between two vertices} \end{array} \tag{1}$$

Finally, in order to prove the connectivity of DFON, all the powers of the *AM* matrix (from 0 to (order of matrix) -1) must be added together, and if the resulting matrix does not have a zero element, the DFON is connected.

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$$AM^0 + AM^1 + AM^2 + AM^3 + AM^4 + AM^5 = \begin{pmatrix} 15 & 15 & 33 & 14 & 15 & 33 \\ 15 & 14 & 22 & 15 & 18 & 26 \\ 33 & 33 & 22 & 33 & 26 & 22 \\ 14 & 15 & 33 & 15 & 15 & 33 \\ 15 & 18 & 26 & 15 & 14 & 22 \\ 33 & 26 & 22 & 33 & 22 & 22 \end{pmatrix} \quad (2)$$

As shown in Equation (2), there is no zero in the resulting matrix, so the proposed DFON is connected. Now suppose that the connection between vertices 1 and 3 is made from route 1-6-4-3, which is considered active edges A $(A \subseteq E)$. Therefore, $G^{'} = (V, A)$ is defined as a power set of G. The probability of reliability of the power set is expressed as Equation (3):

$$R(G^{'}) = \prod_{s \in A} P_s * \prod_{s \notin A} q_s \quad (3)$$

Equation (3),$R(G^{'})$ indicates the reliability of power set A, p is the probability of proper operation of the route, and q is the probability of non-functioning of the route. Finally, the reliability of DFON is calculated as Equation (4):

$$R(X) = \sum_{A \in \zeta} \prod_{s \in A} P_s * \prod_{s \notin A} q_s \quad (4)$$

Equation (4), ζ indicates all of the power sets in the $G(V, E)$. Given that the number of elements ζ is equal to $2^{|E|}$ so the complexity of the problem is $O(2^n)$, with increasing the number of vertices, the complexity of the problem will increase significantly.

Due to the high complexity of calculating reliability in the DFON in Equation (4), Equation (5) is used to calculate reliability.

$$\begin{aligned} &R(X) \leq H(k) \\ &H(k) = 1 - \left[\sum_{i \in N} q^{k_i} * \prod_{j=1}^{m_i} (1 - q^{k_i - 1}) * \prod_{j=m_i+1}^{i-1} (1 - q^{k_i}) \right] \\ &m_i = min\{k_i, i-1\} \end{aligned} \quad (5)$$

In Equation (5), k_i indicates the degree sequence of vertices. As can be seen, the complexity of this situation has changed to $O(n^2)$. Equation (5) is well-known as Jan's Upper Bound, which approximates the overall reliability of the DFON.

Finally, the reliability objective function is defined as the minimization of reliability as Equation (6).

$$\begin{aligned} &Min(1 - R(X)) \\ &St: \\ &R(X) \leq H(k) \\ &H(k) = 1 - \left[\sum_{i \in N} q^{k_i} * \prod_{j=1}^{m_i} (1 - q^{k_i - 1}) * \prod_{j=m_i+1}^{i-1} (1 - q^{k_i}) \right] \\ &m_i = min\{k_i, i-1\} \end{aligned} \quad (6)$$

As previously discussed, the first objective function of the proposed DFON is minimizing network costs, which we define as Equation (7):

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$$Min \sum_{i\in V} \sum_{\substack{j\in V \\ j\neq i}} C_{ij} X_{ij} \tag{7}$$

In Equation (7), X_{ij} indicates the binary decision variable of establishing the connection between *i* and *j*. When the connection between *i* and *j* is selected, X_{ij} takes one, and otherwise, it takes zero. Also, C_{ij} shows the costs of establishing the connection between *i* and *j*, which is considered uncertainty in this study.

Another condition of the proposed DFON is TCT, which is to be considered in the mathematical model. TCT in the proposed DFON is defined as Equation (8):

$$\sum_{\substack{j\in V \\ j\neq i}} X_{ij} \geq 2 \qquad \forall i \in V \tag{8}$$

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4. Multi-objective algorithms

As previously discussed, the proposed model in this study is multi-objective, so one of the multi objectives algorithms should be used to solve the model. Owing to the complexity of the proposed model, meta-heuristic algorithms have been used.

4.1. Non-dominated Sorting Genetic Algorithm (NSGA)

The genetic search (GA) approach was first proposed by Rosenberg (1970) to simulate the genetic and chemical characteristics of a single-celled population with multiple properties or goals. The first applied algorithm proposed was the Vector Evaluated Genetic Algorithm (VEGA), which was not welcomed due to excessive bias toward Pareto optimal solutions (Schaffer, 1985). Due to the problems of the VEGA, a non-dominated sorting procedure was introduced by Golberg (1989) to cover the defects of VEGA. Inspired by the model presented by Golberg (1989), Non-Dominated Sorting Genetic Algorithm (NSGA) was developed by Srinivas and Deb (1994). Although NSGA seems very efficient, by implementing this algorithm on different problems with different dimensions, issues have been disclosed. Computational complexity of NSGA is *O(MN3)*; therefore, as the problem variables increase, the complexity of the algorithm increases sharply. One of the things that can increase the efficiency of GA is elitism, which has not been considered in the NSGA (Deb et al., 2002). Owing to the problems raised and the improvement of NSGA, the Elitist Non-dominated Sorting Genetic Algorithm was presented by (Deb et al., 2002). In this section, we have tried to describe the different parts of the Elitist Non-Dominated Sorting Genetic Algorithm.

4.2. Elitist Non-dominated Sorting Genetic Algorithm (NSGA-II)

In the NSGA-II, to sort the population of size *N*, each solution must be compared with each of the solutions, which requires *O (M, N)* comparisons for each solution, where M is the number of objectives. When this process of NSGA-II is continued to search the members of the first non-dominated class for all population members, the total complexity is $O(M{*}N^2)$. In this section, we define set P' and enter the first solution of the population into P'. Then each new solution *p* that is generated is compared with all the members P'. If the solution *p* dominates any member *q* of P', then solution *q* is removed from P'. Otherwise, if solution *p* is dominated by any member of P', the solution *p* is ignored. If solution *p* is not dominated by any member of P', it is entered in P'. When all solutions of the population are checked, the remaining members of P' constitute the non-dominated set.

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Table 2. Fast-Non-dominated-sort(p).

$P' = \{1\}$	include first member in P'
for each $p \in P \wedge p \notin P'$	take one solution at a time
$P' = P' \cup \{p\}$	include p in P' temporarily
for each $q \in P' \wedge q \notin p$	compare p with other members of P'
$if\ \ p \prec q, then\ P' = P' \backslash \{q\}$	if p dominates a member of P', delete it
$elseif\ \ q \prec p, then\ P' = P' \backslash p$	if p is dominated by other members of P', do not include p in P'

4.2.1. Density estimation

To obtain the density of solutions around a particular solution, we consider the average distance of the solution from the previous and next response along each of the objectives. The following algorithm is applied to determine the crowding distance of each point in the set τ.

Table 3. Crowding-distance-assignment.

$l = \|\tau\|$	Number of solutions in τ
for each i, set $\tau[i]_{\text{distance}} = 0$	Initialize distance
$\tau = \text{sort}(\tau, m)$	Sort using each objective value
$\tau[1]_{\text{distance}} = \tau[l]_{\text{distance}} = \infty$	Boundary points are always selected.
for $i = 2$ to $(l-1)$	
$\tau[i]_{\text{distance}} = \tau[i]_{\text{distance}} + (\tau[i+1].m - \tau[i-1].m)$	Calculate crowding distance for all points

Here, $\tau.m$refers to the objective function value (m) of individual i in the set τ. The complexity of this procedure is reported *O (M*N*log N)*.

4.2.2. Crowded comparison operator

The crowded comparison operator ($\prec$) helps the selection process at the various stages of the algorithm towards a uniformly spread-out Pareto-optimal front. In the NSGA-II, every individual i in the population has two attributes. Non-domination rank (i_{rank}), Local crowding distance ($i_{distance}$). Here is a definition8 for choosing between two solutions according to their features.

$$i \prec j \quad \text{if } (i_{rank} < j_{rank}) \text{ or } \left((i_{rank} < j_{rank}) \text{ and } i_{distance} > j_{distance}\right) \tag{9}$$

According to Definition 9, we prefer to choose a solution with the lowest rank among the solutions with different rankings. If the rank of the solution is equal, we choose the solution that is in the Pareto area with a lesser number of points.

4.2.3. Main loop

Initially, a random parent population P_0 is generated. The population is sorted based on the non-Domination. Each solution is assigned a fitness equal to its non-domination level. In this section, Binary tournament selection, cross over, and mutation operators are used to create a child population Q_0 of size N. The elitism procedure for (t >1) is shown in Table 4:

Table 4. The elitism procedure.

$R_t = P_t \cup Q_t$	Mix parent and offspring population
ξ = fast-nondominated-sort(R_t)	$\xi = (\xi_1, \xi_2, \dots)$, all non dominated fronts of R_t
$P_{t+1} = \emptyset$	
until $\|P_{t+1}\| < N$	
Crowding distance assignment (ξ_i)	Calculate crowding distance in ξ_i
$P_{t+1} = P_{t+1} \cap \xi_i$	Include non-dominated front i in the parent population
$Sort\ P_{t+1}, \prec$	Sort in descending order using $\prec$
$P_{t+1} = P_{t+1}[0{:}\,N]$	Select the first N solution of P_{t+1}
Q_{t+1} = make-new-pop(P_{t+1})	Use selection, cross over and mutation to create a new population Q_{t+1}
t=t+1	

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First, a population $R_t = P_t \cup Q_t$ is formed, so that the size of R_t is $2N$. Then, the population R_t is sorted according to non-Domination. The new parent population P_{t+1} is formed by adding solutions from the first front till the size exceeds N. After that, the solutions of the last accepted front are sorted according to $\prec$, and a total of N solutions are picked. This population of size N is now used for selection, crossover, and mutation to create a new population Q_{t+1} of size N.

Finally, the complexity of one iteration of NSGA-II is reported as follows:

- Non-dominated sort is O(M*N2),
- The crowding distance assignment is O (M*N*log N),
- Sort on is O(2N*log(2N)).

4.3. Particle swarm optimization

Another optimization algorithm is the Particle Swarm Optimization (PSO) algorithm, which is one of the population-based algorithms. In PSO, a set of N particles is considered a population P_t in the generation t. Suppose the search space is D-dimensional. Then particle i from the population (swarm), can be represented by a D-dimensional vector. Thus, the position and velocity of each particle i defined in Definition 10:

$$\begin{array}{ll} \text{Position of particle } i & X_i = \{X_{i1}, X_{i2}, X_{i3}, \ldots, X_{id}\} \\ \text{Velocity of particle } i & V_i = \{V_{i1}, V_{i2}, V_{i3}, \ldots, V_{id}\} \end{array} \tag{10}$$

In iteration $t + 1$, the velocity and position of each particle i is updated as Equation (11):

$$\begin{aligned} V_{id}^{t+1} &= \omega^t V_{id}^t + C_1 R_1 \left(Pbest_{id}^t - X_{j,t}^i\right) + C_2 R_1 \left(Gbest_{id}^t - X_{j,t}^i\right) \\ X_{id}^{t+1} &= X_{id}^t + V_{id}^{t+1} \end{aligned} \tag{11}$$

where $d = 1,2,\ldots,D$, ω is the inertia weight of the particle, C_1 and C_2 are two positive constants for personal best experience and group best experience, respectively, and R_1 and R_2 are random values in the range [0,1]. $Gbest_{id}^t$ is the position of the best global particle in the population, and $Pbest_{id}^t$ is the best position that particle i could explore so far. In the PSO, $Pbest_{id}^t$is as a memory for each particle i and is updated after each iteration. The inertia weight w is applied to control the impact of the previous history of velocities on the current velocity (Mostaghim and Teich, 2003; Shi and Eberhart, 1998).

4.4. Binary particle swarm optimization

The Binary Particle Swarm Optimization (BPSO) algorithm, due to its nature, is often used in Continuous Problems (CP), and the results show that this algorithm has better performance in solving CP. On the other hand, owing to the powerfulness of PSO, attempts have been made to use it to solve Discrete Problems (DP). BPSO was first introduced by Kennedy and Eberhart (1997) and was implemented and used to solve DP. In the BPSO, the particle swarm formula Equations remain unchanged, except that $X_{id}$and $Pbest_{id}$ are integer in [0,1] (Mathur et al., 2010). The velocity of a particle can take only binary value 0 or 1, therefore applicable to CP PSO is modified as Equation (12):

$$X_{id}^{t+1} = \left\{ \begin{array}{ll} 1 & \text{if Rand } \leq \dfrac{1}{1 + e^{-V_{id}^t}} \\ 0 & \text{otherwise} \end{array} \right\} \tag{12}$$

Finally, the pseudo-code of the BPSO algorithm is shown in Figure 2:

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```
Begin
    Initialize Swarm position X (0) and velocity V (0)
    Set iteration count, t=0
    Repeat
        Compute fitness function for each individual of swarm
        Begin (Perform BPSO operation)
            Compute V(t+1)
            Compute X(t+1)
        End
        Set t, t+1
    Untie termination criteria is satisfied
End
```

Figure 2. pseudo-code of the BPSO algorithm.

4.5. Multi-objective particle swarm optimization

In the number of articles, researchers are paying more and more interest to PSO to solve multi-objective problems (Coello Coello and Lechuga, 2002; Hu and Eberhart, 2002; Parsopóulos and Vrahatis, 2002). Changing a PSO to Multi-Objective Particle Swarm Optimization (MOPSO) requires a redefinition of what a guide is to obtain a front of optimal solutions. In the MOSO, the Pareto-Optimal Solutions (POS) should be used to ascertain the guide for each particle (Mostaghim and Teich, 2003). One of the main drawbacks of MOPSO is determining the guide from a set of the POS for each particle of the population (Fieldsend and Singh, 2002). Therefore, the crucial part of MOPSO is determining $Gbest_{id}^{t}$ for each particle *i* of the population.

In the PSO, determining $Gbest_{id}^{t}$ is easy by choosing the particle which has the best position. Since, in the MOPSO, we encounter POS as optimum solutions, each particle of the population should select one of the POS as $Gbest_{id}^{t}$. Pseudo-code of the MOPSO algorithm is disclosed in Figure 3.

Begin
Input: Optimization Problem
Output: Non-dominated solution in archive (A)
Step1 t=0
Step2 initialization:
  Initialize Population P^t
  For *i*=1 to N
    Initialize X_{id}^{t},$V_{id}^{t} = 0$ and $P^t = X_{id}^{t}$
  End
  Initialize the archive $A^t = \{\,\}$
Step3 Evaluate P_t
Step4 $A^{t+1} = update(A^t, P^t)$
Step5 $P^{t+1} = Generate(A^t, P^t)$
  For *i*=1 to N
    a) $Gbest_{id}^{t} = findGlobalBest(A^{t+1}, X_{id}^{t})$
    b) For *j*=1 to n
$$V_{id}^{t+1} = \omega^t V_{id}^{t} + C_1 R_1 \left(Pbest_{id}^{t} - X_{j,t}^{i}\right) + C_2 R_1 \left(Gbest_{id}^{t} - X_{j,t}^{i}\right)$$
$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1}$$
    End
    c) If $\left(X_{id}^{t+1} \prec P_{id}^{t}\right)$
      $P_{id}^{t+1} = X_{id}^{t+1}$
    else
      $P_{id}^{t+1} = P_{id}^{t}$
    End
  End
Step 6 Unless a termination criterion is met.
    t=t+1 and go to step3
End

Figure 3. pseudo-code of the MOPSO algorithm.

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Figure 3 demonstrates a structure of MOPSO with elitism, where *t* describes the iteration index, P_{id}^{t} the population, and A^{t} the archive at iteration *t*. The function named evaluate, evaluates each particle in P_{id}^{t} and function "$update(A^{t}, P^{t})$" compares whether members of the current population P_{id}^{t} are non-dominated to the members of the actual achieve A^{t} and determines which of such candidates should be considered for archive and which should be removed. Namely, an archive is called domination-free if no two points in the archive do dominate each other. In the "$findGlobalBest(A^{t+1}, X_{id}^{t})$" selects global best particle for each particle *i*. In this function, each particle *i* has to change its position X_{id}^{t} towards the position of a local guide which must be selected from the updated set of *POS* stored in the archive A^{t+1}. In Step 5. c, P_{id}^{t} of particle *i* should update. P_{id}^{t} is the last non-dominated position of each particle *i*. Finally, in Step 6, the termination conditions of the algorithm are checked. if the conditions are met, the algorithm is terminated, and if the termination conditions are not met, the algorithm is executed again and returned to Step 3.

4.6. Representation solutions

In the proposed DFON, the decision variable is defined as binary, which can be displayed as a $V \times V$ matrix. It is important to note that the representation solutions matrix is symmetric and does not require calculations of the lower half of the original diameter. Namely, when the upper half of the original diameter is calculated in the algorithm, the lower half is calculated. Similarly, the representation solutions are defined in Definition 13:

$$\begin{pmatrix} X_{i,j} & X_{i,j+1} & X_{i,j+2} & \ldots & X_{i,V} \end{pmatrix} \qquad \begin{array}{l} i \in V \\ j \in V, \qquad j = i+1 \end{array} \tag{13}$$

For example, suppose the representation solution for vertices 2 is as follows:

$$\text{representation}\ \begin{pmatrix} 1 & 0 & 0 & \ldots & 1 \end{pmatrix} \rightarrow \quad Solution = X_{23} = 1, X_{24} = 0, X_{25} = 0, \ldots, X_{2V} = 1$$

5. Fuzzy mathematical programming

Commonly, fuzzy mathematical programming methods can be gathered into two main classes: 1) Flexible Programming and 2) Possibility Programming methods. Flexible Programming deals with elasticity in objective function and flexibility of constraints (Inuiguchi and Ramík, 2000; Pishvaee et al., 2012). The second category deals with uncertain and ambiguous parameters in the objective functions and constraints. Owing to the nature of the introduced model, and the Possibility Programming methods used in this study (Zahiri et al., 2015). Due to the possible changes in the parameters, it is necessary to provide an approach that is less sensitive to the possible changes in the parameters (Dehghani et al., 2018). Therefore, a robust solution must be provided that can be suitable for all uncertain parameters and provide a near-optimal solution. For the goal of using the advantages of both fuzzy programming and robust programming, a new possibility programming approach named Robust Possibility Programming (RPP) is applied in this study, which has been manufactured based on the possibility chance-constrained programming (PCCP) (Pishvaee et al., 2012). In the proposed model in this study, trapezoidal possibility distribution has been utilized to demonstrate the uncertain parameters in Figure 4:

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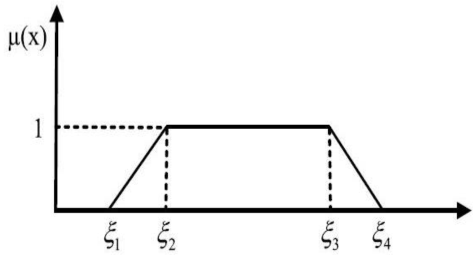

Figure 4. Trapezoidal possibility distribution of fuzzy parameter.

In the following, we introduce the proposed hybrid mathematical model. RPP in this study is defined in Equation (14):

$$\begin{aligned} &Min\ Z = \tilde{C}X \\ &AX \leq U \\ &NX = 1 \\ &X \in \{0,1\} \end{aligned} \tag{14}$$

where, $\tilde{C}$is the connection cost between two vertices and A, N are coefficient matrices. Additionally, Xrepresents a binary decision variable.

Based on the PCCP model, the RPP model can be formulated as Equation (15):

$$\begin{aligned} &Min\ Obj = \frac{C_1 + C_2 + C_3 + C_4}{4} X + (C_4X - C_1X) \\ &AX \leq U \\ &X \in \{0,1\} \end{aligned} \tag{15}$$

where the first term of the objective function indicates the expected value Z and $(C_4X - C_1X)$ represents the difference between two extreme possible values of Z.

6. Case study

One of the most important companies that has a key role in creating communication and information infrastructure in Iran is the Telecommunication Infrastructure Company (TIC)[1]. TIC commonly contributes to various fields such as core network bandwidth development, the development of Internet connection ports, the development of traffic, transit network and in the field of information infrastructure, the development of traffic exchange centers, and creation of cloud infrastructure. Due to the high demand for services provided by TIC in Iran and the multiplicity of services, it is necessary to provide a platform so that services can be provided to customers at the lowest cost and highest speed. At the beginning of the TIC, its services were provided to customers through platforms such as satellite and radio communications. Still, with the passage of time and the development of technology, the TIC's managers decided to add FOT to the network of the company in addition to existing platforms.

For this purpose, 30 centers (number of provinces of Iran) have been purchased by TIC. The goal is to make the connections between these centers with the lowest cost and the most reliability and survivability. Since the location of the centers of TIC is considered fixed, the distance between the centers can be calculated accurately and from the map. Considering that the communication between

[1] www.tic.ir

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the centers in this network is of fiber optic, it is necessary to determine the cost of providing each meter of fiber optic cable. The fiber optic centers of the TIC are shown in Figure 5:

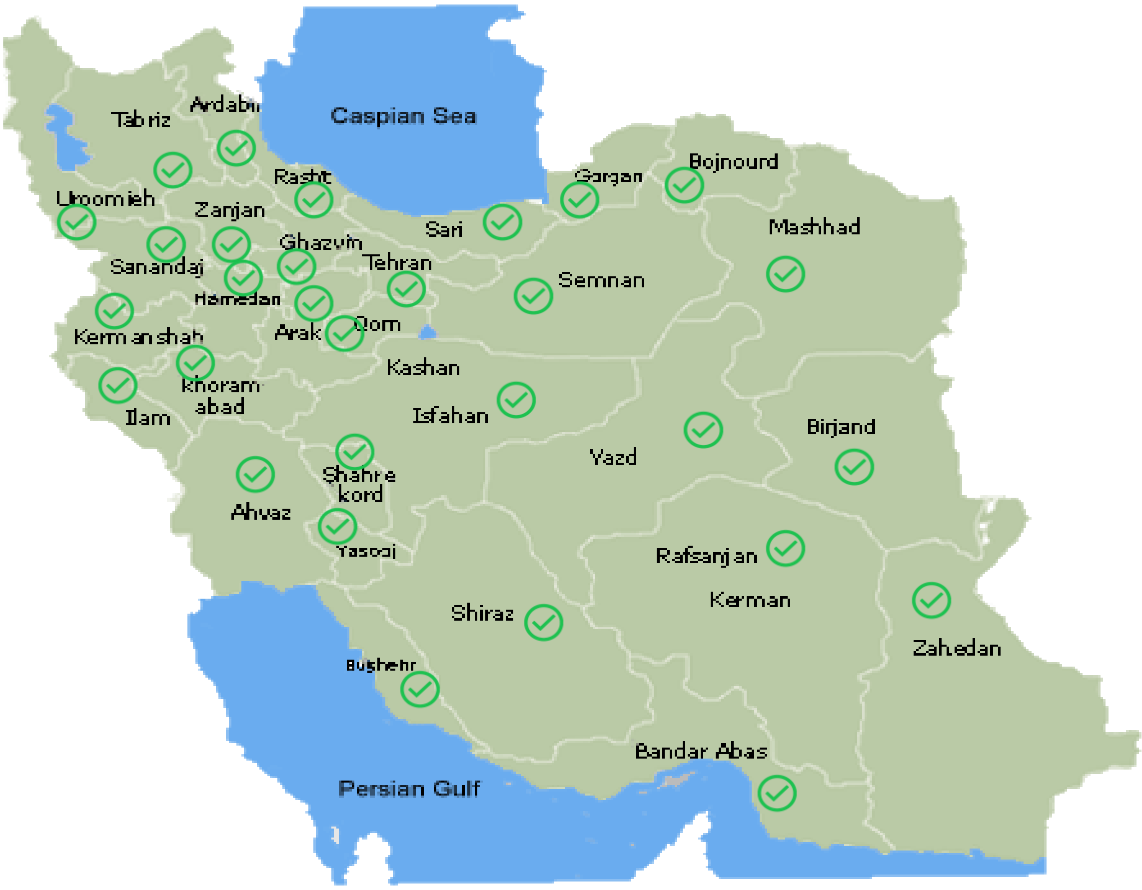

Figure 5. Centers of TIC in Iran.

7. Computational results

This section aims to validate the theoretical proposed model. Due to the complexity and multi-objective nature of the proposed model, NSGA-II and MOPSO algorithms have been implemented using MATLAB commercial software (MATLAB R2014b) on system Intel® core™ i7-6500U CPU@ 2.5 GHz, and the results are presented in the following sections.

7.1. NSGA-II results

In the NSGA-II algorithm, the condition of stopping the maximum number of iterations is considered, and the results of 100 iterations of the algorithm are reported in Figure 6.

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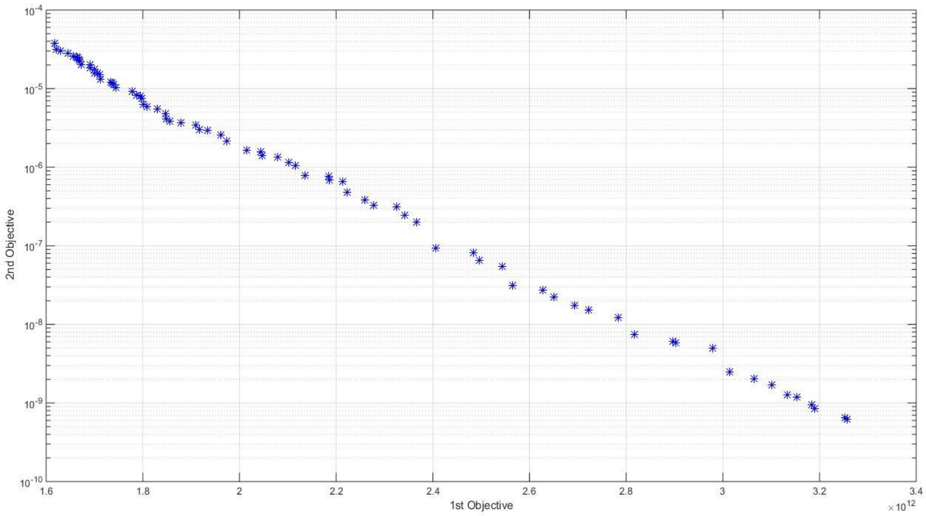

Figure 6. NSGA-II results.

According to Figure 6, the Number of Optimal Pareto Solutions (NOPS) is 80, and due to the scaling of the two objective functions, the logarithm value of the objective function minimization of unreliability is included in the figure. As previously discussed, the Solution matrix is 30 *30, and due to the symmetry of this matrix, 435 decision variables have been calculated in the NSGA-II. The best value of the Economic Objective Function (EOF) among the NOPS is 1.6183×10^{12}, and the best value for the Unreliability Objective Function (UOF) is 6.2679×10^{-10}. Also, the number of activated edges in the best value EOF is 146, and in the best value UOF is 254. Namely, the priority of EOF, the goal is to minimize costs by considering an acceptable level of reliability, but in the priority of UOF, the goal is to maximize reliability.

7.2. MOPSO results

In the MOPSO algorithm, the condition of stopping the maximum number of iterations of the algorithm is considered, and the results of 200 iterations are reported in Figure 7.

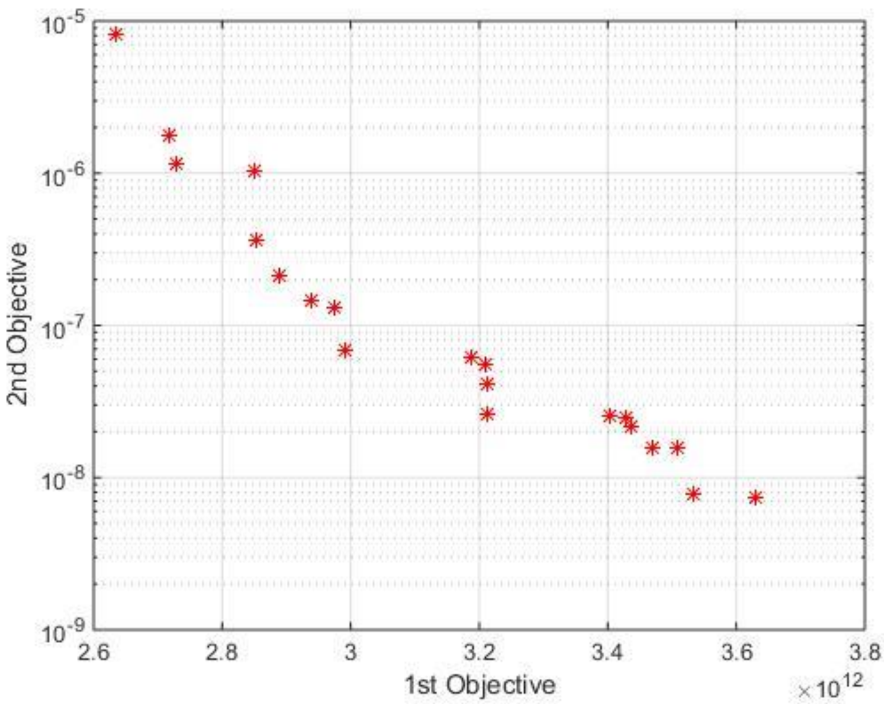

Figure 7. MOPSO results.

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According to the results of the MOPSO algorithm, the Number of Repositories (NOR) in the population size 150 is 30. The best value of the EOF among the NOR is 2.6348×10^{12}, and the best value for the UOF is 7.3656×10^{-9}. Also, the number of activated edges in the best value EOF is 189, and in the best value UOF is 260. As can be seen, MOPSO produced a worse solution than NSGA-II for EOF and UOF despite the higher number of iterations. It is also observed that the number of activated edges in MOPSO is more compared to NSGA-II. Finally, in Table 5, the performance of the two algorithms is evaluated according to different aspects.

Table 5. Comparing NSGA-II and MOPSO.

Algorithm	Iteration	Population size	NOPS/NOR	Best of EOF	Best of UOF
NSGA-II	100	80	80	1.6183×10^{12}	6.2679×10^{-10}
MOPSO	200	150	30	2.6348×10^{12}	7.3656×10^{-9}

7.3. Parameter tuning

Appropriate design of the initial parameters of the algorithm has a significant impact on its performance. In this section, determining the proper level for the parameters is done in such a way as to optimize the performance of the algorithm. Many articles have implemented full-factorial design and finally selected the optimal levels (Montgomery, 2017; Ruiz et al., 2006). The full-factorial design increases dramatically with an increasing parameter, and it may be costly for the system to perform each experiment (Hamzadayi and Yildiz, 2013; Simpson et al., 2001; Taguchi, 1986). Therefore, according to the drawback of full-factorial design, Taguchi Method (TM) was proposed by Taguchi (1986) to perform part of the experiments instead of all the experiments, so that if the number of parameters increases, it will face fewer tests than full-factorial design.

TM applies a design of orthogonal arrays to investigate the entire parameter space with a small number of experiments only. Therefore, the time and cost required to undergo the experiments can be reduced (Hamzadayi and Yildiz, 2013). TM divides the factors into two bundles: controllable and noise factors (uncontrollable). Controllable factors can be controlled by parameter setting, but uncontrollable factors are inevitable. TM tries to minimize the effect of noise and to distinguish optimal levels of controllable factors based on the robustness (Menten, 1991).

7.3.1. Signal to noise (S/N) ratio

The original use of the S/N was in the field of electronic communications to demonstrate signals in terms of desired values. S/N is also used in the TM to determine the output performance of experiments. Thus, TM merges experimental design using orthogonal arrays with the S/N ratio to assess the quality of system signals (Al-Aomar, 2006). The S/N ratio is determined according to the nature of the problem. When the output variable (Response) is maximization, mode "S/N: larger is better", and in the case of the response is minimization, mode "S/N: smaller is better" should be considered.

7.3.2. Taguchi method for multi-objective

The proposed DFON in this research has two objectives, so determining the value of the response variable to implement the TM is unlike the single-objective mode. In the single-objective mode, the value of the Objective Function (OF) is used as the response in the TM, but in the dual-objective mode, we must convert the set of (OF1, OF2) into a final response variable. Therefore, need to be definite indicators and convert the set of (OF1, OF2) to the final response variable. In the following, we will evaluate these indicators.

- Mean Ideal Distance (MID)

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This index evaluates the proximity of Pareto optimal solutions to the ideal optimal points (f_1^{best}, f_2^{best}). The MID index is calculated as Equation (16):

$$MID = \frac{\sum_{i=1}^{n} \sqrt{\left(\frac{f_{1i} - f_1^{best}}{f_{1,total}^{Max} - f_{1,total}^{Min}}\right)^2 + \left(\frac{f_{2i} - f_2^{best}}{f_{2,total}^{Max} - f_{2,total}^{Min}}\right)^2}}{n} \tag{16}$$

where, n indicates the number of non-Dominated solutions, f_{total}^{Min} and f_{total}^{Max} represents the minimum and maximum of OF_i among all of the iterations. The lower the value of MID, the performance of the algorithm will improve.

- **Diversification Metric (DM)**

This indicator shows the diversification of Pareto solutions and is defined as Equation (17):

$$DM = \sum_{i=1}^{n} \sqrt{\left(\frac{Max(f_{1i}) - Min(f_{1i})}{f_{1,total}^{Max} - f_{1,total}^{Min}}\right)^2 + \left(\frac{Max(f_{2i}) - Min(f_{2i})}{f_{2,total}^{Max} - f_{2,total}^{Min}}\right)^2} \tag{17}$$

Given that the diversification of solutions generated is one of the advantages of the proposed algorithm, the more significant DM is desired.

- **Spacing Metric (SM)**

This indicator shows the uniformity of the extent of the set of non-dominated solutions and defines as Equation (18):

$$SM = \frac{\sum_{i=1}^{n-1} |d_i - \bar{d}|}{(n-1)\bar{d}} \tag{18}$$

where, n indicates the number of non-dominated solutions, d_i describes the Euclidean distance of consecutive non-dominated solutions, and $\bar{d}$ is the average of d_i. Finally, the lower the value of this index, the higher the desirability.

7.3.3. Implement TM on NSGA-II and MOPO

The proposed DFON is solved by two algorithms, NSGA-II and MOPSO, and in this section, we want to adjust to their parameters to have the best performance. In the NSGA-II, the number of Maximum iterations (Maxit), probability of crossover (Pcrossover), probability of mutation (Pmutation), and mutation rate (Mu) are considered basic parameters, and in the MOPO, the number of Maximum iterations (Maxit), number of population (nPop), Leader Selection Pressure (Beta) and Leader Selection Pressure (Gamma) are considered as basic parameters. According to the reviewed articles and expert opinions for the introduced parameters, three suggested levels have been considered, presented in Table 6.

Table 6. Levels of basic parameters.

NSGA-II				MOPSO			
Level	1	2	3	Level	1	2	3
Maxit	100	150	200	Maxit	100	200	300
Pcrossover	0.4	0.5	0.6	nPop	100	150	200
Pmutation	0.6	0.65	0.7	Beta	1	1.5	2
Mu	0.2	0.25	0.3	Gamma	1	1.5	2

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According to the levels set for the basic parameters, Design "L9" was performed by the Minitab19 software, and the results are reported in Figures 8 and 9:

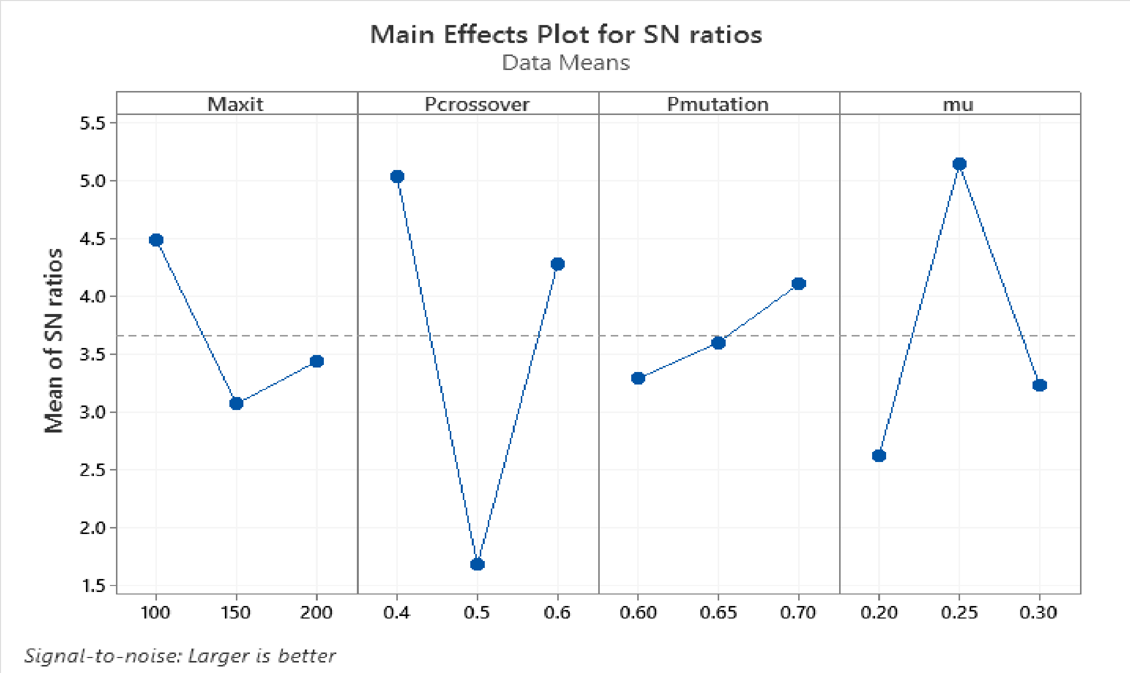

Figure 8. Results of TM for NSGA-II.

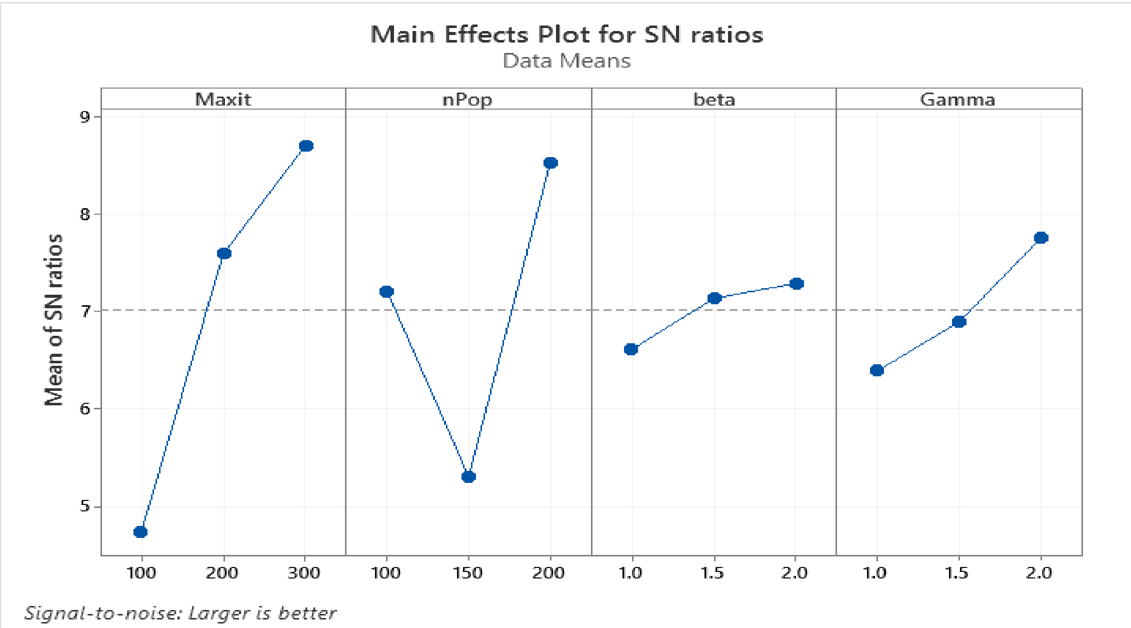

Figure 9. Results of TM for MOPSO.

According to Figures 8 and 9, since the response variable is considered maximized, it is necessary to consider the mode "S/N: larger is better" in the TM. Finally, the optimal levels for each of the basic parameter are defined in Table 7.

Table 7. optimum Levels of basic parameters.

NSGA-II		MOPSO	
Optimum Level		Optimum Level	
Maxit	100	Maxit	300
Pcrossover	0.4	nPop	200
Pmutation	0.7	Beta	2
Mu	0.25	Gamma	2

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7.4. NSGA-II versus MOPSO

As discussed in the previous section, the optimal levels of the basic parameters of NSGA-II and MOPSO were determined. Now in this section, the goal is to compare the performance of the two proposed algorithms. To evaluate the performance of the two proposed algorithms, as in the previous section, SM, DM, and MID indicators are used. In addition to the introduced indicators, we can also use the index Quality Metric (QM). The meaning of this indicator is that we have to put all the optimal Pareto solutions of each algorithm together and compare them in pairs. Dominated solutions should be eliminated, and the ratio of the remaining responses to the total number of initial responses indicates the QM. An algorithm has a better performance with a value more excellent than the QM. Finally, two algorithms with the optimal level of basic parameters are implemented, and the results are reported in Table 8.

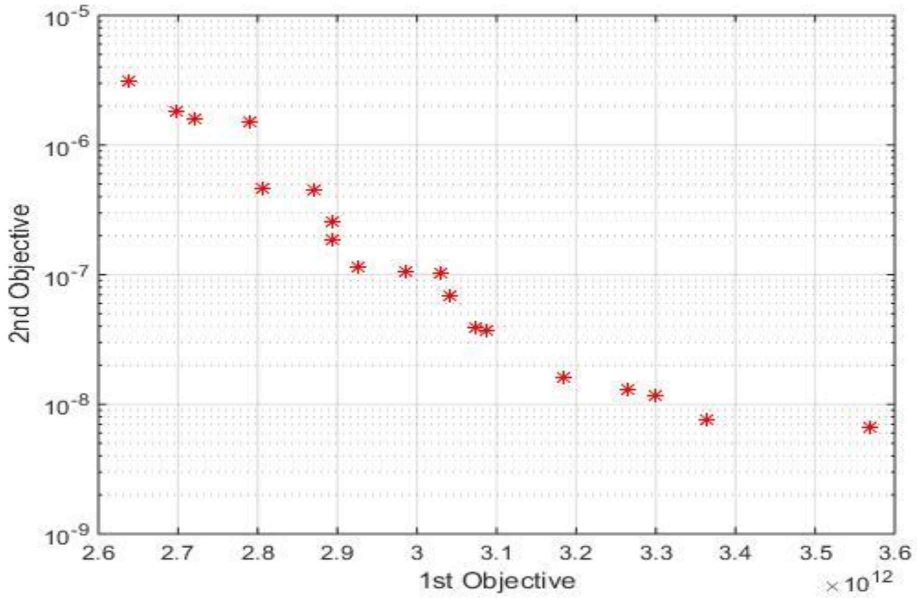

Figure 10. Optimal Pareto solutions in MOPSO.

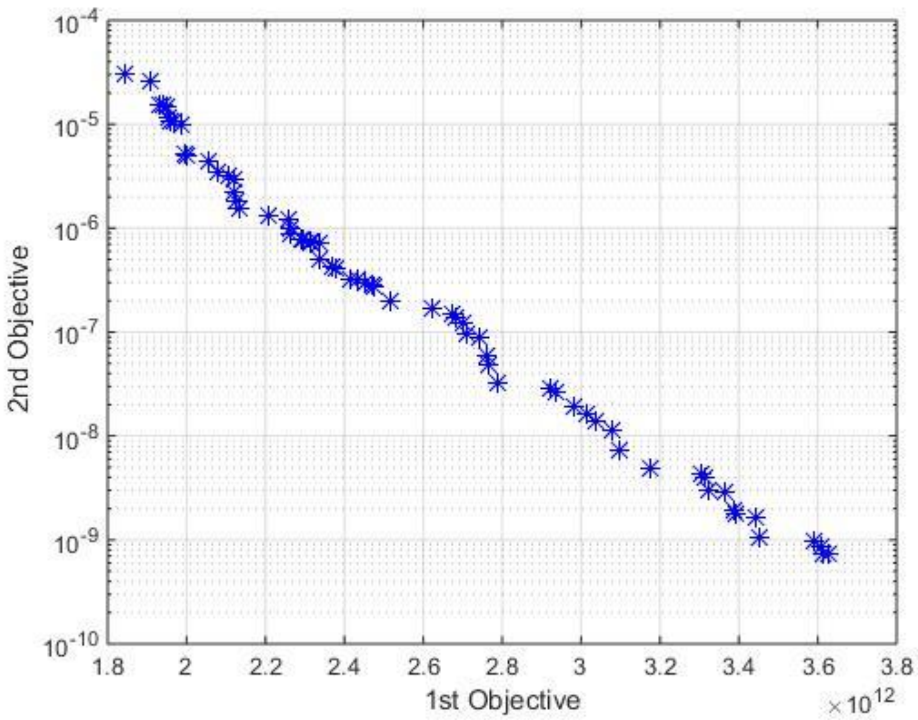

Figure 11. optimal Pareto solutions in NSGA-II.

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Table 8. NSGA-II versus MOPSO.

Algorithm	Indicator				
	QM	MID	DM	SM	Final Score
NSGA-II	0.725	0.0627	1.4142	0.64	0.5799
MOPSO	1	0.0599	0.5343	0.9713	0.36

According to Table 8, MOPSO performs better than NSGA-II regarding QM because none of its optimal Pareto solutions have been dominated. Also, MOPSO in MID has shown better performance than NSGA-II. Namely, in MOPSO, the closeness of Pareto optimal solutions to the ideal solutions is more observed. But in DM, NSGA-II has performed better than MOPSO, and the diversification of optimal Pareto solutions in NSGA-II is visible. Also, the SM indicator shows the superiority of NSGA-II over MOPSO. According to the issues raised, it can be concluded that MOPSO performs better than NSGA-II in terms of intensification, and on the other hand, NSGA-II performs better than MOPSO in terms of diversification.

8. Managerial implication

This section provides managerial insights related to economic, reliability, and survivability impacts on the development of DFON. Given the conflict of objectives of the presented model, it is clear that it will not be possible to achieve the desired amount of economical and reliable objective function simultaneously. Therefore, based on the preference of the DM, Pareto optimal solutions are determined, and optimal strategies are presented accordingly. According to the results of the implementation of NSGA-II, in the most economical case, 189 connections will be established between the centers. In contrast, the number of activated edges in the most reliable network will be 260. Optimal Pareto solutions can be seen in Figure 12:

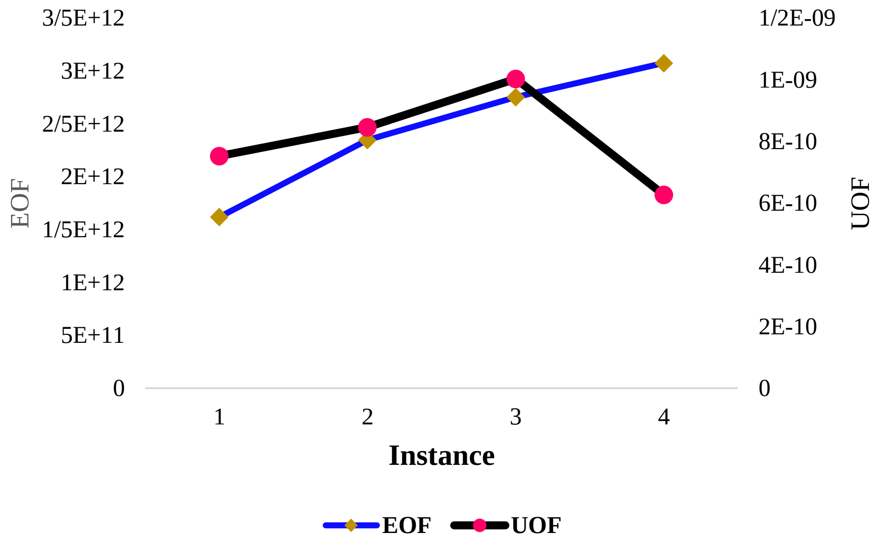

Figure 12. optimal Pareto solutions.

According to Figure 12, it is inferred that based on the policies of stakeholders and the available budget, the DFON will be established. If the goal is to find a network with high reliability, establishing DFON will need more budget.

Based on the obtained results, NSGA-II found a better solution for EOF and UOF than MOPSO, so the optimal amount of EOF and UOF in NSGA-II is improved by 40 and 90%. Therefore, due to the intensification of NSGA-II, more acceptable solutions can be extracted for the proposed model.

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9. Concluding

Recently, the IT industry has grown significantly, and due to the change in people's lifestyles and increasing demand for IT services, governments' view of IT has changed. One of the services with the most increasing demand is the Internet service, which can be provided through various platforms. FOT is one of the platforms through which IT services can be provided to customers. FOT, despite its advantages, such as high capacity and cost-effectiveness, is highly vulnerable to hazards such as natural disasters. Therefore, in this study, DFON with reliability and survival has been investigated. In DFON, TCT is exploited to increase the reliability and stability of the network. The concerned DFON encompasses two objectives: the first objective refers to minimizing network design costs, and the second function refers to minimizing network unreliability. Due to the complexity of the proposed DFON and its multi-objective, NSGA-II and MOPSO algorithms have been devised to solve it. Eventually, the actual data of the TIC is used to validate the proposal. The results corroborate that NSGA-II has produced better solutions than MOPSO. For example, the best value for EOF is reported in NSGA-II with 146 activated edges, but for MOPSO, the value of EOF is with the number of activated edges is 189. Meanwhile, the results reveal that in the proposed DFON, MOPSO performs better in the intensification, but NSGA-II performs better than MOPSO in the diversification.

The following suggestions are also suggested for future research:

- Considering the backbone for the DFON to increase network resilience.
- Paying attention to environmental considerations under the guidelines of the Environmental Protection Agency.
- Implementing a hub system to improve service quality and increase reliability and survivability.

References

Al-Aomar, R. (2006). Incorporating robustness into genetic algorithm search of stochastic simulation outputs. *Simulation Modelling Practice and Theory*, **14**(3), 201-223.

Angilella, V. (2018). *Optimal Design of Fiber to The Home Networks*. Institut National des Télécommunications.

Angilella, V., Chardy, M. and Ben-Ameur, W. (2018). Fiber cable network design in tree networks. *European Journal of Operational Research*, **269**(3), 1086-1106.

Badri Ahmadi, H., Hashemi Petrudi, S. H. and Wang, X. (2017). Integrating sustainability into supplier selection with analytical hierarchy process and improved grey relational analysis: A case of telecom industry. *International Journal of Advanced Manufacturing Technology*, **90**, 2413-2427.

Büyüközkan, G. and şakir Ersoy, M. (2009). Applying fuzzy decision making approach to it outsourcing supplier selection. System, **2**, 2.

Cardwell, R. H., Fowler, H., Lemberg, H. L. and Monma, C. L. (1988). Determining the impact of fiber optic technology on telephone network design. *Bellcore Exchange Magazine*, 27-32.

Cardwell, R. H., Monma, C. L. and Wu, T. H. (1989). Computer-aided design procedures for survivable fiber optic networks. *IEEE Journal on Selected Areas in Communications*, **7**(8), 1188-1197.

Chudley, R., and Greeno, R. (2020). The structure. *Building Construction Handbook*, **3**(3), 17-23.

Coello, C. C. and Lechuga, M. S. (2002). MOPSO: A proposal for multiple objective particle swarm optimization. In *Proceedings of the 2002 Congress on Evolutionary Computation, CEC'02 (Cat. No. 02TH8600)*, **2**, 1051-1056, IEEE.

Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T. A. M. T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, **6**(2), 182-197.

Dehghani, E., Pishvaee, M. S. and Jabalameli, M. S. (2018). A hybrid markov process-mathematical programming approach for joint location-inventory problem under supply disruptions. *RAIRO-Operations Research*, **52**(4-5), 1147-1173.

Dengiz, B., Altiparmak, F. and Smith, A. E. (1997). Local search genetic algorithm for optimal design of reliable networks. *IEEE transactions on Evolutionary Computation*, **1**(3), 179-188.

Fieldsend, J. E. and Singh, S. (2002). A multi-objective algorithm based upon particle swarm optimisation, an efficient data structure and turbulence.

Golberg, D. E. (1989). *Genetic Algorithms in Search, Optimization, And Machine Learning. Addion Wesley.* Reading.

Hamzadayi, A. and Yildiz, G. (2013). A simulated annealing algorithm based approach for balancing and sequencing of mixed-model U-lines. *Computers & Industrial Engineering*, **66**(4), 1070-1084.

Hu, X. and Eberhart, R. (2002). Multiobjective optimization using dynamic neighborhood particle swarm optimization. In *Proceedings of the 2002 Congress on Evolutionary Computation, CEC'02 (Cat. No. 02TH8600)*, **2**, 1677-1681.

Inuiguchi, M. and Ramık, J. (2000). Possibilistic linear programming: a brief review of fuzzy mathematical programming and a comparison with stochastic programming in portfolio selection problem. *Fuzzy Sets and Systems*, **111**(1), 3-28.

Kennedy, J. and Eberhart, R. C. (1997). A discrete binary version of the particle swarm algorithm. In *1997 IEEE International conference on systems, man, and cybernetics. Computational cybernetics and simulation*, **5**, 4104-4108, IEEE.

Koh, S. J. and Lee, C. Y. (1995). A tabu search for the survivable fiber optic communication network design. *Computers & Industrial Engineering*, **28**(4), 689-700.

Mathur, Y. P., Kumar, R. and Pawde, A. (2010). A binary particle swarm optimisation for generating optimal schedule of lateral canals. *The IES Journal Part A: Civil & Structural Engineering*, **3**(2), 111-118.

Menten, T. (1991). Quality engineering using robust design. *Technometrics*, **33**(2), 235-236.

Monma, C. L. and Shallcross, D. F. (1989). Methods for designing communications networks with certain two-connected survivability constraints. *Operations Research*, **37**(4), 531-541.

Montgomery, D. C. (2017). *Design and Analysis of Experiments.* John wiley & sons.

Mostaghim, S. and Teich, J. (2003). Strategies for finding good local guides in multi-objective particle swarm optimization (MOPSO). In *Proceedings of the 2003 IEEE Swarm Intelligence Symposium. SIS'03 (Cat. No. 03EX706)*, 26-33, IEEE.

Journal of Decision Making Theory and Practice

Parsopóulos, K. E. and Vrahatis, M. N. (2002). Particle swarm optimization method in multiobjective problems. In *Proceedings of the 2002 ACM symposium on Applied computing*, 603-607.

Pishvaee, M. S., Razmi, J. and Torabi, S. A. (2012). Robust possibilistic programming for socially responsible supply chain network design: A new approach. *Fuzzy sets and systems*, **206**, 1-20.

Rabbani, M., Ravanbakhsh, M. and Taheri, M. (2018). Designing of fiber-optic network for the three-level by considering the backbone network and local access networks simultaneously. *Advances in Industrial Engineering*, **52**(3), 379-388.

Rosenberg, R. S. (1970). Stimulation of genetic populations with biochemical properties: i. The model." *Mathematical Biosciences*, **7**(3-4), 223-57.

Ruiz, R., Maroto, C. and Alcaraz, J. (2006). Two new robust genetic algorithms for the flowshop scheduling problem. *Omega*, **34**(5), 461-476.

Schaffer, J. D. (1985). *Some Experiments in Machine Learning Using Vector Evaluated Genetic Algorithms*. Vanderbilt Univ., Nashville, TN, USA.

Shi, Y. and Eberhart, R. C. (1998). Parameter selection in particle swarm optimization. In *Evolutionary Programming VII: 7th International Conference, EP98 San Diego, California, USA, March 25-27, 1998 Proceedings 7*, 591-600, Springer Berlin Heidelberg.

Simpson, T. W., Poplinski, J. D., Koch, P. N. and Allen, J. K. (2001). Metamodels for computer-based engineering design: survey and recommendations. *Engineering with computers*, **17**, 129-150.

Srinivas, N. and Deb, K. (1994). Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation*, **2**(3), 221-248.

Taguchi, G. (1986). *Introduction to Quality Engineering: Designing Quality into Products and Processes*. Tokyo: Asian Productivity Organization, Kraus International.

Tajik, M., Makui, A. and Mansouri, N. (2020). Suppliers' evaluation and ranking in telecommunication infrastructure company using the TOPSIS method in an uncertain environment. In *International Conference on Logistics and Supply Chain Management*, 84-99.

Tubert-Brohman, I., Sherman, W., Repasky, M. and Beuming, T. (2013). Improved docking of polypeptides with glide. *Journal of Chemical Information and Modeling*, **53**(7), 1689-1699.

Wu, X., Lü, Z. and Glover, F. (2020). A matheuristic for a telecommunication network design problem with traffic grooming. *Omega*, **90**, 102003.

Yazar, B., Arslan, O., Karaşan, O. E. and Kara, B. Y. (2016). Fiber optical network design problems: A case for Turkey. *Omega*, **63**, 23-40.

Zahiri, B., Torabi, S. A., Mousazadeh, M. and Mansouri, S. A. (2015). Blood collection management: Methodology and application. *Applied Mathematical Modelling*, **39**(23-24), 7680-7696.

Tajik, Makui, Barzin Pour, Babazadeh, Dehghani| JDMTP, 1(1) 115-136