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Health care network design with multiple objectives and stakeholders

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Abstract This paper aims to address the problem of locating/upgrading health care facilities with appropriate service levels while considering the preferences of all stakeholders mapped across a hierarchical decision network. To this end, an extended network goal programming model is adapted to ensure that a mix of balance and optimisation is attained in order to offer the decision that best satisfies the objectives of the national health care system, which are: network coverage, service level, network cost, and social impact of health centres. In addition, due to the highly uncertain environment of the health care systems, the robust counterpart of this model using the budget-of-uncertainty approach is developed in order to analyse the health care network's performance to deal with uncertain parameters such as the national allocated budget and social impact. Key parameters which indicate the level of non-compensation between objectives, level of non-compensation between stakeholders, and level of centralisation in the health network along with the uncertainty budget are utilised to analyse the dynamics of decision network. The effectiveness of the model is demonstrated through use of a case study. The best-worst method is used to select a number of appropriate potential projects that serve as an input for the proposed model. To highlight the practical implications, different parametric analyses under both deterministic and uncertain environments are conducted. In addition, these experiments explore the compensatory behaviour between objectives and stakeholders in the network. Finally, some managerial insights are provided arising from the analytical results.

Keywords OR in health services · Multiple stakeholders · Robust optimisation · Hierarchical decision network · Extended network goal programming

1 Introduction

Health care systems may require a variety of resources such as medicines and medical equipment, personnel, care facilities and, last but not least, funds in order to offer a satisfactory level of health care services. Having access and fairly allocating these resources may become more challenging in the time of global crisis

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such as the COVID-19 pandemic (Ma et al, 2022). During this pandemic, medical facilities around the world were not adequately prepared for the enormous challenges posed by the daily surge of COVID-19 patients, the lack of adequate personal protective equipment, and insufficient numbers of medical personnel. Governments have attempted to mitigate the pandemic's impact, but the measures taken have not always been effective in preserving access to and quality of health services at pre-pandemic levels (Tuczyńska et al, 2021). Moreover, the urgent allocation of resources and personnel towards establishing COVID-19 facilities resulted in compromises to essential non-COVID-19 services, exacerbating the challenges faced by those in need (Pujolar et al, 2022; Kumari et al, 2020; Kc et al, 2020).

In essence, providing health care services at a satisfactory level to all people may not be attainable for a very simple reason: the available resources cannot satisfy the growing demand for health care services (Ransom and Olsson, 2017). Hence, allocating these resources, which is often called 'strategic resource allocation' in an efficient and equitable manner will always be an immense challenge for all the stakeholders involved in a health care system (Hasani and Sheikh, 2023; Kluge, 2007; Rice and Smith, 2001). Indeed, the methodological approaches used to address strategic resource allocation have faced a serious challenge due to: (i) intricate relationships between the decisions and their outcomes as all stakeholders' conflicting goals involved at the decision making process can never be simultaneously fulfilled; (ii) the impact of the decision outcomes on service quality dimensions, and consequently to human health; and (iii) the ethical and social responsibilities due to the fact that health care services are perceived as a human right(Angelis et al, 2017).

Access to health services is generally more limited for people living in poorer countries compared to those in wealthier countries, and even within countries, individuals with lower income levels often have reduced access to health services (Peters et al, 2008). In recent years, many developing countries have been reforming their health care systems and increasing funding to achieve more social justice despite the contradiction between involved stakeholders' goals. The aim, of course, is to improve the accessibility of people to the health care system (Han, 2012). However, challenges in ensuring the provision of high-quality health care remain (Chukwu and Nnogo, 2022). This phenomenon can occur due to many reasons. But the fundamental reason is the negligence of other stakeholders' preferences whom may be affected by the outcomes of decisions. The decisions are generally made by governmental authorities without fully taking into consideration other stakeholders. It is often the case where imbalanced solutions are produced that governmental authorities fail to take the needs of all stakeholders into consideration in a fair and balanced way. More importantly, in some situations there is a danger that decisions are made in the absence of any formal analysis and modelling. In this case, it is hard to imagine that the expected outcome decisions will be the most effective ones (Shahid et al, 2019).

Often the government is not the sole stakeholder in this context. Many other stakeholders whom are potentially connected over a hierarchical decision network are involved, while the government is at the top of the decision network hierarchy. This is particularly the case in countries with nationalised health care systems. As such stakeholders, we can name governors, municipalities, city councils, and non-governmental organisations, each with a variety of interests and preferences (Angelis et al, 2017). In addition, the interest and preferences of stakeholders might be influenced not only by the government, but also by other neighbourhood stakeholders. For instance, providing a good level of health care services to one small community may raise the expectation of the neighbouring regions.

The impact of a health care project on developing a neighbouring area can be significant. A well-functioning health care system can improve the health and well-being of the population in the area, which can have positive effects on economic and social development. The opening of centers that provide employment opportunities for medical staffs can enhance the pace of regional employment, which can have a positive impact on regional economic and employment growth, particularly in underdeveloped districts (Shiri et al, 2023). Moreover, a health care system can attract investment and talent to the area, which can lead to the growth of the local economy. It can create jobs, increase demand for goods and services, and promote innovation (McKee et al, 2011; Jagrič et al, 2021; Jagrič et al, 2022). The social impact, which has received relatively little attention in the literature, pertains to compelling non-governmental organisations to prioritise employment opportunities and economic development for local communities due to the social repercussions of their operations (Sharifi et al, 2020; Zhalechian et al, 2016). We utilise the concept of "Social Impact" to evaluate the possible social impacts linked with a potential health care project. Social impacts refer to the concerns that may affect individuals and communities residing in the vicinity of the project. These impacts could include changes in access to and quality of infrastructure, services, and health care facilities, as well as alterations in livelihoods, such as the impact on people's jobs, properties, or businesses.

The health care resource allocation problems have potential to become very complex as each activity undertaken by different stakeholders may involve some degree of uncertainty that may arise from a variety of sources (Han et al, 2019). Without taking into consideration the uncertainty, some negative consequences for decision-making, quality of care, and patient management are inevitable (Pomare et al, 2019). To ensure the stability of decisions made and their outcomes in an uncertain environment, the preferences of all the stakeholders and their potential influence on each other should be taken into account. In another words, the methodology should be able to ensure that a combination of balance and efficiency of the multiple stakeholders and objectives involved are considered while accounting for the preferences of stakeholders that are subject to a degree of uncertainty. Incorporating uncertain parameters into the model allows for a more realistic and robust analysis of health care network design. It helps to identify health care facilities that are most likely to remain effective under a range of conditions and provides a more comprehensive understanding of their potential impact on the surrounding community.

Last but not least, in the modern era of technology and advances in medicine, health care systems have to constantly move forward in order to provide a service fit for the future (NHS England, 2020). To this end, in order to develop a comprehensive and integrated plan for the delivery of health care services in a given geographic region as part of the strategic health care planning (Winston et al, 2012), resources such as upgrading/downgrading facilities and budget funding should be planned according to the current and future projected requirements. For instance, in order to decentralise the health decision network, each health care centre may be permitted to consider reinvestment strategies. More precisely, the net revenue of each health centre obtained at each time period can be used to upgrade the level of service in the subsequent periods. This sort of modelling can aid the decision makers to find the best health care service locations at each time period and allocate appropriate services in order to promote the regional development and better satisfy the health service requirements.

In line with the broad health care context, this study introduces a novel technique to incorporate multiple stakeholders' preferences using an extended network goal programming technique proposed by Jones et al (2016). Although a location–allocation health care model is not in itself novel, most research has focused on a single objective model rather than multiple objectives (Zhang et al, 2016). To fill this gap, we have considered some common objectives in the health care such as cost and service coverage along with the social impact of the health care services, which has received little attention in the health care decision modelling literature (Shiri et al, 2023). Incorporating the social impact may facilitate the promotion of sustainable development. Furthermore, the majority of models have assumed that all the parameters of the system are deterministic which is not aligned with the nature of many health care systems. To address this gap, the uncertain environment of the health care system, robust optimisation which has rarely employed in the literature of health care (Ahmadi-Javid et al, 2017) is utilised. Finally, a dynamic location-allocation model including some practical yet interesting features such as reinvestment strategies is developed. The aim is to help the decision maker to select the best development projects for each region over different time periods. In order to better manage the budget and to investigate the effect of decentralised budget allocation, all health care centres are allowed to upgrade their health services for future periods using their net revenue.

The remainder of this paper is organised as follows: Section 2 presents a review on resource allocation in health care. Section 3 describes the problem and the proposed deterministic extended goal programming model. Section 4 details the robust counterpart of the deterministic model along with some analytical insights. A description of an Iranian province's health care network system is presented in Section 5. Section 6 presents the analytical results of the proposed methodology. Section 7 draws conclusions.

2 Literature review

In this section a brief overview of the relevant studies in the area of health care facility location and its extensions is given. To this end, the relevant literature is investigated with regards to the following aspects: (i) Location-allocation models and their contribution to health care; (ii) Multiple objective health care problems and utilising the goal programming technique for health care; (iii) functioning of health care systems under an uncertain environment; (iv) the gap of the literature addressed in this study along with its contributions.

2.1 Location-allocation models

Location–allocation models have been long used as decision support tools for health care network planning (Daskin and Dean, 2004). The purpose of location-allocation models is to concurrently determine optimal health facility locations and the assignment of patients or health care practitioners to open facilities (Syam and Côté, 2010). Three classic location-allocation models (i.e. set covering, maximal covering and p-median model) are the primary origin of almost all the health care facility location models.

The models can also be further categorised as static(one period) and dynamic (multi-period) models. The multi-period models try to react to changes in the system over a time horizon by revising the parameters of the model in some predefined periods (Moeini et al, 2015). Although most practical problems stimulate using dynamic models, the static models have received much more attention when compared with dynamic models (Ahmadi-Javid et al, 2017). Sharma et al (2019) develop a dynamic location-allocation model for locating temporary blood banks during and post-disaster conditions. More recently, Karatas (2021) proposes a dynamic model to optimise the location and allocation of search and rescue boats and helicopters to improve the performance of maritime boats' missions. Hasani and Sheikh (2023) propose a robust goal programming model for a dynamic multi-echelon health care network design problem under disruption to minimise network cost, maximise network coverage, and maximise network reliability. As there exists a considerable body of literature on health care facility location models, no attempt is made here to provide a comprehensive review. For more details, interested readers are refereed to various surveys on this subject carried out by Rahman and Smith (2000); Brailsford and Vissers (2011); Rais and Viana (2011); Ahmadi-Javid et al (2017).

Instances of the application of location-allocation models in the context of health care network service include geographical considerations in health care planning (Harper et al, 2005), supply chain redesign of the health care products (Nagurney, 2021), locating ambulances (Schmid and Doerner, 2010), specialised health care services such as trauma care resources (Siddhartha S. Syam, 2012), organ transplant services (Bruni et al, 2006; Zahiri et al, 2014), locating blood banks (Reihaneh and Ghoniem, 2017), emergency medical service designs (Ünlüyurt and Tunçer, 2016), and preventive health care facility network designs (Zhang et al, 2012). More recent application of the location-allocation modelling can also be noticed in the literature of health care. In order to eliminate the effects of test alternatives and their harmful effects on the spread of viruses, Kuvvetli (2022) formulates a location-allocation model to find out the the location of test sampling centres. Devi et al (2022) develop a location-allocation model to ensure that test samples from various geographical locations reach temporary testing laboratories as soon as possible.

2.2 Multiple objective health care problems

Conflicting multiple objectives are commonplace when it comes to dealing with health care facility location problems. However, the literature on multiple objective health care facility location is relatively scarce. For this reason, more and more researchers and practitioners have been interested in formulating and resolving multiple objective health care problems (Zhang et al, 2016). The most common objectives considered in the literature are equity of access, service quality, investment cost, coverage range, and access time. For instance, Jones et al (2021) investigate the problem of allocating a small number of novel robotic devices to a set of potential treatment centres in the South of the UK. The ultimate goal of their project was to deliver enhanced access to the new prostate cancer diagnosis and treatment technology. Steiner et al (2015) try to improve the current health services in the municipalities of Parana in Brazil with respect to objectives such as the variety of medical procedures offered in the region and travelled distances by patients. Maleki Rastaghi et al (2018) aim at minimising the total opening cost of health facilities along with balancing workload between opened facilities.

A variety of techniques have been developed to deal with multiple objectives problems in the literature. The goal programming technique, amongst others, has been widely used in many variants and fields of application (Jones and Tamiz, 2010), its use in health care has not been as prevalent compared to other fields (Ahmadi-Javid et al, 2017). The initial goal programming model is introduced by Charnes and Cooper (1961). Romero (2001, 2004) introduced extended goal programming to analyse the trade-off between efficiency and balance between the levels of achievement of the goal target values. Jones et al (2016) further developed this technique to ensure that a mix of balance and optimisation is achieved across a hierarchical decision network.

The goal programming technique and its variants has been used to analyse various health care applications. Safaei et al (2017) utilise goal programming to solve a model addressing a group purchasing organisation structure for a set of pharmacies in health care. Considering response time to incidents, work balance and budget as objectives, Karatas (2021) deploys a non-preemptive goal programming in order to minimise the unwanted deviations from the target value of each objective. Malekpoor et al (2022) propose a novel TOPSIS case based reasoning goal programming approach to optimise the dose plan for prostate cancer treatment. Oddoye et al (2009) combine simulation and goal programming in order to address health care planning in a medical assessment unit of a hospital. In order to efficiently manage the limited human resources and budget in a health-care organisation, Turgay and Taşkın (2015) propose a fuzzy goal programming model based on the data obtained from a private hospital in the Sakarya region of the Turkey.

2.3 Health care systems and uncertainty

health care systems function in an uncertain and variable environment (Harper et al, 2005). Several significant factors contribute to determining the location of health care facilities, including the size of the local population, various types of costs, service coverage standards, service and resource capacity, and changes in demand. However, it is apparent that many activities and events in health care services are prone to considerable uncertainties. Consequently, these uncertainties can have a detrimental effect on the quality of decisions made at the strategic, tactical, and operational levels of health care services (Mohammadi et al, 2014).

Over the past few decades, numerous optimisation techniques have emerged to address uncertainties present in input data. These techniques are typically categorised as fuzzy, stochastic, or interval mathematical programming approaches (Wang et al, 2012). Researchers have frequently applied the stochastic programming to tackle the uncertainty inherent in health care network design problems. In stochastic programming, non-deterministic parameters are represented as random variables with specified probability distribution functions. For example, Fattahi et al (2023) develop a novel integrated resource sharing and demand redistribution problem during pandemics. The number of patients requiring scarce health care resources is considered as an uncertain parameter and therefore, a multi-stage stochastic program is developed to optimise various strategies for planning limited and necessary health care resources. Acar and Kaya (2019) focus on disaster preparedness through the utilisation of mobile hospitals, which can improve health care services in the event of a disaster. More precisely, they examine the decisions surrounding facility location and allocation, taking into account the mobility of the hospitals so that they can be relocated to another area after a disaster occurs. A two-stage stochastic model is developed to tackle the impact of uncertainties of the disaster damages.

The studies employed stochastic programming have assumed access to complete information on the probability distribution function of uncertain variables, which may not be valid in real-world planning scenarios. To address this challenge, the robust optimisation technique can be employed as it is not dependent on any assumptions regarding the probability distribution function of the non-deterministic situation (Ben-Tal et al, 2009). In recent years, some studies have aimed to utilise either robust optimisation techniques to address the inherent randomness present in the parameter data of health care network design problems (Hasani and Sheikh, 2023; Zahiri and Pishvaee, 2017; Cheraghi et al, 2016) or a combination of stochastic programming and robust optimisation (Attari et al, 2022).

2.4 Research gap and our contributions

Overall, to the best our knowledge, a hierarchical decision network with multiple objectives and stakeholders while dealing with uncertain parameters has not been addressed in the literature. Below, more details are provided to explore the gaps in the literature from different aspects.

2.4.1 Health care network design with multiple stakeholders and objectives

To the best of our knowledge, the consideration of multiple stakeholders, along with their objectives and preferences, involved in the health care services across a hierarchical decision network has not been investigated so far.

Although a location–allocation health care model is not in itself novel, most research has focused on a single objective model rather than multiple objectives (Zhang et al, 2016). Also, social impact is also barely investigated in this context. Shiri et al (2023) recently incorporated the concept of social responsibility as one of the objectives in their health care model, which encompasses promoting employment opportunities and regional economic development. Apart from dealing with multiple conflicting objectives, the presence of various regional and national stakeholders such as villager, municipality, provincial government, and ministry of health and medical education, their interests, and their potential influence on others have received relatively little attention in models to date, most likely because the modelling techniques to consider these matters have only been recently introduced into the multi-objective modelling paradigm. In addition, according to the World Health Organisation, there exists a hierarchical structure among different levels of health care services, i.e., paramedical services, clinics and hospitals and health homes. As such a hierarchical decision network would be more practical (Mostafayi Darmian et al, 2021). Considering a hierarchical decision network would allow the decision makers to better investigate and hence optimally set the level of non-compensation between objectives, level of non-compensation between stakeholders, and level of centralisation in the network.

2.4.2 health care network design under uncertainty

As far as the health care network design is concerned, most studies, except for emergency medical services in health systems, have developed deterministic models. (Ahmadi-Javid et al, 2017). More ever, elements such as the number of patients or the disruption of health care facilities have been frequently considered by researchers as uncertain input for the decision model (Motallebi Nasrabadi et al, 2020). There are other uncertain parameters in which have received less attention and need to be addressed though. As an example, there will always be a chance that the allocated budget for operating health care facilities will be exceeded (Chalabi et al, 2008). The national allocated budget is often subject to changes due to economic or political factors, and these changes can impact the feasibility of certain facility locations. Another parameter that receives less attention in the literature of health care network design is social impact. More importantly, when it comes to measuring the social impact of a health care facility on a region in the long term, the outcome is even more variable and uncertain. (Shiri et al, 2023). Lastly, little attention is given to the simultaneous consideration of uncertainty programming and multi-objective programming in the context of health care network design, despite the fact that the nature of health care applications calls for models to include both aspects. (Mohammadi et al, 2014).

2.4.3 Strategic health care network design planning and its challenges ahead

Providing quality health care within available resources and budget has become a daunting challenge for any health care system due to the rising cost of health care resulting from the adoption of new technologies and increased demand (Bhattacharjee and Ray, 2014). Additionally, there is a lack of research on the strategic planning challenges for health care network design in the face of technological advances and financial crises. Specifically, the future of health care network design must address the challenges posed by the rapid advancement of technology and the need to balance financial constraints with the delivery of high-quality health care services. As such, there is a significant gap in the literature when it comes to the intersection of strategic health care network design planning, technology, and financial challenges (Elorza et al, 2022). To improve budget management and study the impact of decentralised budget allocation, it would be beneficial to enable all health care centers to utilise their net revenue for upgrading their health care services in the future.

2.4.4 Contributions

In this paper, we propose a holistic methodology for the health care services network design using a goal programming based technique. The main contributions of this study are as follows:

i. Involving all stakeholders in the health care decision-making process, considering their potentially diverse preferences within a hierarchical network;
ii. Considering the national allocated budget and social impact of each health development project, which have received little attention in the literature, as uncertain parameters;
iii. A robust extended goal programming methodology is developed to address the challenges faced during the modelling phase. This methodology combines the extended network goal programming variant

developed by Jones et al (2016) and the budget-of-uncertainty approach introduced by Bertsimas and Sim (2004). By using the extended goal programming approach, we ensure a balanced optimisation considering multiple stakeholders and their preferences. Additionally, the robust approach allows us to handle data uncertainty and generate less conservative solutions;

iv. A dynamic location-allocation modelling within this decision support system is embedded in order to reflect the realistic constraints and objectives concerning strategic health care planning.

3 Optimisation model

In this section, we describe the proposed health care location-allocation model with a network of multiple objectives and stakeholders.

3.1 Problem definition

To better address the strategic resource planning problem, a multi-period model is developed in which at each period the decision maker is able to either open new health facilities, (i.e. investment strategy) or upgrade/downgrade existing facilities, (i.e. reinvestment strategy). For instance, as a result of increase (decrease) in population number of one region or residents' expectations, level of located health care facility could be upgraded (down graded) in term of diversity as well as the capacity of health care services. Existing facilities in the current health care network are subject to reinvestment project while establishing a new health care facility at a potential location is considered as the investment project. These investment and reinvestment strategies are assumed to be known at the beginning of each period as a set of potential health care network development projects (N). These potential projects may also vary depending on the type of the health facility ($k \in K$) and the type of the health services needed ($t \in T$). There are several types of health facilities that can be launched such as clinics and urban health centres. The type of services may also range from visiting a General Practitioner to hospitalisations. It is worth noting that the decision maker takes into account the current net revenue of the health centres for upgrading/downgrading the level of health services. Overall, the challenge for the decision maker is to select the projects at each period which suit best the health care service system and ultimately promote sustainable development. Moreover, a decision maker may consider the impact of a investment/reinvestment project of one region on the projects planned for other neighbouring regions. Primarily, a development project (either investment or reinvestment one) can increase the rate of employment, quality of life, and health indicators. Therefore, upgrading service level quality in one region may have an impact on other neighbouring regions and increase their expectations.

The objectives considered in this model are: network coverage, service level, network cost, and social impact. The network coverage targets the total population through the whole region that receive health care service from the developed network. The network service level is measured based on the sum of health service capacities of the health facilities. The network cost is concerned with the whole budget needed to run the health care network. Lastly, we consider three sub social impact measurements: the number of job opportunities created through indirect and indirect employment of network development (Q1), impact on development of a deprived region by facilitating access to provided health care services (Q2), and health centre space per capita (Q3). The total social impact of the network development in each region is estimated based on the experts' opinions. To do so, we benefit from designed questionnaires including Q1, Q2, and Q3 based on the Social Impact Assessment guideline proposed by Queensland Health (2018). The process involves identifying, analysing, assessing, managing, and monitoring both positive and negative social impacts of a project. Social impacts, which include both direct and indirect effects on people and their communities throughout the project life cycle, need to be evaluated. The assessment should take into account the varying levels of impact at different geographic scales and must involve consultation with stakeholders. The target levels associated with these objectives are AG, TS, AC, and SI, respectively.

A decision maker may incorporate the interest of other stakeholders in order to avoid making decisions that do not accurately reflect the preferences of all involved (Rahman and Smith, 1999). Often, the stakeholders, whom have some influence or interest on the final decision are heterogeneously scattered across a hierarchical network, each with possibly different preferences and view points on the objectives under consideration. Hence, the proposed model seeks to comprehensively evaluate an appropriate mix between balancing and optimisation philosophies over an interrelated network of stakeholders. To this end, we benefit from the extended network goal programming technique introduced by Jones et al (2016).

The structure of the considered health care network consists of 2 layers with multiple objectives and multiple stakeholders. This network is controlled by a single decision maker placed at the top of the hierarchical network, i.e., national level. The role of this decision maker is to incorporate the preferences of all stakeholders in the decisions to be made. Each region represents a stakeholder and therefore associated with one particular node at the second level of the network, i.e. regional level. This level includes j nodes. We define a set J of $j+1$ nodes, $J = \{0, 1, \ldots, j\}$, which node 0 denotes the one at the national level and the remaining nodes represent the j nodes at the regional level. It is worth noting that the network could be extended to the lower levels by considering sub-regions. Similar to the generic framework developed by Jones et al (2016), each stakeholder has their own preferences, i.e. important, of no importance or somewhere in between, on each objective. Each stakeholder may also have different views on the level of allowable compensation between objectives. In addition, we extend the model proposed by Jones et al (2016) to reflect the influence of a stakeholder's preferences on neighbouring stakeholders' preferences. This model is able to consider balance and efficiency both amongst objectives at a given node and amongst stakeholders at the regional level. The efficiency and balance are controlled by three principal parameter sets:

1. $0 \leq w \leq 1$ is a relative importance weight which is assigned to each network level, i.e. the national level (w) versus regional level $(1-w)$. A high value of w corresponds to higher emphasis on the centralisation strategy of the network.
2. $0 \leq \alpha_j \leq 1$ controls the level of consideration of balance versus optimisation amongst objectives at each node at network level l (i.e., national level α_0 versus regional level α_j). $\alpha_j = 0$ means the stakeholder associated with that node is only interested in the (weighted sum) efficiency of the objectives as opposed to $\alpha_j = 1$, which emphasises the (minmax) balance of the objectives.
3. $0 \leq \beta \leq 1$ controls the level of consideration of balance versus optimisation amongst stakeholders' scores at the regional level. A higher value of β corresponds to giving more importance to the maximal stakeholder dissatisfaction rather than to the average stakeholder dissatisfaction.

Either or both of the negative and positive deviations from the target value of each objective function at each node are penalised via considering the weights associated with penalising positive and negative deviations. If an objective is not of concern at a decision node, both associated weights should be set to zero.

A diagrammatic illustration is given in Figure 1 in order to present the hierarchical network composed of two levels of stakeholders and four objectives.

3.2 Data, sets, parameters and variables

The sets, parameters and decision variables used in the mathematical model are given in Tables 1, 2 and 3, respectively.

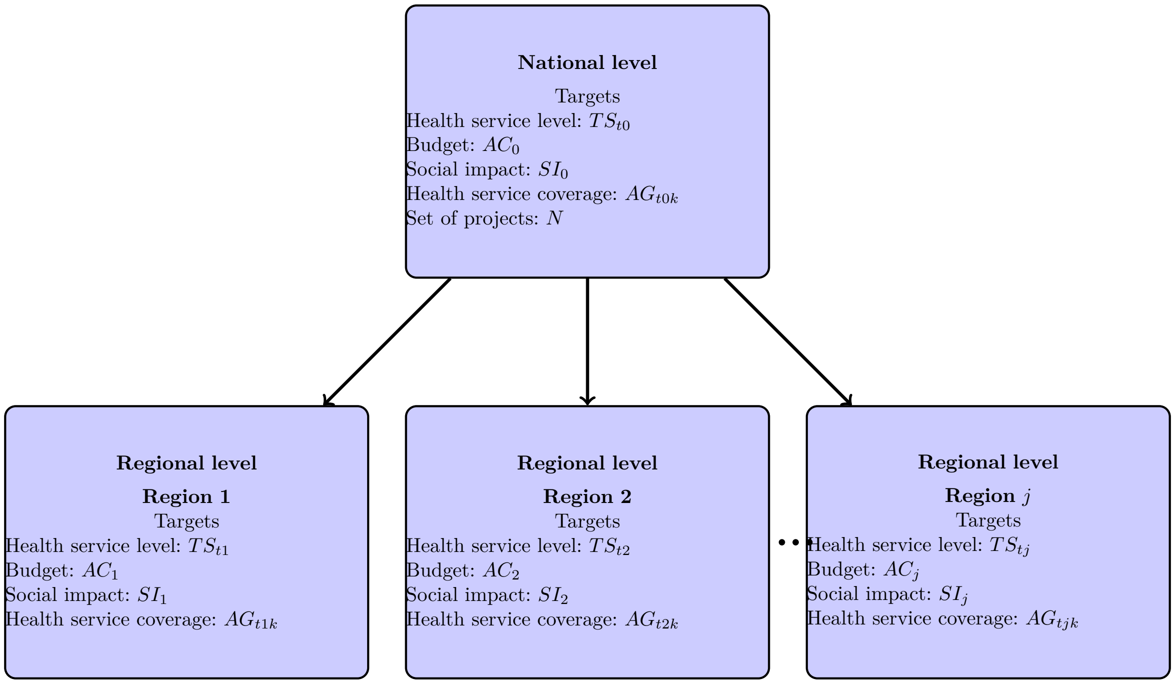


Fig. 1 Diagrammatic illustration of a hypothetical health care network system

Table 1 Data sets

Set	Description
J	Set of nodes $0, 1, \ldots, J$ with node 0 representing the one at the national level and the remaining nodes represent the j nodes at the regional level
N	Set of potential investment (N') and reinvestment (N'') health care projects ($N = N' \cup N''$)
K	Set of health care facility types
T	Set of health care service types
C	Set of current (active) facilities
Z	Set of planning periods
A	Set of goal programming deviation types, i.e., positive(+) and negative(-)

Table 2: Parameters

Parameter	Description
E_{kt}	Capacity of health service of type t of facility type k
TS_{tj}	Target value of health service of type t for node j
AC_j	Available budget for health service provision for node j
SI_j	Target value of social impact for node j
AG_{tjk}	Target value of health service coverage of type t of facility type k for node j
EI_{kj}	Potential social impact of facility of type k for node j
w	Weight of trade-off between national and regional concerns
α_j	Control parameter of efficiency and balance for node j
β	Control parameter of efficiency and balance at a set of potential regions for health care facility establishment
U^a_{Etj}	Weight of deviation from national health service level targets of type a for node j

Continued on next page

Table 2 – continued from previous page

Parameter	Description
U_{Cj}^{la}	Weight of deviation of type a from the target of health care service providing cost at network level l in region j
U_{Hj}^{a}	Weight of deviation of type a from the target of health care service providing social concerns for node j
U_{tjk}^{a}	Weight of deviation of type a from the target of health care service coverage at facility k, of type t and node j
U_{ν}^{a}	Weight of deviation of type a from the total net present value of cost at the national level
$\rho_{jkj'k'}$	Correlation between project type k for node j and project type k' ($k \neq k'$) at node j' ($j \neq j'$)
$SC_{tjj'}$	Service coverage of type t at node j by establishing facility at node j'
CF_{kj}	Expected traditional net cash flow of facility of type k at node j per year
$EC_{kk'j}$	Fixed cost of change of type of facility from k to k' at node j
IC_{kj}	Establishment cost of facility of type k at node j
MC_{kj}	Operational cost of facility of type k at node j
ES_{kj}	Represents the state of current facility of type k activity at node j
T_k	Number of planning periods for management horizon of facility of type k
S_k	Number of required periods for establishment facility of type k
NPV	Net present value of total cost of health care service network
r	Interest rate per annum

Table 3 Decision variables

Variable	Description
yn_{kj}	binary variable representing if a new health facility in type k is established at node j $(k, j \in N')$
$yc_{kk'j}$	binary variable representing if a current health facility in type k is changed to k' at node $j(k, k', j \in N'')$
λ_j	Maximum deviation from set of normalised weighted goals at node j
D	Maximal measure from amongst the set of regions (the worst performing region)
$n_{\nu j}^{a}$	Deviation in type a from national health care service cost target at node j
n_{Hj}^{a}	Deviation in type a from social target at at node j
n_{tjk}^{a}	Deviation in type a from health care service type t target at facility k for node j
n_{Etj}^{a}	Deviation in type a from health care service for service type t target at node j
n_{Cj}^{a}	Deviation in type a from national cost target at node j

3.3 Mathematical model

The proposed extended network goal programming model considering balance and efficiency of multiple objectives and stakeholders at each network node level is presented as follows by Equations (1)-(20).

$$
\begin{aligned}
Min\ a = w & \left[\alpha_0.\lambda_0 + (1-\alpha_0) \left(\begin{array}{l} \sum_t \frac{U_{Et0}^{-}.n_{Et0}^{-}}{TS_{t0}} + \frac{U_{C0}^{+}.p_{C0}^{+}}{AC_0} + \frac{U_{H0}^{-}.n_{H0}^{-}}{SI_0} + \sum_t \sum_k \frac{U_{t0k}^{-}.n_{t0k}^{-}}{AG_{t0k}} \\ + \frac{U_v^{-}.n_v^{-}}{NPV} \end{array} \right) \right] \\
+ (1-w) & \left[\begin{array}{l} \beta D + (1-\beta) \sum_j \alpha_j^R.\lambda_j^R \\ + \left(1-\alpha_j^R\right) \left(\sum_t \sum_j \frac{U_{Etj}^{-}.n_{Etj}^{-}}{TS_{tj}} + \frac{U_{Cj}^{+}.n_{Cj}^{+}}{RC_j} + \frac{U_{Hj}^{+}.n_{Hj}^{+}}{SI_j} + \sum_k \frac{U_{tjk}^{-}.n_{tjk}^{-}}{AG_{tjk}} \right) \end{array} \right]
\end{aligned} \tag{1}
$$

Constraints

$$
\begin{aligned}
& \sum_k \sum_{z=s_k}^{T_k} \frac{CF_{kj}.yn_{kj}}{(1+r)^z} + \sum_j \sum_k \sum_{k'} \frac{CF_{kj}.ES_{kj}.\left(1-yc_{kk'j}\right)}{(1+r)^z} + \\
& \sum_j \sum_k \sum_{k'} \frac{CF_{k'j}.yc_{kk'j}}{(1+r)^z} - \sum_j \sum_k \sum_{z=0}^{s_k-1} \frac{IC_{kj}.yn_{kj}}{(1+r)^z} - \sum_j \sum_k \sum_{z=s_k}^{T_k} \frac{MC_{kj}.yn_{kj}}{(1+r)^z} - \\
& \sum_j \sum_k \sum_{z=0}^{s_{k'}-1} \frac{EC_{kk'j}.yc_{kk'j}}{(1+r)^z} - \sum_j \sum_k \sum_{z=s_{k'}}^{T_{k'}} \frac{EC_{kk'j}.yc_{kk'j}}{(1+r)^z} + n_v^{-} - n_v^{+} = NPV
\end{aligned} \tag{2}
$$

$$
\sum_j \sum_k \sum_{j'} \sum_{k'} E_{kt} \cdot (1+\rho_{jkj'k'}) \cdot yn_{kj} + \sum_j \sum_k \sum_{j'} \sum_{k'} E_{kt} \cdot (1+\rho_{jk'j'k}) \cdot yc_{kk'j} + n_{Et0}^{-} - n_{Et0}^{+} = TS_{t0} \quad \forall t \in T \tag{3}
$$

$$
\sum_k E_{kt} \cdot yn_{kj} + \sum_k \sum_{k'} E_{k't} \cdot yc_{kk'j} + n_{Etj}^{-} - n_{Etj}^{+} = TS_{tj} \qquad \forall t \in T, j \in J \backslash \{0\} \tag{4}
$$

$$
\sum_k \sum_j IC_{kj} \cdot yn_{kj} + \sum_k \sum_{k'} \sum_j EC_{kk'j} \cdot yc_{kk'j} + n_{c0}^{-} - n_{c0}^{+} = AC_0 \tag{5}
$$

$$
\sum_k IC_{kj} \cdot yn_{kj} + \sum_k \sum_{k'} EC_{kk'j} \cdot yc_{kk'j} + n_{Cj}^{-} - n_{Cj}^{+} = AC_j \qquad \forall j \in \ J \backslash \{0\} \tag{6}
$$

$$
\sum_k \sum_j EI_{kj} \cdot yn_{kj} + \sum_k \sum_{k'} \sum_j EI_{k'j} \cdot yc_{kk'j} + n_{H0}^{-} - n_{H0}^{+} = SI_0 \tag{7}
$$

$$
\sum_k EI_{kj} \cdot yn_{kj} + \sum_k \sum_{k'} EI_{k'j} \cdot yc_{kk'j} + n_{Hj}^{-} - n_{Hj}^{+} = SI_j \quad \forall j \in J \backslash \{0\} \tag{8}
$$

$$
\sum_j \sum_{j'} SC_{tjj'} \cdot yn_{kj} + \sum_j \sum_{j'} \sum_{k'} SC_{tjj'} \cdot yc_{kk'j} + n_{t0k}^{-} - n_{t0k}^{+} = AG_{t0k} \qquad \forall t \in T, k \in K \tag{9}
$$

$$
\sum_{j'} SC_{tjj'} \cdot yn_{kj} + \sum_{j'} \sum_{k'} SC_{tjj'} \cdot yc_{kk'j} + n_{tjk}^{-} - n_{tjk}^{+} = AG_{tjk} \quad \forall t \in Tk \in K, j \in J \backslash \{0\} \tag{10}
$$

$$\sum_j \sum_k \sum_{z=0}^{s_k-1} IC_{kj} \cdot yn_{kj} + \sum_j \sum_k \sum_{z=s_k}^{T_k} MC_{kj} \cdot yn_{kj} + \sum_j \sum_k \sum_{z=0}^{s_k-1} EC_{kk'j} \cdot yc_{kk'j}$$
$$+ \sum_j \sum_k \sum_{z=s_{k'}}^{T_{k'}} EC_{kk'j} \cdot yc_{kk'j} \leq \sum_k \sum_j CF_{kj} \cdot yn_{kj} + \sum_j \sum_k \sum_{k'} CF_{kj} \cdot ES_{kj} \cdot (1 - yc_{kk'j}) \tag{11}$$
$$+ \sum_j \sum_k \sum_{k'} CF_{k'j} \cdot yc_{kk'j} + AC_j \quad \forall j \in J \backslash \{0\}$$

$$\sum_t \frac{U^-_{Et0} \cdot n^-_{Et0}}{TS_{t0}} \leq \lambda_0, \quad \frac{U^+_{C0} \cdot n^+_{C0}}{AC_0} \leq \lambda_0, \quad \frac{U^+_{H0} \cdot n^+_{H0}}{SI_0} \leq \lambda_0, \quad \sum_{k,t} \frac{U^-_{t0k} \cdot n^-_{t0k}}{AG_{t0k}} \leq \lambda_0,$$
$$\frac{U^-_v \cdot n^-_v}{NPV} \leq \lambda_0 \tag{12}$$

$$\sum_t \frac{U^+_{Etj} \cdot n^+_{Etj}}{TS_{tj}} \leq \lambda_j, \quad \frac{U^+_{Cj} \cdot n^+_{Cj}}{AC_j} \leq \lambda_j, \quad \frac{U^+_{Hj} \cdot n^+_{Hj}}{SI_j} \leq \lambda_j \qquad \forall j \in J \backslash \{0\} \tag{13}$$

$$\alpha_j \cdot \lambda_j + (1 - \alpha_j) \left(\sum_t \frac{U^-_{Etj} \cdot n^-_{Etj}}{TS_{tj}} + \frac{U^+_{Cj} \cdot n^+_{Cj}}{AC_j} + \frac{U^+_{Hj} \cdot n^+_{Hj}}{SI_j} + \sum_k \frac{U^+_{tjk} \cdot n^+_{tjk}}{AG_{tjk}} \right) \leq D$$
$$\forall j \in J \backslash \{0\} \tag{14}$$

$$yn_{kj} \in \{0, 1\} \qquad \forall k \in K, j \in J \backslash \{0\} \tag{15}$$

$$yc_{kk\prime j} \in \{0, 1\} \qquad \forall k \& k\prime \in K, j \in J \backslash \{0\} \tag{16}$$

$$n^+_{Et0}, n^-_{Et0}, n^-_{C0}, n^+_{C0}, n^-_{H0}, n^+_{H0}, \lambda_0 \geq 0 \tag{17}$$

$$n^-_{t0k}, n^+_{t0k} \geq 0 \qquad \forall k \tag{18}$$

$$n^-_{Etj}, n^+_{Etj}, n^-_{Cj}, n^+_{Cj}, n^-_{Hj}, n^+_{Hj}, \lambda_j \geq 0 \qquad \forall j \in J \backslash \{0\} \tag{19}$$

$$n^-_{tjk}, n^+_{tjk} \geq 0 \qquad \forall j \in J \backslash \{0\}, k \in K \tag{20}$$

Equation (1) represents the achievement function, considering the two levels, regional and national, for health network development planning. The second term in the achievement function (1) refers to the regional layer. The achievement function minimises the unwanted deviation variables presented in Equations (2)–(10). Equation (2) represents the expected net cash flow of health service facilities including the cost/revenue of upgrading/downgrading the service level of health facilities. Equations (3), (5), (7), and (9) ensure that the deviations from targets at the national level are taken into consideration. On the other hand, Equations (4), (6), (8), and (10) consider the targets' deviations at the regional level. Equations (3) and (4) give the national and regional level goals for health care service respectively. Equation (3) ensures the impact of launching or upgrading the service level of a facility on neighbouring regions with respect to national health care service level is considered. Equations (5) and (6) give the national and regional goals for budgets of health care service respectively. Equations (7) and (8) give the national and regional goals for health care network cost respectively. Equations (9) and (10) give the national as well as regional goals for health service coverage. The notion of reinvestment strategy is represented by Equation (11). In another words, Equation (11) ensures that the development of the projects for the next periods are planned considering the revenue of the existing facilities at each period along with the available public budget. Equations (2) and (10) give the national and regional goals for network cost, health service cost, health care social impact, and health service coverage respectively. Equality set (12) guarantees that the weighted, normalised, unwanted deviation from each national goal target is less than or equal to the maximal national value (λ_0). Inequality set (13) ensures that for each region j, the weighted, normalised, unwanted deviation from each goal target is less than or equal to the maximal value for that region (λ_j). Inequality set (14) ensures that each region's composite score (i.e. the parametric combination of the worst case and average deviations) is less than or equal to the worst case regional score (D). Equations (15)-(16) impose binary restrictions on decision variables. Equations (17)-(20) give the set of sign restrictions for the deviation variables in the model.

4 Health care network design performance in an uncertain environment

In this section, two key parameters of the model detailed in Section 3.3 are considered as uncertain: the social impact of each health care facility on the region (EI_{kj}) and total available budget (AC_0). The social impact of each health care facility can be affected by its location, the type of health services provided by this facility, and the quality of health services in neighbouring regions. In essence, establishing a health care facility in a region can contribute to the promotion of sustainable development paradigms. However, measuring to what extent the development of a region is affected by the established health care and its level of services is not straightforward. In another words, the real value (contribution) of the social impact of the health care facilities is not certain. The budget allocated to each region is also uncertain. Although each regional health care system aims at increasing the amount of budget year by year, this may not be the case. The reason is that the demand for health care services is constantly increasing and the government needs to be able to create a balance in terms of allocated budget to all the regions. An explanation of the proposed robust counterpart of the model is given next.

4.1 Robust model

In the proposed model, the two uncertain parameters are modelled using the concept of an uncertainty budget in interval robust optimisation (Bertsimas and Sim, 2004). This concept corresponds to real-world situations, where the probability of all uncertain parameters is very small in deviating from their nominal values. Therefore, the number of the uncertain parameters deviating from their nominal values is bounded by a predetermined value named the uncertainty budget. This value represents the decision maker's degree of conservativeness. Smaller values represent a limited effect of uncertainty (i.e., a risk-neutral model), while larger values depict a more significant effect (i.e., a risk-averse model).

To build the robust model, the approach proposed by Bertsimas and Sim (2004) is used. The proposed robust extended goal programming model for the considered health care problem uses Equation 1 as the minimisation objective. Constraints (2-3) and (6-20) are still valid for the robust model. In order to tackle the two uncertain parameters, available budget and social impact, constraints 4 and 5 are replaced by their robust counterpart constraints. The details of the proposed robust model and its equations are explained in 7.

5 Case study profile

The Iranian primary health care system was initially established in 1979 in order to better allocate the health care services, in terms of quality and equity, countrywide including rural areas (Tabrizi et al, 2017). The Ministry of Health and Medical Education (MOHME) of Iran aims to provide high quality health care services to the entire population. The MOHME is the main stakeholder of the health care service system in the country. Additionally, there are regional authorities such as regional councils and municipalities that play an important role in designing and implementing MOHME' policies. It should be noted that the main priority of local authorities is the regional development of the health care network rather than national concerns. As a consequence, traditionally there has always been a level of conflict between local (i.e., regional) and national authorities.

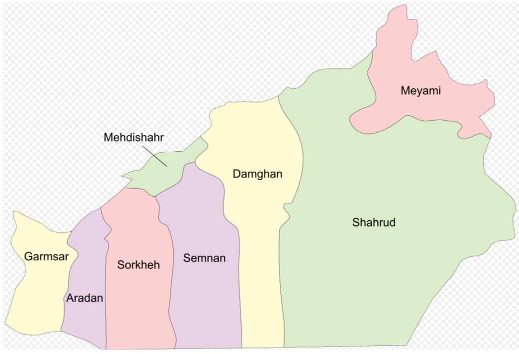
The population distribution in Iran is very heterogeneous. Some areas have a high population density, while some others have low population density. Climate is one of the main factors affecting the population distribution in Iran. Many efforts have been made to improve the efficiency of the health system over the past years and provide a reasonable level of equity and quality among regions. To name a few benefits, among others, a dramatic decrease in infant, maternal and neonatal mortality rates, population growth rate, increasing life span and a marked shift towards non-communicable diseases have been noticed (Asadi-Lari et al, 2004). However, despite these encouraging indicators, there still remain many challenges ahead in order to improve the efficiency, equity and quality of the health care service system. These challenges can be categorised as follows (Davari et al, 2012): increasing health expenditures, lack of systematic health technology assessment, very limited financial resources, challenging management and regulation, and uncovered portions of the population.

To improve the efficiency, equity and quality of the health care services in rural areas, which currently represent 25.1% of the whole population, the health care system in Iran has been reforming the configurations of its health care facilities, i.e. opening/closing health facilities and upgrading/downgrading the level of services at some of the existing facilities. In particular, health houses with limited capabilities are being established in remote and sparsely populated villages. The required skilled staff for these health houses, known as behvarzan, are mostly recruited from local neighbourhood communities. However, since the amount of public budget devoted to health is limited, reliably financing these sort of projects is always a challenge. Therefore, the government should ideally consider the interest of all the stakeholders involved in order to provide a long-lasting health care plan. Besides, inefficiency of the current system and high administrative costs has made the problem more critical (Lankarani et al, 2013).

In order to test and illustrate the model, we consider a specific geographic zone, i.e. the Semnan province of Iran with 8 counties, 20 cities, 15 regions, and 31 rural districts (Figure 2). This province has approximately 700,000 inhabitants and its area is about $97491km^2$.

There are approximately 480 zones including rural areas within this province. Population distribution in this province is very heterogeneous. Some areas have high density of population, while some others have low density. Due to the restrictions on the available resources, it is not possible to locate one facility in each of these regions. To select the final set of projects, i.e., either opening a new facility or upgrading/downgrading the service level of the existing facility, we benefit from the Fuzzy best-worst method introduced by Guo and Zhao (2017). The reason for employing this method is that there are a number of quantitative and qualitative criteria involved in the process of project selection and these class of methods are capable of handling both quantitative and qualitative criteria simultaneously. More information on this can be found in 7. The required data for applying this method such as the criteria have been formulated by consultation with the experts working in Iranian health care organisations. It is worth noting that after applying this

Map of Iran



Semnan province

Fig. 2 Map of the study area (https://www.amar.org.ir/english/Iran-at-a-glance/Iran)

method, $N = 46$ potential projects have been identified as either potential locations to open new facilities (investment projects) or to upgrade/downgrade their service level (reinvestment projects).

The considered assessment criteria according to the experts' opinions are as follows: (C_1) distance between a demand point and the closest health centre (it should be less than the distance traveled by 1 hour of walking); (C_2) closeness to main routes and roads; (C_3) amount of population of each region; (C_4) trend of population growth; (C_5) placing other types of health care facilities such as public and governmental facilities in each region; (C_6) appropriate access to essential services such as refined water, electricity network, gas network and telephones; (C_7) dependency of the development trends of each region with the neighbouring regions; (C_8) specific cultural and social features of each region; (C_9) common diseases in each region; (C_{10}) potential capacity of attracting popular donations.

The population of each candidate area is an accumulated sum of the populations of the neighbouring sub-areas. It should be noted that some of these 46 facilities have already been established. However, the decision maker is willing to make sure that they are providing the right type of service level at those facilities. Therefore, there is a possibility to upgrade/downgrade the level of provided health services. There are three types of service level: (I) the most comprehensive services including specialised medical services, hospitalisation, and dentistry services; (II) includes services such as Nursing, Radiology, Environmental health, and Occupational health; (III) refers to services such as General Practitioner and Midwifery Services. There are three types of potential facilities, i.e. health centres: urban health centre, rural health centre, and home health. As can be seen in Table 4, health centre type 1 is able to provide all the three types of services. Facility type 2 is able to cover service type II and III. Finally, facility type 3 can only provide the service type III. Figure 3 displays the geographical location of 46 facility types scattered throughout 8 counties and 15 regions.

Table 4 Types of health centres and type of services provided in the centres

Health centre		Type of health services		
Name	Type	I	II	III
Urban health centre	1	✓	✓	✓
Rural health centre	2		✓	✓
Home health	3			✓

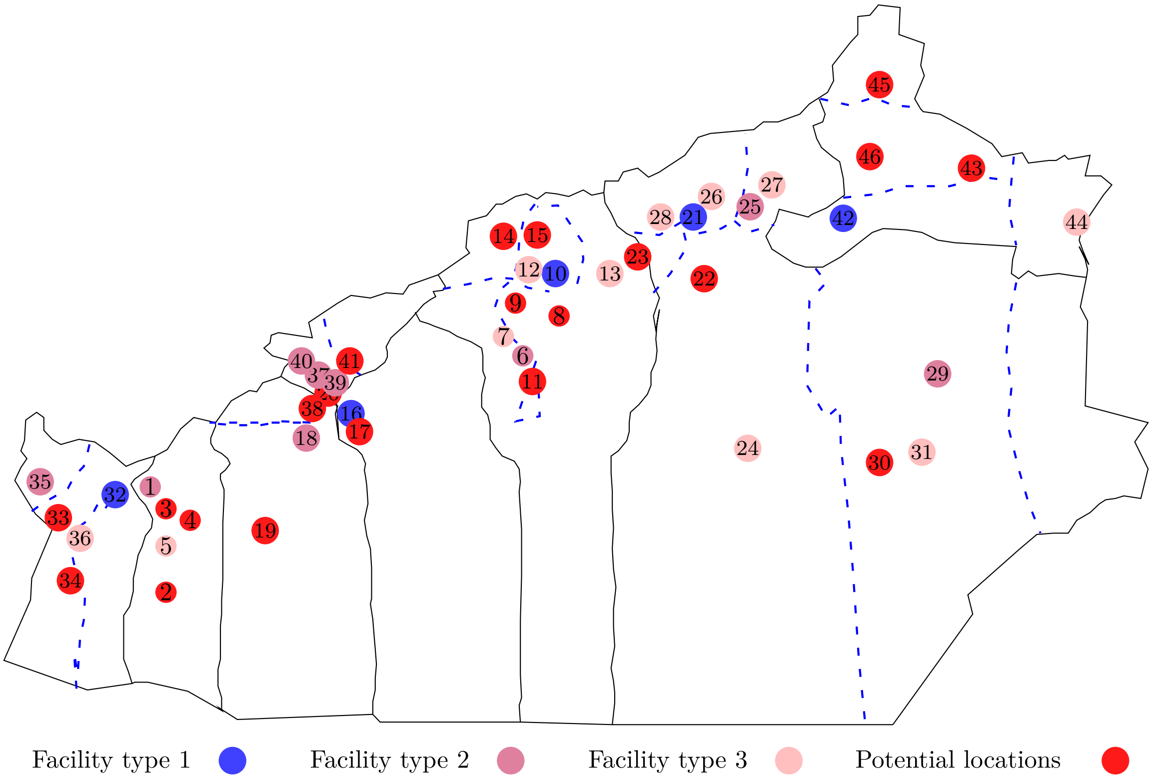


Fig. 3 Existing health care network facilities in Semnan province containing 8 counties and 15 regions

Regarding the multidisciplinary stakeholders, according to the experts' opinions two levels are considered in this network: regional stakeholders, which illustrate the preferences of the 46 areas and a national one, which represents the preferences of the Iranian health ministry representative of the Semnan province. No intermediate stakeholders whom may represent the counties are included since these do not exist in practice.

6 Parametric analysis of the key parameters

This section details the parametric analysis performed on the deterministic model developed in Section 3.3 in order to illustrate its efficiency and generate a relevant set of solutions in decision and objective spaces. The proposed model is solved by the GAMS software on a personal computer with 3.10 GHz processor speed and 4GB RAM. The model is solved to optimality in less than one second.

As mentioned earlier, the proposed model is able to analyse the level of non-compensation between objectives, level of non-compensation between stakeholders, and level of centralisation in the health care decision network. The effects of these key parameters in decision making is first investigated via conducting one-way and two-way sensitivity analyses. For this purpose, the current state of the underlying network is considered for applying all the analyses (Figure 3). Eventually, the results of solving the model with 10 diverse configurations of parameters are presented in order to analyse the solution in the decision space. It should be noted that the data used to demonstrate the model is generated according to the experts' advice. In order to get a good approximation of the real situation, 10 experts who have been working as a top/intermediate manager in the health care system of Semnan province are interviewed in order to obtain the required data such as social impact assessment and potential projects analysis using the best-worst fuzzy method. The generation schemes are reported in Table 5.

Table 5 Parameter generation scheme

Parameter	Generation Method	Parameter	Generation Method
T_k	10 (unit: year)	E_{kt}	$U[2000, 10000]$
TS_{tj}	$U[0.5, 1]$	AC_0	50000 (unit: 10 million IRR)
AC_j	$U[500, 2000]$ (unit: 10 million IRR)	EI_{kj}	$U[0, 1]$
SI_0	46	SI_j	$U[0, 1]$
AG_{t0k}	$U[0.5, 1]$	AG_{tjk}	$U[0.5, 1]$
$\rho_{jkj\prime k\prime}$	$U[0, 1]$	$SC_{tj\prime j}$	$U[0, 1]$
CF_{kj}	$U[10, 100]$ (unit: 10 million IRR)	$EC_{kk\prime j}$	$U[200, 800]$ (unit: 10 million IRR)
IC_{kj}	$U[600, 1200]$ (unit: 10 million IRR)	MC_{kj}	$U[40, 100]$ (unit: 10 million IRR)
ES_{kj}	$\{0, 1\}$	S_k	1
NPV	10000 (unit: 10 million IRR)	r	0.2
BUD_z	$U[10000, 20000]$ (unit: 10 million IRR)	U^-_{Et0}	$U[0, 1]$
U^+_{C0}	$U[0, 1]$	U^+_{H0}	$U[0, 1]$
U^-_{t0k}	$U[0, 1]$	U^-_v	$U[0, 1]$
U^+_{Etj}	$U[0, 1]$	U^+_{Cj}	$U[0, 1]$
U^+_{Hj}	$U[0, 1]$	U^+_{tjk}	$U[0, 1]$

6.1 One-way sensitivity analyses

Firstly, a one-way sensitivity analysis with respect to the three key parameters of the proposed model, i.e. w, α, and β is conducted. Six points ranging from 0 to 1 are assigned to each parameter $(0.01, 0.2, 0.4, 0.6, 0.8, 0.99)$. Therefore, 216 experiments need to be run. For each run, the average and maximal deviations at national and regional level are measured.

Figure 4 shows how changes in one parameter (i.e. w, α, and β) may affect the maximal and average deviations at national and regional level. To this end, each run includes the mean of the relevant measure over the 36 values of the other two parameters. Following the suggested measurement scheme of Jones et al (2016), the four measures used are:

- NND_{Avg}: Average national normalised deviation:
  $\sum_t(\frac{U^-_{Et0} \cdot n^-_{Et0}}{TS_{t0}}) + \frac{U^+_{C0} \cdot n^+_{C0}}{AC_0} + \frac{U^+_{H0} \cdot n^+_{H0}}{SI_0} + \sum_{k,t} \frac{U^-_{t0k} \cdot n^-_{t0k}}{AG_{t0k}} + \frac{U^-_v \cdot n^-_v}{NPV}$
- NND_{Max}: Maximum national normalised deviation:
  $max(\sum_t(\frac{U^-_{Et0} \cdot n^-_{Et0}}{TS_{t0}}), \frac{v^+_{C0} \cdot n^+_{C0}}{AC_0}, \frac{U^+_{H0} \cdot n^+_{H0}}{SI_0}, \sum_{k,t} \frac{U^-_{t0k} \cdot n^-_{t0k}}{AG_{t0k}}, \frac{U^-_v \cdot n^-_v}{NPV})$
- RND_{Avg}: Average regional normalised deviation:
  $\sum_{t,j} \frac{U^-_{Etj} \cdot n^-_{Etj}}{TS_{tj}} + \sum_j \frac{U^+_{Cj} \cdot n^+_{Cj}}{AC_j} + \sum_j \frac{U^+_{Hj} \cdot n^+_{Hj}}{SI_j} + \sum_{k,t,j} \frac{U^+_{tjk} \cdot n^{+R}_{tjk}}{AG_{tjk}}$
- RND_{Max}: Maximum regional normalised deviation:
  $max(\sum_{t,j} \frac{U^+_{Etj} \cdot n^+_{Etj}}{TS_{tj}}, \sum_j \frac{U^+_{Cj} \cdot n^+_{Cj}}{AC_j}, \sum_j \frac{U^+_{Hj} \cdot n^+_{Hj}}{SI_j}, \sum_{k,t,j} \frac{U^-_{tjk} \cdot n^+_{tjk}}{AG_{tjk}})$

As mentioned earlier, an increase in w means a higher level of centralisation of the decision making process. As can be seen in Figure 4, the increase in w improves all of the four measures, i.e. showing an advantage at the national level as well as the regional level. This shows the benefits that can be gained by efficient national level co-ordination. Besides, the results reveal that the measures of maximal types (NND_{Max} and RND_{Max}) have a sharper tendency towards improvement.

As far as parameter α is concerned, an increase in this parameter means an increase in the level of non-compensation amongst objectives for all stakeholders across the network. In other words, the amount of flexibility of the stakeholders in terms of trade-offs between objectives is decreased. Figure 4 proves that increasing the level of non-compensation amongst objectives in the network causes worse values for all four measures, i.e. the worse global solution for both national and regional levels.

An increase in the parameter β implies an increase in the level of non-compensation between stakeholders at different nodes in the network. That is, stakeholders are less willing to accept a worsening in their position in order that the overall position is improved (Jones et al, 2016). Figure 4 illustrates that increasing the level of non-compensation between stakeholders in the network improves all of the four measures.

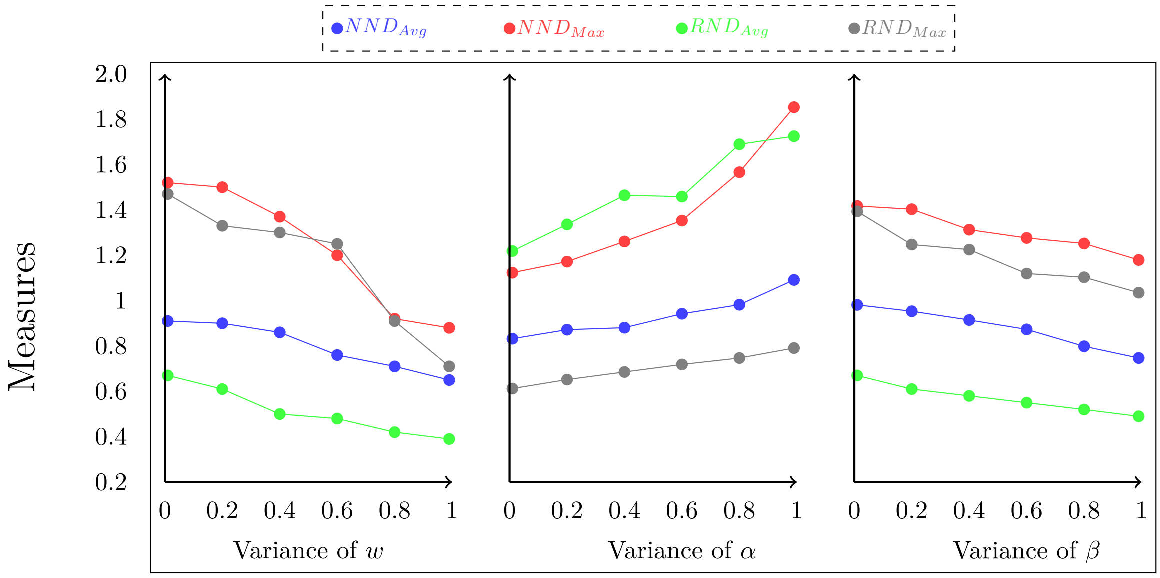


Fig. 4 Effect of variance of parameters (w, α and β) on set of measures (i.e., NND_{Avg}, NND_{Max}, RND_{Avg}, and RND_{max}.)

The results of the analyses for α and β show the importance of involving all the stakeholders in the process of decision making and ensuring that their preferences are respected to the greatest possible level. As previously stated, the results of the analysis for w suggests this should be done in a centrally coordinated manner.

6.2 Two-way sensitivity analyses

Similarly to varying one parameter at a time, It might also be of interest to analyse the impact of changing two of the three parameters within their defined range values at once. Figures 5–7 show the results of the analysis. The same four measures as in Figures 4 (NND_{Max}, NND_{Avg}, RND_{Max}, RND_{Avg}) are used. This time, each optimisation run associates with the mean of the six values of the third parameter.

The results show that for extreme parameter values, the model is less sensitive to the changes in another parameter. For instance, for extreme value of parameter w, changes in parameter β do not considerably affect any measures. Therefore, it can be concluded that at the highest level of centralisation, the sensitivity amongst the stakeholders has lost some of its effectiveness (As shown by Figure 6). Some of the two parameter analyses also demonstrate areas of stability in parameter space. For example, we can conclude from Figure 5 that low w and α, i.e. a low level of centralisation and non-compensation between objectives, may also lead to good values of all the four measures. Similarly, the analysis results in Figure 6 show that low w and β, i.e. a low level of centralisation and non-compensation between stakeholders, may lead to good values with respect for all of the four measures. While, with regard to the level of non-compensation between objectives(α) and stakeholders (β), high values α and β may guarantee a good value for all the measures (see Figure 7). These results from the two way sensitivity analyses show that alternative, decentralised strategies yielding good results with respect to the measures utilised are also possible.

6.3 Analytical results

In order to investigate the impact of uncertainty on the performance of the proposed robust model, three different levels of uncertain budget are estimated for each uncertain parameter: 0%, 50%, and 100%. Zero

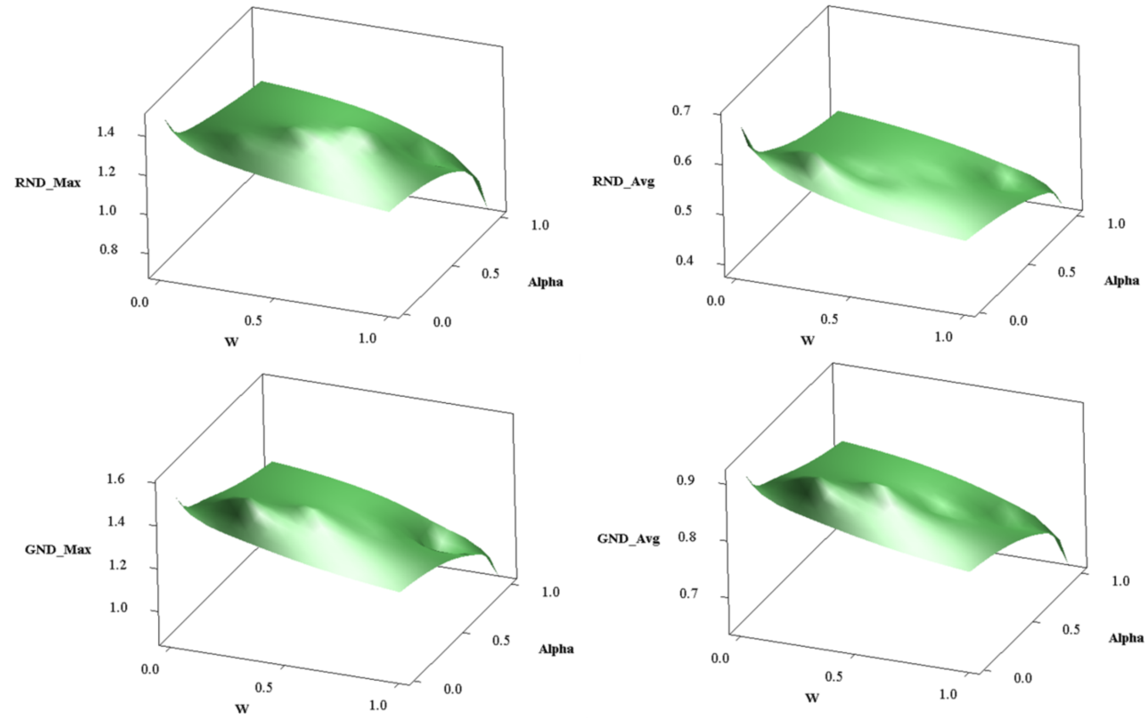


Fig. 5 Effect of variance of parameters w (the level of centralization) and α (the level of non-compensation between the objectives) on set of measures

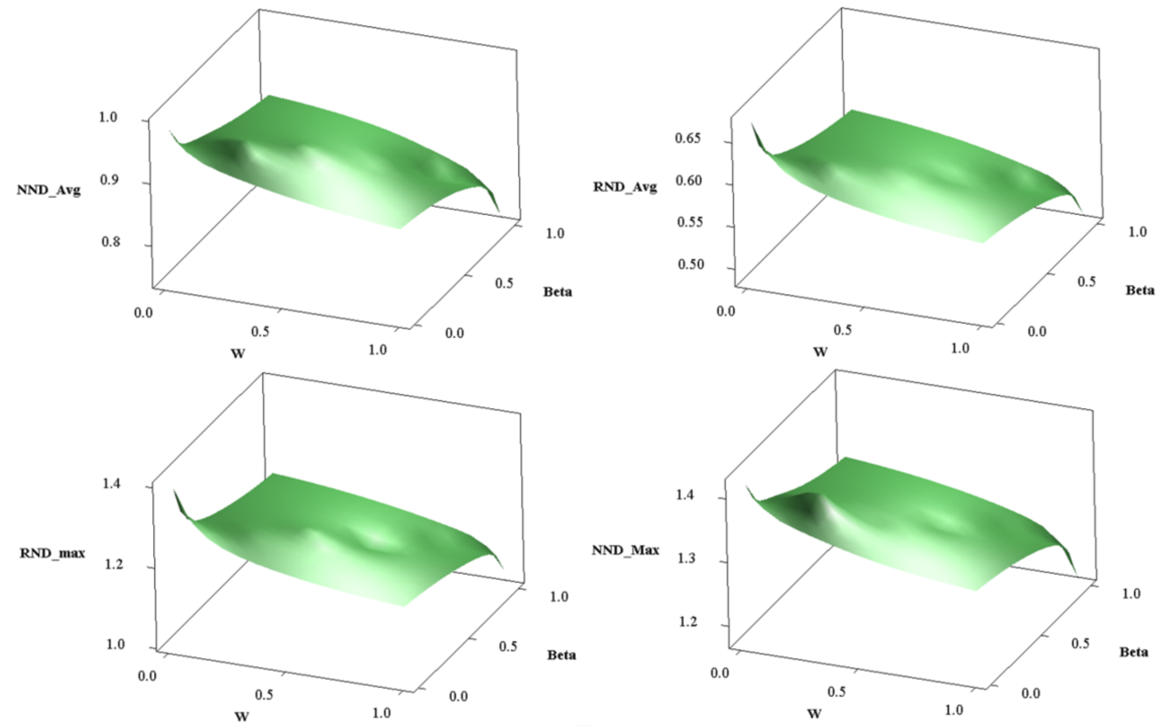


Fig. 6 Effect of variance of parameters w (the level of centralization) and β (the level of non-compensation between the stakeholders) on set of measures

budget level implies a deterministic situation, whilst a 100% budget level indicates complete uncertainty. By doing so, a range of conservatisms is analysed from complete conservatism, i.e., uncertainty budget

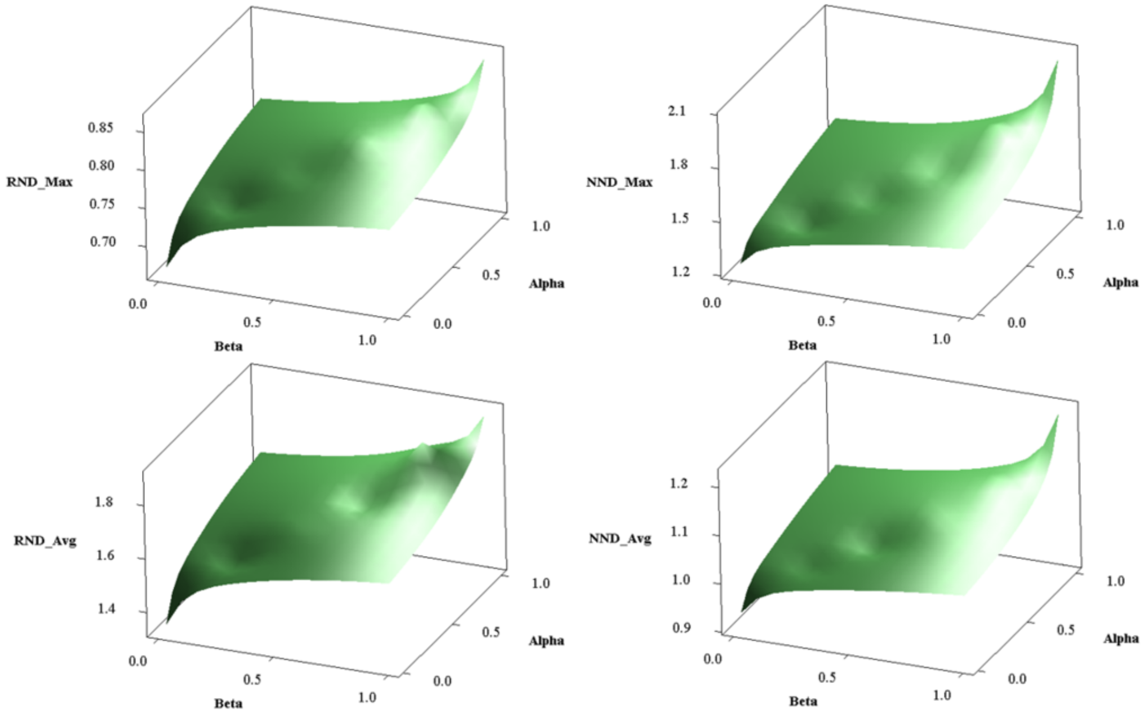


Fig. 7 Effect of variance of parameters α (the level of non-compensation between the objectives) and β (the level of non-compensation between the stakeholders) on set of measures

0%, to lack of conservatism, i.e., uncertainty budget 100%. This trade-off analysis presents the price of budget-based robustness.

Tables 6 - 8 present the results of solving the proposed model with 4 diverse parameter configurations: (i) level of centralisation of the decision making process (w); (ii) level of non-compensation between objectives for all stakeholders across the network (α); (iii) level of non-compensation between stakeholders at different nodes (β); and (iv) uncertainty budget (conservatism range).

Columns $2-4$ clarify the situation of the health care network in parameter space. Configurations 1 and 2 investigate decentralised health care networks with a low level of non-compensation between objectives and the situation where there are strong collaborations among stakeholders (Configuration 1) against the one that all the stakeholders individually seek their goals, i.e., high level of non-compensation among stakeholders. Configurations 3 and 4, on the contrary, consider decentralising health care networks with high levels of non-compensation between objectives and the situations where there are strong collaborations among stakeholders (Configuration 3) against the one that all there is a high level of non-compensation between stakeholders. Configurations 5 and 6 present the balance situations with respect to these three parameters. Configurations 7 and 8 consider centralised health care networks with low level of non-compensation between objectives and the situations where there are strong collaborations among stakeholders (Configuration 7) against the one that all the stakeholders individually seek their goals (Configuration 8). Finally, Configurations 9 and 10 represent the comparison between two centralised networks in which one has a low level of non-compensations between stakeholders against the one with a high level of β. In both configurations, the level of non-compensation between objectives is assumed to be high.

Columns $5-8$ report the value of the 4 performance measurements of the network. Columns $9-11$ show the objectives value achieved after solving the proposed model optimally, and columns $12-13$ present the value of some of the key decision variables, i.e. which health centres are opened and at which health centres the level of health service has been upgraded/downgraded.

Table 6 Key solutions in meta-objective and decision space for health care network (HN)- Uncertain budget 0

Config#	w	α	β	NND_{Avg}	NND_{Max}	RND_{Avg}	RND_{Max}	HN cost 10^9	HN service level	HN social impact	New established facilities	Updated facilities (Facility: Type $k \rightarrow$ Type k')
1	0.2	0.2	0.2	0.8041	1.5134	0.6349	1.3127	596	27.8	31.2	3(3), 8(3), 22(3), 23(2), 38(2), 41(3), 43(2), 45(2)	6(2→1), 12 (3→ 2), 39 (3→ 2), 42(2→ 1)
2	0.2	0.2	0.8	0.8041	1.5134	0.6349	1.3127	597	28.12	32.4	22(3), 23(3), 30(3), 38(3), 46(2)	6(2→1), 12(3→ 2), 39 (3→ 2), 40(2→1)
3	0.2	0.8	0.2	0.9372	1.8131	0.7237	1.7945	560	28.1	33.1	9(3), 11(3), 14(2), 30(2), 41(3)	1(2→1), 27(3→ 2), 37(2→ 1), 44 (3→ 2)
4	0.2	0.8	0.8	0.9372	1.8131	0.7237	1.7945	543	29.7	33.6	8(2), 23(2), 43(2)	13 (3→ 2), 28(3→ 2),24 (3→ 2),25 (2→ 1),29(2→1), 39 (2→ 1)
5	0.4	0.4	0.4	0.8234	1.6031	0.6591	1.3069	381	39.6	42.7	2(2), 8(2), 14(3), 15(2), 45(2)	26(3→ 2), 31 (3→ 2), 40(2→ 1)
6	0.6	0.6	0.6	0.8234	1.6031	0.6591	1.3069	376	40.1	43.5	4(2), 8(2), 33(2), 34(3), 45(2)	13(3→ 2), 26 (3→ 2), 31(3→ 2), 40 (2→ 1), 12(3→ 2)
7	0.8	0.2	0.2	0.766	0.91	0.647	0.975	486	29.3	36.9	9(2),23(2), 38(3), 41(3), 43(2)	7(3→ 2), 13(3→ 2), 18(2→ 1), 26 (3→ 2), 39(2→ 1), 40(2→ 1)
8	0.8	0.2	0.8	0.764	0.876	0.623	0.945	506	32.7	38.1	3(2), 14,(2), 30(2), 38(2), 38(2), 41(3)	7(3→2), 12(3→ 2), 13(3→ 2), 27(3→ 2), 44 (3→ 2),
9	0.8	0.8	0.2	0.746	0.824	0.547	1.346	463	31.2	40.5	38(3), 23(2), 30(3), 41(3), 43(2)	6(2→1), 7(3→ 2), 24(3→ 2), 25 (2→ 1), 29(2→1),39 (2→ 1), 40(2→ 1)
10	0.8	0.8	0.8	0.746	0.824	0.547	1.346	460	33.9	41.3	23(2), 30(3), 41(3), 45(2)	5(3→ 2), 13 (3→ 2), 18(2→ 1), 24 (3→ 2), 25(2→ 1),29(2→1), 40(2→ 1)

Table 7 Key solutions in meta-objective and decision space for health care network- Uncertain budget 50

Config#	w	α	β	NND_{Avg}	NND_{Max}	RND_{Avg}	RND_{Max}	HN cost 10^9	HN service level	HN social impact	New established facilities	Updated facilities (Facility: Type $k \rightarrow$ Type k')
1	0.2	0.2	0.2	1.0737	1.0778	1.0908	1.0782	494	38.9	41.7	3(2), 8(2), 11(3), 22(2), 23(2), 38(2), 41(2), 46(2)	6(2→1), 13(3→ 2), 39(3→ 2), 40(2→ 1), 42(3→ 2)
2	0.2	0.2	0.8	1.0969	1.0859	1.0722	1.0794	614	35.6	39.5	22(3), 23(3), 30(3), 38(3), 46(2)	6(2→1), 12(3→ 2), 39(3→ 2), 40(2→1)
3	0.2	0.8	0.2	1.0944	1.0835	1.0924	1.0816	509	37.2	38.1	9(2), 11(2), 14(2), 17(3), 30(2), 41(2)	1(2→1), 26(3→ 2), 27(3→ 2), 28 (3→ 2), 44(3→ 2)
4	0.2	0.8	0.8	1.0934	1.0922	1.0747	1.0965	622	34.1	35.2	8(2), 23(2), 30(2), 43(2), 45(3)	5(3→ 2), 13(3→ 2), 24(3→ 2), 28(3→ 2), 25(2→ 1), 29(2→1), 39(2→ 1)
5	0.4	0.4	0.4	1.0799	1.0983	1.0755	1.0987	640	35.6	37.1	2(3), 4(2), 8(2), 14(3), 15(2), 34(3), 45(2)	12 (3→ 2), 24(3→ 2), 26 (3→ 2), 31(3→ 2), 40 (2→ 1)
6	0.6	0.6	0.6	1.086	1.0923	1.0876	1.0724	679	31.9	34.8	3(2), 8(3), 9(2), 34(2), 45(2)	12(3→ 2), 13 (3→ 2), 24(3→ 2), 28 (3→ 2), 35(2→ 1), 39 (2→ 1)
7	0.8	0.2	0.2	1.0866	1.0877	1.0967	1.0823	736	36.6	37.5	8(2), 19(2), 22(2), 41(3), 43(2), 45(3)	28 (3→ 2), 37(2→ 1), 7(3→ 2), 18(2→ 1), 28(3→ 2)
8	0.8	0.2	0.8	1.0754	1.0914	1.0773	1.0885	737	27.6	29.8	4(2), 38(3), 14(3), 15(2), 43(3), 45(2)	7(3→2), 12(3→ 2), 13(3→ 2), 27(3→ 2), 39 (2→ 1), 44(3→ 2)
9	0.8	0.8	0.2	1.0918	1.0918	1.0844	1.0816	791	24.3	26.4	19(2), 22(3), 23(2), 17(3), 41(3), 43(2)	5(2→1), 7(3→ 2), 24(3→ 2), 25(2→ 1), 29(2→1), 31(3→ 2), 36(3→2), 37(2→ 1),39 (2→ 1)
10	0.8	0.8	0.8	1.0856	1.0872	1.0817	1.0931	795	23.5	25.8	23(2), 30(2), 41(2), 43(2), 45(2)	5(3→ 2), 13(3→ 2), 18(2→ 1), 24 (3→ 2), 25(2→ 1), 26 (3→ 2), 31(3→2), 37(2→ 1)

Table 8 Key solutions in meta-objective and decision space for health care network- Uncertain budget 100

Config#	w	α	β	NND_{Avg}	NND_{Max}	RND_{Avg}	RND_{Max}	HN cost 10^9	HN service level	HN social impact	New established facilities	Updated facilities (Facility: Type $k \rightarrow$ Type k')
1	0.2	0.2	0.2	0.8634	1.6311	0.6925	1.4154	562	35.1	36.8	4(2), 8(2), 11(3), 14(2), 19(3), 34(2), 43(2), 45(2)	5(3→2), 12(3→2), 24(3→2), 36(3→2), 37(2→1), 44(3→2)
2	0.2	0.2	0.8	0.882	1.6434	0.6807	1.4169	564	32.7	34.3	4(2), 8(2), 11(3), 14(2), 19(2), 34(3), 46(2)	5(3→2), 31(3→2), 36(3→2), 44(3→2)
3	0.2	0.8	0.2	1.0257	1.9645	0.7906	1.9409	700	33.2	31.4	2(3), 4(2), 9(2), 11(3), 14(2), 23(3), 19(3), 34(2), 43(2), 45(2)	5(3→2), 12(3→2), 24(3→2), 31(3→2), 36(3→2), 37(2→1), 44(3→2)
4	0.2	0.8	0.8	1.0247	1.9803	0.7778	1.9677	712	31	28.6	4(2), 8(2), 11(3), 14(2), 15(3), 23(3), 42(1), 45(2)	12(3→2), 24(3→2), 26(3→2), 31(3→2), 36(3→2), 39(2→1), 44(3→2)
5	0.4	0.4	0.4	0.8892	1.7607	0.7089	1.4359	748	29.3	27.4	4(2), 8(2), 11(3), 14(2), 19(2), 34(2), 43(2), 45(2), 46(2)	5(3→2), 12(3→2), 24(3→2), 27(3→2), 36(3→2), 31(3→2), 35(2→1), 37(2→1), 44(3→2)
6	0.6	0.6	0.6	0.8942	1.7511	0.7168	1.4015	762	25.9	26.1	2(2), 4(2), 14(3), 15(2), 33(2), 43(2), 46(2)	1(2→1), 12(3→2), 13(3→2), 24(3→2), 29(2→1), 31(3→2), 35(2→1), 39(2→1)
7	0.8	0.2	0.2	0.8323	0.9898	0.7096	1.0552	825	31.5	29.4	8(2), 15(2), 19(2), 34(2), 43(2), 45(3)	1(2→1), 12(3→2), 24(3→2), 31(3→2), 36(3→2), 37(2→1)
8	0.8	0.2	0.8	0.8216	0.9561	0.6712	1.0286	828	27.7	27.6	8(2), 15(2), 19(2), 34(2), 43(2), 46(2)	1(2→1), 12(3→2), 24(3→2), 31(3→2), 36(3→2), 39(2→1)
9	0.8	0.8	0.2	0.8145	0.8996	0.5932	1.4558	878	24.3	25.7	3(3), 4(3), 9(2), 14(2), 19(2), 23(3), 34(2), 43(2), 45(2)	1(2→1), 5(3→2), 13(3→2), 24(3→2), 36(3→2), 37(2→1), 44(3→2)
10	0.8	0.8	0.8	0.8099	0.8959	0.5917	1.4713	912	20.4	22.8	2(3), 4(1), 14(3), 15(2), 33(2), 43(3), 45(2)	1(2→1), 12(3→2) 13(3→2), 24(3→2), 29(2→1), 31(3→2), 35(2→1), 37(2→1), 44(3→2)

The results of Table 6 - 8 show that increasing the level of uncertainty motivates the system to open or upgrade health care facilities with higher level of services provided on average in order to secure itself against unforeseen events. In other words, due to the budget limitations for further developing the system, the health care network in an uncertain environment is designed such that it could satisfy the ongoing demands while respecting the budget limitations. Evidently, providing a higher level of services increases the cost of the system compared to the certain environments. In addition, centralising the health care network causes lower achievements for the service level and social impact targets. The reason is that a centralised health care network provokes a network with fewer facilities. Although these facilities can potentially provide a higher level of services, they are widely dispersed over the whole region. Therefore, remote regions can not benefit from a health care facility in their vicinity.

Figure 8 illustrates the performance of the health care network under the ultimate uncertainty given the data presented in Table 8. The horizontal axis represents the level of centralisation, level of non-compensation between objectives, and level of non-compensation between stakeholders. More precisely, a value 0 indicates the low level of centralisation and high level of non-compensation between objectives and stakeholders ,i.e., $w = 0.2$, $\alpha = 0.8$, and $\beta = 0.8$, and a value 1 indicates, on the contrary, the high level of centralisation and low level of non-compensation between objectives and stakeholders i.e., $w = 0.8$, $\alpha = 0.2$, and $\beta = 0.2$. These two levels of network setting present the highest preferences for the stakeholders at the regional and national levels, respectively. It can be perceived from this figure that a health care network with a low level of centralisation and high level of non-compensation between objectives and stakeholders is more effective with respect to cost, service level and social impact when uncertainty is considered. Indeed, a decentralised network that has been developed based on the preferences of the stakeholders at the regional level can be more agile and responsive in an uncertain environment.

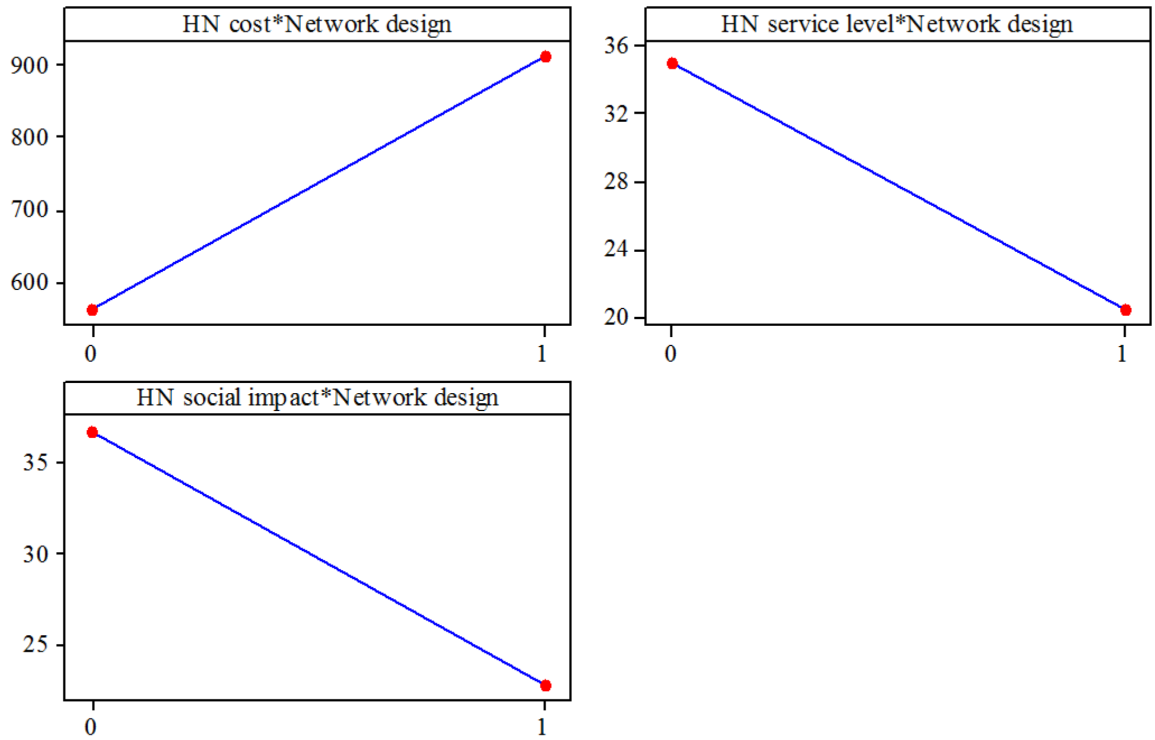


Fig. 8 Analysing health care performance measures under the ultimate uncertainty (uncertain budget %100)

Figure 9 also investigates the sensitivity of each of the three key parameters of the model under an uncertain environment. To this end, four different types of health care networks are selected. The horizontal axis represents these four types (i.e. $1 : (w = 0.2, \alpha = 0.2, \beta = 0.2)$, $2 : (w = 0.2, \alpha = 0.2, \beta = 0.8)$, $3 : (w = 0.2, \alpha = 0.8, \beta = 0.2)$, and $4 : (w = 0.8, \alpha = 0.2, \beta = 0.2)$). As can be seen in the figure, the level of the centralisation is the most sensitive parameter and the level of the non-compensation between objectives is the least sensitive one. Therefore, decentralising health care facilities is recommended as an efficient risk mitigation strategy to handle uncertainty.

Table 9 presents the impact of considering a reinvestment strategy and the correlation between development projects on the performance of the health care network in various aspects. To achieve this, we considered high levels of non-compensation among objectives, stakeholders, and network centralisation under various uncertainty budgets. The obtained results indicate that considering a reinvestment strategy

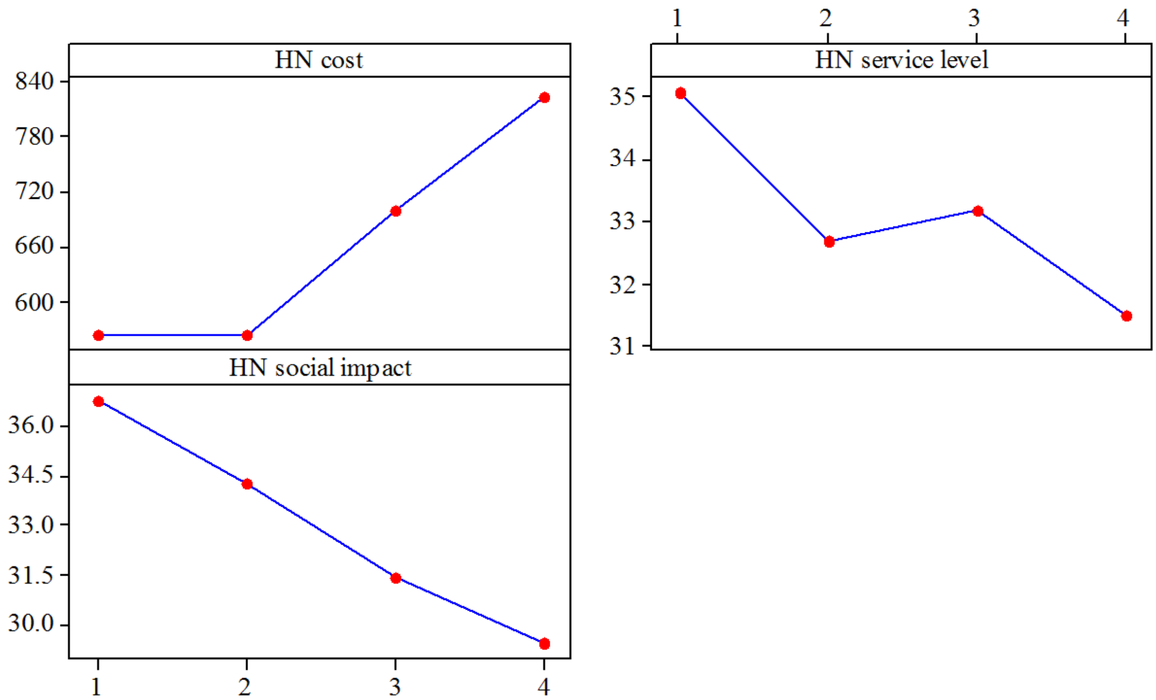


Fig. 9 Analysing the sensitiveness of the key parameters of the model under the ultimate uncertainty (uncertain budget %100)

has significant impacts on network performance due to the development based on the potentials of active facilities and earned income during the planning periods. This funding strategy leads to more balanced development despite the presence of various stakeholders with different preferences, resulting in better social impacts. By using the earned income of each facility for its upgrade, network development is limited based on the realised demands and required capacity to cost-efficiently respond to demands. Therefore, network development will be less affected by the stakeholders' expectations, regardless of the current and required capacities, and provide a better service level. As a result, health care network costs decrease, the level of health care service increases, and social impact enhances. Additionally, ignoring the correlation impact of network development projects leads to unbalanced network development, especially in neighbouring regions. Thus, the performance measures of the network deteriorate without considering the potential impacts of network development such as the establishment of new facilities and upgrades to existing facilities.

Table 9 Analysing the impact of reinvestment strategy and correlation effect on the health care network performance

Strategy	Uncertainty budget (%)	HN cost	HN service level	HN social impact	Established new facility #	Updated Current facility # (Type $k \rightarrow$ Type k')
With reinvestment and correlation effect	0	460	33.9	41.3	23(2), 30(3), 41(3), 45(2)	5(3→2), 13 (3→2), 18(2→1), 24(3→2), 25(2→1), 29(2→1), 40(2→ 1)
	50	795	23.5	25.8	23(2), 30(2), 41(2), 43(2), 45(2)	5(3→2), 13(3→2), 18(2→1), 24 (3→2), 25(2→1), 26 (3→2), 31(3→2), 37(2→1)
	100	912	20.4	22.8	2(3), 4(1), 14(3), 15(2), 33(2), 43(3), 45(2)	1(2→1), 12(3→2) 13(3→2), 24(3→2), 29(2→1), 31(3→2), 35(2→1), 37(2→1), 44(3→2)
Without reinvestment	0	793	25.1	30.6	8(2), 15(3), 19(2), 23(2), 30(1), 34(1), 38(1), 43(2), 45(2)	25 (3→2), 29(3→2), 37(3→2), 39 (3→2), 40(3→2)
	50	1569	18.9	19.3	19(2), 22(3), 23(1), 17(1), 41(1), 43(1), 45(1)	5(3→2), 25(3→2), 29(3→2), 37(3→2), 39 (3→2)
	100	2301	16.4	16.7	2(1), 4(2), 14(1), 15(2), 19(2), 23(1), 34(2), 43(1), 45(1)	5(3→2), 13(3→2), 24(3→2), 36(3→2), 35(3→2), 37(2→3), 44(3→2)
Without correlation effect	0	642	27.8	34.5	8(1), 15(1), 19(1), 34(1), 43(1), 45(1)	1(3→2), 37(3→2)
	50	1139	22.1	21.2	23(1), 30(1), 41(1), 43(1), 45(1)	8(3→2), 25(3→2), 37(3→2)
	100	1765	18.7	18.3	2(1), 4(1), 14(1), 15(1), 33(1), 43(1), 45(1)	1(3→2), 29(3→2), 35(3→2), 37(3→2)

6.4 Managerial insights

Based on the results obtained in Section 6.3, following managerial insights are drawn.

i. **Network centralisation level:**
The configuration of health care networks can adopt different levels of centralisation to satisfy various preferences at national and regional levels. For instance, in countries where health care is decentralised, policymakers may prefer a more decentralised network to align with the existing governance structure. However, a centralised network may be preferred in countries where health care decisions are made at the national level to ensure standardisation and consistency in service delivery. For example, the Netherlands' health care system operates under a centralised network, allowing policymakers to control costs and ensure quality of care across the country.

ii. **Compensation between objectives and stakeholders:**
When designing a health care network, it is essential to consider the preferences of all stakeholders, including patients, health care providers, policymakers, and the public. Stakeholder engagement and cultural efforts can help align regional and national preferences, leading to a more coordinated network. For instance, in Norway, the government has worked closely with regional stakeholders to develop a more integrated and coordinated health care system. As a result, Norway has one of the best health care systems in the world, with high patient satisfaction rates and good health outcomes.

iii. **Level of uncertainty:**
In situations where there is a high level of uncertainty, decentralised health care networks tend to perform better by providing higher service levels at each facility. For instance, during a pandemic, a decentralised network may be better equipped to handle the surge in demand for health care services. However, a decentralised network can also lead to higher network costs. Therefore, policymakers must strike a balance between service level and network cost. For example, during the COVID-19 pandemic, Germany's decentralised health care system proved to be effective in responding to the surge in demand for health care services.

iv. **Investment/reinvestment strategy:**
health care networks require ongoing investment to ensure that they can respond to changing demands and provide high-quality care. A balanced development of the network can be achieved by reinvesting in existing facilities based on their performance and potential. For example, in the UK, the National Health Service (NHS) uses a reinvestment strategy to upgrade existing facilities based on their performance and potential, leading to more efficient use of available resources.

Furthermore, our study contributes to SDGs from the social pillar perspective. The SDGs emphasise the importance of universal access to health care, the reduction of health inequalities, and the provision of affordable and quality health care services for all. By considering the preferences of all stakeholders, our study provides a tool for policymakers to design a coordinated and effective health care network that can improve health outcomes and reduce health inequalities.

7 Conclusion

This paper investigates a health care network system encompassing multiple stakeholders and objectives. In this context, all stakeholders are assumed to be connected over a hierarchical decision network. A governmental decision maker is placed at the top of this decision network, and other regional stakeholders are associated with nodes at the lower level. In order to involve the preferences of all the stakeholders in the process of decision making the extended network goal programming technique proposed by Jones et al

(2016) is used. In addition, this method is extended to include the influence of a stakeholder's preferences on the neighbouring ones.

Parametric analysis of the model is focused on three aspects: the level of non-compensation between objectives, level of non-compensation between stakeholders, and level of centralisation in the network. By doing so, it could be recognised the effect of these aspects. One of the most interesting findings was the fact that increasing the level of centralisation could improve all the performance measures at both national and regional levels. However, the level of improvement at the national level is more recognisable compared to the regional one. It is also noted that increasing the level of non-compensation between stakeholders in the network improves all of the four measures. On the contrary, decreasing the level of non-compensation between objectives does not improve all the four measures.

Given the fact that a sustainable and agile solution will likely be of interest to decision makers and stakeholders, integrating disruption issues with the proposed model is one of the main future research directions of this work. There might be cases where multi-choice aspiration levels can better cope with the desire of the decision makers. As a consequence, using the multi-choice goal programming variant combined with extended network goal programming could also be a promising research area.

Conflict of interest

The authors declare that they have no conflict of interest

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Appendix

A: Robust Model

To present robust optimization framework, let us consider equations 21 to 23 presented below such that parameters a^1 and b^2 can be described with interval uncertainty.

$$A^1 x \leq B^1 \tag{21}$$

$$A^2 x \leq B^2 \tag{22}$$

$$l \leq x \leq u \tag{23}$$

It is assumed that each uncertain parameter takes value according to a symmetric distribution with mean equal to the nominal value such as $\left[a_{ij}^1 - a\prime_{ij}^1, a_{ij}^1 + a\prime_{ij}^1\right]$ and $\left[b_i^2 - b\prime_i^2, b_i^2 + b\prime_i^2\right]$. $a\prime_{ij}^1$ and $b\prime_i^2$ are shift values. Zro_i^1 and Pro_j^1 are the supplementary variables for the robust counterpart of the uncertainty of a^1. Zro_i^2 and Pro_j^2 are the supplementary variables for the robust counterpart of the uncertainty of b^2. The role of the parameter Γ , as an uncertainty budget, is to adjust the robustness of the proposed method against the level of conservatism of the solution. According to the approach proposed by Bertsimas and Sim (2004), the tractable robust counterpart of the aforementioned uncertain equations 21 to 23 is as follows:

$$zro^0 + pro_j^0 \geq \hat{c}_j \cdot y_j^0 \tag{24}$$

$$\sum_j a_{ij}^1 x_j + \Gamma_i^1 \cdot zro_i^1 + \sum_{j \in J_1} pro_j^1 \leq b_i^1 \tag{25}$$

$$zro_i^1 + pro_{ij}^1 \geq a\prime_{ij}^1 \cdot y_j^1 \tag{26}$$

$$\sum_j a_{ij}^2 x_j + \Gamma_i^2 \cdot zro_i^2 + \sum_{j \in J_1} pro_j^2 \leq b_i^2 \tag{27}$$

$$zro_i^2 + pro_j^2 \geq \hat{b}_i^2 \tag{28}$$

$$- y_j^0 \leq x_j \leq y_j^0 \tag{29}$$

$$- y_j^1 \leq x_j \leq y_j^1 \tag{30}$$

Uncertain parameters in the proposed model are EI_{kj} and AC_0. EI'_{kj} and AC'_0 are shift values in symmetric distributions of $\left[EI_{kj} - EI'_{kj}, EI_{kj} + EI'_{kj}\right]$ and $[AC_0 - AC'_0, AC_0 + AC'_0]$, respectively.

Constraints 31 to 36 are imposed to develop the robust counterpart optimization model by considering the specific auxiliary variables (i.e., first, second, and third) under interval uncertainty of potential social impact of each facility in each type at each region. Similarly, Constraints 37 to 42 are imposed to develop the robust counterpart optimization model under interval uncertainty of national available budget for health service providing.

$$\begin{pmatrix} \sum_{k,j} EI_{kj} \cdot y^n_{kj} + \sum_{k,k',j} EI_{kj} \cdot y^c_{kkj} + n^N_H - p^N_H \\ +\Gamma^1_1 \overline{zro}^1_1 + \sum_{j \in J_1, k \in K_1} \overline{pro}^1_{kj} \\ +\Gamma^1_2 \overline{zro}^1_2 + \sum_{j \in J_1, k' \in K_1} \overline{pro}^2_{k'j} \end{pmatrix} \leq SI_0 \tag{31}$$

$$\begin{pmatrix} -\sum_{k,j} EI_{kj} \cdot y^n_{kj} - \sum_{k,k',j} EI_{kj} \cdot y^c_{kkj} - n^N_H + p^N_H \\ +\Gamma^1_1 \underline{zro}^1_1 + \sum_{j \in J_1, k \in K_1} \underline{pro}^1_{kj} \\ +\Gamma^1_2 \underline{zro}^1_2 + \sum_{j \in J_1, k' \in K_1} \underline{pro}^2_{k'j} \end{pmatrix} \leq -SI_0 \tag{32}$$

$$\overline{zro}^1_1 + \overline{pro}^1_{kj} \geq EI'_{kj} \cdot y^n_{kj} \tag{33}$$

$$\overline{zro}^1_2 + \overline{pro}^2_{kj} \geq EI'_{kj} \cdot y^n_{kj} \tag{34}$$

$$\underline{zro}^1_1 + \underline{pro}^1_{kj} \geq -EI'_{kj} \cdot y^n_{kj} \tag{35}$$

$$\underline{zro}^1_2 + \underline{pro}^2_{kj} \geq -EI'_{kj} \cdot y^n_{kj} \tag{36}$$

$$\begin{pmatrix} \sum_{k,j} IC_{kj} \cdot y^n_{kj} + \sum_{k,k',j} EC_{kk'j} \cdot y^c_{kk'j} + n^N_c - p^N_c \\ +\Gamma 1^2 \cdot \overline{zro}^2 + \sum_{k \in K_1, j \in J_1} \overline{pro}'^1_{k,j} \\ +\Gamma 2^2 \overline{zro'}^2 + \sum_{k \in K_1, k' \in K_1, j \in J_1} \overline{pro}'^2_{kk'j} \end{pmatrix} \leq AC_0 \tag{37}$$

$$\begin{pmatrix} -\sum_{k,j} IC_{kj} \cdot y^n_{kj} - \sum_{k,k',j} EC_{kk'j} \cdot y^c_{kk'j} - n^N_c + p^N_c \\ +\Gamma 1^2 \cdot \underline{zro}^2 + \sum_{k \in K_1, j \in J_1} \underline{pro}'^1_{k,j} \\ +\Gamma 2^2 \underline{zro}'^2 + \sum_{k \in K_1, k' \in K_1, j \in J_1} \underline{pro}'^2_{kk'j} \end{pmatrix} \leq -AC_0 \tag{38}$$

$$\overline{zro}^2 + \overline{pro}'^1_{kj} \geq AC'_0 \tag{39}$$

$$\overline{zro}'^2 + \overline{pro}'^2_{kk'j} \geq AC'_0 \tag{40}$$

$$\underline{zro}^2 + \underline{pro}'^1_{kj} \geq AC'_0 \tag{41}$$

$$\underline{zro}'^2 + \underline{pro}'^2_{kk'j} \geq AC'_0 \tag{42}$$

$$\overline{zro}_1, \overline{pro}_{k,j}^1, \overline{zr_o}^1, \overline{pro}_{k,j}^2, \underline{zro}_1^1, \underline{pro}_{k,j}^1, \underline{zro}_2^1, \underline{pro}_{k,j}^2 \geq 0 \tag{43}$$

$$\overline{zro}^2, \overline{pro'_{kj}}, \overline{zro'}^2, \overline{pro'_{kk'j}}^2, \underline{zro}^2, \underline{pro}'^1_{kj}, \underline{zro}'^2, \underline{pro}'^2_{kk'j} \geq 0 \tag{44}$$

B: Potential projects analysis using the best-worst fuzzy method

At first, a set of possible potential projects of health network development is ranked for each region. There are various potential choices at each region for health care network development such as new facility establishment at different levels and upgrading/downgrading the level of health services at the existing health centre facilities. Besides, in order to evaluate potential network development projects in each region, there may exist various qualitative and quantitative criteria. Often, the expert qualitative judgements include a certain level of ambiguity and intangibility. Hence, the crisp values of criteria may not be precise enough to model the real-life multi-criteria decision-making. That is the reason the best-worst method, one of the recent MCDM methods, under fuzzy environment is utilised in this study. This method introduced by Guo and Zhao (2017) extends the best-worst method to the fuzzy environment. After applying this method, only top-ranked projects are considered to be evaluated in the next stage, i.e. extended goal programming model.

These different criteria, $\{C_1, \ldots, C_{10}\}$, develop the decision criteria system which their values indicate the performance of considered alternatives associated with each specific criteria. This method aims at obtaining practical preference ranking for alternatives as well as greater comparison consistency. For this purpose, the best and the worst criterion presented as C_B and C_W, respectively are determined based on the experts' opinions. Then, the fuzzy reference comparisons using the linguistic terms of experts is deployed for the best criterion in two steps: (i) pairwise comparison between the best criterion and others criteria; and (ii) pairwise comparison between considered criteria and the worst one. Using transformation rules, these extracted fuzzy preferences are then transformed to triangular fuzzy numbers (TFNs) as follows: equally important $(EI) \sim (1, 1, 1)$, weakly important $(WI) \sim (2/3, 1, 3/21)$, fairly important $(FI) \sim (3/2, 2, 5/2)$, very important $(VI) \sim (5/2, 3, 7/2)$, and absolutely important $(AI) \sim (7/2, 4, 9/2)$. Then, fuzzy Best-to-Others as well as Others-to-worst vector are obtained as $\tilde{A}_B = (\tilde{a}_{B1}, \tilde{a}_{B2}, \ldots, \tilde{a}_{Bn})$ and $\tilde{A}_W = (\tilde{a}_{1W}, \tilde{a}_{2W}, \ldots, \tilde{a}_{nW})$, respectively. Eventually, the optimal fuzzy weights, $(\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n)$, of considered criteria are determined by solving the following optimisation problem (Guo and Zhao, 2017).

$$\min \max_j \left\{ \left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj} \right|, \left| \frac{\tilde{w}_j}{\tilde{w}_w} - \tilde{a}_{jw} \right| \right\} \tag{45}$$

$$\sum_{j=1}^{n} R(\tilde{w}_j) = 1 \tag{46}$$

$$l_j^w \leq m_j^w \leq u_j^w \quad \forall j = 1, \ldots, n \tag{47}$$

$$l_j^w \geq 0 \quad \forall j = 1, \ldots, n \tag{48}$$

Objective function (45) could be transformed to a simpler one by using maximum definition. Equation (46) presents a weight normalisation. Equations (47-48) demonstrate the smallest likely, most probable, and largest possible values of any fuzzy event.