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A sustainable and efficient home health care network design model under uncertainty

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ABSTRACT

To cater to the increasing demands, particularly during diseases such as Covid-19, the design and planning of home health care systems is of significant importance. The current study proposes a multi-objective mixed-integer linear model for a home health care network in two stages; the first is the opening of efficient health centres, and the second is the routing and scheduling considering corporate social responsibility and efficiency. There are multiple objectives that we consider, including minimization of total costs and inefficiency considerations, and maximization of social aspects. A novel aspect of this study is the consideration of social responsibility, which includes employment opportunities and regional economic development, and efficiency in terms of time, energy, and mismanagement of budgets. To measure efficiency, an augmented version of the data envelopment analysis approach is incorporated into the proposed optimization model. Additionally, the TH approach is developed as an interactive fuzzy method to deal with the proposed multi-objective model. Within the HHC problem, costs, social factors, and service time are inherently uncertain, and hence, to solve this problem, a robust-fuzzy approach is proposed. The ensuing model is applied to a real case study of Kermanshah in Iran. Moreover, several problem instances motivated by real cases are generated with different characteristics to measure the performance of the proposed model and approach. The results show that decision-makers' preferences play a key role in human resource planning and regional development. Furthermore, the results confirm the efficiency of the proposed approach in different instances within reasonable time frames.

1. Introduction

Nowadays, Home Health Care (HHC) networks are an essential part of the health sector. These networks serve patients in their homes so that they may stay close to their family and friends while being treated in a stress-free environment compared to hospitals (Fikar & Hirsch, 2017). HHC provides a wide range of medical services in the homes of patients and the elderly. These services include treatments (e.g., injections) for patients with serious illnesses, care for acute injuries, visiting patients with unstable health statuses, psychiatric care, physical therapy, etc. In this network, typically, a nurse travels from a health centre to patients' homes to visit them within the pre-specified time windows. At the end of each visiting tour, the treatments or samples taken from patients should be reported and submitted to a laboratory to investigate the health results (Fathollahi-Fard, Ahmadi, & Karimi, 2020). In several studies, each tour starts from and finishes at a nurse's home (Nikzad, Bashiri, & Abbasi, 2021).

In order to provide HHC services effectively, a number of significant decisions need to be made, including opening health centres, assigning nurses to patients, and routing and scheduling of nurses (Nikzad et al., 2021). The ensuing problem of scheduling is very complex and requires a great deal of effort and time to obtain effective plans, which can lead to significant benefits to patients and hospitals. On the one hand, it allows decreasing costs and increasing patient satisfaction (Grenouilleau, Legrain, Lahrichi, & Rousseau, 2019), and on the other hand, hospitals benefit from the beds being freed. Moreover, due to aging populations, the demand for HHC services has increased significantly; for example, the number of nurses required in the HHC network in the United States has doubled over the past ten years (Span, 2016). In addition, a pandemic such as the Covid-19 outbreak has significantly raised the demand for HHC services as people are required to stay at their place of residence while still requiring health services. For this reason, Home Health Care News (HHCN-https://homehealthcarenews.com) states that 31 percent of HHC companies have been negatively impacted by the

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Covid-19 outbreak in 2020. Thus, an efficient HHC network can be of critical importance in dealing with this situation.

With raising awareness of sustainability among communities, industry, and government over the last two decades, policy-makers worldwide have tried to find a way to include sustainability issues in industrial and urban development, and the health care industry has not been an exception (Fiksel, 2006). Sustainability is mostly defined as an equilibrium between economic and social issues involved in human development. The social aspect, which has not been considered in the literature a lot, relates to forcing non-governmental organizations to take employment opportunities and economic development for local communities for the social impacts of their activities (Sharifi, Hosseini-Motlagh, Samani, & Kalhor, 2020; Zhalechian, Tavakkoli-Moghaddam, Zahiri, & Mohammadi, 2016). In addition, the World Health Organization emphasizes the important relationship between economic development and health (Zahiri, Zhuang, & Mohammadi, 2017), where improved health directly contributes to improving the economy. For example, a worker's good state of health increases productivity, reduces production losses due to worker sickness, and decreases absenteeism rates. Additionally, more employment opportunities for nurses in centres that have been opened improve the speed of regional employment, thereby affecting regional economic and employment development, particularly in less-developed districts. Hence, the motivation for our study is to employ social impact explicitly as an objective, namely, Corporate Social Responsibility (CSR).

Inefficiency, if not carefully considered, can lead to a waste of resources, time, energy and mismanagement of budgets in the network (Haeri, Hosseini-Motlagh, Ghatreh Samani, & Rezaei, 2020). The opening of the centres is an initial component of an HHC network, and selecting them appropriately, significantly based on several main factors, improves the efficiency of the network. To measure the inefficiency of the network, the Data Envelopment Analysis (DEA) method has previously been shown to be effective (Cook, Roll, & Kazakov, 1990). This method has two main advantages compared to other methods; 1) the factors remain in their natural physical units, 2) multiple factors are used simultaneously to assess which candidates work most efficiently. Additionally, most studies focus on the total cost of the HHC network, while the efficiency of centres and their social impacts have not been investigated simultaneously. These reasons motivate us to develop a Multi-Objective Linear Programming (MOLP) model for the design and planning of an HHC network. To solve the MOLP model, we utilize an interactive fuzzy method proposed by Torabi and Hassini (2008) called the TH method. A key aspect of this method is to consider the satisfaction levels of decision-makers, which are the normalization values of objective functions or membership values. This method allows decision-makers to effectively trade off their preferences concerning multiple objectives (Torabi & Hassini, 2008). In other words, it is a promising and interactive fuzzy approach that can produce high-quality solutions based on the preferences of decision-makers, and at the same time affords flexibility.

Due to the changes in the status of patients, their service times are uncertain and can vary greatly, thereby affecting the design of the network. Additionally, the knowledge of the nurses and the medical history of patients provide an estimation of the patients' service times as a fuzzy and scenario-based parameter. In the literature, fuzzy programming and robust approaches have been employed to deal with such problems with uncertainty (Samani, Hosseini-Motlagh, & Homaei, 2020). Hence, we develop a *p*-robust approach to tackle this problem, which in particular minimizes the deviation between the objectives and optimal values under each scenario. Furthermore, data such as cost and social parameters are uncertain, with no prior or historical knowledge. These parameters are considered epistemic uncertainties, effectively estimated using fuzzy logic and trapezoidal fuzzy numbers. To deal with the uncertainty, Possibilistic Chance Constrained Programming (PCCP) is one of the most widely used fuzzy programming methods. This method can be applied to possibilistic data and provide a minimum satisfaction level for decision-makers. In other words, the minimum degree of confidence in the possibilistic chance constraint should be provided to satisfy the decision-makers. Therefore, the proposed model incorporates mixed uncertainty in fuzzy data and scenarios. For these reasons, this study presents a robust-fuzzy approach to cope with the complexity induced by the uncertainty surrounding the parameters.

Motivated by a case study in Kermanshah, Iran, where an HHC network helps the health system to visit the patients at their homes, we aim to generalize HHC for the real case study and answer the following pertinent and important questions:

- How can the HHC be designed and planned to consider several important aspects such as total network costs, efficiency, and social responsibility?
- How can a number of the important factors with different units be used simultaneously to affect the selection process of efficient health centres?
- What procedure should be followed to promote CSR issues within a sustainable HHC network?
- How can the patients get multiple services within a specific time window?
- How can the uncertain scenarios and fuzzy parameters be dealt with?
- How can an approach be devised to efficiently manage the different types of uncertain data?

Underpinned by these questions, this paper presents a new mathematical model for integrated locating, assignment, routing, and scheduling decisions for the HHC problem. Locating is the basic phase of designing an HHC network and significantly improves the delivery of services and development of regions. The proposed model arises from the classic Location Routing Problem (Prodhon and Prins, 2014). In the proposed model, an important strategic decision affects opening the appropriate health centres with a high population, low traffic, and low pollution. To do so, the DEA tool is used to select appropriate centres by input and output factors with various units and without any weight. In the proposed model, patients can get multi-services, request required drugs, and take tests within their pre-defined time window. The employment opportunity for nurses and regional economic development are considered to increase social responsibility. In addition to social responsibility, total network costs and CSR are considered as objective functions and we use a multi-objective decision-making approach. In particular, the TH approach as an interactive strategy is developed to solve the proposed multi-objective model. Therefore, the aim of this model is to determine the set of efficient and sustainable health centres, while taking into account fixed and variable costs. In this HHC network, the nurses start their visiting tour from an appropriate health centre. Based on our review of real case situations, the health centre often tries to allocate its nurses to patients who live as close as possible to the health centre. At the end of each visiting tour, nurses finish their work at a laboratory; therefore, this model is an open vehicle routing problem. The time windows of patients are pre-defined based on patients' preferences as to when they want to be visited. Additionally, the capacity of the nurse's vehicle and the number of required services for each patient are known to be important points in the tactical decisions assignment, routing, and scheduling. In the real world, the service time for visiting each patient is undetermined and can be characterized in different scenarios based on the patient's medical history and nurses' knowledge. Moreover, the costs and social parameters in the HHC network are uncertain, and there is no information and historical data for them. Thus, the fuzzy logic theory is used, and these parameters are considered as trapezoidal fuzzy numbers. For solving the resulting model, this study proposes a mixed robust-fuzzy approach to cope with uncertain service times, costs, and social parameters. In the model concerned, identifying the location of health centres is the first decision, followed by assignment, scheduling, and routing. Overall, this study has three phases. In the first phase, we apply the p-robust approach to deal with the scenarios of service time. We utilize PCCP to cope with fuzzy parameters (costs, and social data) in the second phase. The first and second phases together represent a robust-fuzzy approach to deal with mixed uncertain parameters (fuzzy and scenario-based parameters). In the third phase, we develop the TH approach to solve the multi-objective HHC model. To achieve these aims, we present a novel sustainable and efficient HHC network design, namely Design and Planning of Home Health Care (DPHHC) under uncertainty. Finally, to validate our approach, we consider a real case study from Kermanshah in Iran, following which we design a data set with the help of expert knowledge to carry out a comprehensive computational study.

The paper is organized as follows: Section 2 reviews similar recent research on the HHC network. Section 3 provides the problem statement and mathematical formulation. Section 4 introduces a hybrid methodology to tackle the uncertainty and an interactive fuzzy method to deal with the multi-objective model. A real case study, results, and sensitivity analyses are defined in Section 5. Finally, findings, discussions, and some important directions for future research are provided in the last section.

2. Literature review

The DPHHC problem in an uncertain environment is a relatively new but rapidly evolving field of research. There is a vast literature on health care systems, though our focus is on recent research closely related to the problem being investigated. The readers are referred to the latest review publication by Fikar and Hirsch (2017), which presents a comprehensive overview of papers in the areas of the Home Health Care Routing and Scheduling Problem (HHCRSP). They classify problems into two classes based on whether they consist of single or multi-time periods.

In recent studies, Rodriguez-Verjan, Augusto, and Xie (2018) proposed two Mixed Integer Linear Programming (MILP) models to design an HHC network with two separate aims to locate health facilities and manage the activities of the health facilities. They implement a real case study of the Loire department in France. Grenouilleau et al. (2019) propose an MILP model for HHCRSP to minimize the total costs of nurses' overtime, routes, unscheduled visits, and idle time. They apply their model and a Large Neighborhood Search (LNS) method for a dataset from Alayacare in Montreal. Liu, Yuan, and Jiang (2020) model a periodic HHC server assignment problem to minimize the maximum workload between servers in various periods. They propose an efficient region-partition-based algorithm, which effectively solves large-scale problems. In another study, Cinar, Salman, and Bozkaya (2021) formulate a multi-period model for the HHCRSP to visit patients based on their priorities. They develop an adaptive LNS approach to tackle the problem.

We review several relevant studies to find the gaps in existing research in Table 1. The papers related to this study can be broadly classified into three main categories: 1. multi-objective HHC problems, 2. HHC problems under uncertainty, and 3. multi-depot and multi-care HHC problems.

2.1. Multi-objective HHC problems

Rest and Hirsch (2016) introduce a Mixed Integer Programming (MIP) formulation for HHC daily scheduling services, where nurses use public transport. They utilize a weighted objective function to minimize the shift lengths, overtime, the number of second shifts, and overqualification. They develop three Tabu Search (TS) strategies to apply to the Austrian Red Cross data. Braekers, Hartl, Parragh, and Tricoire (2016) propose a meta-heuristic based on a multi-directional local search to find a set of non-dominated schedules for a multi-objective HHCRSP. They apply the epsilon constraint method to solve the model with two objective functions: minimizing nurses' routes and overtime cost. They use a dataset from the public employment service of Austria. In another study, Fathollahi-Fard, Hajiaghaei-Keshteli, and Tavakkoli-Moghaddam (2018) investigate a bi-objective green HHC routing problem and propose hybridizations of Simulated Annealing (SA) and Salp Swarm algorithms. The objective functions consist of environmental pollution and total costs. The epsilon constraint method is used to deal with the multi-objective model. Zhang, Yang, Chen, Bai, and Chen (2018) study an HHCRSP for a real case in China and formulate a novel MIP model with uncertain service times, match qualities, and time windows. They aim to minimize travel costs, waiting time, and service time, and use the weighted method to solve the multi-objective model. They also develop an Ant Colony Optimization method to solve large instances of the problem. Carello, Lanzarone, and Mattia (2018) present a set of Integer Linear Programming (ILP) models for a home care system. They model the nurse-to-patient assignment problem under continuity of care and consider minimizing cost, maximizing utilization, and minimizing the total number of reassignments as the objective. They use the threshold method to find the optimal solutions for the multi-objective model. Habibnejad-Ledari, Rabbani, and Ghorbani-Kutenaie (2019) propose a multi-objective Non-Linear Programming (NLP) model to address staff assignment problems in a home care system. They aim to minimize the costs and employees for each service and maximize the worker satisfaction level. They apply a new version of NSGA-II with a heuristic initialization for solving this model.

In another study in this category, Regis-Hernández, Carello, and Lanzarone (2020) formulate a multi-objective Linear Programming (LP) model for HHC services and a matheuristic approach to solve a real case. The model can determine the numbers of physicians, nurses, technicians and devices to acquire that are needed to meet the demand. Gong, Geng, Zhu, Matta, and Lanzarone (2020) propose an ILP model for the home care scheduling problem and develop a matheuristic approach to solving this problem. They minimize costs, the penalty of the continuity of care violation, and the preference mismatch, and then use the weighted method to solve it. Entezari and Mahootchi (2021) propose an MILP model for staff routing and scheduling in HHC and develop a Genetic Algorithm (GA) to find near-optimal solutions. They aim to minimize their objective functions: travel times, tardiness in providing services, staff overtime, violation of care continuity, and violation of the staff's time windows by the weighted method. Lin, Ma, and Ying (2021) design an MILP model for HHC and propose a branch and price method for matching demand to supply. They minimize total costs, maximize customer satisfaction, and use a lexicographic method to solve the model. Goodarzian, Abraham, and Fathollahi-Fard (2021) propose a bi-objective model for HHC logistics to minimize total costs and time by considering route balancing. To solve the problem, they use the epsilon constraint method and a metaheuristic approach for large instances. Malagodi, Lanzarone, and Matta (2021) formulate an MILP model for a home care vehicle routing problem. They aim to minimize the mismatches of strict and soft preferences over the works, overtime, and total travel time for all caregivers. The weighted method is used to cope with the multi-objective model.

2.2. HHC problems under uncertainty

Rodriguez, Garaix, Xie, and Augusto (2015) present a two-stage MILP model for a health care company in France. The authors aim to find the minimum number of nurses that can cover all possible routes. They consider uncertainty in demand and use a stochastic approach to deal with this uncertainty. In another study, Shi, Boudouh, and Grunder (2017) design a vehicle scheduling problem for an HHC system and consider patients' demand for drugs as fuzzy data, which they tackle with fuzzy chance constraint programming. Cappanera, Scutellà, Nervi, and Galli (2018) propose a cardinality-constrained robust approach considering routing, assignment, and scheduling decisions under uncertain demand. They propose a decomposition approach as a feasible option to increase computational efficiency and apply it to real-world data. Shi, Boudouh, Grunder, and Wang (2018) propose a stochastic

Table 1
A classification of recent publications.

Reference	Modelling Approach	Constraint			Objective Function	Uncertainty Approach				Solution Method		Multi-Objective Method	Performance Measure	Case Study
		Multi Depots	Multi Cares	Time Window		Stochastic	Fuzzy	Robust	Robust-fuzzy	Exact	Heuristic			
Nickel, Schröder, and Steeg (2012)	NLP		×	×	Multi						×	Weighted method	Unscheduled tasks, Loyalty, Time, Distance	×
Allaoua, Borne, Létocart, and Calvo (2013)	ILP			×	Single						×		Number of nurses	
Milburn and Spicer (2013)	MIP				Multi						×	Epsilon constraint method	Number of nurses, Workload, Cost	×
Mankowska, Meisel, and Bierwirth (2014)	MILP		×	×	Multi						×	Weighted method	Distance, Time	
Lanzarone and Matta (2014)	MILP				Single			×		×			Time	×
Mutingi and Mbohwa (2014)	LP			×	Multi						×	Fuzzy simulated evolution	Workload, Time, Clustering efficiency	
Carello and Lanzarone (2014)	LP				Single			×		×			Cost	×
Rodriguez et al. (2015)	MILP				Single	×				×			Cost of staff	×
Fikar and Hirsch (2015)	LP			×	Single						×		Time	×
Rest and Hirsch (2016)	MIP			×	Multi						×	Weighted method	Time, Shift lengths, #Shifts, qualification	×
Braekers et al. (2016)	MIP			×	Multi						×	Multi-directional local search	Cost, Client inconvenience	×
Yalçındağ, Matta, Şahin, and Shanthikumar (2016)	MIP				Multi						×	Weighted method	Time	×
Errarhout, Kharraja, and Corbier (2016)	LP				Single					×			Time, Workload	
Decerle, Grunder, El Hassani, and Barakat (2016)	MILP			×	Single						×		Cost	
Shi et al. (2017)	MIP			×	Single		×				×		Distance	
Cappanera et al. (2018)	MILP				Single			×		×			Workload	
Shi et al. (2018)	LP			×	Single	×					×		Cost	
Fathollahi Fard et al. (2018)	MILP			×	Multi						×	Simulated Annealing	Environmental pollution, Cost	
Veenstra, Roodbergen, Coelho, and Zhu (2018)	MILP				Single						×		Cost	×
Rodriguez et al. (2018)	MILP				Single					×			Cost	×
Decerle, Grunder, El Hassani, and Barakat (2018)	MIP				Single			×		×			Cost	×
Fathollahi-Fard et al. (2019)	MILP	×		×	Multi						×		Cost, Environmental pollution	
Erdem and Koç (2019)	MILP	×		×	Single						×		Time	
Shiri, Ahmadizar, Mahmoudzadeh, and Bashiri (2019)	MILP			×	Single			×		×			Cost	
Entezari and Mahootchi (2021)	MILP		×	×	Multi						×	Weighted method	Cost	
Fathollahi Fard et al. (2020a)	MILP	×		×	Multi		×				×	Weighted method	Cost, Environmental pollution	
Fathollahi Fard et al. (2020b)	MILP	×		×	Multi			×			×	Weighted method	Gas emissions, Costs	
Shiri, Ahmadizar, and Mahmoudzadeh (2021)	MILP			×	Multi			×		×		Nimbus method	Cost, Qualification, Qualitative factors	×
Shahnejat-Bushehri, Tavakkoli-Moghaddam, Boronoos, and Ghasemkhani (2021)	NLP			×	Single			×			×		Cost	
Liu, Dridi, Fei, and El Hassani (2021)	MILP		×	×	Single						×		Cost	
Fathollahi-Fard et al. (2021)	NLP	×	×	×	Multi			×			×	Red Deer Algorithm	Cost, Unemployment time, Continuity of care	
Yalçındağ and Lanzarone (2021)	MILP				Multi					×		Weighted method	Utilization rate, Workload	
Our research	MILP	×	×	×	Multi				×	×		TH Method	Cost, Efficiency, Social impact	×

programming model for vehicle scheduling within an HHC routing problem. They consider travel and service times as stochastic parameters and devise an efficient SA method to solve the problem. In another study, Khodaparasti, Bruni, Beraldi, Maleki, and Jahedi (2018) present a multi-period location-allocation model for nursing home network planning. They consider uncertain demand and use a robust approach to cope with this uncertainty. They aim to minimize the number of unvisited times for patients and consider a real case study of Shiraz city. Nikzad et al. (2021) consider a two-stage model for planning of resources in an HHC problem and propose a variant of the progressive Frank, Wolfe and Hedging algorithms. This study aims to minimize the travel costs considering uncertain travel and service times. Addis et al. (2015) present a cardinality-constrained model to handle health care management problems under uncertainty. This model is a robust optimization approach, and surgery duration is uncertain. Lanzarone, Matta, and Sahin (2012) develop several mathematical programming models for home care services and assume that the demands of patients are either uncertain or deterministic. The authors use Stochastic Programming to deal with uncertainty. Lanzarone and Matta (2012) balance the workload between the operators to minimize the expected cost value in the home care network. They consider the patients' demands as stochastic and deterministic. Carello and Lanzarone (2021) introduce the nurse-to-patient assignment problem in the HHC system under uncertain service times. They formulate the uncertainty set and use the implementor-adversary method to solve the robust model. Shi, Boudouh, and Grunder (2019) develop a model for an HHCRSP under uncertain travel and service times. The authors use a robust optimization based on budget uncertainty. They present multiple solution approaches to solve the problem, including a commercial mixed-integer programming solver, namely Gurobi, TS, Variable Neighborhood Search, and an SA algorithm.

In the papers related to both multi-objective problems and uncertainty, Fathollahi-Fard, Ahmadi, and Karimi (2020) propose an MILP model for a multi-period, multi-depot, and multi-objective HHC network. They consider travel and service times as fuzzy parameters and use Jimenez's method (Jiménez, 1996) to deal with the uncertainty. They consider total costs and patient satisfaction objectives and employ the epsilon constraint method to solve the bi-objective model for small instances. Moreover, they show that the Non-dominated Sorting Genetic Algorithm (NSGA-II) can be adapted to solve the problem efficiently. Fathollahi-Fard, Ahmadi, Goodarzian, & Cheikhrouhou (2020) develop a bi-objective robust optimization model for HHCRSP. The authors consider travel and service times as uncertain parameters and use a robust approach underpinned by the Keshtel algorithm to cope with the uncertainty. This study minimizes two objectives, namely greenhouse gas emissions and total costs. They consider weights for the objective functions based on their priorities and use the weighted method to solve the bi-objective model. Fathollahi-Fard, Ahmadi, and Karimi (2021) propose a mixed-integer non-linear program for a multi-objective HHC problem. They consider minimizing the total network cost, minimizing the unemployment time for the worker, and minimizing the continuity of care by reducing the number of patients visited by the worker as objective functions. They utilize the Red Deer Algorithm for solving the multi-objective functions. Additionally, they use the Mulvey method to deal with uncertain travel and service time parameters based on scenarios. Yang, Ni, and Yang (2021) present a multi-objective HHCRSP. They minimize costs and improve workload balance and service consistency. The authors consider travel and service times as uncertain. They develop a multi-objective artificial bee colony metaheuristic to solve the model and use the Pareto dominance strategy to compare the solutions of multi-objective optimization. Zheng, Wang, Li, and Wu (2021) propose two-stage stochastic programming considering maximizing the expected income for HHCRSP under demand uncertainty. The first stage is capacity planning and service authorization, and the second stage is resource allocation. They consider the minimization of the total operating cost for all customers, minimization of the value of caregiver inconsistency, and minimization of workload imbalance as objective functions.

2.3. Multi-depot and multi-care HHC problems

Bahadori-Chinibelagh, Fathollahi-Fard, and Hajiaghaei-Keshteli (2019) formulate a novel multi-depot HHC routing model to minimize total costs. They assume an equal number of laboratories and pharmacies in the model and present two simple constructive algorithms as solution methods. Erdem and Koç (2019) propose an analysis of electric vehicles in the HHC problem by considering multiple depots. They assume a team of nurses performs a number of patients' demands via electric vehicles. In addition, Fathollahi-Fard, Govindan, Hajiaghaei-Keshteli, and Ahmadi (2019), Fathollahi-Fard, Ahmadi, & Karimi (2020), and Fathollahi-Fard, Ahmadi, Goodarzian et al. (2020) investigate the multi-depot ability for the HHCRSP. They consider pharmacies and laboratories as depots. Among the multi-care HHC problems, Manavizadeh, Farrokhi-Asl, and Beiraghdar (2020) develop a model for HHCRSP and solve it with SA. Multiple (interdependent) services are considered for the benefit of patients. Nasir and Kuo (2020) develop an MILP model for HHC logistics planning to serve elderly people. They aim to minimize the costs of route assignment for vehicles and nurses and travel costs. They propose a hybrid GA to tackle the problem. Entezari and Mahootchi (2021) study staff routing and scheduling in HHC industries, where a patient can require more than one service (independent or interdependent).

In the following, we summarize several studies in routing and scheduling to help identify gaps. Ghannadpour and Zarrabi (2019) develop an MIP model and evolutionary approaches for the multi-objective heterogeneous VRP and vehicle scheduling problem. They have two scenarios formulated as objectives: minimizing the total number of vehicles for serving customers and the vehicle fuel, maximizing the customers' satisfaction rate, and minimizing the number of rental vehicles, travel distance, and fuel of personal vehicles while maximizing customer satisfaction. Rahbari, Nasiri, Werner, Musavi, and Jolai (2019) design a model for a VRP and cross-dock scheduling problem under uncertain travel times. To deal with uncertainty, they use a budget of uncertainty approach to bound the variations between the uncertain and nominal values of parameters. Kisialiou, Gribkovskaia, and Laporte (2019) provide reliable supply vessel planning and scheduling by minimizing costs. Furthermore, the authors consider the effect of uncertain demand on schedule performance and impose requirements on the reliability of voyages through the construction of vessel schedules using an ALNS metaheuristic. Barma, Dutta, and Mukherjee (2019) study a multi-depot VRP with homogeneous vehicles to minimize the total routing distance in the network. They tackle this problem using the discrete Ant Lion optimization algorithm and investigate a 2-opt local search algorithm. Weiszer, Burke, and Chen (2020) develop a multi-objective shortest path algorithm for routing and scheduling an airport's ground movements. This problem aims to obtain the optimal (or near-optimal) routes for a fixed aircraft sequence. The study considers fuel consumption and taxi time as objective functions. Wang, Liao, Li, Yan, and Chen (2021) investigate a multi-objective model for a dynamic VRP with time windows. They develop a novel dynamic evolutionary algorithm using ensemble learning to solve the multi-objective model. The authors compare their approach with four algorithms in the literature and consider minimizing route distances and customer waiting times as objective functions.

Table 1 summarizes the studies in HHC, including the proposed approach, type of constraint, type of uncertainty, and whether or not the research tackles a real case study. In addition to the usual considerations in the problem, aspects such as mixed uncertainty, employment opportunities, and economic development have not been considered by previous studies. We aim to address these gaps by providing a comprehensive formulation of the problem. Moreover, the proposed robust-fuzzy method effectively deals with fuzzy and scenario-based data, which is the first attempt at such a problem. Moreover, the simultaneous consideration of multi-care and multi-depot factors is the first attempt in the literature.

3. Problem description

We formally define the problem for the design and planning of HHC, called Design and Planning of Home Health Care (DPHHC), and then present a multi-objective MILP model for the problem. In this problem, nurses start their routes at centers, and visit patients in their homes. After the visits, the nurses finish their routes at a laboratory where they report the status of patients to the laboratory. The patients must be visited during a pre-specified time window based on their preferences. More than one center (multi-depot) is typically opened in this problem, and a multi-care option is also considered, where patients can request more than one service. The location of the laboratories and the potential locations of centers are predefined. Based on this description, we propose a model with the following details:

The proposed model is a two-stage model that includes strategic and tactical decisions. In the first stage, the strategic decision is determined that involves opening p locations among candidates $n \in N$ as centers. The fixed cost for opening center n is equal to f_n. In the second stage, the tactical decisions are defined, such as transportation decisions, assigning nurses to patients, and routing and scheduling of nurses. At first, the nurse $v \in V$ moves from center $n \in N$ to serve patient $m \in M$ within the specified time window $[a_m, b_m]$. After visiting all patients assigned to nurse $v \in V$ based on their scheduling, the nurse travels to laboratory $h \in H$ to transfer medical tests or treatments taken from patients. The travel time and travel cost from node $i \in I$ to node $j \in I$ are represented by tr_{ij} and co_{ij}, respectively. The number of services required by patient $m \in M$ is shown by β_m, and each patient can receive multiple services (interdependent services).[1] Besides, patients demand a number of drugs in each service (d_m), and the vehicles transporting nurses have limited capacity (cap_v).

In the problem, the factors of the input set $r \in R$ and output set $g \in G$ are defined by experts as important criteria for selecting efficient centers. These factors are used to measure the inefficiency of candidates based on the DEA method. This method can handle such factors (traffic, pollution, population density, etc.) on different scales. For candidate n, the quantities of input factor $r \in R$ and output factor $g \in G$ are given by k_{nr} and o_{ng}, respectively. The problem aims to optimize three objective functions simultaneously, which is typical in real settings. The first objective function concerns the total cost, including costs of opening centers and transportation. The second objective minimizes the inefficiency of centers, and the third objective considers social impacts to maximize the employment opportunities of nurses as human capital and economic development.

A schematic example problem is presented in Fig. 1. It shows 10 center candidates, 11 patients, three nurses, and one laboratory. The first decision is to determine the selected centers; in this example, candidates 3 and 8 are chosen to be opened (strategic decision). The second set of decisions shows the path of each nurse to carry out their activities. For example, in the dashed route, a nurse starts her/his activity at Center 8 and visits Patients 4, 1, 5, 7, and 2. Patient 2 needs to receive two services, and hence, nurses of Centers 3 and 8 visit Patient 2 during the patient's time window. Moreover, medical tests and treatment are conducted for patients and transported to the laboratory, which is the endpoint of a route. For the purposes of this study, we make the following assumptions to clarify the scope of the study undertaken:

- A nurse starts from a center to visit patients, and after serving all patients, the nurse finishes the route at the laboratory;
- The number of patients and locations of patients' homes are predefined (i.e., patients give all information to the HHC network before getting the service);
- The required services for a patient should be provided by nurses with consideration of the desired time windows for respective patients;
- All patients need services in a certain time window;
- The potential locations of center candidates and the location of the laboratories are predefined;
- There is one nurse at least, and some centers need more than one nurse;
- No nurse arrives at patients' homes before the opening time and after the closing time specified by the time windows of the patients;
- The vehicles of nurses are heterogeneous and have different capacities, so different types of vehicles are taken into consideration. These vehicles may be the nurses' own vehicles or a third-party logistic organization may be used to provide vehicles;
- All patients must be visited at least once, and some patients need multiple services during their time window;
- The service time, costs, and social parameters are considered as uncertain parameters;
- The patient's demand and the capacity for drugs in each nurse's vehicle are known;
- There is no direct movement of nurses between the centers and laboratories;
- The social impacts and efficiency of candidate locations are considered.

3.1. Deterministic mathematical model

We now provide a comprehensive mathematical programming model of the DPHHC problem in the deterministic environment. We first define the sets, parameters, and decision variables used in the mathematical formulation.

3.1.1. Notations

The notations related to the deterministic proposed model are described as follows:

Sets	
$v \in V$	The set of all nurses
$m \in M$	The set of patients
$n \in N$	The set of center candidates
$h \in H$	The set of laboratories
$i.j \in I$	The set of all nodes (patients, center candidates, and laboratories,$M \cup N \cup H$)
$g \in G$	The sets of input factors
$r \in R$	The sets of output factors
Parameters	
f_n	The fixed cost for opening center candidate n
d_m	The demand for drugs for patient m
cap_v	The capacity of nurse's vehicle v
ts_{iv}	The service time for node i visited by nurse v (where $ts_{nv} = ts_{hv} = 0$ for all $h \in H$ and $n \in N$)
co_{ij}	The travel costs for moving from node i to node j
tr_{ij}	The traveling time from node i to node j
o_{ng}	The quantity of input factor g for center candidate n
k_{nr}	The quantity of output factor r for center candidate n
a_m	The earliest time to visit patient m, i.e., the starting time of the time window for patient m
b_m	The latest time to visit patient m, i.e., the ending time of the time window for patient m
kn_n	The number of employment opportunities at candidate location n
ce_n	The employment rate, which is the number of nurses employed in candidate location n in a year
je_n	The regional economic value at candidate location n
de_n	The factor of regional development, i.e., a value of development for a candidate location n that is between 0 and 1

(*continued on next page*)

[1] For example, giving medication to a patient before/after a meal with a predetermined time required between services.

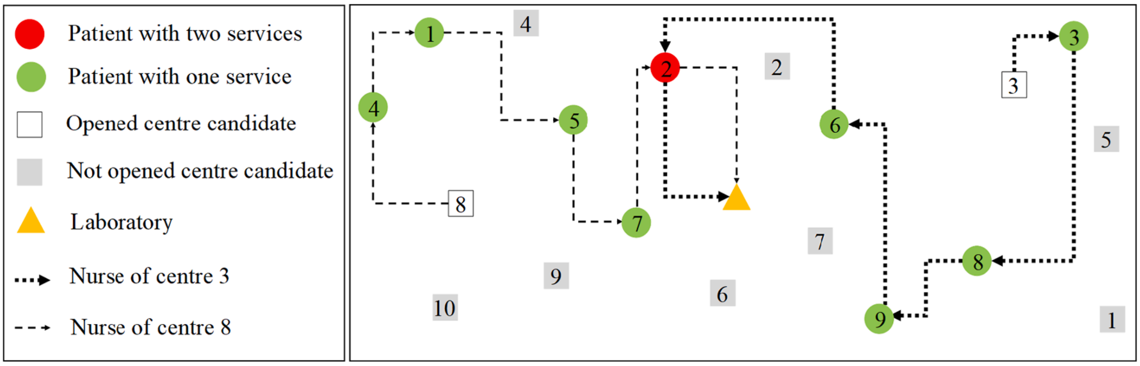

Fig. 1. An example shows the opening of centers, assigning nurses to patients, and nurses' routes. Three centers are opened among 10 candidates, and a nurse travels from each center to visit patients (highlighted routes). Some patients require two services (red circles).

(*continued*)

Sets	
β_m	The number of services required for patient m
p	The number of center candidates that are allowed to be opened
$\mathscr{M}$	A large number
ω	A small number
Variables	
y_n	A binary variable, which is 1 if center candidate n is selected, and 0 otherwise.
x_{ijv}	A binary variable, which is 1 if nurse v travels from node i to node j, and 0 otherwise.
st_{iv}	A positive continuous variable, which is the starting time for visiting node i by nurse v
φ_n	A positive continuous variable, which is the summation of the negative and positive weight deviation for candidate location n
ar_i	A continuous variable, which is used to eliminate sub-tours
wo_{ng}	A positive continuous variable, effectively the weight or importance of output factor g for candidate location n
wi_{nr}	A positive continuous variable, effectively the weight or importance of input factor r for candidate location n

We now discuss the constraints related to the DPHHC problem and detail each of these one by one.

$$ar_i - ar_j + cap_v x_{ijv} \leq cap_v - d_j \quad \forall v \in V,\ i,\ j \in I \tag{1}$$

$$\sum_{j\in I}\sum_{v\in V} x_{mjv} = \beta_m \quad \forall m \in M \tag{2}$$

$$\sum_{i\in I} x_{imv} - \sum_{j\in I} x_{mjv} = 0 \quad \forall v \in V, m \in M \tag{3}$$

$$\sum_{n\in N}\sum_{m\in M} x_{nmv} = 1 \quad \forall v \in V \tag{4}$$

$$\sum_{i=n+1}^{m+n+1} x_{ihv} = 1 \quad \forall v \in V, h \in H \tag{5}$$

$$st_{iv} + ts_{iv} + t_{ij} - \mathscr{M}\left(1 - x_{ijv}\right) \leq st_{jv} \quad \forall i,\ j \in I, v \in V \tag{6}$$

$$a_m \leq st_{iv} \leq b_m \quad \forall i \in I, m \in M, v \in V, i = m \tag{7}$$

$$\sum_{m\in M} d_m \sum_{j\in I} x_{mjv} \leq cap_v \quad \forall v \in V \tag{8}$$

$$\sum_{n\in N} y_n = p \tag{9}$$

$$\sum_{i\in I}\sum_{v\in V} x_{niv} \leq \mathscr{M} y_n \quad \forall n \in N \tag{10}$$

$$x_{ijv},\ y_j \in \{0,1\}, st_{iv} \geq 0 \quad \forall i,\ j \in N,\ v \in V \tag{11}$$

Constraint (1) is the sub-tour elimination constraint. Constraint (2) guarantees that patients requiring medical services are visited by nurses within the patients' time windows. In Constraint (3), nurses must leave the patient's home after completing a service. Constraint (4) states that each nurse starts a route from an opened center to travel to a patient's home. Constraint (5) determines that all nurses finish their routes at the laboratory after meeting all patients. Constraint (6) denotes that the service for the next patient can commence after serving the previous patient. Constraint (7) prohibits the violation of each patient's time window and limits the start time of services for each patient, i.e., the patients must be visited during their time window. Constraint (8) prevents exceeding the capacity of the vehicle-carrying nurses. Constraint (9) chooses a certain number of potential location candidates that must be opened. Constraint (10) requires that if a center is opened, a route can be started by a nurse from that center. Constraint (11) defines binary and positive decision variables.

$$\sum_{g\in G} o_{n'g} wo_{ng} - \sum_{r\in R} k_{n'r} wi_{nr} + \varphi_n = 0 \quad \forall n,\ n' \in N,\ n \neq n' \tag{12}$$

$$\sum_{g\in G} o_{ng} wo_{ng} + \varphi_n = y_n \quad \forall n \in N \tag{13}$$

$$\sum_{r\in R} k_{nr} wi_{nr} = y_n \quad \forall n \in N \tag{14}$$

$$\omega y_n \leq wi_{nr} \quad \forall n \in N, r \in R \tag{15}$$

$$\omega y_n \leq wo_{ng} \quad \forall n \in N, g \in G \tag{16}$$

Constraint (12) guarantees that the maximum efficiency score obtained for each center is achieved by adding the total deviations (inefficiency or φ_n). Constraint (13) computes the total quantity of output factors plus the inefficiency of each center if that center is opened. Constraint (14) indicates the total quantity of input factors for each center if that center is opened. Constraints (15) and (16) guarantee that the weights assigned to the output and input factors of each center have at least a few values if that center is opened. There are three objective functions considered in this study, which were briefly discussed earlier. We provide the details of these functions in the following.

3.2. *Objective function 1: Total Cost*

The total cost is composed of two different costs. The first is the fixed costs for opening the centers, and the second is the traveling costs, which are the cumulative cost of the movements of nurses from one location to another. The total cost is:

$$\text{MinZ}_1 = \sum_{n\in N} f_n y_n + \sum_{i\in I}\sum_{j\in I}\sum_{v\in V} co_{ij} x_{ijv} \tag{17}$$

where co_{ij} are calculated by $c \times d_{ij}$ in which c is the travel cost for traveling one kilometer and d_{ij} is the distance between two nodes i and j.

3.3. Objective function 2: Inefficiency

To provide accessible, high-quality, and equitable care, presenting an appropriate method to evaluate the inefficiency of centers is critical to identify ideal design interventions that promote efficiency. For this purpose, the DEA is an appropriate approach that is widely used as a non-parametric method for measuring the inefficiency of a set of Decision Making Units (DMUs) by a combination of qualitative factors (Cook et al., 1990). There is no set standard for factors; therefore, the DEA presents a relative inefficiency measure. Meanwhile, this approach has two advantages over other techniques as it simultaneously uses multiple input and output factors to find which units (districts/center candidates) are inefficient. Furthermore, the weights of the factors do not need to be determined, and being on different scales does not pose a problem. The DEA model compares weighted input factors to weighted output factors, common to all DMUs. To do this, we consider the DMUs as the center candidates in the DPHHC, and the input and output factors for each center are identified via an expert team's knowledge. In the previous studies, researchers applied efficiency to evaluate the design of a network like a supply chain (Chen, Liang, & Yang, 2006; Liang, Yang, Cook, & Zhu, 2006; Parmigiani, Klassen, & Russo, 2011). Omrani, Adabi, and Adabi (2017) and Klimberg and Ratick (2008) incorporated the efficiency into location-allocation models by using the DEA model.

This study considers two input factors, traffic and pollution, and two output factors, population density and appropriate workplace. Based on the employees' judgment in the municipality, these factors are considered important in selecting the best candidates for centers and are therefore considered here:

1) **Traffic**: This factor indicates the ease of nurses' access to each center before starting their routes. The lower the congestion in a district, the lower the energy and time required to arrive at each center, reflecting the advantage and superiority of the center. Therefore, traffic is considered as an input factor measured based on the average time a nurse takes to arrive at a center.
2) **Pollution**: Districts with a lower level of air or noise pollution are more desirable for the nurses in terms of health and safety. Thus, pollution is also considered as an input factor for centers.
3) **Population density**: The number of people that live in each district is the population density of that district. The greater the population density, the greater the demand for services; hence, the greater the significance of centers in those districts. Therefore, population density is used as an output factor for centers.
4) **Appropriate workplace**: Acceptable temperature, humidity levels, natural light, etc., are needed for nurses to work effectively. Hence, an appropriate workplace is used as an output factor for centers.

Herein, to calculate the inefficiency of the center candidates, a common weight of DEA is chosen that leads to a Goal Programming (GP) model. GP is a branch of multi-objective optimization, which in turn is a branch of multi-criteria decision analysis (Jones & Tamiz, 2016). Essentially, the idea is to minimize the deviation of common weights from the obtained values of the DEA model. The DEA model is specified as follows:

Given a set of N DMUs ($n = 1,\cdots,N$), R input factors ($r = 1,\ldots,R$), and G output factors ($g = 1, \ldots, G$), Equations (18)-(19) denote a Multi-Objective Fractional Programming (MOFP) model, with the aim of maximizing the efficiency scores for DMUs at the same time:

$$\text{Max}w = \left\{ \frac{\sum_{g=1}^{G} wo_g o_{g1}}{\sum_{r=1}^{R} wi_r k_{r1}}, \frac{\sum_{g=1}^{G} wo_g o_{g2}}{\sum_{r=1}^{R} wi_r k_{r2}}, \cdots, \frac{\sum_{g=1}^{G} wo_g o_{gn}}{\sum_{r=1}^{R} wi_r k_{rn}} \right\} \tag{18}$$

$$\text{s.t}: wo_g,\ wi_r \geq \omega \quad \forall g \in G,\ r \in R \tag{19}$$

where the maximum score of efficiency for each DMU is equal to 1. Based on this optimization method (GP), Equation (18) can be rewritten as follows to identify a set of common weights.

$$\text{Min} \sum_{n=1}^{N} (\varphi_n^- + \varphi_n^+) \tag{20}$$

$$\text{s.t}: \frac{\sum_{g=1}^{G} wo_g o_{gn}}{\sum_{r=1}^{R} wi_r k_{rn}} + \varphi_n^- - \varphi_n^+ = A_n \quad \forall n \in N \tag{21}$$

where φ_n^- and φ_n^+ are positive continuous variables and reflect the negative and positive deviations from the n^{th} goal, respectively. In the optimization model, A_n is the maximum level for the n^{th} objective function as a goal for the n^{th} DMU. When$A_n = 1$, it implies that the n^{th} objective function approaches its goal and variable φ_n^+ cannot have a positive value. Therefore, Equation (21) can be rewritten as:

$$\sum_{g=1}^{G} wo_g o_{gn} + \varphi_n^- \left(\sum_{r=1}^{R} wi_r k_{rn} \right) = \sum_{r=1}^{R} wi_r k_{rn} \times A_n \quad \forall n \in N \tag{22}$$

Due to the nonlinear Equations (20)–(22), the GP approach is utilized again to linearize the model. In the revised model, A_n=1 is considered in Equation (21), and the efficiency score of the n^{th} DMU is calculated as $\frac{\sum_{g=1}^{G} wo_g o_{gn} + \varphi_n^+}{\sum_{r=1}^{R} wi_r k_{rd} - \varphi_n^-}$. Therefore, for decreasing inefficiency, the numerator must increase and the denominator decrease. For this purpose, φ_n^+ is added to the numerator, and φ_n^- is subtracted from the denominator. Consequently, Equation (18) can be reformulated as:

$$\text{Min} \sum_{n=1}^{N} (\varphi_n^- + \varphi_n^+) \tag{23}$$

$$\text{s.t}: \frac{\sum_{g=1}^{G} wo_g o_{gn} + \varphi_n^+}{\sum_{r=1}^{R} wi_r k_{rd} - \varphi_n^-} = 1 \quad \forall n \in N \tag{24}$$

The objective function can be further simplified as follows, where φ_n is replaced with $(\varphi_n^- + \varphi_n^+)$ and, as a result, Equations (23) and (24) can be rewritten as follows:

$$\text{Min}\, Z_2 = \sum_{n=1}^{N} \varphi_n \tag{25}$$

$$\text{s.t}: \sum_{g=1}^{G} wo_g o_{gn} - \sum_{r=1}^{R} wi_r k_{rn} + \varphi_n = 0 \quad \forall n \in N \tag{26}$$

where φ_n is a positive continuous variable. Let $(wo_g^*, wi_r^*, \varphi_n^*)$ be the optimal solution, the efficiency score of the n^{th} DMU is obtained from:

$$\theta_n^* = \frac{\sum_{g=1}^{G} wo_g^* o_{gn}}{\sum_{r=1}^{R} wi_r^* k_{rn}} = 1 - \frac{\varphi_n^*}{\sum_{r=1}^{R} wi_r^* k_{rn}} \quad \forall n \in N \tag{27}$$

Finally, Equation (25) is the second function of the proposed model that is the deviation of common weights from the value calculated by the basic DEA model for centers.

3.4. Objective function 3: Social impacts

The third objective is a "social" objective, which measures the social impacts/CSR of centers, and can be formulated as:

$$\text{Max}Z_3 = w_1 \left(\sum_{n \in N} kn_n ce_n y_n\right) + w_2 \left(\sum_{n \in N} je_n de_n y_n\right) \tag{28}$$

where w_1 and w_2 are the weights of the employment opportunity and economic development, respectively. These weights are adjusted according to their importance, where $w_1+w_2=1$. In Equation (28), the first part specifies the employment opportunities gained from opening centers in line with the employment rate. In other words, kn_n and ce_n are defined as the number of employment opportunities and the employment rate (which is the number of nurses employed in the candidate location in a year) at candidate location n. By multiplying kn_n in ce_n, the employment opportunities gained from opening centers are in line with the employment rate (Sharifi et al., 2020). The second part of the equation calculates economic development, which aims to improve districts' economic, fiscal, and social conditions. It is computed as the product of the two regional development and economic values of each district. Regional development is a broad term but can be seen as a way to improve living standards and enhance well-being in the district, with the regional economic value being a measure of the benefits of a service to a district.

3.5. Mixed Robust-Fuzzy model

The model presented in Section 3.1 is formulated in the deterministic environment. Hence, in this section, we modify the model to develop a hybrid robust-fuzzy formulation that incorporates uncertainty by considering the scenarios of service time and several fuzzy parameters. In particular, the costs, number of employment opportunities, employment rate, and regional economic and regional development values are imprecise and uncertain, estimated by municipal employees using trapezoidal fuzzy numbers. In the following, we provide details of the sets, parameters, and decision variables, then update the constraints and revised objective functions. Note that Objective 2 (associated with inefficiency) does not depend on uncertainty and is exactly the same as that presented in the previous section. In the following, the set of scenarios is denoted by $s \in S$. In real settings, the service time for a patient is not deterministic because a patient's status is changeable; therefore, it is uncertain data and shown by $\widetilde{ts}^s_{mv}$ under scenario s. The parameters and decision variables used in the robust-fuzzy model are as follows:

Parameters	
$\widetilde{f}_n$	The fixed cost for opening center n obtained as a trapezoidal fuzzy number ($\widetilde{f}_n = f^1_n, f^2_n, f^3_n, f^4_n$)
$\widetilde{ts}^s_{mv}$	The service time for patient m visited by nurse v with a trapezoidal fuzzy number under scenario s ($\widetilde{ts}^s_{mv} = ts^{s1}_{mv}, ts^{s2}_{mv}, ts^{s3}_{mv}, ts^{s4}_{mv}$)
$\widetilde{co}_{ij}$	The traveling cost from node i to node j with a trapezoidal fuzzy number ($\widetilde{co}_{ij} = co^1_{ij}, co^2_{ij}, co^3_{ij}, co^4_{ij}$)
$\widetilde{kn}_n$	The number of employment opportunities at center n with a trapezoidal fuzzy number ($\widetilde{kn}_n = kn^1_n, kn^2_n, kn^3_n, kn^4_n$)
$\widetilde{ce}_n$	The employment rate at center n with a trapezoidal fuzzy number ($\widetilde{ce}_n = ce^1_n, ce^2_n, ce^3_n, ce^4_n$)
$\widetilde{je}_n$	The regional economic value at center n with a trapezoidal fuzzy number ($\widetilde{je}_n = je^1_n, je^2_n, je^3_n, je^4_n$)
$\widetilde{de}_n$	The regional development factor at center n with a trapezoidal fuzzy number ($\widetilde{de}_n = de^1_n, de^2_n, de^3_n, de^4_n$)
pr^s	The probability of scenario s
ρ	The level of desired robustness ($\rho \ge 0$)
Variables	
ar^s_i	A continuous variable used to eliminate sub-tours
st^s_{mv}	A positive continuous variable, the starting time of a visit for patient m by nurse v under scenario s
x^s_{ijv}	A binary variable, 1 if the nurse v moves from node i to node j under scenario s, and otherwise 0.

In the uncertain version of the model, Equations (1)-(8) and (10)-(11) from the deterministic model should be updated using uncertain parameters and variables. In particular, Equation (6) is rewritten incorporating uncertainty as follows:

$$st^s_{iv} + t_{ij} + \left(\frac{(\alpha-\lambda)}{(1-\lambda)}\left(ts^{s1}_{iv}\right) + \frac{(1-\alpha)}{(1-\lambda)}\left(ts^{s2}_{iv}\right)\right) - \mathscr{M}\left(1 - x^s_{ijv}\right) \le st^s_{jv} \quad \forall i,\ j \in I, v \in V,\ s \in S \tag{29}$$

where α and λ reflect a minimum confidence level and an optimistic–pessimistic parameter, respectively, that are related to the PCCP approach (with respect to *Phase 2* in Section 4.2). Constraint (29) states that service for the next patient can commence after serving the previous patient, considering uncertain scenarios related to the patient's service time. Other constraints under the uncertain environment are presented in Appendix A.

3.5.1. Objective function 1: Total Cost in uncertain environment

This objective function minimizes the total cost, including set-up and transportation costs, under fuzzy and scenario-based parameters. The first item of the cost objective function is the fixed costs for the opening centers, and the second item is the travel costs to move the nurses from one node to another under scenario s. Thus, the total cost is equal to:

$$Z^s_1 = \sum_{n\in N}\left(\frac{(1-\lambda)}{2}\left(f^1_n + f^2_n\right) + \frac{\lambda}{2}\left(f^3_n + f^4_n\right)\right)y_n + \sum_{i\in I}\sum_{j\in I}\sum_{v\in V}\left(\frac{(1-\lambda)}{2}\left(co^1_{ij} + co^2_{ij}\right) + \frac{\lambda}{2}\left(co^3_{ij} + co^4_{ij}\right)\right)x^s_{ijv} \tag{30}$$

where $\widetilde{f}_n$ and $\widetilde{co}_{ij}$ are the trapezoidal fuzzy numbers. As can be seen, the cost objective function is based on scenarios. Therefore, we use a p-robust approach to calculate the expected value of Z^s_1. According to *Phase 1* in Section 4.1, Equation (31) and Constraint (32) are proposed.

$$\mathrm{Min}E[Z^s] = \sum_{s\in S} pr^s Z^s_1 \tag{31}$$

$$\mathrm{s.t}: Z^s_1 \le Z^{s^*}_1(1+\rho) \quad \forall s \in S \tag{32}$$

where ρ is defined as the desired level of robustness and $Z^{s^*}_1$ is the optimal value of the first objective function under scenario s.

3.5.2. Objective function 3: Social impacts in uncertain environment

The third objective associated with the social impacts of centers includes the employment opportunities and economic development and is measured within the fuzzy setting as follows:

$$Z_3 = w_1\sum_{n\in N}\left(\frac{(1-\lambda)}{2}\left(kn^1_n + kn^2_n\right) + \frac{\lambda}{2}\left(kn^3_n + kn^4_n\right)\right)\left(\frac{(1-\lambda)}{2}\left(ce^1_n + ce^2_n\right) + \frac{\lambda}{2}\left(ce^3_n + ce^4_n\right)\right)y_n + w_2\sum_{n\in N}\left(\frac{(1-\lambda)}{2}\left(je^1_n + je^2_n\right) + \frac{\lambda}{2}\left(je^3_n + je^4_n\right)\right)\left(\frac{(1-\lambda)}{2}\left(de^1_n + de^2_n\right) + \frac{\lambda}{2}\left(de^3_n + de^4_n\right)\right)y_n \tag{33}$$

where w_1 and w_2 are assigned to parts 1 and 2 and reflect the importance of each part. Equation (33) incorporates uncertain parameters, where $\widetilde{kn}_n$, $\widetilde{ce}_n$, $\widetilde{je}_n$ and $\widetilde{de}_n$ are the fuzzy parameters. This objective function consists of two parts, employment opportunities and economic development.

4. Solution methodology

To deal with the complexity of the above model with uncertain parameters, a novel solution technique is proposed. As shown previously, the proposed model aims to optimize three different objectives: minimizing the total cost of the network, minimizing inefficiency, and maximizing the employment opportunities and economic development arising from opening centers. The inherent uncertainty of the model

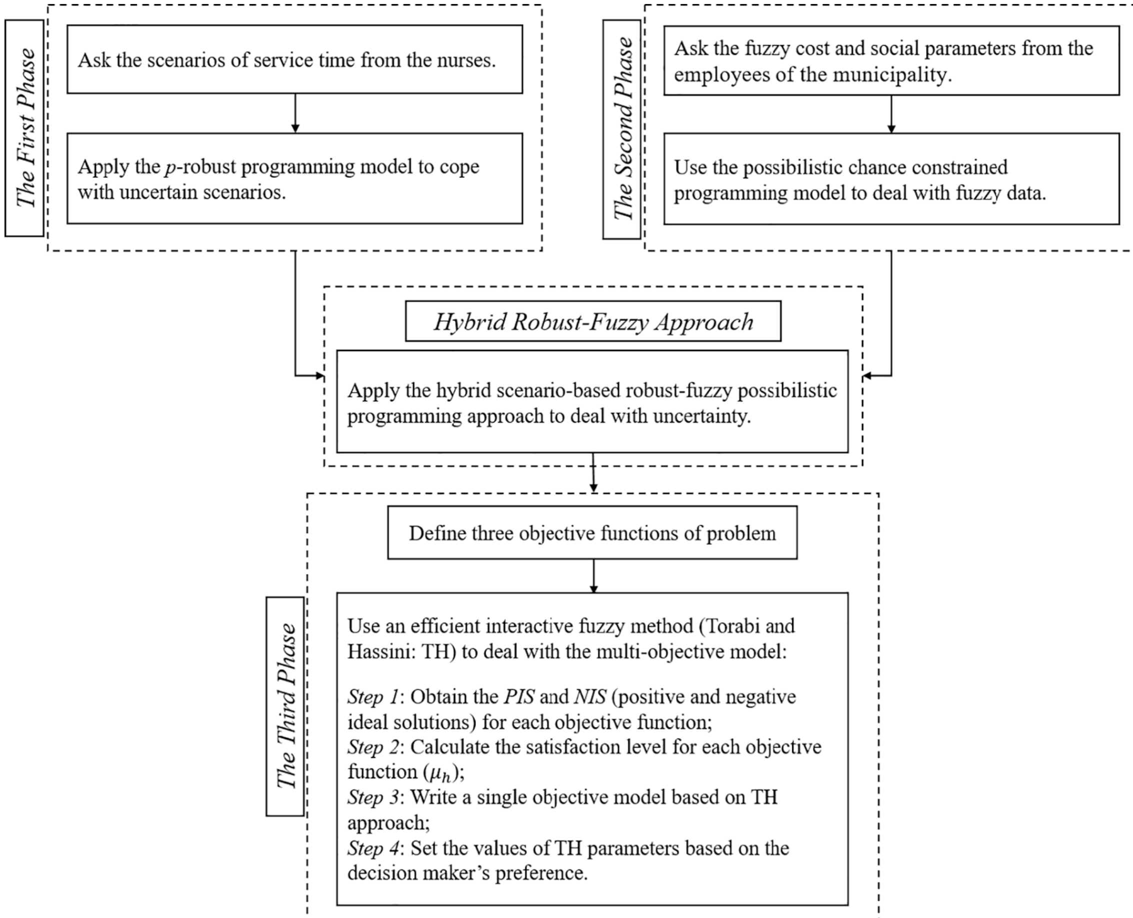

Fig. 2. Flowchart of the solution methodology including three phases: in Phase 1) to deal with the scenarios of service time, we apply the p-robust approach, in Phase 2) PCCP is utilized to cope with fuzzy parameters that are the cost and social data. Phases 1 and 2 together represent a hybrid robust-fuzzy approach to deal with mixed uncertainty, and in Phase 3) the TH approach is presented to solve the multi-objective model.

derives from the service times, costs (including the fixed cost of the opening centers and transportation cost), the number of employment opportunities for each district, the employment rate for nurses, the regional economic value, and regional development value. All these aspects further complicate the problem, and thus the resulting model. The solution approach for the DPHHC splits the solution process into three phases, as depicted in Fig. 2. *Phase 1* presents a *p*-robust model to deal with imprecise parameters by using a scenario-based approach. In *Phase 2*, the PCCP is applied to tackle the possibilistic data and possibilistic chance constraint. In *Phase 3*, the Torabi and Hassini (TH) approach is used, specifically designed for solving a multi-objective model.

4.1. Phase 1: The P-robust model

Due to the uncertainty of the service time parameter, the nurses report data as scenarios based on their knowledge and the patient status. In this regard, the *p*-robust approach is defined, which is utilized to model the DPHHC problem under uncertain scenarios. The robust approach tries to minimize the maximum regret or the expected value of cost, in which the obtained solution is optimal for realizing uncertainties in predefined sets. Therefore, we aim to build a reliable design and planning for the HHC under different scenarios. Let us consider a set of scenarios $s \in S$ in which no disruption is seen (Snyder & Daskin, 2006). In this regard, the *p*-robust model keeps the value of the objective function within 100 % and 100 $+\rho$% of the optimal objective function under each scenario, where$\rho \geq 0$ (the desired level of robustness). As mentioned previously, two strategic and tactical decisions are considered in our model simultaneously, incorporating the location-allocation and transportation decisions. The compact form of the *p*-robust programming model is as follows:

$$\text{Min } E[Z^s] = \mathbb{A}y + \sum_{s \in S} p^s \mathbb{B}x^s \tag{34}$$

$$\text{s.t: } \frac{Z^s(y, x^s) - Z^{s^*}}{Z^{s^*}} \leq \rho \quad \forall s \in S \tag{35}$$

where $\mathbb{A}$ and $\mathbb{B}$ reflect the fixed and transportation costs, respectively. And y is a binary variable corresponding to strategic decisions to be made, and x^s is a vector of assignment variable (positive continuous variable) under scenario s that is related to tactical decisions. Index s illustrates the scenario associated with the service times of patients, and p^s is the probability of scenario s. The function $E[Z^s]$ is the expected value of the objective function under scenario s, and Z^{s^*} is the optimal value resulting from solving the deterministic model under each scenario s. Note that $\frac{Z^s(y,x^s)-Z^{s^*}}{Z^{s^*}}$ is the maximum regret under each scenario.

4.2. Phase 2: Possibilistic chance constrained programming

As mentioned previously, costs and social parameters are fuzzy, and hence the PCCP approach is used to deal with fuzzy data. This approach is considered as one of the well-known fuzzy programming methods to tackle uncertain models (Pishvaee, Torabi, & Razmi, 2012), particularly possibilistic data and possibilistic chance constraints. In this context, a minimum confidence level can be obtained for decision-makers to meet the chance constraints. Here, two measures and standards can be adopted, namely possibility *Pos* and necessity *Nec*, and we now provide the details of its implementation.

Let $\widetilde{\psi}$ be a trapezoidal fuzzy number that is $\widetilde{\psi}=(\psi_1,\psi_2,\psi_3,\psi_4)$, where ψ_1 (most pessimistic) $<\psi_2$ (pessimistic) $<\psi_3$ (optimistic) $<\psi_4$ (most optimistic) and the membership function is as follows:

$$\mu(x)=\begin{cases}\dfrac{x-\psi_1}{\psi_2-\psi_1} & \psi_1\le x\le\psi_2\\ 1 & \psi_2\le x\le\psi_3\\ \dfrac{\psi_4-x}{\psi_4-\psi_3} & \psi_3\le x\le\psi_4\\ 0 & \textit{otherwise}.\end{cases} \tag{36}$$

The possibilistic values of the possibility *Pos*, necessity *Nec*, and the expected value of the fuzzy number $\widetilde{\psi}$ are calculated based on Inuiguchi and Ramík (2000) and Liu and Iwamura (1998). In the following, to fluctuate between these two optimistic and pessimistic extremes, a fuzzy compensatory measure, namely the *Me* measure, was proposed by Xu and Zhou (2013). The *Me* measure enables decision-makers to impose a level of optimism and pessimism regarding their preference by choosing any convex combination between the *Pos* and *Nec* measures:

$$Me\{e\}=\lambda\, Pos\{e\}+(1-\lambda)\, Nec\{e\} \tag{37}$$

where e denotes an event, and λ defines an optimistic–pessimistic parameter that can be changed to fall within the interval [0, 1] based on the decision-makers' preference. In this respect, when the decision-makers' preferences are extremely pessimistic ($\lambda=0$), the measure *Nec* is yield, which shows the possible level of minimum occurrence for the possibilistic event e. Alternatively, when the decision-makers' preference is optimistic ($\lambda=1$), the measure *Pos* is yield, which shows the maximum occurrence possibility level for the possibilistic event e. Consequently, according to Xu and Zhou (2013), the measure *Me* as well as the expected value of $\widetilde{\psi}$ can be obtained considering$\alpha\ge 0.5$ and$\psi\ge 0$. As a result, when$\lambda<0.5$, it needs to be close to *Nec* to back a decision-maker's pessimistic attitude. The following constraints show the re-written formulation of the *Me* measure:

$$Me\{\widetilde{\psi}\le x\}\ge\alpha\Leftrightarrow\lambda+(1-\lambda)\times\frac{x-\psi_3}{\psi_4-\psi_3}\ge\alpha\Leftrightarrow x\ge\frac{(\alpha-\lambda)\psi_4+(1-\alpha)\psi_3}{1-\lambda} \tag{38}$$

$$Me\{\widetilde{\psi}\ge x\}\ge\alpha\Leftrightarrow\lambda+(1-\lambda)\times\frac{\psi_2-x}{\psi_2-\psi_1}\ge\alpha\Leftrightarrow x\le\frac{(\alpha-\lambda)\psi_1+(1-\alpha)\psi_2}{1-\lambda} \tag{39}$$

where α is a minimum confidence level for decision-makers to meet the chance constraints. In the following, the compact form of the PCCP model can be represented as:

$$\mathrm{Min}E[Z_1]=E\left[\widetilde{A}\right]y+E\left[\widetilde{B}\right]x \tag{40}$$

$$\mathrm{Min}Z_2=y$$

$$\mathrm{Max}E[Z_3]=E\left[\widetilde{C}\right]y$$

$$\mathrm{s.t}:Dy=G$$

$$Fy\le 1$$

$$Me\left\{\widetilde{K}\ge x\right\}\ge\alpha$$

$$Hx\le I$$

$$x\le My$$

where Z_1, Z_2, and Z_3 are cost, inefficiency, and social impact functions, respectively. And $\widetilde{A}$, $\widetilde{B}$, $\widetilde{C}$ and $\widetilde{K}$ are inherently uncertain parameters that reflect the fixed costs of centers, the variable costs of the network, social parameters, and service times for the patients, respectively. Vector y represents the binary decision variable, and x is the positive continuous variable. Additionally, D, G, F, H, and I are the coefficient matrices, and M is a large constant ("Big M"), typically used in integer programming formulations. The uncertain parameters in the objective functions were replaced by their corresponding expected values $E[Z]$, while the measure *Me* was employed in the possibilistic chance constraints. Also, certain scenarios for service time are generated using a nurse's preference. Therefore, according to Equation (38), model (40) can be reformulated with model (41) as follows:

$$\mathrm{Min}\ E[Z_1]=\left(\frac{(1-\lambda)}{2}(A_1+A_2)+\frac{\lambda}{2}(A_3+A_4)\right)y+\sum_{s\in S}p^s\left(\frac{(1-\lambda)}{2}(B_1+B_2)+\frac{\lambda}{2}(B_3+B_4)\right)x^s \tag{41}$$

$$\mathrm{Min}Z_2=y$$

$$\mathrm{Max}E[Z_3]=\left(\frac{(1-\lambda)}{2}(C_1+C_2)+\frac{\lambda}{2}(C_3+C_4)\right)y$$

$$\mathrm{s.t}:Dy=G$$

$$Fy\le 1$$

$$x^s\le\frac{(\alpha-\lambda)K_1^s+(1-\alpha)K_2^s}{1-\lambda}$$

$$Hx^s\le I$$

$$x^s\le My$$

4.3. Phase 3: Torabi and Hassini approach

A major component of this research is a development of an optimization model that integrates different decisions and objectives (cost, inefficiency, and social impact) in HHC. To solve the ensuing MOLP, there are many approaches available in the literature, with several fuzzy

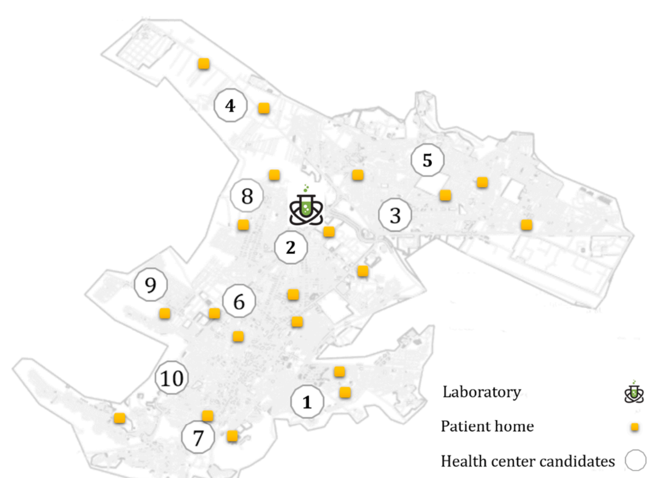

Fig. 3. A virtual map of Kermanshah in Iran. The map shows the locations of the laboratory, patients' homes (rectangles), and potential locations of centers (circles).

Table 2
The results of the case study using the parameter settings $\rho = 0.5$, $\alpha = 0.5$, $\lambda = 0.2$, and $\gamma = 0.5$.

Combination	*Cost*	*Inefficiency*	*Social Impact*	Opened Centers	Objective Function			Routes
					Cost (E + 7)	*Inefficiency*	*Social Impact*	Scenario 1
1	✓			459	2.19	3	17.28	N_1: 9,14,25,13,15,26,29,31N_2: 9,18,15,20,31N_3: 5,20,12,16,30,27,24,11,31N_4: 4,22,17,23,19,12,21,31N_5: 4,28,11,24,19,31
2		✓		1710	2.92	0	18.91	N_1: 1,15,25,31N_2: 1,30,27,31N_3: 1,13,18,31N_4: 7,12,17,23,21,31N_5: 10,21,19,27,16,20,24,18,14,12,25,28,29,22,11,26,13,31
3			✓	135	2.88	3	20.72	N_1: 3,20,15,28,27,13,22,31N_2: 3,16,11,17,25,31N_3: 1,22,17,26,18,31N_4: 5,29,19,30,23,12,15,24,31N_5: 5,25,14,12,21,26,31
4	✓	✓	✓	159	2.41	1.41	19.45	N_1: 5,11,24,31N_2: 5,20,12,14,25,17,22,26,29,31N_3: 1,19,30,15,13,18,31N_4: 9,23,16,12,27,24,21,31N_5: 5,28,11,16,31
5	✓	✓		145	2.43	1.28	19.15	N_1: 5,28,11,23,31N_2: 4,20,12,27,24,21,31N_3: 5,19,20,21,31N_4: 1,19,30,15,13,18,31N_5: 1,23,16,12,14,25,17,22,26,29,31
6	✓		✓	159	2.41	1.41	19.45	N_1: 5,17,31N_2: 5,20,12,19,30,15,13,18,31N_3: 1,23,16,12,27,24,21,31N_4: 9,14,25,17,22,26,29,30,31N_5: 5,28,11,18,25,29,31
7		✓	✓	1510	2.63	0.46	20.06	N_1: 10,14,25,17,22,26,29,31N_2: 5,20,12,19,30,15,13,18,31N_3: 5,28,11,14,31N_4: 1,23,16,12,27,24,21,31N_5: 5,23,11,31

methods being widely adopted. These methods enable decision-makers to effectively trade off their preferences concerning multiple objectives (Torabi & Hassini, 2008). Herein, an efficient fuzzy technique is used to solve the proposed MOLP model. This interactive fuzzy technique introduced by Torabi and Hassini (2008), the so-called Torabi and Hassini (TH) approach, is capable of obtaining an efficient solution and works as follows:

Let's consider the following compact MOLP form for the proposed mathematical model:

$$\text{Min} Z_1(\text{Cost}) \tag{42}$$

$$\text{Min} Z_2(\text{Inefficiency})$$

$$\text{Max } Z_3(\text{CSR})$$

$$\text{s.t} : \mathscr{A}x \le \mathscr{B}$$

$$x \in X$$

where $\mathscr{A}$ and $\mathscr{B}$ are the coefficient matrices.

Step 1: For each objective function h (h={1,2,3}), Positive Ideal Solutions (*PIS*) and Negative Ideal Solutions (*NIS*) need to be calculated. If the *PIS* of the proposed MOLP is available (Z_h^{PIS}, x_h^{PIS}), the *NIS* can be obtained from Equations (43)-(45).

$$Z_1^{NIS} = \text{Max}\left\{Z_1\left(x_2^{PIS}\right), Z_1\left(x_3^{PIS}\right)\right\} \tag{43}$$

$$Z_2^{NIS} = \text{Max}\left\{Z_2\left(x_1^{PIS}\right), Z_2\left(x_3^{PIS}\right)\right\} \tag{44}$$

$$Z_3^{NIS} = \text{Min}\left\{Z_3\left(x_1^{PIS}\right), Z_3\left(x_2^{PIS}\right)\right\} \tag{45}$$

Step 2: For each objective function h (h={1,2,3}), the satisfaction level (normalization) should be calculated under solution vector x, represented by $\mu_h(x)$. Following this, the linear membership functions are:

$$\mu_1(x) = \begin{cases} 1 & Z_1 \le Z_1^{PIS} \\ \dfrac{Z_1^{NIS} - Z_1}{Z_1^{NIS} - Z_1^{PIS}} & Z_1^{PIS} \le Z_1 \le Z_1^{NIS} \\ 0 & Z_1 \ge Z_1^{NIS} \end{cases} \tag{46}$$

$$\mu_2(x) = \begin{cases} 1 & Z_2 \le Z_2^{PIS} \\ \dfrac{Z_2^{NIS} - Z_2}{Z_2^{NIS} - Z_2^{PIS}} & Z_2^{PIS} \le Z_2 \le Z_2^{NIS} \\ 0 & Z_2 \ge Z_2^{NIS} \end{cases} \tag{47}$$

$$\mu_3(x) = \begin{cases} 1 & Z_3 \ge Z_3^{PIS} \\ \dfrac{Z_3 - Z_3^{NIS}}{Z_3^{PIS} - Z_3^{NIS}} & Z_3^{NIS} \le Z_3 \le Z_3^{PIS} \\ 0 & Z_3 \le Z_3^{NIS} \end{cases} \tag{48}$$

Step 3: According to Equations (49) and (50), a model with a single objective can be written with respect to the TH aggregation function. By changing the value of the compensation coefficient (γ), Equations (49) and (50) result in a trade-off between the minimum satisfaction level of each objective and their relative importance within the feasible district. Additionally, γ controls the minimum satisfaction level of each objective as well as the trade-off between the objectives. The following formulation determines the compensation coefficient for each objective function by γ, which helps balance[2] the optimized solution. The first term in Equation (49) is ($\gamma \times Z_0$), which calculates the minimum satisfaction level of objective function h ($Z_0 = \min\{\mu_h(x)\}$). In the second term, the aggregation of $\mu_h(x)$ is weighted by θ_h, based on the decision-maker's preference.

$$\text{Max } Z(x) = \gamma \times Z_0 + (1-\gamma)\sum_h \theta_h \times \mu_h(x) \tag{49}$$

$$\text{s.t: } Z_0 \le \mu_h(x) \quad \forall h = 1, 2, 3 \tag{50}$$

where θ_h and γ represent the relative weights (priorities) of the satisfaction level for each objective function and compensation coefficient, respectively. To have the same positive scale, these weights are determined between 0 and 1 according to the decision-makers' preferences, where $\sum_h \theta_h = 1$. Moreover, the satisfaction level of objective function h for vector x is denoted by $\mu_h(x)$. Moreover, the lower bound of $\mu_h(x)$ is defined by Constraint (50).

Step 4: Finally, to generate an efficient solution for the proposed MOLP model, the values of parameters should be set based on the decision-makers' preference.

[2] Balance is defined achieving similar satisfaction levels among the membership functions μ based on changes in γ (Torabi & Hassini, 2008).

Routes		Time (s)
Scenario 2	Scenario 3	
N_1: 4,28,20,12,26,22,17,25,13,15,16,29,31N_2: 9,14,12,21,31N_3: 5,19,23,30,27,24,18,31N_4: 5,11,24,19,31N_5: 5,11,20,15,31	N_1: 5,20,12,27,24,21,31N_2: 4,28,18,20,31N_3: 5,19,12,14,25,17, 23,13,15,30,16,29,31N_4: 5,11,15,19,31N_5: 9,22,26,24,31	13.7
N_1: 7,12,30,31N_2: 1,27,21,18,31N_3: 7,29,20,19,24,28,22,11,12,27,31N_4: 10,18,15,17,25,13,16,13,14,26,31N_5: 1,23,21,25,31	N_1: 10,29,26,13,19,31N_2: 1,12,17,20,13,28,21,31N_3: 7,16,24,30,18,27,31N_4: 7,12,11,22,25,14, 15,18,25,31N_5: 7,23,27,21,31	13.8
N_1: 5,27,23,16,13,15,12,30,25,24,15,26,28,29,21,31N_2: 3,11,17,12,14,31N_3: 1,18,26,31N_4: 1,22,20,25,31N_5: 1,19,17,22,31	N_1: 1,13,27,16,22,23,30,12,28,24,15,26,19,20,29,14,11,31N_2: 3,15,31N_3: 5,18,25,26,31N_4: 3,12,17,31N_5: 1,21,17,22,25,31	13.9
N_1: 5,11,16,31N_2: 9,23,16,12,14,25,17,22,26,29,31N_3: 1,19,30,15,13,18,31N_4: 5,28,11,24,31N_5: 5,20,12,27,24,21,31	N_1: 5,28,11,24,31N_2: 5,11,16,31N_3: 5,20,12,27,24,21,31N_4: 9,23,16,12,14,25,17,22,26,29,31N_5: 1,19,30,15,13,18,31	82.3
N_1: 5,28,20,19,31N_2: 1,19,30,15,13,18,31N_3: 4,23,16,12,14,25,17,22,26,29,31N_4: 5,11,21,23,31N_5: 5,20,12,27,24,21,31	N_1: 5,11,31N_2: 5,28,19,31N_3: 1,23,16,12,27,24,21,20,31N_4: 1,19,30,15,13,18,31N_5: 4,20,12,14,25,17,22,26,29,21,23,31	39.5
N_1: 5,11,18,30,31N_2: 5,20,12,27,24,21,31N_3: 1,23,16,12,19,30,15,13,18,29,25,31N_4: 9,14,25,17,22,26,29,31N_5: 5,28,17,31	N_1: 5,28,11,31N_2: 1,23,16,12,19,30,15,13,18,31N_3: 5,20,12,27,24,21,31N_4: 5,17,18,25,29,31N_5: 9,14,25,17,22,26,29,30,31	47.7
N_1: 5,11,23,31N_2: 1,23,16,12,27,24,21,31N_3: 5,28,11,31N_4: 10,14,25,17,22,26,29,31N_5: 5,20,12,19,30,15,13,18,14,31	N_1: 5,11,14,31N_2: 5,20,12,27,24,21,31N_3: 1,23,16,12,19,30,15,13,18,31N_4: 10,14,25,17,22,26,29,31N_5: 5,28,11,23,31	55.7

5. Experimental evaluation

The experimental evaluation in this study consists of two parts. First, we present a case study motivated by the real data in Kermanshah city in Iran. The aim here is to demonstrate the validity of our approach in a real-world setting. Second, we conduct a numerical study by varying different aspects of the problem, including sensitivity analysis with the parameter λ within the possibilistic chance constraints and a sensitivity analysis on γ in the TH approach. This second part aims to explore different problem characteristics that we may encounter in reality, and to measure the performance of our approach in these different contexts. Our proposed mathematical formulation is implemented within GAMS 29.1.0 using the CPLEX solver (https://www.ibm.com/au-en/analytics/cplex-optimizer). All computational experiments were carried out on a PC with Intel Core i7, CPU 2.67 GHz, and RAM 16 GB.

5.1. Case study

We investigate a real case study of Kermanshah in Iran within our proposed framework. The city of Kermanshah is divided into 10 main districts, an overview of which can be seen in Fig. 3. Ten locations – Districts 1 to 10 – have been chosen as potential locations for opening centers by the municipality of Kermanshah. The data for the case study (in a de-identified form) was provided by Taleghani hospital and the municipality of Kermanshah. There are 20 patients, 5 nurses, and 10 potential center candidates. Among the centers, 3 are allowed to open. Furthermore, there are 2 input factors (traffic and pollution), 2 output factors (population density and appropriate workplace), 3 scenarios, and a single laboratory. These three scenarios, each of which corresponds to a different service duration, are: pessimistic, most likely, and optimistic. These scenarios are set by a team including four nurses and one physician in the Taleghani hospital. This team decides based on patients' health conditions and medical history.

In the following, we present the results of applying our proposed model to the case study. Then, we carry out a sensitivity analysis of key parameters of interest. This analysis is particularly useful in providing valuable insights for health managers so that they can make informed decisions on the best location/s to open centers.

5.1.1. Effect of different objective weights

In this section, we solve our model to identify which locations are ideal for opening up new centers in the case study. We analyze the objective functions, total *Cost*, *Inefficiency*, and *Social Impact*, in various Combinations that are shown in Table 2. In addition, the route of each nurse (N_v) in each scenario is reported.

Combinations 1–3: Optimizing single objectives. To identify which Centers are best considering one objective, we run the model and optimize each of the three objectives, one at a time. Fig. 4a shows that Districts 4, 5, and 9 are selected as the least expensive Centers to open in Kermanshah city, whereas, if we consider *Inefficiency* or *Social Impact*, Centers 4 and 9 are excluded (Fig. 4b and c). In particular, Centers 1, 7, and 10 are ideal considering the *Inefficiency* measures (Fig. 4b), as they have low traffic, low pollution, a high population density, and an appropriate workplace. According to Fig. 4 and Table 2, Centers 7 and 10 are not inexpensive or ideal social locations; hence they are not chosen to be opened. Considering *Social Impact*, the model selects Centers 1, 3, and 5 to be opened (Fig. 4c), as these Centers (especially Center 3) have excellent employment opportunities and economic development. We see that Center 1 is ideal considering *Inefficiency* and *Social Impact*, while Center 5 has low *Cost* and excellent *Social Impact*.

Combination 4: Equal weighting of all objectives. To reiterate, the overall goal of the model is to find the best-fit locations for opening Centers so as to minimize the total *Cost* and *Inefficiency* while maximizing *Social Impact*. For this purpose, according to the steps of the TH method outlined in Section 4.3, the model is solved considering all three objectives with equal weights ($\theta_1 = \theta_2 = \theta_3$) of their satisfaction levels. The results of solving this model are shown in Fig. 5a. We see that among the 10 candidate districts in Kermanshah, three Centers, namely 1, 5, and 9, are chosen to be opened, which simultaneously leads to a minimum total *Cost*, minimum *Inefficiency*, and maximum employment opportunities and economic development. This analysis combines the first three Combinations (Combination 1 is *Cost*, Combination 2 is *Inefficiency*, and Combination 3 is *Social Impact*), where we observed that Centers 1, 5, and 9 are ideal for opening up, and Center 9 is the best of the remaining options.

Combination 5: Equal weighting of Cost and Inefficiency measures. In this setting, we optimize the *Cost* and *Inefficiency* measures and ignore *Social Impact*. This leads to three Centers being opened up, namely 1, 4, and 5 as shown in Fig. 5b. In Table 2, the value of *Social Impact* in Combination 5 is lowest compared to its values in Combinations 4 (equal weighting of all objectives), 6 (equal weighting of *Cost* and *Social Impact*), and 7 (equal weighting of *Inefficiency* and *Social Impact*), since we explicitly avoid optimizing this objective. The first (just *Cost*) and second (just *Inefficiency*) Combinations are combined in this section, which shows among all the opened Centers in those Combinations (*Cost*: 4, 5, 9 and *Inefficiency*: 1, 7, 10), that Centers 1, 4, and 5 are selected with equal weight importance (0.5) considering *Cost* and *Inefficiency*. In other words, Centers 4 and 5 have low *Cost* and reasonable levels of *Inefficiency*, while Center 1 has a low level of *Inefficiency* and reasonable *Cost*.

Combination 6: Equal weighting of Cost and Social Impacts. We now focus on total *Cost* and *Social Impact* while ignoring *Inefficiency*. Three Centers 1, 5, and 9 are opened, as shown in Fig. 5c. These Centers are also selected in Combination 4 (equal weighting of all objectives).

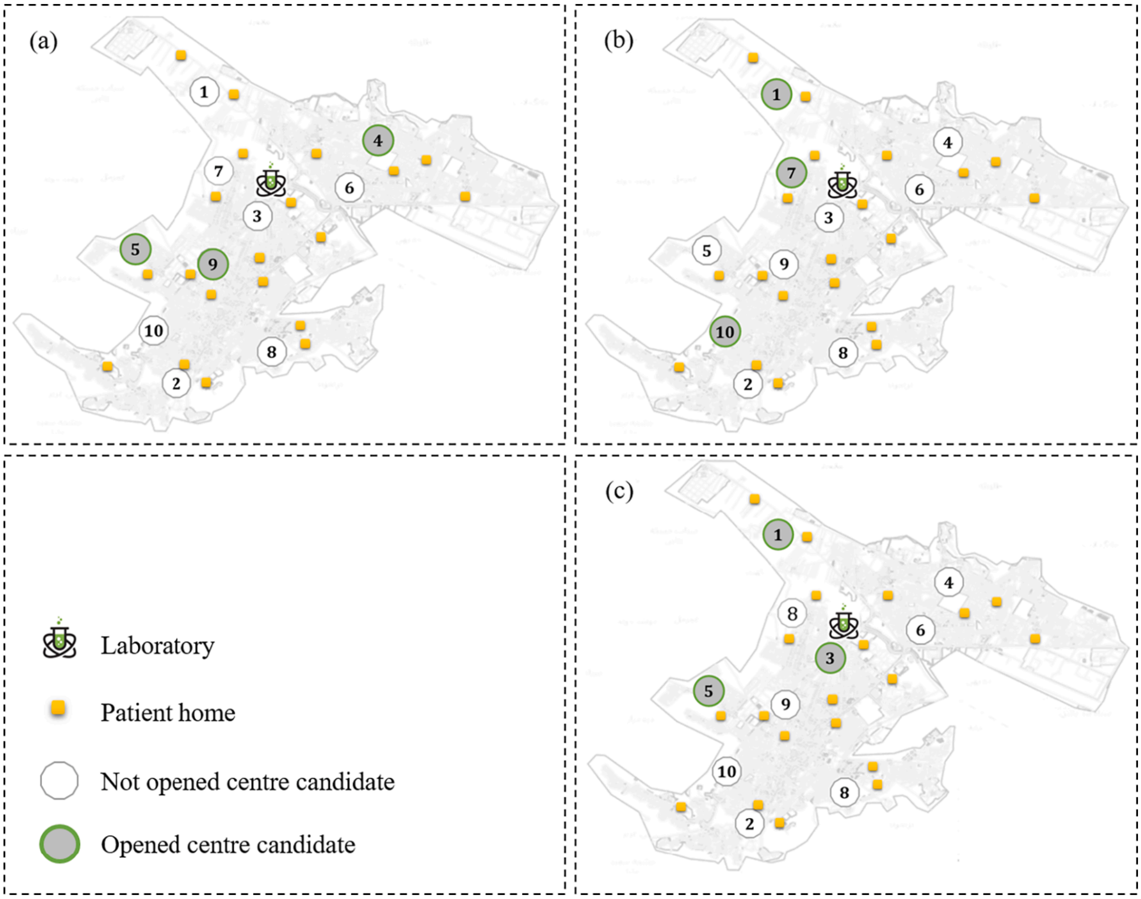

Fig. 4. Best fit locations for the centers considering only one objective function. Based on Cost: 4, 5 and 9; Inefficiency: 1, 7 and 10; Social Impacts: 1, 3 and 5 candidates are opened.

Centers 1, 5, and 9 have relatively good levels of *Cost* and *Social Impact* (Combination 6) simultaneously. Moreover, if we consider *Inefficiency* in addition to *Cost* and *Social Impact*, the same Centers are chosen for the same reasons previously discussed. Centers 1, 5, and 9 are in districts with low *Cost* of living, and Center 1 has a high *Social Impact*.

Combination 7: Equal weighting of Social Impacts and Inefficiency measures. Here, we investigate *Social Impact* and *Inefficiency* measures with equal weightings. This leads to selecting three Centers 1, 5, and 10, as seen in Fig. 5d. This analysis combines Combinations 2 (*Inefficiency*) and 3 (*Social Impact*), where Centers 1, 7, 10 and 1, 3, 5 were opened for *Inefficiency* and *Social Responsibility*, respectively. Centers 1 and 10 are very efficient, and Center 5 has a high *Social Impact*; hence these are chosen to be opened. As can be seen, the first candidate (Moallem) is selected in Combinations (1–7), which is because Moallem is located in the northwest of Kermanshah with the lowest levels of traffic. Moreover, its population density, economic development, and employment opportunities are high relative to other candidates.

This analysis shows that three objective functions can be considered in different Combinations, which allow decision-makers to decide on the best candidates for Centers. For example, if the first and second objective functions are considered based on the decision-makers' preferences and the third objective function is ignored, according to Combination 5 (*Cost* and *Inefficiency*), candidate locations 1, 4, and 5 are selected as Centers.

5.1.2. A sensitivity analysis of the case study

We further analyze the case study to understand the behavior of the model and approach. The relative importance weighting parameter (θ_h) for each satisfaction level of objective functions ($\theta_1, \theta_2, \theta_3$) is determined by the decision-makers ($\sum_h \theta_h = 1$, h= 1, 2, 3). In consultation with the decision-makers, we identified that *Cost* has a higher priority than *Inefficiency* and *Social Impact* and decided that their relative importance can be split as 0.5 for *Cost*, 0.4 for *Inefficiency*, and 0.1 for *Social Impact*. Additionally, we set the value of the compensation coefficient (γ) for the TH function to 0.5, which is a mid-point leading to a solution that is neither balanced nor unbalanced. We note that the *p*-value (ρ) of the *Cost* objective is set to 0.5, which allows the *Cost* to be up to 50 percent of the best-known *Cost* in each scenario, while the solution remains robust. The decision-makers assume that the optimistic–pessimistic parameter (λ) is equal to 0.2. When λ is<0.5, this shows that the attitude of the decision-makers is pessimistic, and their goal is to evaluate the model under pessimistic conditions. In the following, an analysis of λ is presented in Table 3, where α is set to 0.5.

First, we solve the case study with different values of λ, while the other parameters are kept constant ($\rho = 0.5, \alpha = 0.5, \gamma = 0.5, \theta_1 = 0.5, \theta_2 = 0.4$, and $\theta_3 = 0.1$). The results are shown in Table 3, where the first column shows the values of λ, the next four columns show the overall (TH) *Cost*, *Inefficiency*, and *Social Impacts* objective functions, respectively. The final column shows the time required to solve the model. We see that with increasing values of λ, *Cost* and *Social Impact* increase while *Inefficiency* is not affected (not surprising since uncertainty does not directly affect this objective). When a decision-maker's preferences are pessimistic (λ close to 0), we see a minimum "possibility" level concerning a possibilistic event, leading to the values of *Cost* and *Social Impact* being at the minimum level. Alternatively, from an optimistic viewpoint (λ close to 1), we see the opposite, where *Cost* and *Social Impact* increase.

We have seen that *Cost* and *Social Impact* are very sensitive to λ, and the attitude of decision-makers can be effectively modeled by varying this parameter. Fig. 6 shows the trade-off between the objectives by varying λ, where *Social Impact* improves and *Cost* increases with

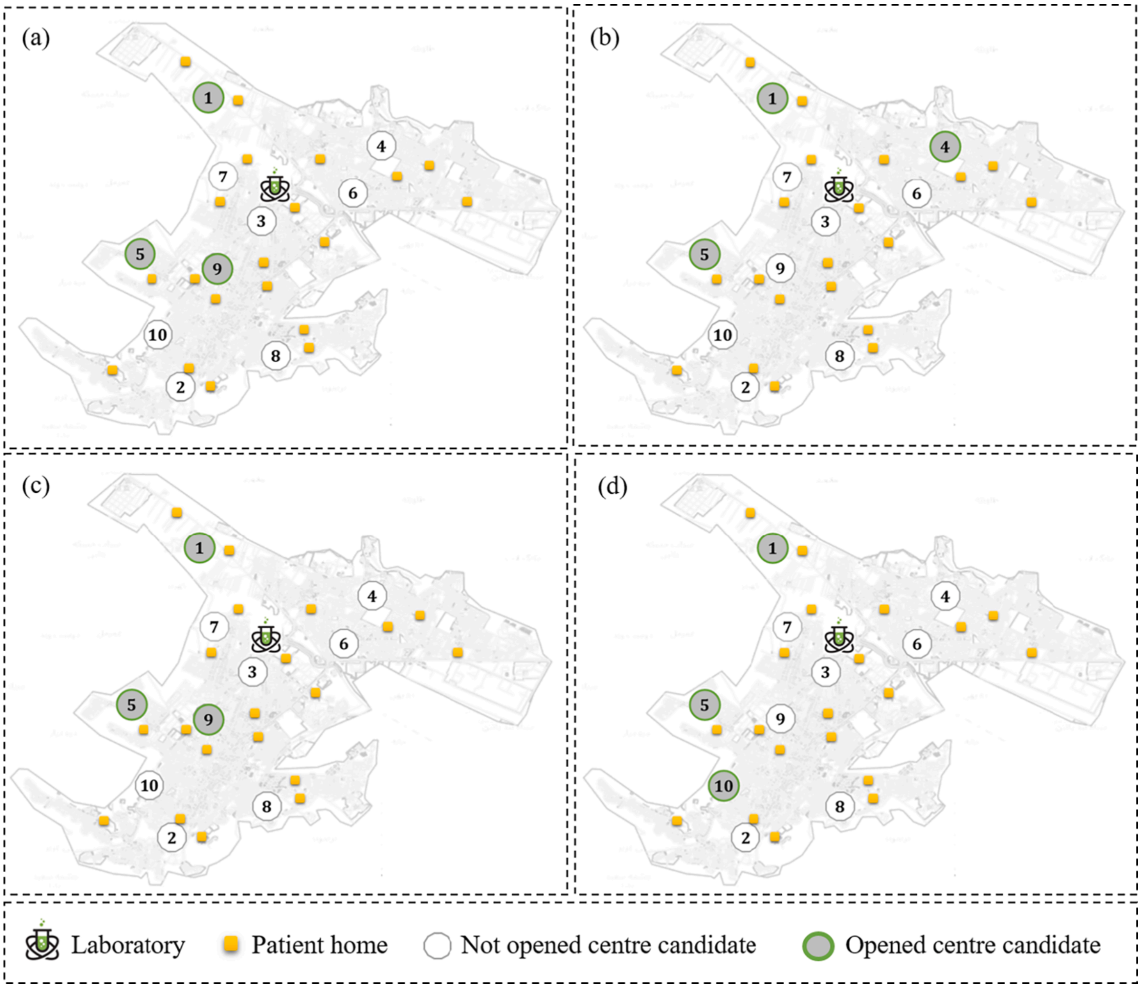

Fig. 5. Best-fit candidate locations for Centers with different Combinations of weights for three objective functions.

Table 3
An overview of performance according to the various levels of λ.

Instance	λ	Objective Function				Time (s)
		TH	*Cost*	*Inefficiency*	*Social Impact*	
1	0	0.583	2.338E + 7	1.282	17.69	207.6
2	0.1	0.581	2.387E + 7	1.282	18.42	190.8
3	0.2	0576	2.416E + 7	1.416	19.45	192.4
4	0.3	0.575	2.486E + 7	1.282	19.88	263.1
5	0.4	0.573	2.535E + 7	1.282	20.06	275.5
6	0.5	0.572	2.563E + 7	1.416	21.72	286.4

increasing λ. We see that there is no point that dominates another point. As a final note, we find that decision-makers tend to be pessimistic. In the following, we analyze the performance of the proposed model on different values of ρ in Table 4. Note here that *Inefficiency* and *Social Impact* are not dependent on the scenarios, and ρ does not affect them directly. The results are shown in Table 4, including all the objective functions and the maximum regret for the DPHHC model. These measures are calculated to examine the model performance while varying ρ in Constraint (32). This analysis is a trade-off between the p-robustness value and *Cost*. We also see that the *Inefficiency* and *Social Impact* tend to improve when the *Cost* increases.

The next parameter of interest is γ (compensation coefficient) within the TH method. Higher γ values lead to balanced solutions or similar satisfaction levels for all objective functions, while decreasing the value of γ leads to unbalanced solutions that emphasize the importance of the

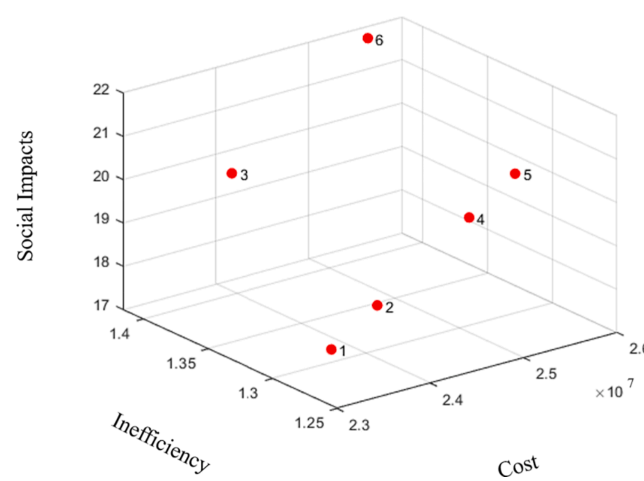

Fig. 6. Effect of λ on Cost against Inefficiency and Social Impact.

satisfaction levels of the objective functions (θ_h). Table 5 demonstrates that the analysis of the TH method aims to balance the values of the membership functions, namely *Cost*, *Inefficiency*, and *Social Impact*. In other words, decision-makers prefer to find solutions that are balanced considering the objectives. Finally, the results show that increasing values of γ lead to relatively equal satisfaction levels of just over 0.5. Moreover, as Fig. 7 shows, when the value of γ approaches 1.0, the

Table 4
An overview of performance according to the various levels of ρ.

ρ	Objective Function				Maximum Regret	Time (s)
	TH	*Cost*	*Inefficiency*	*Social Impact*		
$0 < 0.1$	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible	Infeasible
0.10	0.343	2.181E + 7	2.234	17.28	0.0008	142.1
0.15	0.458	2.378E + 7	1.416	18.19	0.0910	149.5
0.20	0.538	2.416E + 7	1.416	19.45	0.1086	897.7
0.25	0.565	2.417E + 7	1.416	19.45	0.1088	208.3
0.30	0.538	2.416E + 7	1.416	19.45	0.1086	632.1
0.35	0.578	2.436E + 7	1.282	19.15	0.1178	349.5
0.40	0.579	2.436E + 7	1.282	19.15	0.1178	219.2

Table 5
An overview of performance according to the various levels of γ.

γ	Satisfaction Level 1 (μ_1)	Satisfaction Level 2 (μ_2)	Satisfaction Level 3 (μ_3)
0–0.2	0.699	0.528	0.632
0.3–0.4	0.672	0.573	0.544
0.5	0.699	0.528	0.632
0.6	0.672	0.573	0.544
0.7	0.654	0.573	0.544
0.8–0.9	0.672	0.573	0.544
1	0.583	0.544	0.544

satisfaction levels for all objectives approach each other. Conversely, considering the vertex$\gamma = 0–0.2$ (the top point in the figure), the satisfaction levels of the objective functions (0.69, 0.63, 0.52) are unbalanced.

The final parameter of interest is θ_h, which specifies the relative weightings of *Cost*, *Inefficiency*, and *Social Impact* and prioritizes weights. The results are shown in Table 6. We consider different Combinations of the objective functions and give them weights between 0.1 and 0.7 as a measure of their importance. For example, in Combination 6, the second objective has the highest priority based on an expert's preference, and hence it is given the value of 0.7. We see as a result that *Inefficiency* is the lowest (0.464) compared to those Combinations where this objective is not a priority. As a final note, we see two additional points from the analyses conducted and the tables presented. Firstly, we are able to find the optimal solutions. Secondly, all run-times are reasonable, between 13 and 1421 s. This demonstrates that our approach is particularly suitable in practical settings.

In this paper, based on the several parameters of the problem under uncertainty, a robust-fuzzy approach was utilized to solve the problem. The robust approach used in this paper is the scenario-based robust

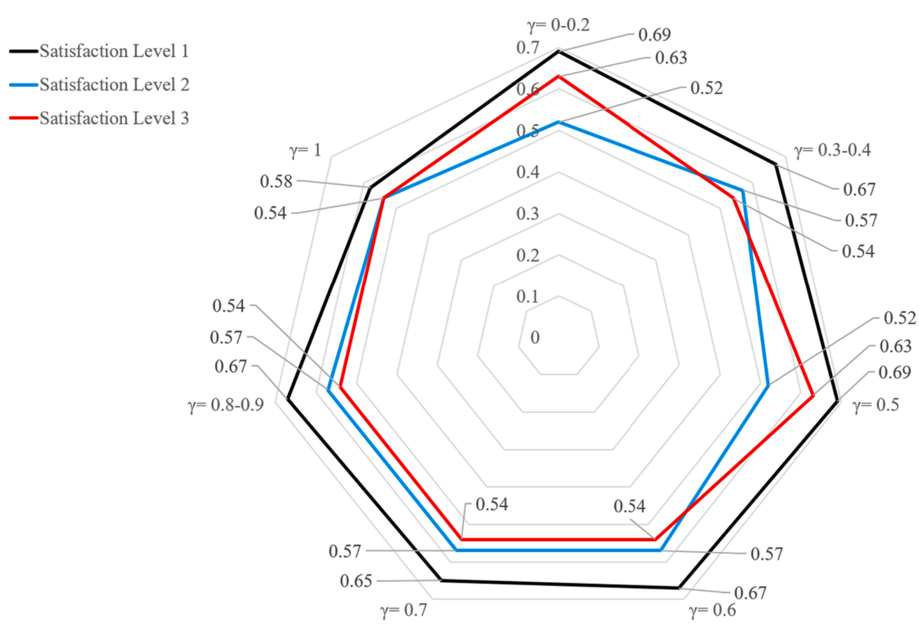

Fig. 7. Effect of γ on the satisfaction level of each objective.

Table 6
The results of the relative weightings of objectives' satisfaction levels θ_1, θ_2 and θ_3.

Combination	θ_1	θ_2	θ_3	Objective Function				Time(s)
				TH	Cost	Inefficiency	Social Impact	
1	0.50	0.25	0.25	0.581	2.416E + 7	1.416	19.45	642.8
2	0.25	0.50	0.25	0.566	2.436E + 7	1.282	19.15	201.5
3	0.25	0.25	0.50	0.574	2.416E + 7	1.416	19.45	196.7
4	0.70	0.20	0.10	0.589	2.416E + 7	1.416	19.45	932.4
5	0.10	0.20	0.70	0.587	2.629E + 7	0.464	20.06	188.2
6	0.20	0.20	0.10	0.575	2.629E + 7	0.464	20.06	254.6

approach first introduced by Kouvelis, Kurawarwala, and Gutierrez (1992). Additionally, the PCCP approach was used to deal with fuzzy parameters that can be applied to possibilistic data and provide a minimum satisfaction level for decision-makers. By using this approach and applying it to the proposed model, its effectiveness was evaluated. The model is also measured by real case study data and the results are presented in the relevant tables.

All the results obtained are exact, where the gap is always 0.00 %. Hence, it can be concluded that the answers are accurate, and the GAMS software achieves optimal results within reasonable computational times, thereby requiring no need for heuristic and metaheuristic algorithms for the real case. It should be noted that, due to the circumstances of the ambiguous parameters of the problem and their inherent nature, this approach was proposed and proved effective.

The proposed robust-fuzzy approach allows uncertain parameters to be adjusted as the parameter values are realized. This approach has the flexibility of adjusting the level of conservativeness of solutions while preserving the computational complexity of the nominal problem. This method offers full control of the degree of conservation for every constraint. Additionally, this approach protects against the violation of constraints deterministically when only a pre-specified number of the coefficient changes. This advantage can be observed in the results of the solution to the model, in which all the results from the proposed approach are solved efficiently. Moreover, the results demonstrate that the performance of the developed approach is similar to the result of Torabi and Hassini (2008). Furthermore, this method is more robust and reliable because it is able to set balanced and unbalanced solutions based on the preferences of decision-makers, and the solutions of this method are consistent with the decision preferences (i.e., there is consistency between the satisfaction level μ and weight vector θ_h). In addition, the TH method is more flexible as it can find various efficient solutions for instances with a certain weight vector θ_h through changing the γ, and it is particularly suited to solving multi-objective MILP models.

5.2. Investigating problem characteristics

In the previous section, we demonstrated that the proposed mathematical model is effective at solving a real-world problem. We also see that there is sufficient flexibility to allow different solutions to be found depending on the specific requirements of decision-makers. However, a key aspect that warrants further investigation is how the proposed approach works when varying different characteristics of the DPHHC problem. Hence, this section considers six numerical examples with different sizes and parameter settings, and details of how the problems are generated. Then, we conduct an experimental evaluation of the performance of the mathematical model in solving these problem instances.

5.2.1. Generating problem instances

The characteristics of the problem instances, including the number of patients (*M*), nurses (*V*), center candidates (*N*), input factors (*R*), output factors (*G*), and scenarios (*S*), are shown in Table 7. For each instance, the social parameters, service time, and cost parameters are the trapezoidal fuzzy numbers from which the second (pessimistic value ψ_2) and third (optimistic value ψ_3) values of each fuzzy number are generated based on uniform distribution in the range [lower limit, upper limit]. Experts kindly provided the lower and upper limits based on their experience and knowledge. Two values (ψ_1: most pessimistic value and ψ_4: most optimistic value) of each fuzzy number are obtained based on the method proposed by Jiménez (1996). In other words, we suppose that $\widetilde{\psi}$ is a trapezoidal fuzzy number that is $\widetilde{\psi} = (\psi_1, \psi_2, \psi_3, \psi_4)$, where $\psi_1 < \psi_2 < \psi_3 < \psi_4$. First, the value of the pessimistic (ψ_2) and optimistic points (ψ_3) are generated randomly, followed by the value of the most pessimistic (ψ_1) and most optimistic points (ψ_4). These are calculated using the following equations (Jiménez, 1996):

$$\psi_1 = (1 - \delta_1)\psi_2 \tag{51}$$

$$\psi_4 = (1 - \delta_2)\psi_3 \tag{52}$$

where (δ_1, δ_2) are considered in a range of 0.1 to 0.3 by experts (Uniform (0.1,0.3)).

5.2.2. Results

Table 8 shows the results of the proposed approach on the problem instances. The table shows the TH objective value, satisfaction levels, processing time, and gaps for each value of γ considering different problem sizes. We see that the TH function is not very sensitive to changes of γ. For example, in Instance 3 with γ between 0.6 and 0.9, an appropriately unique balanced solution is produced. This is further demonstrated in Fig. 8, which shows how increasing γ impacts three different satisfaction levels. By increasing γ, we see that all satisfaction levels approach the value of 0.55. The important point is that Instances 5 and 6 are considerably large, requiring significant processing times, so we consider a gap of 0.5 % to obtain solutions in reasonable times. Nonetheless, we still see that solutions of a reasonable quality cannot be found for the largest Instance (6). Hence, the current solution approach is limited in its ability to scale to deal with a large number of patients, nurses, and centers. Additionally, the optimistic–pessimistic parameter (λ) can be considered as one of the more important parameters, so we carry out a sensitivity analysis of it, the results of which are presented in Table 9. Similar to the case study, when the robust-fuzzy model is solved with the lower value of λ, *Cost* and *Social Responsibility* are also low. On the other hand, the opposite is true when increasing the value of λ. Moreover, the best value of *Inefficiency* will remain fixed because λ does not directly affect this objective. For example, in Instance 3, when λ approaches 0.5, the values of *Cost* and *Social Impact* increase while the value of *Inefficiency* stays fixed. In the other instances, *Inefficiency* changes only slightly due to changes in some of the variables.

As mentioned previously, the TH approach is used for the MOLP model to find a trade-off between the *Cost, Inefficiency,* and *Social Impact* objective functions. In this approach, the weightings of the *Cost*, *Inefficiency*, and *Social Impact* satisfaction levels are shown by θ_1, θ_2, and θ_3, respectively. As seen in Table 10, we consider three combinations of the relative weights of objectives and prioritize them in each Combination. For example, if decision-makers want to have an efficient HHC network, θ_2 should be given a higher weight (similar to Combination 2 of Instance 1, where the value of *Inefficiency* is 0). Therefore, the results

Table 7
The numerical instances.

Instance	Node(*I*)	Patient(*M*)	Nurse(*V*)	Center Candidate(*N*)	Opened Center	One[1] Service	Two[2] Services	Input Factor(*R*)	Output Factor(*G*)	Scenario
1	15	9	3	5	2	6–10	5,11	2	2	2
2	18	12	3	5	3	6–11	12–14			
3	25	15	4	9	3	10–22	23,24			
4	30	18	4	11	4	14–29	12,13			
5	45	28	6	16	6	23–44	17–22			
6	60	35	7	24	7	25–56	57–59			

[1] The set of patients who need one medical service.
[2] The set of patients who need two medical services.

Table 8
Sensitivity analysis on γ value in the TH method. A "-" implies that no solution was obtained and the time limit expired. For instances with ranges of γ, we report the average values for the TH objective, time, and gap measures.

Instance	γ	TH Function	Satisfaction			Time (s)	Gap%
			Level 1	Level 2	Level 3		
1	0.00	0.643	0.999	0.935	0.000	1.044	0.000000
	0.05	0.611	1.000	0.935	0.000	2.266	0.000000
	0.10	0.585	0.341	1.000	0.494	2.567	0.000000
	0.20–0.60	0.504	0.342	1.000	0.494	23.28	0.000000
	0.70	0.422	0.341	1.000	0.494	5.743	0.000000
	0.80–0.90	0.382	0.342	1.000	0.494	33.79	0.000000
	1.00	0.342	0.342	0.342	0.494	11.05	0.000000
2	0.00–0.10	0.701	0.677	0.741	0.693	21.20	0.000000
	0.20	0.698	0.676	0.741	0.693	23.77	0.000000
	0.30–0.90	0.687	0.677	0.741	0.693	73.58	0.000100
	1.00	0.677	0.677	0.677	0.693	19.06	0.000000
3	0.00–0.10	0.750	1.000	0.852	0.398	434.1	0.000000
	0.20–0.50	0.636	0.994	0.852	0.436	4691	0.000016
	0.60–0.90	0.563	0.540	0.712	0.652	2320	0.000004
	1.00	0.539	0.539	0.539	0.652	522.3	0.000000
4	0.00–0.05	0.783	1.000	0.678	0.681	2850	0.000035
	0.10	0.775	0.999	0.678	0.681	2459	0.000000
	0.20–0.40	0.765	1.000	0.678	0.681	9569	0.000004
	0.50	0.732	0.999	0.678	0.681	1070	0.000000
	0.60	0.728	0.742	0.736	0.723	859.2	0.000015
	0.70–0.90	0.725	0.743	0.736	0.723	5502	0.000005
	1.00	–	–	–	–	–	–
	0.00–0.50	0.674	0.795	0. 916	0.312	207.3	0.000233
5	0.10	0.638	0.794	0.916	0.312	1912	0.000538
	0.20	0.613	0.469	0.882	0.597	1002	0.000917
	0.30–0.40	0.586	0.468	0.882	0.597	990.5	0.011152
	0.50	0.559	0.469	0.882	0.597	1165	0.020526
	0.60	0.541	0.468	0.882	0.597	1025	0.027894
	0.70	0.556	0.552	0.839	0.548	999.4	0.000870
	0.80–0.90	0.539	0.523	0.839	0.548	1031	0.000352
	1.00	0.480	0.480	0.791	0.496	1036	0.043126
6	0.00–0.30	0.731	0.775	0.781	0.667	629.4	0.000099
	0.40	0.657	0.607	0.768	0.695	3173	0.054662
	0.50	0.704	0.775	0.781	0.667	1032	0.000911
	0.60	0.700	0.688	0.737	0.723	1030	0.000070
	0.70–0.80	0.696	0.689	0.737	0.723	1026	0.004729
	0.90	0.692	0.690	0.737	0.723	2989	0.000158
	1.00	0.689	0.689	0.689	0.723	1063	0.000421

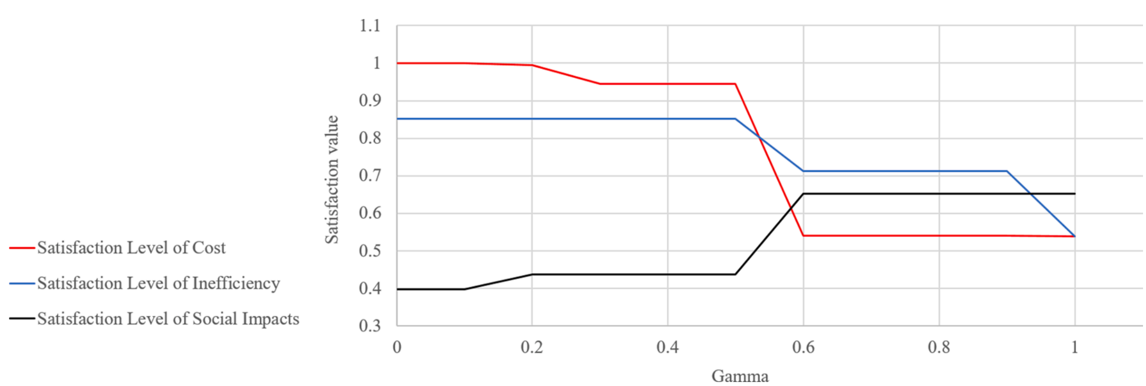

Fig. 8. The effect of γ on the satisfaction level of each objective function in Instance 3.

show that each objective function with a larger value of θ_h has a greater improvement (the value of the improved function is highlighted in each Combination) compared to other functions. In this section, we could find optimal solutions in most cases, particularly in small and medium sizes of instances. For some large-scale problems where the solutions are not provably optimal, the gaps are very close to 0. In future research, approaches like metaheuristics and hybrid approaches such as matheuristics can be of great potential for very large size problems.

6. Conclusion

Home health care centres are increasingly playing an important role in improving health care systems. The sustainable and efficient design of an HHC can significantly impact health care services by reducing costs and inefficiency and increasing the positive social impact. This paper presents a comprehensive multi-objective efficient and sustainable optimization model to tackle this problem. Two main measures, DEA and CSR, are included in this study. The DEA measure inserted in the HHC network makes it possible to reduce the inefficiency of centres. In

Table 9
Sensitivity analysis on λ value in the robust-fuzzy method. A "-" implies that no solution was obtained and the time limit expired.

Instance	λ	TH Function	Objective Function			Time (s)	Gap%
			Cost	*Inefficiency*	*Social Impact*		
1	0.1	0.634	2.341E + 8	0.240	11.57	3.117	0.000000
	0.2	0.477	2.736E + 8	0.000	11.93	7.419	0.000000
	0.3	0.658	3.212E + 8	0.240	12.38	0.920	0.000000
	0.5	0.518	3.986E + 8	0.000	13.10	2.412	0.000000
2	0.1	0.692	2.572E + 8	0.517	11.93	46.70	0.000000
	0.2	0.690	3.002E + 8	0.517	12.35	13.01	0.000000
	0.3	0.697	3.433E + 8	0.517	12.77	27.45	0.000000
	0.5	0.648	4.002E + 8	0.794	13.53	587.7	0.000067
3	0.1	0.702	3.538E + 8	0.442	17.80	1437	0.000155
	0.2	0.590	4.084E + 8	0.442	18.12	3320	0.000081
	0.3	0.635	4.741E + 8	0.442	18.75	175.1	0.000000
	0.5	0.697	6.055E + 8	0.442	20.00	439.3	0.000003
4	0.1	0.590	4.084E + 8	0.442	18.12	8139	0.000070
	0.2	0.732	5.506E + 8	1.284	24.52	1074	0.000014
	0.3	0.734	6.384E + 8	1.284	25.28	3467	0.000000
	0.5	–	–	–	–	–	–
5	0.1	0.648	7.428E + 8	0.984	35.71	1112	0.000221
	0.2	0.559	8.698E + 8	0.883	37.00	1165	0.020526
	0.3	–	–	–	–	–	–
	0.5	–	–	–	–	–	–
6	0.1	0.707	8.607E + 8	1.999	41.68	1070	0.000120
	0.2	0.704	1.003E + 9	1.705	42.92	1032	0.000911
	0.3	0.687	1.152E + 9	1.705	44.26	1078	0.000188
	0.5	0.732	1.420E + 9	1.270	46.95	1045	0.000055

Table 10
The results of the relative weightings of objectives in three Combinations: (I) $\theta_1=\theta_2<\theta_3$, (II) $\theta_1=\theta_3<\theta_2$, and (III) $\theta_2=\theta_3<\theta_1$ for all instances.

Instance	Combination	Objective Function			Time (s)	Gap %
		Cost	*Inefficiency*	*Social Impact*		
1	I	2.777E + 8	0.240	11.977	7	0
	II	2.736E + 8	0.000	11.938	9	0
	III	2.656E + 8	0.129	11.900	8	0
2	I	3.002E + 8	0.517	12.355	26	0
	II	2.893E + 8	0.517	11.979	16	0
	III	2.893E + 8	0.517	11.979	16	0
3	I	4.359E + 8	2.991	18.516	30	0
	II	4.084E + 8	0.442	18.126	43	0
	III	4.068E + 8	0.442	18.100	92	0
4	I	5.915E + 8	3.990	24.934	1587	0
	II	–	–	–	–	–
	III	5.506E + 8	1.284	24.527	25.109	0
5	I,II,III	–	–	–	–	–
6	I	1.014E + 9	1.999	43.022	1876	0
	II	1.021E + 9	1.270	42.526	2020	0
	III	1.003E + 9	1.705	42.929	5376	0

CSR, the opening of a new centre in each district not only creates employment opportunities for nurses as human capital, but also increases the economic development in less developed districts. Therefore, the motivation is to provide a feasible approach that can assist stakeholders in identifying the best locations for opening centres. To this end, we conduct a numerical study consisting of two parts. The first is a real case study of the Kermanshah province in Iran, and the second is to understand how the approach scales and deals with varying problem characteristics.

The results demonstrate that practically viable solutions can be found by using the proposed approach, and in reasonable time frames. That is, considering several characteristics of centres (e.g., population, living costs, pollution levels), the proposed model is able to identify a subset of potential locations which are typically the best locations for centres. Moreover, the decision-makers are able to test different scenarios (e.g., prioritizing inefficiency over cost or social impact, for example), leading to different choices for the opening of centres. A study of the different problem characteristics, particularly increasing numbers, shows that our approach scales well.

The managerial implications for health networks in terms of improving collaboration and coordination with home health care services should be complemented by parallel actions by public authorities in order to be effective during an epidemic. Furthermore, if governmental organizations want to decide how to allocate their workers to patients and distribute drugs in future health crises, they will need to develop their health care services and logistics abilities vastly. This needs expertise in proper medicine techniques, logistics planning, potential suppliers, and quality guarantees. Creating these abilities can either be performed internally or, more efficiently, by depending on stand-by professional groups, including logistics services, and home health care systems set up in response to a severe crisis. On the other hand, owing to the dynamic nature of the problem, most of the information on aspects such as the established cost of health centres and the times for services exists in an uncertain environment that is considered here. This shows that this design and proposed approach are useful for policymakers and governments in a real situation. These teams need to support operating performance at regional levels in addition to strategic decision-making.

While we see that the proposed mathematical modeling is effective, it is just an initial step towards tackling HHC problems, and there are a number of potential limitations. For example, one important factor is the approaches to scale in dealing with very large-scale problems, where time considerations also become important (e.g., solving multiple scenarios quickly). Incomplete approaches like metaheuristics and hybrid approaches such as matheuristics may have great potential in such situations. Furthermore, when increasing the number of scenarios, scenario reduction approaches can usefully be used. Given the uncertain aspects of the problem, other methods tailored to deal with uncertainty, such as stochastic programming, can also be of great benefit. Finally, the problem itself can be extended in several ways. For instance, disruptions to the HHC network can pose problems if some locations are affected (such as in earthquakes), leading to increased demands and closure of routes that require additional resiliency measures. Another example is where matching a nurse's skills levels to the requirements of patients may be of significant interest.

The proposed model can be implemented to care for patients with Covid-19. However, if some patients have tested positive for Covid-19, to reduce the transmission rate of the virus, the model can be appropriately modified as part of a future study. Some aspects to consider in this context are whether Covid-19 patients might need to be visited only by certain nurses who are not allowed to treat other patients, in which case nurses need to be categorized. In such circumstances, the network costs increase, but at the same time lead to increased patient satisfaction and help to reduce death rates.

CRediT authorship contribution statement

Mahdyeh Shiri: Conceptualization, Writing – original draft, Methodology, Software. **Fardin Ahmadizar:** Conceptualization, Formal analysis, Writing – review & editing, Supervision. **Dhananjay Thiruvady:** Conceptualization, Formal analysis, Writing – review & editing, Supervision. **Hamid Farvaresh:** Conceptualization, Formal analysis, Writing – review & editing.

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.

Appendix A

$$ar_i^s - ar_j^s + cap_v x_{ijv}^s \leq cap_v - d_j \quad \forall v \in V,\ i,\ j \in I,\ s \in S \tag{A1}$$

$$\sum_{j \in I} \sum_{v \in V} x_{mjv}^s = \beta_m \quad \forall m \in M,\ s \in S \tag{A2}$$

$$\sum_{i \in I} x_{imv}^s - \sum_{j \in I} x_{mjv}^s = 0 \quad \forall v \in V, m \in M,\ s \in S \tag{A3}$$

$$\sum_{n \in N} \sum_{m \in M} x_{nmv}^s = 1 \quad \forall v \in V,\ s \in S \tag{A4}$$

$$\sum_{i=n+1}^{m+n+1} x_{ihv}^s = 1 \quad \forall v \in V, h \in H,\ s \in S \tag{A5}$$

$$a_m \leq st_{iv}^s \leq b_m \quad \forall i \in I, m \in M, v \in V,\ s \in S, i = m \tag{A6}$$

$$\sum_{m \in M} d_m \sum_{j \in I} x_{mjv}^s \leq cap_v \quad \forall v \in V,\ s \in S \tag{A7}$$

$$\sum_{i \in I} \sum_{v \in V} x_{niv}^s \leq \mathscr{M} y_n \quad \forall n \in N,\ s \in S \tag{A8}$$

$$x_{ijv}^s,\ y_j \in \{0, 1\}, st_{iv}^s \geq 0 \quad \forall i,\ j \in N,\ v \in V,\ s \in S \tag{A9}$$

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