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Design of a Reliable Facility Location Model for Health Service Networks

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ABSTRACT

This paper proposes a novel facility location model for health service network design by considering different key elements including the reliability aspects, service capacity, congestion, service quality, surrounding public infrastructures, geographical accessibility and several types of cost such as investment, transportation and operational costs. We formulate the problem as a robust scenario-based stochastic programming model to deal with different categories of uncertainty associated with reliability, demand, service and geographical accessibility such that the minimization of expected costs under all disruption scenarios will be attained. To illustrate the applicability of the proposed model, a real-life case study based on the health service network of Sistan and Baluchestan province is presented. The findings of this research enable the system designers to investigate different strategic and operational decisions in the design and management of the health service networks from both cost and risk perspectives.

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1. INTRODUCTION

Location and allocation decisions play a significant role in the success of private and public sectors such as emergency service systems, post offices, bank branches, automated teller machines, gas stations, etc. To address these strategic decisions, numerous researches have been developed in the literature, among them Alizadeh et al. [1], Karimi et al. [2], Bashiri and Rezanezhad [3] and Arkat and Jafari [4]. Health service network is one of the most important public service provisions in urban and rural areas which is strongly affected by facility location and allocation decisions. As declared by Rahman and Smith [5], these decisions can ensure that the objective of system design such as minimizing social cost or equivalently maximizing the benefits of the people is served. They also provide a framework for investigating service accessibility problems, comparing the quality of previous location decisions and generating alternative solutions.

Despite the importance of location-allocation model in the context of healthcare planning, some of its assumptions are unrealistic. For example it is assumed that a constructed facility will remain operational forever. However, in practice there are many types of disruptive events that can become a facility unavailable from a time moment to another one. Disruptive events may be originated from different reasons including natural disasters, equipment breakdowns, terrorist attacks, labor strikes, changes in ownership, etc [6, 7]. In the occurrence of disruptions, most of the regular services like accepting patients and scheduling surgical procedures cannot be served. In most of research papers, health service facilities are assumed to have enough capacity to serve all the simultaneous demands immediately. However, real health service facilities may be congested in some situations due to the limited capacity to serve heavy and random demands. In the congested situations, the patients may afford to wait until the facility becomes free to serve them, whereas in some other cases such as maternity homes, it is not possible to wait [8, 9]. Consequently, it is crucial to consider reliability aspects and congested situations in the health service network design.

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When planning the health service network, several critical issues must be taken into account including the geographical accessibility, transportation network, service capacity, congestion, service quality, surrounding public infrastructures and different types of cost such as investment, transportation and operational costs. Since most of these issues involve a high degree of uncertainty during operating process, it is important to study their uncertainty in order to obtain an effective and efficient network design. As declared by Shen et al. [10], the uncertainty can be classified into three categories including provider-side uncertainty, receiver-side uncertainty and in-between uncertainty. The first is related to the uncertainty in facility capacity and the reliability of facilities; the second includes the randomness within the demands; and the third corresponds to the uncertain travel time, transportation cost, etc. As the related literature shows, there is no research that applied all the aforementioned relevant aspects of configuration of health service network. Moreover, none of the research paper considered all categories of uncertainty concurrently.

With regard to the enumerated matters, the current research proposes a novel location model for health service network design. We consider the risk of unexpected disruptive events by a set of disruption scenarios each associated with a given probability. The queuing system is considered in the model which handles uncertainty associated with demand as well as service. To ensure the service quality, a maximum limit for patients' expected waiting time is defined. The geographical accessibility of a health service network is considered in terms of the proximity of a facility to the potential patients and its value depends on the realized disruption scenario. We formulate the problem as a robust scenario-based stochastic programming model to deal with different categories of uncertainty including provider-side, receiver-side and in-between. We present a practical case study and several generated instances to illustrate the applicability of the proposed model.The rest of this paper is organized as follows. The next section reviews the related literature. The proposed model is presented in Section 3. Section 4 presents the robust formulation of proposed model. Section 5 describes a real-world case study as well as several generated instances. Section 6 ends with some conclusions and possible directions for future research.

2. LITERATURE REVIEW

The relevant literature in the context of facility location problem for health service network is reviewed in this section. Narula and Ogbu [11] presented a hierarchical location-allocation problem by considering the possibility of referral service. Rahman and Smith [12] proposed a location model to improve the accessibility of people to the healthcare system in a rural area in Bangladesh**.** A hierarchical facility location problem with the objective of maximum coverage of population was studied by Moore and ReVelle [13]. Galvao et al. [14] proposed a location model for maternal and perinatal healthcare facilities in municipality of Rio de Janeiro. Galvao et al. [15] extended the work of Galvao et al. [14] by considering capacity constraints and solved the model by Lagrangian relaxation approach. Sahin et al. [16] formulated a facility location model for regionalization of blood services. A facility location model for seasonally moving populations has been addressed by Ndiaye and Alfares [17]. Smith et al. [18] proposed a number of location models range from *covering* type to *p-median* aimed at planning of community health schemes. Zhang et al. [19] incorporated congestion to the preventive healthcare facility network design and applied it to mammography centers in Montreal. Sorensen and Church [20] estimated the aggregate service levels of emergency medical services by considering expected coverage. Mestre et al. [21] presented a hierarchical model to study decisions on the location and supply of hospital services. Syam and Cote [22] developed a location model for specialized health care services such as the treatment and rehabilitation necessary for strokes or traumatic brain injuries. Benneyan et al. [23] presented single and multi-period location models within the Veterans Health Administration to explore relationships and tradeoffs between costs, coverage, service location and capacity.

Burkey et al. [24] examined the efficiency and equality in accessibility provided by hospitals and compared existing locations with optimal ones. Zhang et al. [25] investigated a facility location model to consider the impact of client choice on preventive healthcare facility network design. A location model for maximizing the perinatal care accessibility in maternity hospitals in France was presented by Baray and Cliquet [26]. Zahiri et al. [27] presented a robust possibilistic programming approach for a multi-period location problem in an organ transplant supply chain. Mestre et al. [28] addressed two location-allocation models for hospital planning in the presence of uncertainty associated with the demand and supply of hospital services. Guerriero et al. [29] compared the existing health care service network of Calabria with the configurations determined by solving well-known facility location models.

3. MODEL FORMULATION

In this section, we present the notation and formulation of reliable facility location model for health service network design.

3. 1. Notation The sets, parameters and decision variables used in the proposed model are defined as follows:

Sets:

I	Set of demand nodes
J	Set of candidate locations for hospitals
K	Set of potential treatment units
S	Set of disruption scenarios

Parameters:

g_j	Fixed installation cost to establish a hospital at candidate location j
f_{jk}	Fixed installation cost to establish treatment unit k at hospital j
fs_{jk}	Fixed staffing cost for treatment unit k of hospital j
fa_{ijk}	Fixed cost per admission associated with patient i at treatment unit k of hospital j
c_{ij}	Transportaion cost from demand node i to hospital j
v_{ijk}	Treatment variable cost per length of time for patient i at treatment unit k of hospital j
ta_{ijk}	Average length of time for patient i at treatment unit k of hospital j
p_s	The probability of disruption scenario s
h_{ik}^s	Demand rate at demand node i for treatment unit k under disruption scenario s
λ_{jk}^s	Total arrival rate at treatment unit k of hospital j under disruption scenario s
W_{jk}^s	Patients' expected waiting time in queue at treatment unit k of hospital j under disruption scenario s
τ_{jk}	Maximum acceptable patients' waiting time at treatment unit k of hospital j
Q	Maximum number of hospitals that can be established
P_j	Maximum number of treatment units that can be established at hospital j
μ_{jk}^s	Service rate of treatment unit k of hospital j under disruption scenario s
d_{ij}	Shortest distance between demand node i and hospital j
$d_{\max}^s$	Maximum acceptable distance for demand nodes to access the service of hospitals under disruption scenario s
pop_j	Population located in candidate location j
$pop_{\min}$	Minimum population required to open a hospital
φ_j^s	1 if hospital j is disrupted under disruption scenario s, 0 otherwise

Decision variables:

z_j	1 if a hospital is located at node j, 0 otherwise
y_{jk}	1 if a treatment unit k is located at hospital j, 0 otherwise
x_{ijk}^s	Portion of patients residing at demand node i is assigned to treatment unit k of hospital j under disruption scenario s

3. 2. Formulation We formulate a comprehensive reliable location model by considering risk of unexpected disruptive events, congestion, service quality, service capacity, geographical accessibility, minimum population required to open a facility and different categories of uncertainty associated with parameters.

We define a scenario with a given probability for each outcome of the random disruptive event that can affect the system in order to cope with the risk of disruptions caused by natural disasters or man-made hazards. We assume that there exists a service team including specialists and service personnel in each treatment unit that can provide health services and each treatment unit behaves as an *M/M/1* queue, implying that the requests for the service appear according to a Poisson process and service time is exponentially distributed. Note that the Poisson process is a good representation of the arrival rates of real-world health service networks in which there is always a variation around scheduled times [19, 25, 30]. Considering the *M/M/1* queuing system, the demand generation rate at each demand node i under disruption scenario s is the Poisson process with average demand rate h_{ik}^s, thus the demand rate at treatment unit k of hospital j under disruption scenario s can be written as:

$$\lambda_{jk}^s = \sum_{i \in I} h_{ik}^s x_{ijk}^s. \tag{1}$$

The stability of the queue at treatment unit k of hospital j under disruption scenario s is assured as follows:

$$\lambda_{jk}^s \le \mu_{jk}^s y_{jk}. \tag{2}$$

According to Gross and Hariss [31], the patients' expected waiting times at treatment unit k of hospital j under disruption scenario s is the following:

$$W_{jk}^s = \frac{1}{\mu_{jk}^s - \lambda_{jk}^s}. \tag{3}$$

To maintain congestion within acceptable limits, a capacity constraint must be considered in the model. The common approach used to consider the capacity constraints in facility location for congested systems is to restrict the expected number of requests for service or waiting time to be less than some small values [32]. The quality of service network can also be expressed in terms of expected or worst case waiting times or queue length for a specific service [19, 25]. Therefore, the service quality for treatment unit k of hospital j is enforced through restriction on the level of congestion to ensure that patients' expected waiting times in system do not exceed maximum acceptable level as the following:

$$W_{jk}^{s} \le \tau_{jk} y_{jk}. \tag{4}$$

By considering Equation (3), the above equation can be stated as follows:

$$1 \le \tau_{jk}\left(\mu_{jk}^{s} - \lambda_{jk}^{s}\right) y_{jk}, \tag{5}$$

The above constraint can be rewritten in a simpler form as follows:

$$1 + \tau_{jk}\lambda_{jk}^{s} y_{jk} \le \tau_{jk}\mu_{jk}^{s} y_{jk}. \tag{6}$$

The cost elements of systems include the fixed installation cost of hospitals (*FCH*), fixed installation cost of treatment units of constructed hospitals (*FSTU*), expected traveling cost from patients to the hospitals (TC_s), expected fixed cost per admission (AC_s), expected fixed staffing cost (SC_s) and expected treatment cost (TRC_s). These cost elements are given in the following:

$$FCH = \sum_{j \in J} g_j z_j. \tag{7}$$

$$FSTU = \sum_{j \in J}\sum_{k \in K} f_{jk} y_{jk}. \tag{8}$$

$$TC_s = \sum_{i \in I}\sum_{j \in J}\sum_{k \in K} h_{ik}^{s} c_{ij} x_{ijk}^{s}. \tag{9}$$

$$AC_s = \sum_{i \in I}\sum_{j \in J}\sum_{k \in K} h_{ik}^{s} fs_{jk} x_{ijk}^{s}. \tag{10}$$

$$SC_s = \sum_{i \in I}\sum_{j \in J}\sum_{k \in K} h_{ik}^{s} fa_{ijk} x_{ijk}^{s}. \tag{11}$$

$$TRC_s = \sum_{i \in I}\sum_{j \in J}\sum_{k \in K} h_{ik}^{s} v_{ijk} ta_{ijk} x_{ijk}^{s}. \tag{12}$$

The formulation of reliable facility location model under disruptions for health service networks can be stated as follows:

$$Min\, Z = FCH + FSTU + \sum_{s \in S} p_s\left[TC_s + AC_s + SC_s + TRC_s\right] \tag{13}$$

$$\sum_{j \in J} x_{ijk}^{s} = 1, \qquad \forall i \in I, k \in K, s \in S, \tag{14}$$

$$x_{ijk}^{s} \le \left(1 - \varphi_j^{s}\right) y_{jk}, \qquad \forall i \in I, j \in J, k \in K, s \in S, \tag{15}$$

$$y_{jk} \le z_j, \qquad \forall j \in J, k \in K, \tag{16}$$

$$\sum_{j \in J} z_j \le Q, \tag{17}$$

$$\sum_{k \in K} y_{jk} \le P_j, \qquad \forall j \in J, \tag{18}$$

$$\sum_{i \in I} h_{ik}^{s} x_{ijk}^{s} \le \mu_{jk}^{s} y_{jk}, \qquad \forall j \in J, k \in K, s \in S, \tag{19}$$

$$1 + \tau_{jk} y_{jk} \sum_{i \in I} h_{ik}^{s} x_{ijk}^{s} \le \tau_{jk}\mu_{jk}^{s} y_{jk}, \quad \forall j, k, s, \tag{20}$$

$$z_j = 0, \qquad \forall j \in \left\{pop_j < pop_{\min}\right\}, \tag{21}$$

$$x_{ijk}^{s} = 0, \qquad \forall i \in I, j \in \left\{j \middle| d_{ij} > d_{\max}^{s}\right\} k \in K, s \in S, \tag{22}$$

$$x_{ijk}^{s} \ge 0, \qquad \forall i \in I, j \in J, k \in K, s \in S, \tag{23}$$

$$y_{jk} \in \{0,1\}, \qquad \forall j \in J, k \in K, \tag{24}$$

$$z_j \in \{0,1\}, \qquad \forall j \in J. \tag{25}$$

The Objective function (13) minimizes the fixed installation cost of hospitals, fixed installation cost of treatment units of constructed hospitals and expected traveling cost, fixed cost per admission, fixed staffing cost and treatment cost under all disruption scenarios. Constraint (14) insures that the patients' demand must be served. Constraint (15) assures that patients must be assigned only to established and survived treatment units under each disruption scenario. Constraint (16) insures that a treatment unit can only be opened in a constructed hospital. Constraint (17) specifies maximum number of hospitals that can be established. Constraint (18) represents maximum number of treatment units that can be opened at each hospital. Constraint (19) guarantees the stability of the queue at the treatment units. Constraint (20) ensures the service quality at each treatment unit. Constraint (21) indicates that each hospital can only be opened in candidate locations that have a population higher than a predefined value. Constraint (22) ensures that patients should not take more than a maximum acceptable distance to access services. Constraints (23) to (25) enforce the non-negativity and binary constraints of decision variables.

The proposed model is non-linear due to the multiplication of binary and integer variables in constraint (20). Let $\varpi_{ijk}^{s} = y_{jk} x_{ijk}^{s}$ and M be a reasonably large number. Therefore, the non-linear constraint can be replaced by:

$$1+\tau_{jk}\sum_{i\in I} h^{s}_{ik}\varpi^{s}_{ijk} \le \tau_{jk}\mu^{s}_{jk} y_{jk}, \quad \forall j\in J, k\in K, s\in S, \tag{26}$$

$$\varpi^{s}_{ijk} \le x^{s}_{ijk}, \quad \forall i\in I, j\in J, k\in K, s\in S, \tag{27}$$

$$\varpi^{s}_{ijk} \le M\, y_{jk}, \quad \forall i\in I, j\in J, k\in K, s\in S, \tag{28}$$

$$\varpi^{s}_{ijk} \le x^{s}_{ijk} - M\left(1-y_{jk}\right), \quad \forall i\in I, j\in J, k\in K, s\in S, \tag{29}$$

$$\varpi^{s}_{ijk} \ge 0, \quad \forall i\in I, j\in J, k\in K, s\in S. \tag{30}$$

4. THE ROBUST MODEL

The proposed model introduced in the previous section involves different categories of uncertainty. To deal with these uncertainties, we have used the robust approach proposed by Leung et al. [33] which is an extension of Mulvey et al. [34]. This procedure involves solution robustness and model robustness. The former seeks to find solution that is optimal in all possible realizations of uncertain parameters and the latter ensures the feasibility of the solution in all possible realizations of uncertain parameters by considering penalty functions [34].

In the following, we briefly describe the robust scenario-based stochastic formulation proposed by Mulvey et al. [34]. Consider the following linear optimization model:

$$Min \quad f(x,y) = c^{T}x + d^{T}y \tag{31}$$

$$Ax = b, \tag{32}$$

$$Bx + Cy = e, \tag{33}$$

$$x, y \ge 0. \tag{34}$$

where, $x \in R^{n_1}$ and $y \in R^{n_2}$ are a vector of the design variables and a vector of the control variables, respectively. The coefficients of constraint (32) are fixed and free of noise while those for constraint (33) are subject to noise. A robust optimization model can be represented as follows:

$$Min \quad \sigma(x, y_1, \ldots, y_S) + \vartheta\rho\left(o_1, \ldots, o_S\right) \tag{35}$$

$$Ax = b, \tag{36}$$

$$B_s x + C_s y_s + o_s = e_s, \quad \forall s\in S, \tag{37}$$

$$x, y_s \ge 0, \quad \forall s\in S. \tag{38}$$

Since the model may become infeasible under some scenarios, the control variable o_s , which represents the infeasibility of the model under scenario *s*, is defined. The first part of objective function (35) represents the solution robustness and the second part is the model robustness weighted by ϑ . Mulvey et al. [34] defined the solution robustness as follows:

$$\sigma(0) = \sum_{s\in S} p_s\xi_s + \Lambda\sum_{s\in S} p_s\left(\xi_s - \sum_{s\in S} p_{s'}\xi_{s'}\right)^2. \tag{39}$$

where ξ_s is the cost or benefit function under scenario *s* and Λ presents the determined weight of the solution variance. Yu and Li [35] proposed the following absolute deviation instead of the quadratic term given by Equation (39)

$$\sigma(0) = \sum_{s\in S} p_s\xi_s + \Lambda\sum_{s\in S} p_s\left|\xi_s - \sum_{s'\in S} p_{s'}\xi_{s'}\right|. \tag{40}$$

We use the procedure proposed by Leung et al. [33] to linearize the absolute value. Therefore, we have:

$$Min \sum_{s\in S} p_s\xi_s + \Lambda\sum_{s\in S} p_s\left[\left(\xi_s - \sum_{s'\in S} p_{s'}\xi_{s'}\right) + 2\theta_s\right] \tag{41}$$

$$\xi_s - \sum_{s'\in S} p_{s'}\xi_{s'} + \theta_s \ge 0, \quad \forall s\in S, \tag{42}$$

$$\theta_s \ge 0, \quad \forall s\in S. \tag{43}$$

Note that when ξ_s is greater than $\sum_{s\in S} p_s\xi_s$, then $\theta_s = 0$. When $\sum_{s\in S} p_s\xi_s$ is greater than ξ_s , then we have:

$$\theta_s = \sum_{s\in S} p_s\xi_s - \xi_s. \tag{44}$$

The violation of control constraint (36) should be penalized to represent the model robustness. As a result, the objective function of robust optimization problem given by (35) , can be written as:

$$Min \sum_{s\in S} p_s\xi_s + \Lambda\sum_{s\in S} p_s\left[\left(\xi_s - \sum_{s'\in S} p_{s'}\xi_{s'}\right) + 2\theta_s\right] + , \ \vartheta\sum_{s\in S} p_s o_s \tag{45}$$

We consider p^{s}_{ik} as the unmet demand of patient *i* for treatment unit *k* under disruption scenario *s* to formulate the robust model. Therefore, the proposed robust scenario-based stochastic programming model can be stated as follows:

$$Min \quad Z = FCH + FSTU + \sum_{s\in S} p_s TOC_s + \Lambda\sum_{s\in S} p_s \tag{46}$$

$$\left[\left(TOC_s - \sum_{s'\in S} p_{s'} TOC_s\right) + 2\theta_s\right] + \vartheta \sum_{s\in S} p_s \left(\sum_{i\in I}\sum_{k\in K} p_{ik}^s\right)$$

$s.t.$ (15) – (19),(21) – (30),(43)

$$\sum_{j\in J} x_{ijk}^s + p_{ik}^s = 1, \qquad \forall i\in I, k\in K, s\in S, \tag{47}$$

$$TOC_s - \sum_{s'\in S} p_{s'} TOC_{s'} + \theta_s \geq 0, \qquad \forall s\in S, \tag{48}$$

$$p_{ik}^s \geq 0, \qquad \forall i\in I, k\in K, s\in S, \tag{49}$$

Note that TOC_S is defined as follows:

$$TOC_S = TC_S + AC_S + SC_S + TRC_S. \tag{50}$$

It should be noted that $TOC_{S'}$ is obtained by replacing s' instead of s in the definition of TOC_S .

5. COMPUTATIONAL STUDY

In this section, a real-world case study and several generated instances are presented to illustrate the applicability of the proposed model. The model is coded in GAMS23.4 optimization software and all the experiments are performed on an INTEL Core 2 CPU with 2.4 GHz processor and 2 GB of RAM. It should be noted that the results are reported based on the formulation of the robust model presented in Section 4. A practical case study based on the vastest province of Iran, Sistan and Baluchestan, is presented. This province coveres 11.5% of Iran with an approximate area of 181,785 km^2. It has 37 population centers with a total population of 2,534,327 and about 51% of the population lives in the rural areas with poor accessibility to health service network. A geographical map including population centers as well as existing health service facilities is shown in Figure 1.

As it can be seen, most of population centers are not equipped with hospitals and their population must incur considerably long distances to access health services. Moreover, most of the existing hospitals have not sufficient capacity to satisfy the potential demand. In some cases, such situations will result in serious health problems or even death. Therefore, we design a reliable health service network with sufficient capacity to serve potential demand such that the improvement in geographical accessibility of health service facilities will be attained.

The data range for the case study is summarized in Table 1. Note that the traveling cost for each patient is calculated based on the Euclidean distance between two population centers obtained from site coordinates and is rounded to its nearest integer value. We set the penalty cost to $\vartheta = \max_{i,j,k}\{fs_{jk} + fa_{ijk} + v_{ijk} ta_{ijk}\}$.

The Sistan and Baluchestan province is considered as a disaster-prone area in the country in which there is risk of various disruptive events such as floods, earthquakes and storms due to the climate and geographical conditions. According to the Department of Disaster Management of Sistan and Baluchestan, over 150 natural disasters were affected this province between 2010 to 2016. Such disruptions can significantly deteriorate the overall system efficiency and responsiveness. Moreover, the current health service network does not work perfectly reliable and health service facilities may become unavailable due to the contaminations of a hospital wing, unexpected delay in drug supply, lack of specialists, service personnel or drug, labor actions, sabotage or changes in ownership, etc.

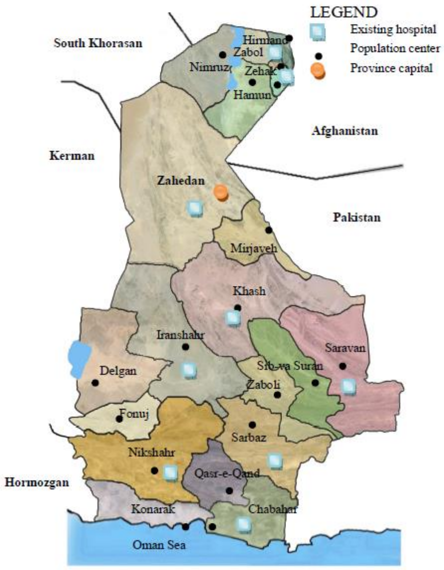
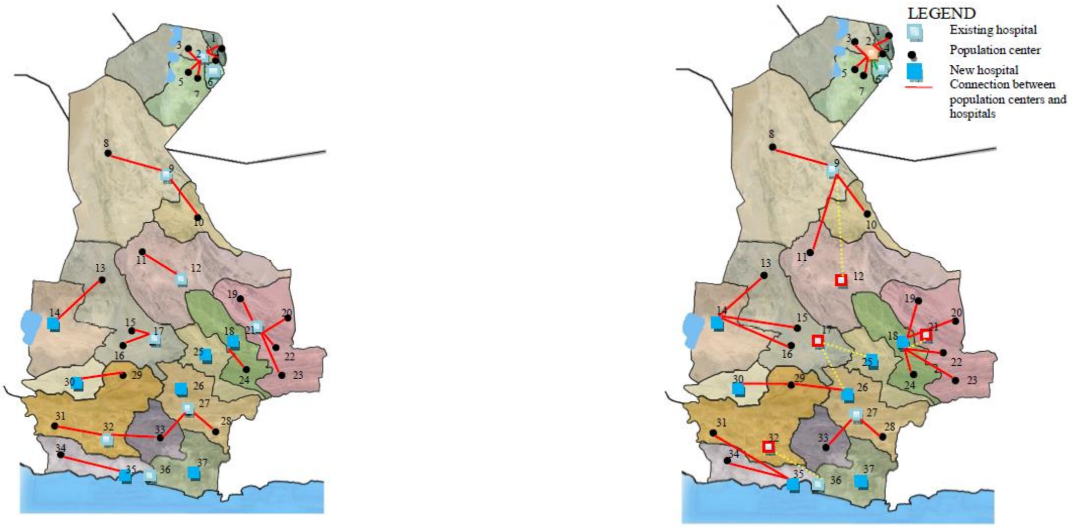


Figure 1. Geographic map of Sistan and Baluchestan province

TABLE 1. Data used in case study

Parameters	Values	Parameters	Values
g_j	U[10,55]×10^5	d_{ij}	U(5,850)
f_{jk}	U[2,7] ×10^5	Q	9
fs_{jk}	U[150,300]	P_j	U[5,15]
fa_{ijk}	U[100,200]	μ_{jk}^s	U[10,55]×10^4
v_{ijk}	U[200,350]	$pop_{\min}$	50000
ta_{ijk}	U[2,15]	$d_{\max}^s$	U[50,150]
c_{ij}	[30,60] $\partial.d_{ij}, \partial \in$	τ_{jk}	U[10,30]



a) Normal situation b) Scenario 1

Figure 2. The optimal solution of the case study

TABLE 2. Impact of reliability on the system

Solution	Normal condition	Disruptive conditions
TCS	1366831235	1437645724
FCH(%)	12.74	10.46
FSTU(%)	19.43	20.11
ETC_s(%)	7.84	6.31
EAC_s(%)	5.62	5.02
ESC_s(%)	9.37	7.45
$ETRC_s$(%)	41.72	44.46
EPC(%)	3.28	6.19
UD (%)	0.37	2.32

Based on the historical data and experts' opinions, we consider several disruption scenarios. These disruption scenarios include earthquake, flood, storm, lack of specialists, lack of service personnel, lack of drug, personnel action, contaminations of a hospital wing, fire and change in ownership and their associated probability is 0.31, 0.06, 0.35, 0.1, 0.05, 0.05, 0.01, 0.05, 0.01 and 0.01, respectively.

Figure 2 illustrates the optimal solution obtained from solving the problem by considering two conditions including normal disruption-free and storm scenario graphically. Since the optimal location of hospitals in all disruption scenarios is fixed and only the allocation of population centers to the health service facilities varies, for the sake of brevity, the optimal solution based on the storm scenario is shown in Figure 2.

Table 2 gives the obtained results regarding normal and disruptive conditions. The *TCS*, *EPC* and *UD* present the total cost of system, expected penalty cost and unsatisfied demand, respectively. Note that *E* before each cost element in this table denotes its expected value. The total cost is given in Monetary Unit (MU). The unsatisfied demand in the normal situation is related to the maximum acceptable distance consideration. By considering disruptions in the model, *TCS* and *UD* increase 4.93 % and 1.95%, respectively, but the system will be protected against the risk of disruptions.

We investigate the structure of current health service network without considering changes in the capacity of existing hospitals or opening new hospitals, to analyze what degree of improvement in the total cost could be obtained by proposed health service network.The results under different ϑ values are presented in Table 3. The results indicate that the proposed network can be expected to perform well. In the current health service network, the significant increase in the total cost is mainly related to lack of enough capacity of existing facilities to satisfy the demand and ignoring the reliability aspects.

TABLE 3. Comparison of current and proposed networks

ϑ	Current network		Proposed network	
	TCS	UD(%)	TCS	UD(%)
1500	1871431312	57.34	914535118	14.76
2500	2321045303	50.51	1217871914	9.13
3500	2614706748	42.33	1429315167	3.54
4500	3015312176	36.95	1601216320	1.78
Ave	2455623885	46.78	1290740202	7.3

Some generated instances are also presented to study the system performance under different disruption scenarios. We consider the data ranges for these instances to be the same as the range of case study's parameters. Table 4 presents the numerical results for the generated instances. Note that the values of ϑ are considered to be in interval [1500,2000]. The reported cost values are rounded to their nearest integer values. We can conclude that the total system cost increases due to the increasing in potential demand for health service network, number of treatment units and number of disruption scenarios. We see that, on average, *FCH*, *FSTU*, ETC_s, EAC_s, ESC_s, $ETRC_s$ and *EPC* constitute 10.54%, 19.58%, 6.34%, 4.22%, 10.54%, 44.22% and 4.56% of total cost, respectively.

Figure 3 presents the impact of ϑ on the system for a 70-node network with |J|=35, |I|=35, |K|=6 and |S|=6.

TABLE 4. Computational results for the generated instances

Problem	|J|	|I|	|K|	|S|	TCS	Cost components							
						FCH	FSTU	ETC_s	EAC_s	ESC_s	$ETRC_s$	EPC
1	15	15	5	4	366678766	34880205	68763834	29897319	19931546	49828865	154128454	9248543
2				8	375153293	41369408	76828901	22067673	14237209	37016743	171624903	12008456
3			10	5	417800232	47183627	87626736	28622092	18465866	47087957	176355423	12458531
4				10	551542384	62971808	116947643	33644036	22429357	56073393	237035151	22440996
5	25	20	5	4	483094698	50853446	94442117	35939802	23951865	59899804	203845350	14162314
6				8	530363448	53709221	99745696	36295223	24196815	61701878	235501442	19213173
7			10	5	586222180	62771258	116575194	38713147	25808765	64521913	259635514	18196389
8				10	642874860	69946221	129800125	41876296	27023352	67558365	274504627	32165901
9	35	25	5	4	551974624	56093185	104173057	38206465	25470976	66234539	243942264	17854138
10				8	624390731	68707132	127598961	38843871	25895914	64139785	262743763	35861305
11			10	5	583164895	61816894	112361376	39107891	26071927	65179819	254214354	24412634
12				10	676696429	66704665	123840150	42142534	28095025	70237556	306286250	39390249
13	45	30	5	4	656070628	67191520	124784252	41830389	27886926	69717315	296127659	28532567
14				8	702001356	75264093	141637024	42501016	28334011	70835026	308184532	35245654
15			10	5	691890207	73319928	139879869	42053595	28035730	70049325	306653123	31898637
16				10	773250338	80476756	153171120	46396223	30930864	74327159	346568512	41379704
17	55	35	5	4	825262735	87391187	162297918	47963139	31975421	79938552	372546703	43149815
18				8	878910656	90451516	164125409	52205563	34803708	87001272	403257715	47065473
19			10	5	844863128	88169785	163743880	50245415	33496943	83742358	381243243	44221504
20				10	898145125	94763104	170974146	53775057	35850039	89625096	404134051	49023632

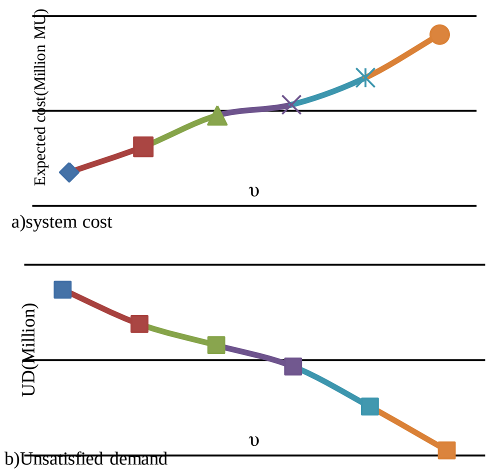


Figure 3. Impact of ϑ on the system

We see that the lower ϑ values would lead to better economic benefit, but the worse risk performance could be expected due to the increase in the unsatisfied demand. Therefore, the system designer should determine the appropriate values of ϑ for hedging against the risk of disruptions.

6. CONCLUSIONS

This paper proposes a reliable facility location model for health service network design that concurrently deals with different categories of uncertainty including provider-side uncertainty reflected in the service capacity and reliability aspect of health service facilities, receiver-side uncertainty reflected in the demand, and in-between uncertainty reflected in the geographical accessibility. The risk of unexpected disruptive events is characterized by a set of disruption scenarios. The queuing system is considered in the model which handles uncertainty associated with demand as well as service. To ensure the service quality, a maximum limit reflected in the expected patients' waiting time is defined. The geographical accessibility of a health service network is considered in terms of the proximity of a facility to the potential patients and its value depends on the realized disruption scenario. The minimum population required to open a facility is determined which insures the selected locations have surrounding public infrastructures, human resources and demand. The proposed model is implemented on a real-life case study in health service network to illustrate its applicability. The findings of this research enable the system designers to investigate different strategic and operational decisions in the design and management of the health service networks from both cost and risk perspectives.

As future research, the proposed model can be extended in the situations in which users have incomplete information about the operational status of service facilities. It would be interesting to investigate the capacity of each facility as a decision variable. Considering other parameters such as cost parameters and traveling time as the uncertain parameters would be another natural direction for future research.

7. REFERENCES

1. Alizadeh, M., Mahdavi, I., Shiripour, S. and Asadi, H., "A nonlinear model for a capacitated location–allocation problem with bernoulli demand using sub-sources", ***International Journal of Engineering-Transactions C: Aspects***, Vol. 26, No. 2, (2013), 1007-1016.
2. Karimi, M., Eydi, A. and Korani, E., "Modeling of the capacitated single allocation hub location problem with a hierarchical approch", ***International Journal of Engineering***, Vol. 27, No. 4, (2014), 573-586.
3. Bashiri, M. and Rezanezhad, M., "A reliable multi-objective p-hub covering location problem considering of hubs capabilities", ***International Journal of Engineering-Transactions B: Applications***, Vol. 28, No. 5, (2015), 717-729.
4. Arkat, J. and Jafari, R., "Network location problem with stochastic and uniformly distributed demands", ***International Journal of Engineering-Transactions B: Applications***, Vol. 29, No. 5, (2016), 654-662.
5. Rahman, S.-u. and Smith, D. K., "Use of location-allocation models in health service development planning in developing nations", ***European Journal of Operational Research***, Vol. 123, No. 3, (2000), 437-452.
6. Snyder, L. V. and Daskin, M. S., "Reliability models for facility location: The expected failure cost case", ***Transportation Science***, Vol. 39, No. 3, (2005), 400-416.
7. Aydin, N. and Murat, A., "A swarm intelligence based sample average approximation algorithm for the capacitated reliable facility location problem", ***International Journal of Production Economics***, Vol. 145, No. 1, (2013), 173-183.
8. Boffey, B., Galvao, R. and Espejo, L., "A review of congestion models in the location of facilities with immobile servers", ***European Journal of Operational Research***, Vol. 178, No. 3, (2007), 643-662.
9. Zarrinpoor, N. and Seifbarghy, M., "A competitive location model to obtain a specific market share while ranking facilities by shorter travel time", ***The International Journal of Advanced Manufacturing Technology***, Vol. 55, No. 5-8, (2011), 807-816.
10. Shen, Z.-J. M., Zhan, R. L. and Zhang, J., "The reliable facility location problem: Formulations, heuristics, and approximation algorithms", ***INFORMS Journal on Computing***, Vol. 23, No. 3, (2011), 470-482.
11. Narula, S. C. and Ogbu, U. I., "An hierarchical location-allocation problem", ***Omega***, Vol. 7, (1979), 137-143.
12. Rahman, S. and Smith, D., "Deployment of rural health facilities in a developing country", ***Journal of the Operational Research Society***, Vol. 50, No. 9, (1999), 892-902.
13. Moore, G. C. and ReVelle, C., "The hierarchical service location problem", ***Management Science***, Vol. 28, No. 7, (1982), 775-780.
14. Galvao, R. D., Espejo, L. G. A. and Boffey, B., "A hierarchical model for the location of perinatal facilities in the municipality of Rio de janeiro", ***European Journal of Operational Research***, Vol. 138, No. 3, (2002), 495-517.
15. Galvao, R. D., Espejo, L. G. A., Boffey, B. and Yates, D., "Load balancing and capacity constraints in a hierarchical location model", ***European Journal of Operational Research***, Vol. 172, No. 2, (2006), 631-646.
16. Sahin, G., Sural, H. and Meral, S., "Locational analysis for regionalization of turkish red crescent blood services", ***Computers & Operations Research***, Vol. 34, No. 3, (2007), 692-704.
17. Ndiaye, M. and Alfares, H., "Modeling health care facility location for moving population groups", ***Computers & Operations Research***, Vol. 35, No. 7, (2008), 2154-2161.
18. Smith, H. K., Harper, P. R., Potts, C. N. and Thyle, A., "Planning sustainable community health schemes in rural areas of developing countries", ***European Journal of Operational Research***, Vol. 193, No. 3, (2009), 768-777.
19. Zhang, Y., Berman, O. and Verter, V., "Incorporating congestion in preventive healthcare facility network design", ***European Journal of Operational Research***, Vol. 198, No. 3, (2009), 922-935.
20. Sorensen, P. and Church, R., "Integrating expected coverage and local reliability for emergency medical services location problems", ***Socio-Economic Planning Sciences***, Vol. 44, No. 1, (2010), 8-18.
21. Mestre, A. M., Oliveira, M. D. and Barbosa-Povoa, A., "Organizing hospitals into networks: A hierarchical and multiservice model to define location, supply and referrals in planned hospital systems", ***OR Spectrum***, Vol. 34, No. 2, (2012), 319-348.
22. Syam, S. S. and Cote, M. J., "A comprehensive location-allocation method for specialized healthcare services", ***Operations Research for Health Care***, Vol. 1, No. 4, (2012), 73-83.
23. Benneyan, J. C., Musdal, H., Ceyhan, M. E., Shiner, B. and Watts, B. V., "Specialty care single and multi-period location–allocation models within the veterans health administration", ***Socio-Economic Planning Sciences***, Vol. 46, No. 2, (2012), 136-148.
24. Burkey, M. L., Bhadury, J. and Eiselt, H. A., "A location-based comparison of health care services in four us states with efficiency and equity", ***Socio-Economic Planning Sciences***, Vol. 46, No. 2, (2012), 157-163.

25. Zhang, Y., Berman, O. and Verter, V., "The impact of client choice on preventive healthcare facility network design", ***OR Spectrum***, Vol. 34, No. 2, (2012), 349-370.
26. Baray, J. and Cliquet, G., "Optimizing locations through a maximum covering/p-median hierarchical model: Maternity hospitals in france", ***Journal of Business Research***, Vol. 66, No. 1, (2013), 127-132.
27. Zahiri, B., Tavakkoli-Moghaddam, R. and Pishvaee, M. S., "A robust possibilistic programming approach to multi-period location–allocation of organ transplant centers under uncertainty", ***Computers & Industrial Engineering***, Vol. 74, (2014), 139-148.
28. Mestre, A. M., Oliveira, M. D. and Barbosa-Povoa, A. P., "Location–allocation approaches for hospital network planning under uncertainty", ***European Journal of Operational Research***, Vol. 240, No. 3, (2015), 791-806.
29. Guerriero, F., Miglionico, G. and Olivito, F., "Location and reorganization problems: The calabrian health care system case", ***European Journal of Operational Research***, Vol. 250, No. 3, (2016), 939-954.
30. Nosek, R. A. and Wilson, J. P., "Queuing theory and customer satisfaction: A review of terminology, trends, and applications to pharmacy practice", ***Hospital Pharmacy***, Vol. 36, No. 3, (2001), 275-279.
31. Gross, D., "Fundamentals of queueing theory, John Wiley & Sons, (2008).
32. Marianov, V. and Serra, D., "Probabilistic, maximal covering location—allocation models forcongested systems", ***Journal of Regional Science***, Vol. 38, No. 3, (1998), 401-424.
33. Leung, S. C., Tsang, S. O., Ng, W. L. and Wu, Y., "A robust optimization model for multi-site production planning problem in an uncertain environment", ***European Journal of Operational Research***, Vol. 181, No. 1, (2007), 224-238.
34. Mulvey, J. M., Vanderbei, R. J. and Zenios, S. A., "Robust optimization of large-scale systems", ***Operations Research***, Vol. 43, No. 2, (1995), 264-281.
35. Yu, C.-S. and Li, H.-L., "A robust optimization model for stochastic logistic problems", ***International Journal of Production Economics***, Vol. 64, No. 1, (2000), 385-397.

Design of a Reliable Facility Location Model for Health Service Networks

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چکیده

این مقاله یک مدل جدید مکان‌یابی تسهیلات برای طراحی شبکه خدمات سلامت با در نظر گرفتن اجزای کلیدی مختلف شامل جنبه‌های قابلیت اطمینان، ظرفیت خدمتدهی، ازدحام، کیفیت خدمتدهی، زیرساختارهای عمومی محیط مورد بررسی، قابلیت دسترسی جغرافیایی و انواع هزینه‌های مختلف نظیر هزینه‌های ثابت استقرار، حمل و نقل و عملیاتی پیشنهاد می‌کند. ما مسئله را به صورت یک مدل استوار برنامه‌ریزی احتمالی مبتنی بر سناریو برای مواجهه با انواع مختلف عدم قطعیت موجود در قابلیت اطمینان، تقاضا، خدمتدهی و قابلیت دسترسی جغرافیایی مدل‌سازی کردیم، به طوری که کمینه‌سازی هزینه‌های مورد انتظار تحت همه سناریوهای اختلال محقق گردد. برای شرح قابلیت کاربرد مدل پیشنهادی، از یک مطالعه موردی بر اساس شبکه خدمات سلامت استان سیستان و بلوچستان استفاده شد. یافته‌های این تحقیق، طراحان سیستم را قادر می‌سازد تا تصمیمات مختلف استراتژیک و عملیاتی را در مدیریت و طراحی شبکه‌های خدمات سلامت از هر دو دیدگاه هزینه و ریسک بررسی نمایند.

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