Engineering Applications of Artificial Intelligence 124 (2023) 106630

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

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

A local search-based non-dominated sorting genetic algorithm for solving a multi-objective medical tourism trip design problem considering the attractiveness of trips

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ARTICLE INFO

Keywords:
Medical tourism trip design
Orienteering problem
Utility function
Attractiveness of trips
Multi-objective optimization
Local search-based non-dominated sorting genetic algorithm (LSNSGA-II)

ABSTRACT

Nowadays, the medical tourism industry encourages many healthcare practitioners to provide high-quality and low-cost medical services for patients worldwide. The development of operations research models and algorithms is one important instrument for improving the medical tourism industry based on the economic, political, social, and cultural aspects. In this paper, a medical tourism trip design problem is developed where patients travel from their city of residence to a destination city that may be in another country to receive high-quality and low-cost medical care. The most important part of this problem is to visit a number of tourist cities for each patient individually in the destination. In addition to the total cost, the patients prefer to increase the attractiveness of trips by referring to the quality of medical services and the attractiveness of visiting tourist cities. As far as we know in the area of medical tourist studies, no study has considered the minimization of total cost and maximization of the attractiveness of trips, simultaneously using utility function. The proposed multi-objective optimization model assigns the patients from the origin country to the hospitals in the destination country while making their routing and scheduling decisions to visit the tourist cities. The proposed model is limited by patients' interests and time restrictions while allocating patients to the hospital and orienteering the patients toward visiting tourist attractions. As a complex optimization problem, another significant novelty of this paper is the proposal of a local search-based non-dominated sorting genetic algorithm (LSNSGA-II) for solving the proposed multi-objective optimization model. The proposed algorithm is compared with the original non-dominated sorting genetic algorithm (NSGA-II) and epsilon constraint (EC) method based on different multi-objective criteria. Finally, one main finding from our analyses is finding a trade-off between the total cost and attractiveness of trips as a challenging decision while proposing high-quality solutions in a reasonable time (i.e., less than one hour).

1. Introduction

Nowadays, the tourism industry plays an important role in economic development while meeting different sustainable development factors including job opportunities, social justice, culture promotion, and so on (Suess et al., 2018). After the petroleum and automobile industries, the tourism industry has a very high impact to attract property and increase the national gross domestic product (Connell, 2011). This fact motivates many practitioners in this industry to facilitate the processes of tourism while attracting more tourists to improve economic growth.

The tourism industry has different aspects based on medical, sports, and cultural fields (Kim et al., 2015). Medical tourism term expresses that a person wants to travel abroad to cure disease and spend leisure time in a destination country (Carrera and Lunt, 2010). Medical care in this country should have lower costs and higher quality in comparison with the origin country at the same time. Hence, hospitals in destination countries should use high-tech and advanced technologies for treatment (Cohen, 2008). Based on these needs and benefits from the medical tourism trip design, this study proposes a multi-objective optimization model for minimizing the total cost of patients' assignments and maximizing the attractiveness of patients' trips.

A definition of medical tourism, World Trade Organization (WTO) defines it as international logistics in healthcare services (Bell et al., 2015). Since medical tourism connects different countries for traveling and presenting transportation services and medical care, it can be

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[1] Google Scholar: https://scholar.google.com/citations?user=YaIA0ioAAAAJ.

https://doi.org/10.1016/j.engappai.2023.106630
Received 27 October 2022; Received in revised form 21 May 2023; Accepted 8 June 2023
Available online 21 June 2023

classified as global healthcare supply chain management (Lee and Fernando, 2015). In this regard, the medical tourism problem should cover different criteria including but not limited to cost, quality of treatment, skills of specialists, level of welfare, and tourist attractions of the destination country (Skountridaki, 2015). The staying time of patients in the destination country may create a conflict between the total cost and attractive trips. The attractiveness of trips not only refers to the quality of medical services but also the attractiveness of tourist places. More time to stay increases the total cost while improving the attractiveness of trips. Such conflicts encourage us to study two objective functions, i.e., the total cost and the attractiveness of trips, simultaneously in this paper.

Between 2020 and 2021, the COVID-19 pandemic limited the medical tourism problem and this industry encountered financial losses (Thananusak et al., 2022). This fact encourages Medical Tour Centers (MTCs) to supply high-quality services for medical tourists at a lower price in comparison with other countries (Sandberg, 2017). In this regard, one of the main factors for the assignment of patients to hospitals is the quality of medical services. The proposed model for the first time contributes to the attractivity of patients' trips as an objective function that defines the quality of the hospital's treatment based on the utility function in comparison with other hospitals. Finally, MTCs should utilize the attractiveness of the destination country to provide good leisure time for passengers (or patients) in this competitive market (Heung et al., 2010). Hence, the attractiveness of cities that tourists visit relies on the length of residence. The MTCs are responsible in charge of transportation planning and tourist trip design planning for recreation tours. Facilitating the journey for medical tourists is prepared by the economic miscellaneous packages for the traveling of patients and healthcare services provided by them.

In conclusion, this paper for the first time develops a multi-objective mathematical model in the medical tourism industry for the allocation of foreign patients to hospitals based on capacity and quality. A utility function is deployed to define the points of each facility at the destination for each patient for maximizing the attractiveness of trips while minimizing the total cost. As a complex multi-objective optimization problem, another contribution of this research is to propose an efficient multi-objective metaheuristic and exact algorithms for solving the proposed model. In this regard, a non-dominated sorting genetic algorithm (NSGA-II) is enhanced by a local search algorithm to propose a local search-based NSGA-II (LSNSGA-II). This proposed metaheuristic algorithm is not only compared with the original NSGA-II but also the epsilon constraint (EC) based on different multi-objective metrics.

Based on the aforementioned discussions regarding our contributions, we can conclude the following highlights regarding this paper:

- A new multi-objective medical tourism trip design problem is developed.
- The proposed model minimizes the total cost while maximizing the attractiveness of the trip for the first time.
- A utility function is applied for determining the variable staying time for visiting tourist cities.
- An efficient local search-based non-dominated sorting genetic algorithm is introduced.

In addition to this introduction, this paper has the following sections: Section 2 collects the relevant works from the literature review to identify the research gaps and highlight our contributions. Section 3 explains the problem setting and establishes the proposed multi-objective model for the medical tourism trip design problem. Section 4 develops our metaheuristic algorithm to heuristically address the search space of our optimization model with innovative search operators. Section 5 performs a comprehensive analysis and comparison of our solutions while performing a set of sensitivity analyses on key parameters. Finally, Section 6 provides a summary of this paper and possible future remarks.

2. Literature review

Many studies have been devoted to the attitudes of the community for analyzing the impacts of tourism on economic growth (Jurowski and Gursoy, 2004; Vincent and Thompson, 2002). In the literature on the medical tourism industry, both qualitative and computational studies have seen a great deal of attention in recent years (Sandberg, 2017). Here, a literature review of the medical tourism industry from both types of studies has been studied.

In a qualitative study, Yu and Ko (2012) reviewed potential infrastructure factors focusing on the reduction of the cost of tourist trips and the time for taking patients' appointments. One finding of their study was the high impact of the organizations' integration criterion in comparison with other studied criteria to improve the quality of services in medical tourism. Buzinde and Yarnal (2012) discussed the privileges of integrated hospitals and airlines in a destination country to decrease expenses while attracting more patients from the origin countries. Han and Hyun (2015) investigated the influence of a set of important criteria including quality, trust, satisfaction, and the pricing of the destination country to attract more patients and tourists. Heung et al. (2011) stated that there are some obstacles to improving the efficiency of the medical tourism industry. One problem is the high price of medical services in developed countries. There is a lack of integration for facilities involved in the medical tourism industry. Last but not least, some governmental policies make it difficult to attract tourists. They showed that solutions are to increase the capacity of facilities and improve the quality of medical services. Momeni et al. (2018) introduced a set of factors having significant impacts on the development of medical tourism in Iran. They analyzed the marketing of attraction to international patients, global interactions, ethics, social culture, language, and state-of-the-art technologies as well as commission, and coordination of structural, managerial, and regulation in the global market.

Another main classification of studies is related to developing mathematical models for tourist trip design problems. In many studies, the base model is categorized as an orienteering problem (OP) which is a challenging decision-making problem with several nodes and a specified score followed by Golden et al. (1987). The purpose of the OP is to find a path with a maximum specified length while maximizing the gathering scores (Golden et al., 1987). Academically, the tourism trip design can be modeled by a combination of knapsack and traveling salesman problems (Vansteenwegen et al., 2011). In some studies, the tourism trip design is modeled as a traveling salesman problem with profit (Rodríguez et al., 2012; Gavalas et al., 2015a). In this case, it is not required to visit all the nodes. However, the objectives were generally to ensure the amount of maximal total collected score, restrict the total cost of the journey, and calculate the difference between travel cost and collected profit. Teng et al. (2004) developed the traveling salesman problem with profit as a two-stage stochastic problem with a recourse function to maximize the total profit collected in a limited time. Erdoğan et al. (2010) presented an attractive salesman problem to find locations by maximizing profit among a set of places.

Among tourism trip design models, Vansteenwegen et al. (2012) proposed a tourism trip design as a traveling salesman problem with the possibility of selection of hotels for the tourists. To solve it, an iterative heuristic method with two initialization methods and several neighborhood procedures was developed and compared with the CPLEX software. Souffriau et al. (2013) offered a multi-constraint team OP with the possibility of many time windows. In this regard, each service time has one or more-time windows with a score. Their optimization model maximizes the total collected scores using a fixed number of trips. A simple greedy randomized neighborhood search was proposed to address it. Hu and Lim (2014) proposed an iterative three-component randomized search for solving a team OP with time windows. Gavalas et al. (2014a) reviewed a systematic method for the state-of-the-art models and algorithms with a classification of mobile tourism systems while suggesting recommendations for the offered services to the tourists. Gavalas et al. (2015b) proposed an optimization model for a personalized tourism trip design considering multiple days and several interest points. They presented a web or mobile application deriving personalized tourist trips while selecting urban attractions.

Many orienteering problem optimization models with different algorithmic solutions for the tourist industry have been developed during the last decade (Gavalas et al., 2014b). Yu et al. (2017) considered different modes of transportation and time windows for a team OP in the tourism industry. Wu et al. (2017) introduced a new optimization model considering time, cost, and tourism attraction suppositions while maximizing the utility function of the tourism experience. Freeman et al. (2018) developed an attractive musical tour problem depending on the time and places' proximity. They used a scatter search improved by local search strategies for solving their model. Liao and Zheng (2018) developed a stochastic time-dependent a-day-tour design problem and solved it with a hybrid evolutionary heuristic approach. Vincent et al. (2019) proposed a tour trip design problem considering different time attributes like budget time, scores, and time windows. Expósito et al. (2019a) developed a clustered tour design model for the tourism trip as an orienteering optimization to maximize the total score. Expósito et al. (2019b) proposed a tour trip design model for tourism planning to maximize the number of visit points of interest. The model was solved using a greedy adaptive randomized search in a fuzzy environment. Uwaisy et al. (2019) proposed a recommendation model based on the tabu search for tourists while optimizing the orienteering and scheduling decisions concerning time, distance, and cost constraints. Zheng and Liao (2019) developed a multi-objective group-based tourist trip tour design problem. In addition to the maximization of the total score, they maximized the minimum score of each member of the group. Trachanatzi et al. (2020) proposed a multi-objective mathematical model for the personalized walking tour design for passengers. Their goal was to find a balance between the minimization of the fixed cost of the suggested trip and the maximization of the total collected score. They applied the firefly algorithm with the guidance of preferences in the algorithm. Zheng et al. (2020) proposed a tourism trip design problem with the possibility of the selection of hotels for multi-day trips. They maximized the total score of the trip and solved it with a hybrid heuristic approach. Karbowska-Chilinska and Chociej (2020) developed a tourist trip design model considering the limited range of the electric vehicle and finding the swapping stations to charge the battery during the trip. Tlili and Krichen (2021) integrated the k-means and simulated annealing methods for solving a tourist trip design considering the maximization of total collected scores. Mancini et al. (2022) developed a sports trip design model to maximize the average collected score of the team using a consensus-based kernel search method.

A conclusion for the aforementioned studies, although many versions of OP for the tourist trip design have been developed (Expósito et al., 2019a; Zheng et al., 2020; Karbowska-Chilinska and Chociej, 2020; Tlili and Krichen, 2021), the medical tourism trip has been rarely contributed. As such, the utility function of the medical tourism trip is a new research term (Freeman et al., 2018). Most notably, there are rarely multi-objective OP models to evaluate the total cost and the attractivity of tourist trips simultaneously (Trachanatzi et al., 2020). To approve these general findings, Table 1 overviews the literature. There are seven criteria to build this table including the base problem which can be OP or team OP (TOP), the number of objectives which can be single or multi-objective functions, variable visiting time, attractivity of trips, utility function, application of models which can be varied from tourist to the medical trips and the solution algorithms. From this table, the main findings are:

- Most of the base problems for the tourism trip design are OP, while a few studies are TOP (Souffriau et al., 2013; Yu et al., 2017; Zheng and Liao, 2019; Mancini et al., 2022).
- Simultaneous optimization of multiple objectives like visit time, the score of trips, and so on, is considered in a few studies (Zheng and Liao, 2019; Trachanatzi et al., 2020).
- The variable visiting time in the relevant models is rarely contributed (Freeman et al., 2018; Liao and Zheng, 2018).
- Except Freeman et al. (2018), no study computationally offered the attractivity of trips.
- Although some studies proposed the utility function for the tourist trip design (Wu et al., 2017; Freeman et al., 2018; Uwaisy et al., 2019; Zheng and Liao, 2019), no study has applied it to the medical tourism trip models.
- Literature is still in favor of metaheuristic algorithms due to the high complexity of orienteering and scheduling problems. In this regard, this study proposes a metaheuristic algorithm, namely, LSNSGA-II which has not been introduced earlier in this research area.

To bridge the existing research gaps, this paper proposes a multi-objective mathematical model for the medical tourism trip design offering different packages of medical services and attractivity of tourist trips. The proposed model in addition to the minimization of the total cost maximizes the attractivity of trips. Another novelty of this study is to apply the utility function for medical services as well as tourist cities to calculate the attractiveness of tourist trips. Since the proposed model is NP-hard in large-scale data sets, the last contribution of this paper is to develop a metaheuristic algorithm as the combination of a local search algorithm and NSGA-II, abbreviated as LSNSGA-II. Based on different multi-objective assessment criteria, the proposed algorithm is not only compared with the original NSGA-II but also the epsilon constraint method.

3. Problem definition

Medical tourism refers to the travel of patients across national borders to receive low-cost and high-quality services in addition to enjoying their leisure time in the destination country. The patients may have conflicts with medical services due to the average treatment costs. In the origin county, the treatment cost is more than the treatment cost in the destination country. The rest of the conflicts for patients refer to the capacity of hospitals. In this study, for the first time, we consider hospitals' capacity in the medical tourism trip design problem where each hospital has a limited capacity during our planning horizon. We assume the capacity of hospitals is known and will be reserved for patients with different arrival times. A trip starts from the origin country of the patient to the hospital. Each patient first stays at a hospital and then visits several tourist cities in a sequence. Each patient will visit one hospital and one or more tourist cities. Patients start their tourism trips after finishing the treatment process at their assigned hospital. It is worth noting that the visiting time of the patients for their tourism trips is a decision variable that is linked to the attractive utility function. At the end of the trip, each patient should be returned to their original country. In the proposed model, the hospitals' attractivity is also calculated through the utility function depending on satisfaction with medical services.

The proposed problem offers a new contribution to the medical tourism industry with the assessment of the attractiveness of trips. The general problem aims to assign patients to hospitals and schedule their visits to determine the stay time of patients in tourist cities. The proposed model is an extension of the classic orienteering problem. This framework includes two main criteria in the objectives to minimize the total cost and maximize the total collected attractivity. In this regard, the attractivity of trips refers to the attractivity of medical services based on the utility function of hospitals and rates of patients' interest in tourist cities. The main challenge for the proposed framework is that the stay time of patients in the destination country has a direct impact on the total cost and the attractiveness of the trips. It means

Table 1
A summary of the literature review on the tourist trip design problem.

References	Base problem		Number of objectives		Variable visiting time	Attractivity of trips	Utility function	Application	Solution
	OP	TOP	Single objective	Multi-objective					
Vansteenwegen et al. (2012)	*		Maximize total score	–				Tourist tour	Exact, Heuristic
Souffriau et al. (2013)		*	Maximize total score	–				Tourist tour	Greedy randomized neighborhood search
Gavalas et al. (2015b)	*		Maximize total score	–				Tourist tour	Web application
Yu et al. (2017)		*	Maximize total score	–				Tourist tour	Two-level particle swarm optimization
Wu et al. (2017)	*		Maximize utility function	–			*	Tourist tour	Heuristic
Vincent et al. (2019)	*		Maximize total score	–				Tourist tour	Artificial bee colony
Freeman et al. (2018)	*		Maximize revenue	–	*	*	*	Concert tour	Local search, Scatter search
Liao and Zheng (2018)	*		Maximize total score	–	*			Tourist tour	Hybrid heuristic
Expósito et al. (2019a)	*		Maximize total score	–				Tourist tour	Greedy randomized adaptive search
Expósito et al. (2019b)	*		Maximize the number of visiting point	–				Tourist tour	Greedy randomized adaptive search
Uwaisy et al. (2019)	*		Maximize utility function	–			*	Tourist tour	Tabu search
Zheng and Liao (2019)		*	–	Maximize the total score of the group, Maximize the minimum interest of each member in a group			*	Tourist tour	Ant colony optimization
Trachanatzi et al. (2020)	*		–	Minimize fixed cost, Maximize total score				Walking tour	Firefly algorithm
Zheng et al. (2020)	*		Maximize total score	–				Tourist tour	Hybrid heuristic
Karbowska-Chilinska and Chociej (2020)	*		Maximize total score	–				Tourist tour	Genetic algorithm
Tlili and Krichen (2021)	*		Maximize total score	–				Tourist tour	K-means simulated annealing
Mancini et al. (2022)		*	Maximize average satisfaction	–				Sport mega-event	Consensus-based kernel search
This study	*		–	Minimize total cost, Maximize trip attraction	*	*	*	Medical tourism tour	Exact, LSNSGAII and NSGA-II

that it creates a conflict between our objective functions. An increase in the attractivity of the trips leads to an increase in the total cost. Another challenge refers to the time limit such as VISA permission for the patients. In this regard, we have a maximum time for the travel of patients in the destination country. The last challenge in this problem is how much time the visitors should stay in each tourist city calculated by utility function which depends on the tourist's interest.

In the proposed model, the planning horizon is considered to be one month. Each patient follows a specific sequence wherein they first stay at a hospital and then visit several tourist cities. Upon traveling to the destination country, a patient's journey begins with a stay at a hospital for a few days, followed by scheduled visits to tourist cities. It is important to note that all patients in our proposed problem initiate their tourist tour at the hospital, serving as their initial point of contact. Consequently, there is a significant overlapping in the treatment periods for all patients. We assume that the maximum duration of treatment for each patient is one week, commencing from the first day of their hospital visit. Therefore, each patient is assigned to visit one hospital and one or more tourist cities. Once the treatment process at the assigned hospital concludes, patients embark on their tourism trips. By incorporating these elements, the problem aims to address the complex interaction between medical treatment and tourism activities in the context of medical tourism.

While the selection of hotels has recently been applied in multi-day tourist itinerary planning, where tourists are typically assigned to hotels at the end of each day (Zheng et al., 2020), our model offers a different perspective. In our proposed approach, we take a comprehensive stance by combining the costs associated with both hotels and tourist cities on a daily basis. This entails considering not only the expenses related to accommodation but also other costs linked to visiting tourist cities. By determining the optimal duration of each patient's stay at each tourist city, our model takes into account the combined costs mentioned above, as well as resource allocations. The aim is to improve the practicality and applicability of our proposed model by integrating these factors, thereby catering to the diverse needs of medical tourists and addressing the realistic aspects of their journeys.

The proposed model includes a set of hospitals ($i \in H$), patients ($n \in N$), origin countries ($o \in O$), and tourist cities ($j \in J$) where the tuple of each patient is defined by (n, o) to say that the patient n is from the origin country o and the marge of this information is indexed by $b \in Pat$. This tuple can be considered as the ID card for these patients. In the proposed medical tourist trip, each hospital has a limited capacity (CAP_i) with a cost of medical services (CH_i). In addition, each hospital has a utility function for medical services (AH_i). The duration of these patients in a hospital is β_{bi} and the maximum staying time in the destination country is η_b. In this model, the interest of each patient in a hospital is defined ($POIH_{bi}$). In addition to the medical services, the patients are interested to visit tourist cities and spend their leisure time ($POIS_{bj}$). Each tourist site has a visit cost depending on the visiting time (RT_j). There is a utility function to define the attractivity of each tourist site (AS_{bj}). To ensure fairness, the interest of patients is limited by a threshold of interest for receiving medical services (TRH) and a threshold of interest for visiting tourist cities (TRS). To create a connection between the hospitals and tourist cities, there are transportation costs (CT_{ij}) and travel time (t_{ij}). There is also a transportation cost from the origin countries to the hospitals in the destination country (CHT_{oi}).

In conclusion, there are two different objectives in our proposed model to minimize the total cost and maximize the total attractivity, simultaneously. In the following, all the notations are defined, and the proposed multi-objective optimization model is established. Next, all the applied utility functions are presented and clarified. Finally, a linearization method is deployed to formulate the proposed model.

3.1. Notations

The proposed model has the following notations:

Sets:

N	Set of patients,
O	Set of origin countries,
H	Set of hospitals,
J	Set of tourist cities,
$Node$	Set of nodes ($O \cup H \cup J$) including origin countries, hospitals, and tourist cities,
Pat	A tuple of each patient (n, o) to identify the number and the origin country of patients,
Indices:	
i, j	Index of nodes,
o	Index of origin countries,
b	Index of tuples for each patient (n, o),
Parameters:	
C_i	Capacity of hospital i,
CHT_{oi}	Cost of transportation from origin country o to hospital i,
CT_{ij}	Cost of transportation from nodes i to j,
CH_i	Cost of medical services in hospital i,
β_{bi}	Duration for the treatment of patient b in hospital i,
t_{ij}	Travel time from node i to j,
η_b	Maximum staying time of patient b in the destination country,
RT_j	Visit cost for a tourist city j,
$POIH_{bi}$	Rate of interest for patient b to receive the medical services at hospital i,
$POIS_{bj}$	Rate of interest for patient b visit the tourist city j,
TRH	Threshold of interest to receive medical services,
TRS	Threshold of interest to visit tourist city,
$BIGM$	A large value in the context of our optimization model,
Functions:	
AH_i	Utility function of hospital i for the medical services to show attractiveness,
AS_{bj}	Utility function of tourist city j for patient b to show the attractiveness,
Decision variables:	
x_{bi}	1 if patient b is assigned to hospital i; otherwise, 0.
y_{bij}	1 if patient b is transported from nodes i to j; otherwise, 0.
z_{bj}	1 if patient b is assigned to tourist city j; otherwise, 0.
T_{bj}	Arrival time of patient b at node j,
st_{bi}	Visiting time of patient b in node i,

3.2. Mathematical model

Here, the proposed optimization model as a non-linear mixed-integer programming approach is presented. The first objective function minimizes the total cost of MTC. The components of the first objective function have been presented in Eqs. (1) to (3), including the total cost of treatment (TCT), the total cost of transportation (TTC), and the total cost of visiting cities (TCVS).

$$\text{Total cost of treatment (TCT)} = \sum_{b\in pat}\sum_{i\in H} CH_i * x_{bi} \tag{1}$$

$$\text{Total transportation cost (TTC)} = \sum_{b\in Pat}\sum_{o\in O}\sum_{i\in H} CHT_{oi} * x_{bi} + \sum_{b\in Pat}\sum_{i\in(H\cup J)}\sum_{\substack{j\in J\\ i\neq j}} CT_{ij} * y_{bij} + \sum_{b\in Pat}\sum_{i\in J}\sum_{j\in O} CT_{ij} * y_{bij} \tag{2}$$

$$\text{Total cost of visiting cities (TCVS)} = \sum_{b\in Pat}\sum_{j\in J} RT_j * st_{bj} \tag{3}$$

$$\text{Total attractivity of hospitals (TAH)} = \sum_{b\in Pat}\sum_{i\in H} AH_i * x_{bi} \tag{4}$$

$$\text{Total attractivity of visiting cities (TAVS)} = \sum_{b\in Pat}\sum_{j\in J} f(st_{bj} * z_{bj}) * POIS_{bj} \tag{5}$$

The total cost of treatment is formulated in Eq. (1) by multiplying the cost of medical services in the hospitals. Eq. (2) addresses the summation of the total cost of transportation from all the origin countries to the hospitals as well as the transportation costs for visiting hospitals and tourist cites and finally, the transportation costs for traveling from a tourist city to the origin counties. Eq. (3) computes the visit costs for the tourist cities depending on the staying time of patients at each node. Eq. (4) calculates the total attractivity of medical services based on the utility function of medical services in hospitals and the rate of patients' interest. Eq. (5) formulates the total attractivity for the tourist cities using a utility function and rate of patients' interests. The sum of Eqs. (1)–(3) is formulated as the total cost function presenting the first objective function as follows:

$$Min\ Z_1 = TCT + TTC + TCVS \tag{6}$$

The second objective maximizes the attractivity of trips consisting of two elements which are presented in Eqs. (4) to (5). It is the sum of the attractivity of hospitals and tourist cities presented in Eq. (7).

$$Max\ Z_2 = TAH + TAVS \tag{7}$$

Finally, these objectives given in Eqs. (6) and (7) are limited by the constraints (8) to (18).

$$\sum_{i\in H} x_{bi} = 1 \qquad \forall b \in Pat \tag{8}$$

$$\sum_{b \in Pat} x_{bi} \le C_i \qquad \forall i \in H \tag{9}$$

$$\sum_{j \in J} Y_{bij} = x_{bi} \qquad \forall b \in Pat,\ \forall i \in H \tag{10}$$

$$\sum_{\substack{i \in H \cup J \\ i \neq j}} y_{bij} = \sum_{\substack{i \in J \cup o(b) \\ i \neq j}} y_{bji} \qquad \forall b \in Pat, \forall j \in J \tag{11}$$

$$\sum_{\substack{i \in H \cup J \\ i \neq j}} y_{bij} = z_{bj} \qquad \forall b \in Pat,\ \forall j \in J \tag{12}$$

$$POIH_{bi} * x_{bi} \ge TRH * x_{bi} \qquad \forall b \in pat,\ \forall i \in H \tag{13}$$

$$POIS_{bj} * z_{bj} \ge TRS * z_{bj} \qquad \forall b \in Pat,\ \forall j \in J \tag{14}$$

$$T_{bi} \le BIGM * x_{bi} \qquad \forall b \in pat, \forall i \in H \tag{15}$$

$$T_{bi} + \beta_{bi} + t_{ij} \le T_{bj} + BIGM * (1 - y_{bij}) \qquad \forall b \in pat,\ \forall i \in H, \forall j \in J \tag{16}$$

$$T_{bi} + st_{bj} + t_{ij} \le T_{bj} + BIGM * (1 - y_{bij}) \qquad \forall b \in pat,\ \forall i \in J, \forall j \in J \cup O(b), i \neq j \tag{17}$$

$$T_{bj} \le \eta_b \qquad \forall b \in pat, \forall j \in O(b) \tag{18}$$

$$x_{bi},\ y_{bij},\ z_{bj} \in \{0, 1\} \qquad \forall b \in pat,\ \forall i, j \in Node \tag{19}$$

$$T_{bi},\ st_{bj} \ge 0 \qquad \forall b \in pat,\ \forall i \in Node \tag{20}$$

Eq. (8) assigns each patient to only one hospital. Eq. (9) defines the capacity limitation of hospitals to be greater than all the assigned patients. Eq. (10) represents that each patient should visit a tourist city after finishing the medical treatment. Eq. (11) represents the balance constraints for the transportation network. From another point of view, Eq. (12) ensures that each patient must be assigned to at least one tourist city. Eqs. (13) and (14) define the threshold to ensure fairness to make a balance between the interests of received medical services and visited tourist cities, respectively, for the patients. In Eq. (15), the service time of patients while receiving medical services is started if this patient is assigned to the hospital providing these services. Eqs. (16) and (17) define the arrival time and staying time of patients at the hospital and tourist cities, respectively. Eq. (18) computes the maximum travel time for each patient. Eqs. (19) to (20) define the binary and non-negative variables, respectively.

3.3. Utility functions

One significant contribution of the proposed optimization model is to have utility functions to show the attractiveness of trips for medical services and tourist cities. In the utility function for medical services, the assignment of patients to their hospitals is directly related to the relative utility function. Skellern (2017) proposed an additive utility function considering a set of hospitals and patients. Here, we propose a multiplicative medical tourism trip design considering the utility function of hospitals and rates of patients' interests. The proposed method simulates the attractivity of the health system considering the view of public health and patients' engagement simultaneously. In Eq. (21), AH_i, u_i, and $POIH_{bi}$ represent the attractivity of hospital i for patient b, the general utility function of hospital i, and the interest of patient b to receive the medical services at hospital i, respectively.

$$AH_{bi} = \frac{u_i}{\sum_{i \in I} u_i} * POIH_{bi} \qquad \forall b \in pat, \forall i \in H \tag{21}$$

The attractivity of a tourist trip is formulated non-linearly. The attractivity of the visiting tourist city is increased using a descending slope (Hasannia Kolaee and Mirzapour Al-e Hashem, 2022) as can be formulated as the following exponential distribution:

$$f(st,\ \alpha) = \begin{cases} \alpha e^{-\alpha * st} & ; st > 0 \\ 0 & ; st \le 0 \end{cases} \tag{22}$$

In Eq. (23), the cumulative distribution is applied to determine how much time the patient should spend at each tourist city to address the attractiveness of tourist trips.

$$F(st) = 1 - e^{-\alpha * st} \tag{23}$$

Having more details for the above function, we have considered $\alpha = 1$ meaning that if a node is selected, the patient will remain at least a unit of time at this tourist city.

3.4. Linearization

As stated in the complexity theory (Parker and Rardin, 1982; Chang, 2002), solving a linear formulation is much easier than its non-linear version even if it has fewer variables and constraints in comparison with the linear one (Mirzapour Al-e-Hashem et al., 2013). Also, we define a new variable v_{bj} to translate the term of $st_{bj} * z_{bj}$ for the linearization of our model. To linearize this term (Mohammadi et al., 2020), three constraints including (24) to (26) are added as follows:

$$v_{bj} \le st_{bj} \qquad \forall b \in Pat,\ \forall j \in J \tag{24}$$

$$v_{bj} \le M * z_{bj} \qquad \forall b \in Pat,\ \forall j \in J \tag{25}$$

$$v_{bj} \ge st_{bj} - M * (1 - z_{bj}) \qquad \forall b \in Pat,\ \forall j \in J \tag{26}$$

The formulation of the attractiveness of tourist cities is a nonlinear function as well. The attractiveness of tourist cities depends on the length of stay time to visit them. Looking at the relevant works in the literature (Rezaei Kallaj et al., 2022), one well-known method is the piecewise linear method that transforms nonlinear function into a linear form. In our model, we use Eq. (27) for calculating the slope of the function and converting it to a linear form as follows.

$$S_l = \frac{f(st_l) - f(st_{l-1})}{st_l - st_{l-1}} \qquad \forall l \in L \tag{27}$$

As mentioned earlier, the length of staying time is a challenging issue in the proposed model. It is linearized as Eqs. (28) and (29):

$$AS_{bj} = f(st_{bj} * z_{bj}) = f\left(v_{bj}\right) \qquad \forall b \in pat,\ \forall j \in J \tag{28}$$

$$f\left(st_l\right) = S_l * st_l + f\left(st_{l-1}\right) \qquad lst_l < st_l \le ust_l \tag{29}$$

4. Solution approach

There are many methods for solving multi-objective optimization problems. Based on the literature on multi-objective optimization algorithms (Mirzapour Al-e-Hashem et al., 2012; Cui et al., 2017), we can divide all the methods into four classifications, i.e., a *priori, a posteriori, interactive, and Pareto-based* methods. Although all the *a priori*, *a posteriori*, and *interactive* methods transform a multi-objective optimization model into a single-objective version, Pareto-based algorithms optimize multiple objectives simultaneously to find an optimal Pareto set (Jakob and Blume, 2014). The *a priori* method addresses the decision maker's preference prior to the optimization of a single-objective model. A sum-weighted method is a popular priori method to define the preferences of decision-makers using a set of weights before optimizing the model.

In posteriori methods, decision-makers are involved in the decision process after obtaining the solution sets to select the most preferable one (Mirzapour Al-e-Hashem et al., 2012). In this classification, EC is one of the famous examples where we optimize other objectives as constraints with allowable bounds. In the EC, we find the upper and lower bounds for each objective function. By updating the bounds of each objective, the EC generates Pareto solutions iteratively (Mavrotas, 2009).

An interactive method is the Tchebycheff method where decision-makers engage in the optimization process to express their preferences based on the preferred solution (Mirzapour Al-e-Hashem et al., 2012). The last classification includes intelligent multi-objective optimization algorithms like NSGA-II. These methods are able to find the Pareto

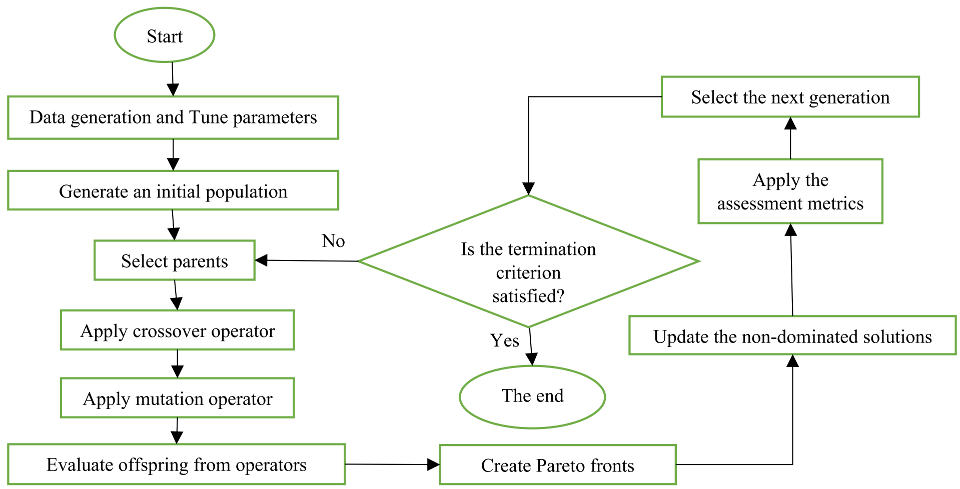


Fig. 1. Flowchart of the original NSGA-II.

solution for solving NP-hard optimization problems while keeping the characteristics of each objective function and optimizing all objective functions simultaneously. Generally, Pareto-based algorithms have higher diversity, robustness, flexibility, and convergence rate than other multi-objective optimization methods introduced earlier. This study contributes to two classifications of multi-objective optimization methods using EC as a posteriori method as well as NSGA-II and its improved version as Pareto-based algorithms.

Since the proposed multi-objective mathematical model is an NP-hard optimization problem (Yu et al., 2017), one of the contributions of this paper is to develop a multi-objective metaheuristic algorithm, namely, LSNSGA-II to compare it against the original NSGA-II and the EC method. Here, we first reformulate the proposed multi-objective model using the EC method (Section 4.1). Then, the original NSGA-II is defined for solving the proposed model (Section 4.2). Finally, the proposed LSNSGA-II algorithm is introduced (Section 4.3).

4.1. EC method

As mentioned earlier, the EC is one of the posteriori methods to generate Pareto solutions in a few iterations. The most important characteristic of the EC is that it does not require scaling the objective functions. Determining the number of grid points helps the EC to find a variety of Pareto solutions for solving multi-objective optimization models exactly (Jakob and Blume, 2014). Therefore, one of the most efficient alternatives is the EC method where we keep one objective as the main one while other ones are limited by allowable bounds in constraints. For finding the allowable bounds, the common approach is calculating the ranges of objectives separately (the best and nadir value of each objective function) in the payoff table. The ranges of each objective function are divided into n equal intervals to provide $n + 1$ grid points for solving a multi-objective optimization model (Mavrotas, 2009). This method was proposed by Haimes (1971) for the first time. We can customize it to our proposed model as follows:

$$Min\ Z_1 \tag{30}$$

s.t.

$$Z_2 \geq \varepsilon$$

$$Eqs.\ (8)\ to\ (20) \tag{31}$$

where ε is the allowable bound to limit the second objective function. To define the range of ε, we should run each objective separately and note the values of the objective function to compute the minimum and the maximum of each objective (Laumanns et al., 2006). This range is divided into a set of grid points. Here, we have considered five grid points. In this regard, the deviation of the minimum and the maximum of the second objective function is divided into five, and accordingly, different values are considered as the allowable bounds.

4.2. NSGA-II

Nowadays, different types of GAs are widely used for solving NP-hard optimization problems like vehicle routing problems, and orienteering problems (Karbowska-Chilinska and Chociej, 2020; Moayedi et al., 2023). This algorithm is considered an evolutionary algorithm and demonstrated successful results by many scholars (Cho et al., 2023). NSGA-II is a multi-objective metaheuristic as an extension to the classic GA, proposed for the first time by Deb et al. (2002). The full algorithmic framework for NSGA-II can be addressed as shown in Fig. 1.

As shown in the flowchart of NSGA-II reported in Fig. 1, after generating the data and tuning the parameters of NSGA-II including the maximum number of iterations (*MaxIt*), the number of initial population (*nPop*), the percentage of crossover (*Pc*), and mutation operators (*Pm*), a random set of the initial population, is generated. Then, the parents are selected to do the crossover and mutation operators. After evaluating the offspring from these operators, the Pareto fronts are created. Subsequently, we select the non-dominated solutions from the Pareto fronts. These solutions are evaluated by popular assessment metrics for solving multi-objective optimization models. After the selection of the next generation, the termination criterion is checked to see if the maximum number of iterations is met. Otherwise, the step of parents' selection is continued.

4.2.1. Solution presentation

Implementing a metaheuristic algorithm is highly linked with the selection of data structure and how to encode a solution (Fathollahi-Fard et al., 2021). Since each metaheuristic may include different neighborhood procedures and evaluations, an efficient design of a solution in metaheuristics, has a high impact on its performance to find an optimal solution in the search space (Seydanlou et al., 2022). Here, the search space includes both feasible and infeasible solutions. The main benefits of infeasible solutions are to escape from the local optimum and to explore new solutions. For the GAs, the solution is defined as a chromosome where its presentation should meet the constraints of our optimization model while ensuring the feasibility of solutions by penalty functions.

An example of a solution presentation in the applied metaheuristic is given in Fig. 2 where each tuple of a patient (n, o) should be assigned to one hospital $(i \in H)$ and the tourist cities are a sub-set of J where the length of tourist places, is variable for each patient. In this regard, Fig. 2

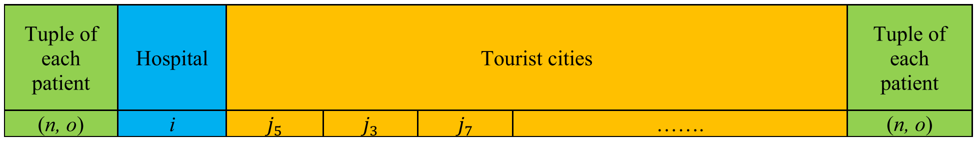


Fig. 2. Solution representation of each patient's trip.

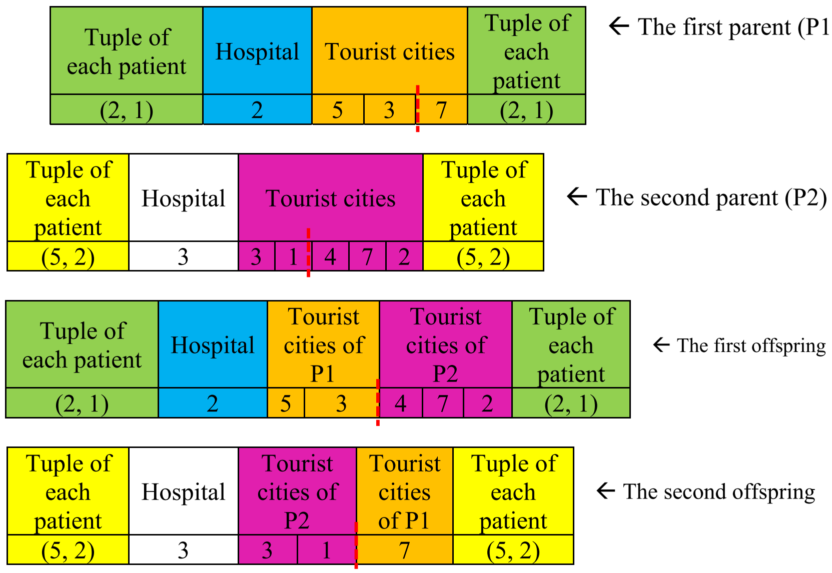


Fig. 3. Proposed crossover operator.

shows each patient's trip where the start point is (n, o) after visiting the hospital i, a set of random tourist cities including $\{j_5,\ j_3,\ j_7,\ \ldots\} \in J$ are scheduled. The endpoint of the patients' trip is their origin country.

In solution representation, all the constraint sets are satisfied except the constraint sets (9), (13), (14), and (18). It goes without saying that to ensure the feasibility of the above solution, a big penalty is imposed on both objective functions if the sequence of visits of each patient does not meet the capacity limitation (the constraint set (9)), fairness constraints (the constraint sets (13) and (14)) and the maximum staying time (the constraint set (18)). In this regard, these constraints are relaxed from the original model and our NSGA-II tries to meet and satisfy all constraint sets as much as possible.

4.2.2. Search operators

After the generation of the initial population where each chromosome is generated randomly according to Fig. 2, first, we select two random chromosomes as the parents. Then, these chromosomes are merged together using a single-point crossover focusing on the visited tourist places of each patient. The result of the crossover operator is two new chromosomes as the offspring as shown in Fig. 3. After the crossover operator, once again, one chromosome is selected randomly as the parent and subsequently, the mutation operator is applied as can be seen in Fig. 4. Accordingly, one new chromosome may be created as the offspring.

As shown in Fig. 3, assume that two random chromosomes are selected and the first parent is the second patient from the first origin country $\{(2,\ 1)\}$ assigned to the second hospital $\{2\}$ and visited the tourist cities of $\{5,\ 3,\ 7\}$. The second parent is the fifth patient from the second origin country $\{(5,\ 2)\}$ assigned to the third hospital $\{3\}$ and visited the tourist cities of $\{3,\ 1,\ 4,\ 7,\ 2\}$. The minimum length of visited tourist cities is three in this example. Accordingly, a random number from [1, 3], is selected randomly (here, the second position of visited tourist cities, is considered). Based on this cross, the first part of the first parent is merged with the second part of the second parent. As such, the second part of the first parent is merged with the first part of the second parent. Then, the repeated tourist cities for each offspring are removed from it. As a result, the first new offspring includes the patient {(2, 1)} assigned to the hospital {2} visiting the tourist cities of {5, 3, 4, 7, 2}. Finally, the patient {(5, 2)} assigned to the hospital {3} visiting the tourist cities of {3, 1, 7}.

As shown in Fig. 4, the mutation operator first selects a chromosome randomly and calls it the parent. To define a new offspring, a new hospital is randomly assigned to this patient. Then, two tourist cities are randomly selected from the sequence of visits. The mutation operator exchanges their position of visits. If the first parent in the last example, is considered in the mutation operator, a new offspring is generated as follows: the patient is assigned to the hospital $\{4\}$ instead of $\{2\}$. As such, the sequence of the visits is changed from $\{5,\ 3,\ 7\}$ to $\{7,\ 3,\ 5\}$.

4.3. Proposed LSNSGA-II

Generally, local search methods are widely used in different population-based metaheuristic algorithms to improve the exploitive behavior of these algorithms (Santos et al., 2022). Among the population-based metaheuristics, genetic algorithms are highly studied and improved by different local search methods in diverse fields of optimization problems. For example, Abadeh et al. (2007) studied a parallel genetic based on a local search algorithm for the optimization of fuzzy rules to detect intrusive functions in computer networks. Akpınar and Bayhan (2011) proposed a hybrid genetic algorithm with different heuristics for solving an assembly line balancing problem. Elsayed et al. (2014) proposed a new genetic algorithm with new crossover and mutation operators for solving a set of constrained optimization benchmark problems. Ganjefar and Tofighi (2017) improved a genetic algorithm using a local search-based gradient decent for training a qubit neural network. More recently, Abreu et al. (2021) developed a genetic algorithm with an iterated greedy local search procedure for solving an open shop scheduling problem with the possibility of routing capacitated vehicles. There are also many other examples of the development of genetic algorithms with local search strategies. In this

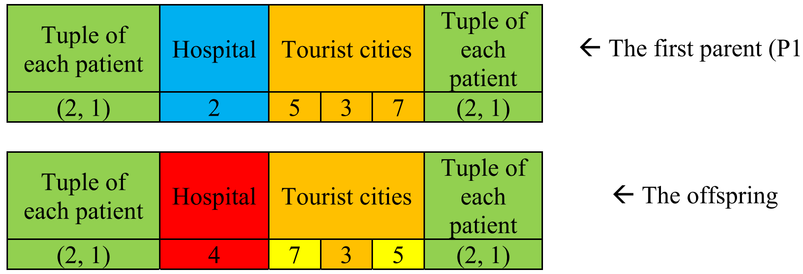


Fig. 4. Proposed mutation operator.

Table 2
A brief review of local search-based genetic algorithms.

Paper	Algorithm name	Single objective	Multi-objective	New added mechanisms	Application
Abadeh et al. (2007)	A parallel genetic based on a local search algorithm	*	–	Fuzzy rules	Computer networks
García-Martínez and Lozano (2010)	A binary-coded local genetic algorithm	*	–	Random multi-start local search, iterated local search, and variable neighborhood search	Constrained optimization benchmark problems
Kabir et al. (2011)	A hybrid GA	*	–	Correlation information of features using a local search operator	Feature selection
Akpınar and Bayhan (2011)	A hybrid GA	*	–	Heuristic algorithms	Assembly line balancing problem
Elsayed et al. (2014)	An improved GA	*	–	New mutation and crossover operators	Constrained optimization benchmark problems
Asadzadeh (2015)	A local search GA	*	–	Agent-based local search strategy	Job shop scheduling problem
Zhang and Chiong (2016)	A multi- objective genetic algorithm with enhanced local search	–	*	Two problem-specific local improvement strategies	Energy-efficient Job shop scheduling problem
Ganjefar and Tofighi (2017)	An improved GA	*	–	A local search-based gradient decent	Training a qubit neural network
Abdelsalam and El-Shorbagy (2018)	Binary real coded genetic algorithm	*	–	A local search with a decision rule	Wind turbines siting optimization problem
Long et al. (2019)	A Pareto-based GA based on decomposition			A local search procedure based on decomposition	Prize-collecting vehicle routing problem
Viana et al. (2020)	A modified GA	*	–	Local search strategies and multi-crossover operators	Job shop scheduling problem
D'Angelo and Palmieri (2021)	A modified GA	*	–	A gradient-descent local search technique	Constrained optimization benchmark problems
Abreu et al. (2021)	An improved GA	*	–	An iterated greedy local search procedure	An open shop scheduling problem
Rezaeipanah et al. (2021)	Improved Parallel GA	*	–	A local search with a decision rule	University course timetabling problem
This study	Local search-based NSGA-II	–	*	Multi-neighbor procedure with decision rules	Medical tourism trip design problem

regard, we have provided Table 2 for analyzing different local search-based genetic algorithms based on their mechanisms and applications for single-objective or multi-objective optimization problems. From this table, we can conclude the following findings:

- Most local search-based genetic algorithms are applied to single-objective optimization problems.
- The majority of local search-based procedures used in the literature have focused on problem-specific operators to improve the initial solutions.
- Local search-based strategies with decision rules are more studied by researchers.
- The majority of applications are related to constrained benchmark optimization problems and production scheduling problems.

To the best of our knowledge, no research contributes a local search-based genetic algorithm applied to tourist trip design problems. Most importantly, there are a few multi-objective algorithms that benefit from GA and local search strategies simultaneously. Although genetic algorithms generally are benefited from the classic mutation operators, they are not usually efficient to do the exploitation phase when the problem complexity increases (Lee, 2018). In this regard, local search-based genetic methods are able to do the exploitation phase better than the classic genetic algorithm. The high performance of similar local search-based genetic methods encourages us to involve it in our proposed multi-objective medical tourist trip design model. Hence, an improvement to the NSGA-II is done by a local search algorithm as a sub-loop.

In the proposed algorithm, at each iteration, after applying the crossover and mutation operators, the best solution ever found at this iteration is sent to a sub-loop where a local search algorithm tries to improve it while finding more non-dominated solutions. In the local search procedure, we have used four different local search techniques. In addition to the mutation of the proposed NSGA-II (Fig. 4), we have defined three local search operators including Swap, Reversion, and Insertion operators (Fathollahi-Fard et al., 2021) which are defined in Fig. 5. These local search operators only change the sequence of

Swap:

3	5	6	4	7
3	4	6	5	7

Reversion:

3	5	6	4	7
3	5	7	4	6

Insertion:

3	5	6	4	7
3	4	5	6	7

Fig. 5. Different neighbor solutions using local search operators.

Data generation for a test problem;
Tune the parameters of LSNSGA-II (*MaxIt, nPop, Pc, Pm, Subit, T0* and ∝);
Initialize a set of initial solutions with the size of 1**nPop*;
Create Pareto fronts;
it=1;
while $\boldsymbol{it \leq MaxIt}$
  Select parents randomly for the crossover (*Pc*) and mutation (*Pm*) operators;
  Apply crossover operator;
  Apply mutation operator;
  Evaluate offspring from operators;
  sub=0;
  while $sub \leq Subit$
   Do mutation operator and local search operators.
   Select Z_m^{new};
   Calculate the deviation of objective functions (ΔZ_m)
  if $\Delta Z_1 \leq 0$ *andand* $\Delta Z_2 \geq 0$
    Update the best solution (Z_m^{best});
    $Z_m^{best} = Z_m^{new}$;
  else if $\Delta Z_1 \geq 0$ *andand* $\Delta Z_2 \geq 0$ || $\Delta Z_1 \leq 0$ *andand* $\Delta Z_2 \leq 0$
    Put this solution in the Pareto set.
  else $\Delta Z_1 \geq 0$ *andand* $\Delta Z_2 \leq 0$
    $P_1 = \exp\left(\frac{-\Delta Z_1}{T0}\right)$, $P_2 = \exp\left(\frac{-\Delta Z_2}{T0}\right)$, *h=rand*
    if $h<P_1$ *and* $h<P_2$
    Use this Z_m^{new} as an input for the next sub-iteration of the mutation operator.
    endif
  endif
  sub=sub+1;
  endwhile
  Update temperature (T0=∝*T0).
  Do non-dominate sorting for Pareto fronts.
  Apply the assessment metrics;
  it=it+1;
endwhile

Fig. 6. Pseudo-code for the proposed LSNSGA-II.

tourist places while keeping the position of the hospital for the patients. It means that the assigned hospital is not changed and different alternatives to visit the tourist cities are considered. Assume that the patient is assigned to the hospital 2. From Fig. 5, the initial sequence of tourist cities is {3, 5, 6, 4, 7}. After using the Swap operator, we exchange the position of tourist places 4 and 5. In this regard, a new neighbor sequence of visits is {3, 4, 6, 5, 7}. After using the Reversion operator, the sequence of visits from tourist cities 6 to 7 is reversed. Hence, a new sequence of visits is {3, 5, 7, 4, 6}. Using the Insertion operator, we insert tourist city 4 earlier than tourist city 5. Accordingly, a new neighbor solution is created as {3, 4, 5, 6, 7}. Using these operators, the proposed local search creates different neighbor solutions simultaneously.

The proposed LSNSGA-II also benefited from decision rules to accept or reject the created neighbor solutions. Assume that Z_m^{best} represents the best solution ever found at this iteration where m is the index of objective functions. After doing a mutation operator on this solution, we have the solution of Z_m^{new}. To decide for accepting or rejecting this new solution, first, we need to compute the following formula:

$$\Delta Z_m = Z_m^{new} - Z_m^{best}, \qquad \forall m \in M \tag{32}$$

Since the proposed optimization model has two objective functions, there are three cases for the assessment of a new solution as explained in the pseudo-code shown in Fig. 6. Generally, the proposed LSNSGA-II has more parameters in comparison with the original NSGA-II. We have *Subit* as the maximum number of sub-iterations. An initial temperature (*T0*) and its reduction rate (∝) which is between zero and one are other parameters of LSNSGA-II algorithm. At each sub-iteration, in this local search, the algorithm tries to improve the best solution ever found while finding more non-dominated solutions.

This proposed algorithm extends the capabilities of the original algorithm and provides improved performance for solving the specific problem of medical tourist trip design as follows:

Firstly, the LSNSGA-II algorithm incorporates local search techniques within a sub-loop, allowing for an enhanced exploitation phase. This integration of local search methods enables a more thorough

Table 3
Size of test problems.

Complexity levels	Number of test problems	N	O	H	J	Number of variables	Number of constraints
Small	T1	6	2	2	4	492	308
	T2	10	4	3	5	1 690	1 313
	T3	14	4	4	6	3 164	2 622
	T4	20	5	4	7	5 800	5 884
	T5	25	6	5	8	10 025	11 230
	T6	40	8	5	9	21 160	28 845
	T7	50	9	8	12	45 100	71 508
	T8	60	10	12	15	86 880	148 812
Large	T9	80	12	15	20	184 880	413 055
	T10	100	14	20	30	424 000	1 328 520
	T11	200	15	30	40	1 484 000	5 063 230
	T12	300	16	40	40	2 829 600	8 201 140

examination of the solution space and facilitates the identification of high-quality solutions. By exploring alternative sequences of tourist places while maintaining the position of the hospital, the algorithm can generate diverse and refined solutions.

Secondly, the LSNSGA-II algorithm incorporates decision rules to guide the acceptance or rejection of the generated neighbor solutions. This adaptive mechanism enhances the exploitation capabilities of the algorithm by considering the deviation of objective functions. By making informed decisions during the local search process, the algorithm is able to focus on promising solutions and improve their quality.

These modifications in the LSNSGA-II algorithm go beyond a simple adjustment of parameters or operators. They introduce novel mechanisms that are specifically tailored to address the complexities and challenges of the medical tourist trip design problem. While the LSNSGA-II algorithm is inspired by NSGA-II, it represents a significant extension of the original algorithm in terms of both methodology and performance.

5. Computational results

Here, an extensive analysis is done on the proposed optimization model for the medical tourism trip design problem as well as our solution methods including LSNSGA-II, NSGA-II, and EC methods. In this regard, we first generate the test problems to analyze the complexity of our optimization model. As such, an illustrative example is defined to show the applicability of this research. Then, the tuning of LSNSGA-II and NSGA-II is performed to ensure that the algorithm works well with the definition of multi-objective assessment metrics. Then, the EC is applied to validate our multi-objective metaheuristic algorithms. Subsequently, the illustrative example is solved, and some sensitivity analyses are done on key parameters to show their impacts on the objectives. Finally, a comprehensive discussion is provided to extract the findings and managerial insights from the results. It should be noted that the EC was implemented in IBM ILOG CPLEX version 12.8, LSNSGA-II, and NSGA-II were coded in MATLAB 2013a where the hardware of the system was Intel®, Core ™ i7-4500U CPU at 2.39 GHz, and 8.00 GB RAM.

5.1. Data generation

To study the complexity of our multi-objective optimization model, 12 test problems from small to large sizes have been defined. Table 3 is the size of the test problems where there are eight small tests numbered T1 to T8 while there are four large tests numbered T9 to T12. As seen in Table 3, the number of constraints and variables from test instances T8 to T9 has increased significantly. This fact shows that T9 is a large-scale test and T8 is a small-scale one. Table 4 shows this range using random functions from MATLAB software. The logic for the generation of test problems is benchmarked from the literature review (Zheng et al., 2020). Some of the parameters did not have a benchmark, therefore, we simulated based on the information from a medical travel agency.

Table 4
Range of parameters.

Parameters	Ranges of random functions
C_i	$randi\left(\left[round\left(\frac{N}{H}\right), 3 * round\left(\frac{N}{H}\right)\right], H, 1\right)$
(x_i, y_i) ; (x_j, y_j)	$randi([100, 300])$
(x_o, y_o)	$randi([0, 1000])$
CHT_{oi}	$\sqrt[2]{(x_o - x_i)^2 + (y_o - y_i)^2}$
CT_{ij}	$\sqrt[2]{(x_j - x_i)^2 + (y_j - y_i)^2}$
CH_i	$randi([10\,000, 100\,000], H, 1)$
β_{bi}	$randi([15, 25], N, H)$
t_{ij}	1
η_b	$randi([30, 40], 1, N)$
RT_j	200
$POIH_{bi}$	$randi([1, 10], N, H)$
$POIS_{bj}$	$randi([1, 10], N, J)$
TRH	2
TRS	2

randi is a function to generate random integer numbers between a lower bound and an upper bound.
round is a function to transform continuous numbers into integer ones.

To show the applicability of the proposed multi-objective framework, a small example from the Middle East region is applied. The Middle East includes different countries, and our illustrative example covers Iran, Qatar, Armenia, Turkmenistan, Pakistan, Azerbaijan, and Iraq. These countries have different historical and cultural tourist cities and patients may need to travel to these countries to receive high-quality and low-cost medical services. Among these countries, Iran has high-quality and cost-effective medical services while Qatar has the most expensive ones.[2] These facts attract patients in this region not only to receive a suitable medical service but also to travel to interesting tourist cities. For example, Shiraz in Iran is a very interesting city with many tourist places like Vakil Bazaar, Eram Garden, Nasir ol-Mulk Mosque, and Persepolis while attracting many tourists yearly.[3] Fig. 7 shows the geographical map to explain our illustrative example.

As can be seen in Fig. 7, our illustrative example covers the tourist cities of Mashhad, Isfahan, Shiraz, Tehran, and Tabriz. The transportation costs for traveling from the capital city of the aforementioned countries to our tourist cities are reported in Table 5. The transportation cost is based on the price of tickets by airplane from Qatar Airways from the period June 2022.[4] Other parameters are simulated in the same way as given in Table 4.

2 https://www.aetnainternational.com/en/about-us/explore/living-abroad/culture-lifestyle/health-care-quality-in-the-middle-east.html.
3 https://theculturetrip.com/middle-east/iran/articles/the-top-10-things-to-do-and-see-in-shiraz/.
4 https://www.qatarairways.com/en-ca/homepage.html.

Fig. 7. Geographical map to represent the hospitals and tourists places.

Table 5
Transportation costs of our illustrative example for traveling by airplanes.

Tourist places	Qatar	Pakistan	Azerbaijan	Armenia	Turkmenistan	Iraq
Mashhad	1690$	1100$	1185$	1167$	2450$	1285$
Isfahan	1470$	857$	780$	1290$	2870$	1062$
Shiraz	1470$	1163$	814$	1177$	2389$	1036$
Tehran	1660$	1052$	1255$	736$	2670$	1887$
Tabriz	2830$	1295$	1087$	1780$	3450$	1239$

5.2. Assessment of multi-objective metrics and tuning of our metaheuristics

To evaluate the robustness of single objective algorithms, certain metrics like average solution and standard deviation are utilized. However, when it comes to multi-objective algorithms, the metrics of the single objective cannot be employed since there are multiple objective functions involved. Therefore, for the assessment of multi-objective solutions, it is essential to define multi-objective metrics to evaluate the robustness of algorithms with more than one objective function. These metrics apply all objective functions to consider the interaction of all objective functions in calculations. Also, we apply the analysis of variance in the confidence level of 95% to analyze the robustness of the proposed algorithm by the introduced metrics in this study. This study uses the following multi-objective metrics (Yan et al., 2007; Seydanlou et al., 2022):

- Numbers of Pareto solutions (NPS): This metric defines the number of non-dominated solutions found by a multi-objective optimization algorithm where a higher value of this metric is preferable.
- Mean ideal distance (MID): This metric computes the distance of non-dominated solutions from positive and negative ideal solutions. If Z_m^s shows the value of solution s for the objective function m where M is the number of objective functions and Z_m^{max} and Z_m^{min} are respectively the maximum and minimum value of mth objective function and Z_m^{best} is one of Z_m^{min} or Z_m^{max} based on the nature of objective functions, the MID is defined as below:

$$MID = \frac{\sum_{s=1}^{NPS}\left(\sqrt{\sum_{m=1}^{M}\left(\frac{\left|Z_m^s - Z_m^{best}\right|}{(Z_m^{max} - Z_m^{min})}\right)^2}\right)}{NPS} \tag{33}$$

where a lower value of MID brings better exploitation of solutions around ideal ones and it is preferable.
- Spread of non-dominated solutions (SNS): This metric focuses on the diversity of non-dominated solutions regarding the MID metric. The SNS can be formulated as follows:

$$SNS = \sqrt{\frac{\sum_{s=1}^{NPS}\left(MID - \sum_{m=1}^{M} Z_m^s\right)^2}{NPS - 1}} \tag{34}$$

Contrary to the MID metric, a higher value of SNS brings a better diversity of non-dominated solutions for a multi-objective optimization algorithm.
- Maximum spread (MS): This metric analyses the domain of positive and negative ideal solutions where the following formula shows its computation:

$$MS = \sqrt{\sum_{m=1}^{M} (Z_m^{max} - Z_m^{min})^2} \tag{35}$$

where a higher value of MS is preferable for a multi-objective optimization algorithm.
- Response metric: This metric can be used for the tuning of a multi-objective metaheuristic algorithm where a combination of MID and MS is used as the most important factors. The following formula is employed to define the response metric (Fathollahi-Fard et al., 2018):

$$Response = \frac{MID}{MS} \tag{36}$$

where a lower value of this metric is preferable similar to the MID metric.

- CPU time: The same criterion between single objective models and multi-objective ones, is the CPU time to analyze the computational time where a lower value is preferable as the metaheuristics should provide an optimal solution quicker than an exact solver.

Before evaluating our multi-objective algorithms by the assessment of multi-objective metrics, we need to do the parameter setting of metaheuristic algorithms. Parameter setting involves finding suitable or optimal configurations within the parameter space. The parameter tuning can be broadly classified into two cases. The first case is parameter tuning, which is also referred to as offline tuning. This involves identifying good parameter values prior to using the algorithm to solve problems. The optimal parameter setting determined during the tuning process is used to solve problems, and these parameter values remain unchanged throughout the run. The second case is parameter control, also known as online tuning. In this case, the values of controlled parameters are modified directly according to certain strategies during the execution of the algorithm. To achieve this, appropriate control strategies for relevant parameters need to be established, which could be deterministic, adaptive, or self-adaptive, and initial values for controlled parameters need to be set (Skakov and Malysh, 2018; Huang et al., 2019).

As mentioned in Section 4.2, the NSGA-II has four input parameters including *MaxIt, nPop, Pc*, and *Pm*. As, such, LSNSGA-II has seven parameters including *MaxIt, nPop, Pc, Pm, Subit, T0* and ∝. We apply offline parameter tuning for all the parameters in the NSGA-II algorithm. Also, for our proposed LSNSGA-II algorithm, we apply offline parameter tuning for all input parameters, although parameter *T0* is tuned prior to using the algorithm and it is modified and updated according to the deterministic equation.

If we consider three candidate values for each parameter based on the literature on the NSGA-II, there are a total of $3^4 = 81$ experiments for each test problem to find the optimal value of parameters. As such, there are $3^7 = 2187$ experiments for the LSNSGA-II. Running all these experiments is too time-consuming and therefore, we need to reduce the number of experiments to save time. This study uses the Taguchi experimental design method to suggest a set of predefined orthogonal arrays including a set of selected experiments from the total existing experiments (Azadeh et al., 2016). For example, instead of 81 experiments for NSGAI-II, the Taguchi method recommends us L_9 orthogonal array including nine selected experiments among 81 ones. As such, it suggests L_{27} where there are 27 selected experiments among 2187 ones for the LSNSGA-II.

For doing the analyses of tuning for NSGA-II and LSNSGA-II, we first provide three candidate values for each parameter. These candidate values for each parameter are reported in Table 6. After doing the analyses using L_9 and L_{27} for NSGA-II and LSNSGA-II, we have computed the average response metric computed in Eq. (34) for each test problem. Finally, the tuned values which have the minimum average response metric are reported in the last column of Table 6. It should be noted that due to the space limitation of the paper, the results of orthogonal arrays L_9 and L_{27} are not reported here.

5.3. Comparison of algorithms

In this sub-section, we have solved all the test problems and evaluated the results of LSNSGA-II, NSGA-II, and EC methods. It should be noted that the EC method was not able to solve the large tests (T9 to T12) in a reasonable CPU time. In this regard, we have not provided the results of the EC method for these tests. First of all, the positive ideal solution (PIS) and negative ideal solution (NIS) of the EC method are analyzed in comparison with the best solution among all non-dominated solutions found by LSNSGA-II and NSGA-II. As we mentioned previously, the EC method has not solved the large-scale

Table 6
Results of tuning of algorithms.

Algorithm	Parameters	Candidate values			Tuned values
		Level 1	Level 2	Level 3	
NSGA-II	*MaxIt*	50	100	200	100
	nPop	150	300	400	300
	Pc	0.5	0.6	0.7	0.7
	Pm	0.05	0.15	0.25	0.15
LSNSGA-II	*MaxIt*	50	100	200	100
	nPop	150	300	400	300
	Pc	0.5	0.6	0.7	0.7
	Pm	0.05	0.15	0.25	0.15
	Subit	10	20	30	10
	T0	500	1000	1500	1000
	∝	0.8	0.9	0.99	0.99

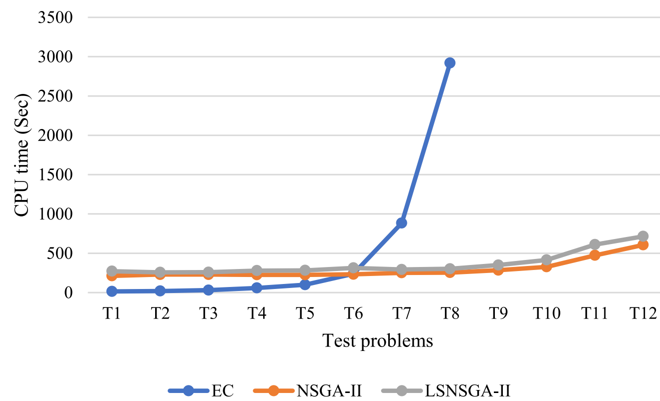


Fig. 8. The CPU time of NSGA-II, LSNSGA-II, and EC methods.

test problems T9 to T12 in a reasonable time; hence, we could not report the value of PIS and NIS for these problems and put them empty. Therefore, we could not calculate the optimality gap of these test problems because the value of PIS and NIS was not in hand. Accordingly, the optimality gap is calculated and reported for other test problems (T1 to T8) of NSGA-II and LSNSGA-II in Table 7.

The best solution is computed by the concept of crowding distance among all non-dominated solutions (Deb et al., 2002). Then, the comparison of EC, LSNSGA-II and NSGA-II based on multi-objective metrics including NPS, MID, SNS, MS, and CPU time, is performed in Table 8. Fig. 8 shows the comparison of NSGA-II, LSNSGA-II and EC methods based on the CPU time criterion. Fig. 9 depicts the non-dominated solutions of these algorithms for two test problems including T4 and T6. Finally, interval plots based on the results of Table 8 are drawn in Fig. 10 to assess the quality of non-dominated solutions obtained by these algorithms, statistically.

What can be concluded from Table 7 is that the mentioned solutions obtained by both NSGA-II and LSNGA-II are reliable as they are close to the PIS found by the EC method. The optimality gap is also computed as the relative deviation of NSGA-II's and LSNSGA-II's solutions from the PIS of EC method for each objective function. Overall, the average optimality gap of the first objective function is 0.2157 and 0.1386, respectively for NSGA-II and LSNSGA-II, while the optimality gap for the second objective is less than the first one with a value of 0.1275 and 0.1107 respectively for NSGA-II and LSNSGA-II. In terms of comparing our proposed method, LSNSGA-II, with the original NSGA-II, the average optimality gap for both the first and second objectives in LSNSGA-II is smaller than that in NSGA-II. This suggests that LSNSGA-II outperforms NSGA-II in terms of the optimality gap. However, while the average optimality gap for the second objective is lower compared to the first objective, the results indicate that LSNSGA-II is particularly effective in optimizing the first objective, which is the primary objective of the problem at hand. There is a significant

Table 7
Comparison of NSGA-II and LSNAG-II based on the PIS and NIS obtained by EC method.

Test problems	The first objective function (Z_1)						The second objective function (Z_2)					
	EC method		NSGA-II		LSNSGA-II		EC method		NSGA-II		LSNSGA-II	
	PIS	NIS	Best value	Optimality gap	Best value	Optimality gap	PIS	NIS	Best value	Optimality gap	Best value	Optimality gap
T1	232 986.67	294 117.52	240 906.6	0.034	245 568	0.054	164.048	20.286	152.158	0.072	151.9084	0.074
T2	411 865.653	470 135.72	414 030.4	0.005	445 638.6	0.082	303.915	11.333	259.695	0.146	274.7392	0.096
T3	491 556.486	1 281 984.431	683 954.7	0.391	617 394.9	0.256	493.745	2.958	427.858	0.133	430.5456	0.128
T4	857 526.128	1 864 714.792	951 588.7	0.110	929 558.3	0.084	798.534	10.2	830.775	0.040	730.6586	0.085
T5	1 389 457.472	2 338 534.806	1 820 127	0.310	1 727 096	0.243	1117.096	5.474	1044.66	0.065	1014.323	0.092
T6	1 730 118.066	2 983 490.248	1 822 327	0.053	1 852 956	0.071	1950.395	107.47	1727.89	0.114	1839.222	0.057
T7	2 099 250.251	4 582 744.256	2 877 900	0.371	2 445 627	0.165	3362.336	5.718	2657.01	0.210	2750.391	0.182
T8	2 587 064.591	6 027 606.783	3 755 967	0.452	2 985 473	0.154	5055.254	5.437	3840.88	0.240	4185.75	0.172
T9	–	–	4 991 093	–	4 841 360	–	–	–	5668.82	–	5782.196	–
T10	–	–	6 927 330	–	6 719 510	–	–	–	10 150.3	–	10 353.31	–
T11	–	–	10 313 900	–	10 004 483	–	–	–	23 925.5	–	24 404.01	–
T12	–	–	19 570 067	–	18 982 965	–	–	–	35 171.5	–	35 874.93	–
Average	–	–	–	0.21575	–	0.138 625	–	–	–	0.1275	–	0.11075
STD	–	–	–	0.18308	–	0.07886	–	–	–	0.07036	–	0.04566

Table 8
Results of assessment metrics for each method (the CPU time is based on seconds and the best values are shown in bold).

Test problems	EC					NSGA-II					LSNSGA-II				
	NPS	CPU time	SNS	MS	MID	NPS	CPU time	SNS	MS	MID	NPS	CPU time	SNS	MS	MID
T1	6	**14.63**	**262796.57**	61 131.02	4.211 653	**299**	212.28	80 264.97	265 527.4	**3.6589**	245	271.7184	87 488.82	**265763.5**	3.6764
T2	6	**19.52**	**467 958.62**	58 270.8	4.175 764	**246.6**	229.3754	46 633.93	**435 032.5**	9.65938	220	256.9004	52 230	434 144.4	**2.9607**
T3	6	**30.81**	**610 858.57**	**790 428.1**	**4.022844**	59.66667	229.2989	374 958	748 267.6	4.272867	**189**	259.1078	423 702.5	749 010.2	4.6626
T4	6	**58.43**	**1 045 013.25**	1 007 189	4.036942	113	225.3869	913 449.5	**1 154 568**	**2.460967**	**154**	279.4798	1 132 677	1 154 500	4.79653
T5	6	**99.58**	**1 761 062.63**	949 078	4.016252	76.66667	225.6884	1 380 422	**2 251 004**	**2.367467**	**86**	282.1105	1 725 528	2 251 002	4.16032
T6	6	239	**2 219 484.934**	1 253 374	4.021676	82.33333	**232.3809**	1 354 870	2 226 939	2.6867	**92**	313.7142	1 829 075	**2 227 520**	**2.18155**
T7	6	883.8	**2 347 399.74**	2 483 496	4.6297	70.66667	**250.891**	1 974 822	**3 366 120**	**2.6598**	**102**	293.5425	2 310 542	3 365 931.2	4.32692
T8	6	2919	**3 814 223.853**	3 440 546	4.019768	91	**254.0465**	2 164 349	**4 378 519**	**2.876233**	**104.5**	302.3153	2 575 575	4 368 254	3.90335
T9	–	–	–	–	–	90.33333	**284.5935**	2 308 044	5 683 535	3.260033	**103.72**	350.05	**2 838 894**	**5 983 768**	**2.30047**
T10	–	–	–	–	–	105.3333	**326.9899**	2 426 261	**7 686 135**	3.836233	**110.83**	415.2772	**3 081 351**	7 285 673.5	**2.08235**
T11	–	–	–	–	–	118.6667	**472.8523**	3 420 759	**11 596 179**	4.0172	**125.43**	609.9795	**4 412 779**	11 589 965	**2.16375**
T12	–	–	–	–	–	**152.6667**	**605.6318**	5 914 647	21 431 307	4.474367	136.82	714.6455	**6 979 283**	**21 720 624**	**4.20362**
Best	0	5	8	1	1	3	7	0	7	5	9	0	4	4	6

difference in the optimality gap between LSNSGA-II and NSGA-II for the first objective. On the other hand, although the average optimality gap for the second objective is lower in LSNSGA-II than in NSGA-II, both approaches yield similar performance, suggesting that there may not be a significant advantage in using our proposed approach over NSGA-II for this objective.

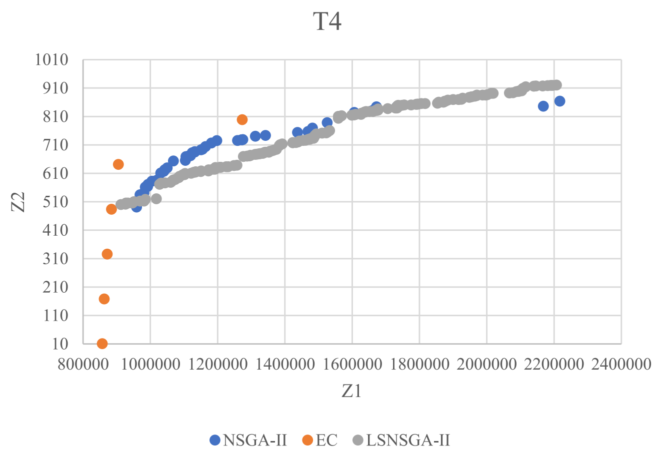
According to the last row of Table 7, the standard deviation of the optimality gap of LSNSGA-II for the first objective function and second objective function are 0.0788, and 0.04566, respectively which are lower than the standard deviation of the optimality gap for the first and second objective function of NSGA- II. Hence, these results also confirm and reflect the superiority of our LSNSGA-II with a lower optimality gap and standard deviation than the original NSGA-II to find a better solution that shows the higher accuracy of the LSNSGA-II algorithm.

As reported in Table 8, we have compared the algorithms with each other based on five important assessment metrics. As mentioned earlier, the EC method was only applied to the small test problems while the NSGA-II and LSNSGA-II were able to solve all the test problems. Generally, the EC was successful in only two criteria including CPU time and SNS metrics. In the CPU time, after T5, the size of the problem increases significantly, and the CPU time of NSGA-II was better than the EC method for T6 to T8. It should be noted that the CPU time of LSNSGA-II was also greater than NSGA-II in all instances. However, the NSGA-II was significantly better than the EC method for NPS, MS, and MID metrics. As such, LSNSGA-II was significantly better than the original NSGA-II in terms of NPS and MID metrics. This comparison reveals that both NSGA-II and LSNSGA-II outperform the EC method while having the highest count of best cases overall by a factor of 23 (LSNSGA-II), 22 (NSGA-II) to 15 (EC).

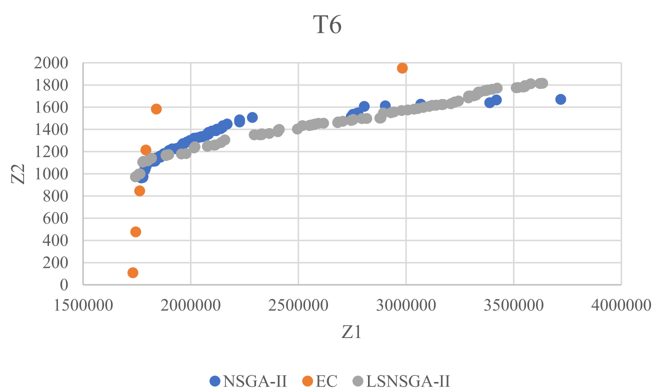
What can be envisaged at first glance from Fig. 8 is that the CPU time of NSGA-II and our proposed LSNSGA-II is acceptable even in large tests while the EC method has unreasonable CPU time after the T6 test problem. It should be noted that the CPU time of our LSNSGA-II is higher than the original NSGA-II due to a local search algorithm which has increased the number of computations for the proposed LSNSGA-II.

As can be seen from Fig. 9, some solutions obtained by NSGA-II and LSNSGA-II in comparison with the Pareto solutions obtained by EC method can be considered as non-dominated solutions. In another view, the solutions obtained by EC cannot dominate all the solutions of NSGA-II and LSNSGA-II. In addition, there is a completion between the non-dominated solutions generated by NSGA-II and LSNSGA-II. Although NSGA-II can dominate a number of non-dominated solutions from LSNSGA-II, generally, the proposed LSNSGA-II can dominate many solutions from NSGA-II. Finally, these charts confirm the diversity and superiority of LSNSGA-II algorithm in comparison with the original NSGA-II.

In Fig. 10, we normalize the results of Table 8 to analyze the metrics via analysis of variance in a confidence level of 95%. For the interval plot, a lower value shows the robustness of a plot. Another criterion for the evaluation of an interval plot is accuracy referring to a lower deviation of the maximum and minimum of an interval plot. Between these criteria, robustness is more important than accuracy (Mirjalili and Dong, 2020). As can be seen in Fig. 10, NPS (Fig. 10(a)), MID (Fig. 10(b)), SNS (Fig. 10(c)) and MS (Fig. 10(d)) are analyzed statistically. Based on the definition of accuracy and robustness, we can say that the EC method based on the NPS metric (Fig. 10(a)) has better accuracy in comparison with those metaheuristics. However, the proposed LSNSGA-II is more robust than other methods and achieves the lowest value in this interval plot. Having a look at the analyses for the MID metric (Fig. 10(b)), the algorithms are the same based on accuracy. However, NSGA-II and LSNSGA-II are significantly better than the EC method based on the robustness criterion. In addition, the proposed LSNSGA-II is more robust than the original NSGA-II. Based on the results of the SNS metric (Fig. 10(c)), we can say that the NSGA-II is more accurate than other methods. However, based on the robustness criterion, the EC method is highly better than both NSGA-II and LSNSGA-II algorithms. Among them, LSNSGA-II is better than



(a)



(b)

Fig. 9. Non-dominated solutions for NSGA-II, LSNSGA-II and EC methods, (a) T4 and (b) T6.

the original NSGA-II in this criterion. What can be resulted from the analyses for the MS metric shown (Fig. 10(d)) is that the accuracy of methods is the same. However, both metaheuristic algorithms are more robust than the EC method and they have a similar performance. In conclusion, from all these criteria, we can see that the proposed LSNSGA-II is more robust than other methods and its accuracy in most of the metrics is the same as other algorithms used in this paper.

5.4. Sensitivity analyses

For solving our illustrative example in the Middle East region, the more efficient algorithm, i.e., LSNSGA-II was considered to address a test including six patients and origin countries, three hospitals, and five tourist cities as their data is provided in Section 5.1. After solving this example, the CPU time was calculated as 208.65 s. The value of the best solution ever found based on the concept of crowding distance is 3.8856e + 05 for the first objective (Z_1) and 173.6122 for the second objective (Z_2) which are found by the EC method. In non-dominated solutions found by our multi-objective metaheuristic algorithm, there is a conflict between these objectives. The set of non-dominated solutions found by LSNSGA-II shown in Fig. 11 confirms this conflict.

To do the sensitivity analyses, we have focused on three factors including the cost of medical services (CH_i) which have a high impact on the total cost of each patient as well as the interest rates of medical services ($POIH_{bi}$) and tourist cities ($POIS_{bj}$) which have a high impact on the attractivity of trips. For each analysis, we have computed the average of objective functions for all the non-dominated solutions found by the proposed LSNSGA-II.

Table 9
Sensitivity analysis of the cost of medical services.

Number of cases	CH_i	Z_1	Z_2	CPU time
C1	[57 444, 45 134, 51 374]	3.8856e+05	173.6122	208.65
C2	[57 444, 68 342, 85 325]	5.0002e+05	175.1679	178.2219
C3	[72 436, 68 342, 62 345]	5.6454e+05	188.8711	191.2625

Table 10
Sensitivity analysis of the interest rates of medical services.

Number of cases	$POIH_{bi}$	Z_1	Z_2	CPU time
W1	$randi([1, 10], N, H)$	3.8856e+05	173.6122	208.65
W2	$randi([5, 15], N, H)$	3.7676e+05	155.4199	199.9563
W3	$randi([10, 15], N, H)$	4.0751e+05	194.586	183.1378

Table 11
Sensitivity analysis of the interest rates of tourist cities.

Number of cases	$POIS_{bj}$	Z_1	Z_2	CPU time
P1	$randi([1, 10], N, J)$	3.8856e+05	173.6122	208.65
P2	$randi([5, 15], N, J)$	3.8772e+05	280.8339	318.1781
P3	$randi([10, 15], N, J)$	4.0149e+05	366.5608	212.9969

The first sensitivity analysis is performed on the cost of medical services where some changes are made to a few hospitals randomly. We have considered three cases numbered C1 to C3. Then, the best values for both objectives and the CPU time are reported in Table 9. While the average cost of medical services has increased, the total cost has significantly increased. However, the attractivity of trips has not varied so much. It should be noted that these changes do not have a high impact on the complexity of solving as the CPU time has a few variations.

Another parameter is the rates of interest in the medical services for the patients. As reported in Table 10, we have done three sensitivity analyses numbered W1, W2, and W3. The changes in the average of the first objective, second objective, and CPU time terms are studied. Generally, as the interest rates have increased, they did not have significant variations for the first objective function. As such, these changes are high while looking at the second objective where it has been increased as compared from W1 to W3. The last finding from Table 10 is that an increase in the interest rates of medical services can reduce the complexity of solving as the CPU time is decreased generally.

This sensitivity analysis is related to the interest rates of tourist cities where we have increased them via three cases from P1 to P3 as reported in Table 11. We can say that the variations of the first objective are not too many. However, the second objective shows a significant improvement through the analyses. An increase in the interest rates of tourist cities not only improves the overall attractivity but also the computational time increases.

Additionally, we have conducted a sensitivity analysis on two fairness constraints, namely constraint (13) and constraint (14), within the mathematical model. These constraints establish the threshold values for patients' interest in receiving medical services and visiting tourist destinations, respectively. Each analysis focused on examining the impact of varying the threshold value on objective functions.

This sensitivity analysis concentrated on the fairness constraint of medical services, where the threshold value for patients' interest in receiving medical services (TRH) was increased. As depicted in Fig. 12, the findings revealed that increasing the threshold for receiving medical

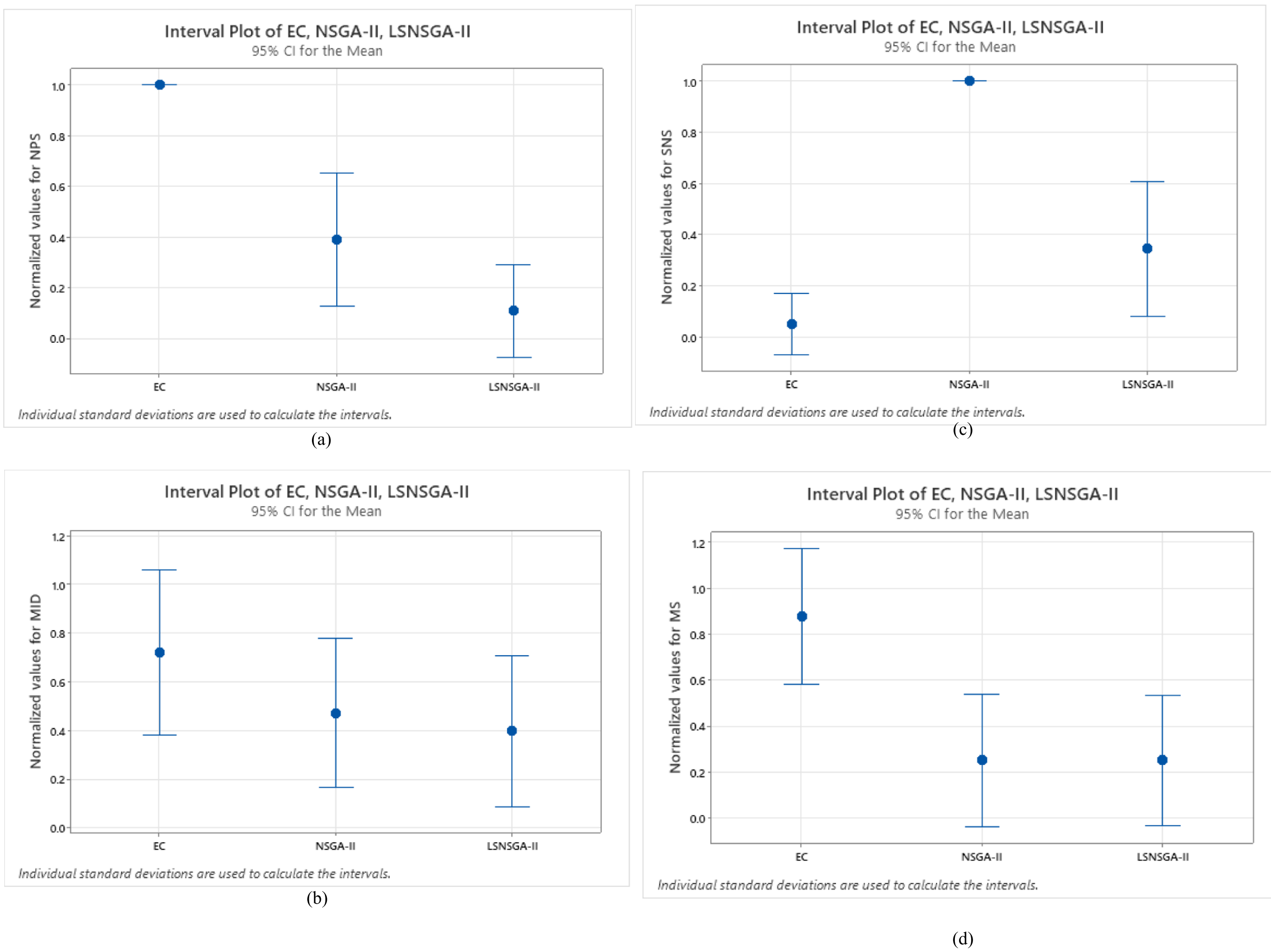


Fig. 10. Interval plots for analyzing the assessment metrics, i.e., (a) NPS; (b) MID; (c) SNS; and (d) MS.

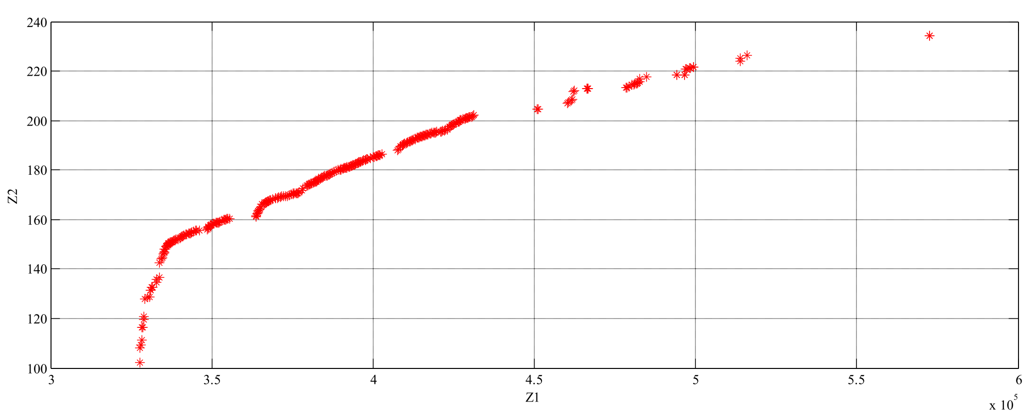


Fig. 11. Set of non-dominated solutions for our real illustrative example.

services not only led to an increase in total costs but also enhanced the attractiveness factor. This observation indicates that by growing the parameter associated with constraint (13), more attention is given to patients' treatment satisfaction, resulting in higher costs incurred for providing superior services. Moreover, this adjustment contributes to heightened customer satisfaction and subsequently improves the appeal of the trips.

The last sensitivity analysis pertains to the fairness constraint associated with visiting tourist cities, as defined in constraint (14). Fig. 13 illustrates the results of this analysis, indicating that an increase in the threshold parameter for visitors' interest in visiting tourist cities (TRS) leads to an increase in total costs while simultaneously decreasing the overall attractiveness of trips. It is important to note that as the threshold for visitors' interest in visiting tourist cities increases, the number of cities visited decreases, resulting in a reduction in total costs.

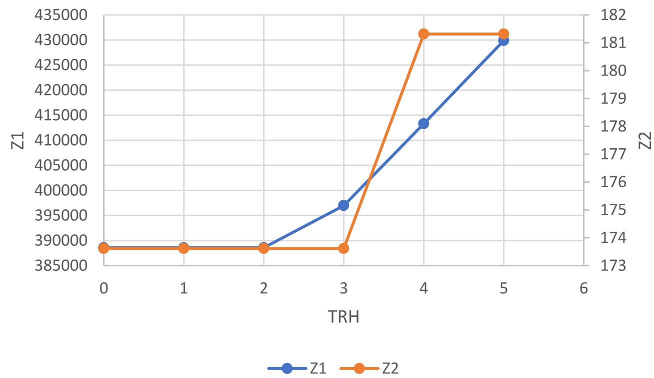


Fig. 12. Sensitivity analysis of the fairness constraint of medical services.

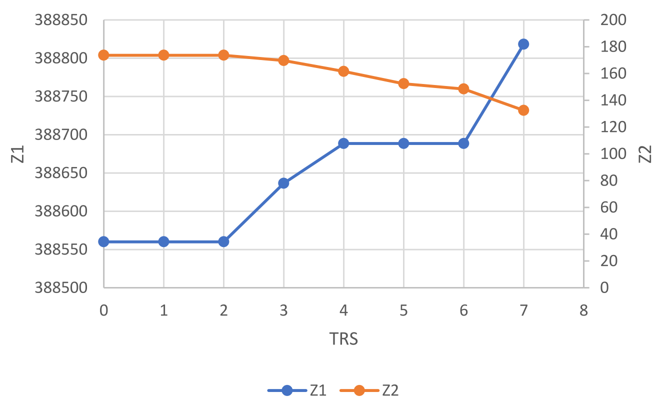


Fig. 13. Sensitivity analysis of the fairness constraint of visiting tourist cities.

Additionally, numerous places fail to meet visitors' interest, which consequently diminishes the overall appeal of the trips.

5.5. Discussion of results

Generally, the tourist trip design problem aims to allocate a set of passengers to the tourist cities while maximizing the score of tourist places. However, this study extends this problem to the medical tourism trip design to assign the patients to the hospitals while planning the orienteering and scheduling of tourist cities to increase satisfaction at the destination country. The proposed problem was modeled by a multi-objective optimization framework to find an interaction between the total cost of patients and the attractivity of trips. As a complex optimization problem, this study proposes an improvement to the NSGA-II using a local search algorithm. The proposed LSNSGA-II uses innovative crossover and mutation operators (Figs. 3 and 4) and a local search procedure (Fig. 5). To approve its high efficiency, it was compared not only with the original NSGA-II, but also with the EC method as explained in Eqs. (30) and (31).

A multi-objective optimization algorithm must be evaluated by different criteria including but not limited to the NPS, MID, SNS, MS, and CPU time metrics in this study. First, we tuned both NSGA-II and the proposed LSNSGA-II using the Taguchi experimental design method as reported in Table 6. Then, the tuned NSGA-II and LSNSGA-II were analyzed by the EC method to validate the quality of non-dominated solutions (Table 7 and Fig. 8). In addition, they were compared with each other by the multi-objective assessment metrics as reported in Table 8 and shown in Figs. 9 and 10. One finding from the aforementioned analyses was the high performance of the proposed LSNSGA-II in comparison with the original NSGA-II and the EC method generally.

To approve the applicability of this research, a real illustrative example collected from the Middle East region was provided as discussed in Section 5.1 and solved in Section 5.4 while analyzing a set of sensitivities. All the possible alternatives regarding the changes in total cost and attractivity of trips were studied by the non-dominated solutions as shown in Fig. 11. These alternatives were evaluated by the sensitivity analyses as reported in Tables 9, 10, and 11 to study the impact of medical services cost, interest rates of medical services, and tourist cities as the most important parameters for our optimization model. Furthermore, the sensitivity analysis concerning customer interest was conducted for both objective functions. The outcomes of varying the threshold of interest in receiving medical services and visiting tourist destinations are presented in Figs. 12, and 13, respectively. Based on all these results and analyses, the following managerial insights can be concluded. The first one is to shift the traditional tourist trip design problem to a novel medical tourism trip design problem considering the total cost and the attractiveness of trips using a multi-objective framework. The second managerial insight is to recommend the developed LSNSGA-II for analyzing very large-scale instances efficiently. Other managerial insights can be referred to our sensitivity analyses where the cost of medical services plays a key role in the financial issues and the interest rates of tourist cities have a very high impact on the attractivity of trips and stay time of patients in the destination country. Therefore, the engineers and practitioners of medical services and the tourist industry should pay more attention to these factors in their analyses and conceptual models.

6. Conclusion and future remarks

In medical tourism, the patients travel outside of their countries to receive exhaustive medical care. This study provided a link between the tourism industry and medical services where the patients are interested in having high-quality and low-cost medical services. In this regard, a new modeling approach for the medical tourism trip design problem was proposed to optimize the total cost and attractivity of tourist cities simultaneously using a bi-objective mathematical model. Each patient from an origin country traveled to the destination country to receive his/her medical services toward visiting tourist attractions. The developed model made the assignment decisions of patients to the hospitals as well as the orienteering and scheduling of patients while visiting several tourist places in a sequence at the destination country. Also, for solving the proposed model, the EC method was applied to solve the small tests while the proposed LSNSGA-II and the original NSGA-II were able to solve the large tests optimally in a reasonable time, i.e., less than one hour. From our results, the positive impact of our local search procedure on the NSGA-II was shown in the high performance of LSNSGA-II in a comparative study based on different multi-objective assessment metrics. In addition, the impacts of medical services cost, interest rates of medical services, and tourist cities as the most important parameters for our optimization model were studied in the analyses. The main finding was that the proposed optimization model that benefited from the offered LSNAGA-II provided high-quality solutions for addressing the conflicts between the total cost and the attractivity of trips.

Although this study examined a significant contribution to merging the tourism industry and medical services, there were some limitations to our model and solution algorithms which can be studied in our future works. First, the proposed model ignored the uncertainty of our proposed problem. In this regard, the operational uncertainties that exist in travel time, resident time, and medical service time can be molded by fuzzy or stochastic theories. Most importantly, a real-time optimization method can be applied to address deep uncertainties. For example, a patient may cancel his or her medical service or disruption may occur to prevent the patient from visiting tourist places. Furthermore, as part of future research, we can extend the proposed model to encompass the scheduling problem of patients that addresses the needs of both medical tourists and regular patients simultaneously. In this extended model, we can consider the hotel selection exclusively for medical tourists, allowing them to have options for choosing accommodations during their visits. We can also add a new assumption to explain that the patients may need to transfer between hospitals due to emergency purposes. Last but not least, the proposed model may need to be reformulated by Benders decomposition or Lagrangian relaxation theories. Finally, new heuristics and metaheuristics can be applied to the proposed model in comparison with the presented results in this paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request

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