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An Integrated Planning Approach Towards Home Health Care, Telehealth and Patients Group Based Care

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ABSTRACT

The availability of patient-centered, cost effective, and quality oriented health care is a huge task for the health care planners in every country. In this study, a Home Health Care (HHC) planning problem is introduced to integrate the resource dimensioning issues and assignment aspects with the telehealth based care and patients' group-based care services. An integer linear programming model is developed and solved through CPLEX. The main aims of the proposed model are: (i) to provide an optimal selection of locations for HHC offices, health care workers, and patients' cluster centres besides their specific assignment; (ii) to schedule the health care session for each patient or patients' group by creating a pair of HHC nurse and telehealth staff against a specific time window; and (iii) to seek the enhancement of patient satisfaction and quality of service considering the penalties for violation of patients' preferences and inappropriate experience gap between the pair of nurses. Subsequently, in order to validate the effectiveness of the proposed integration approach, we employ the Fuzzy c-means to describe the appropriate organization of the HHC offices, health care workers, and patient's data. Finally, a sensitivity analysis is performed to explore the model behavior against the variation in parameter values. The detailed analysis of the results shows the effectiveness of the proposed model and its behavior with respect to different types of cost.

1. Introduction

1.1. Background

Maintaining a sustainable, easily accessible, and effective health-care system is a major challenge across the globe. The costs associated with the health care facilities are increasing in many developed countries due to the need for long term and continuous health care support for an aging population and palliative care requirements for chronic diseases. Although health related budget gets significant increment every year in many countries and substantial extensions are being made to increase the number of hospitals and related health care facilities, the health care sector is continually faced with the problems of capacity constraints and scarce resources. Moreover, long office hours, disengaged and small families, and tiny residential apartments are limiting the scope of family care, while giving rise to the need for alternative care services. In response to these special healthcare demands, new alternatives to the traditional hospitalization concept have been developed, including HHC, telehealth, and telemedicine. HHC organizations provide medical, paramedical and communal services to patients in their homes which not only improve the patient's quality of life but also save significant costs of the overall health care system by avoiding expensive hospital admissions (Carello and Lanzarone, 2014). Health care workers visit the patients at their respective homes following the predetermined schedules, frequency, and patient service requirements. HHC offers an economical alternative to the hospital based health care and the service is useful in reducing hospital readmissions through detailed discharge planning of hospitalized elderly patients (Naylor et al., 1999). Hospital at home care method is feasible and safe for aged population. It reduces the infections and adverse events associated with the hospital based care (Leff et al., 2005).

Nonetheless, the growing HHC industry is new and facing many challenges regarding decisions related to capacity planning, cost effective operations, and service quality. The rapid growth of HHC organizations in different countries also creates uncertainties about the continuous supply of qualified and skilled health care staff to meet the patients' needs. Similarly, the replacements and frequent changes of assigned health care workers considering sickness, employee turnover or other unavoidable circumstances can lead towards poor service quality and patient satisfaction issues. Hence, HHC managers should

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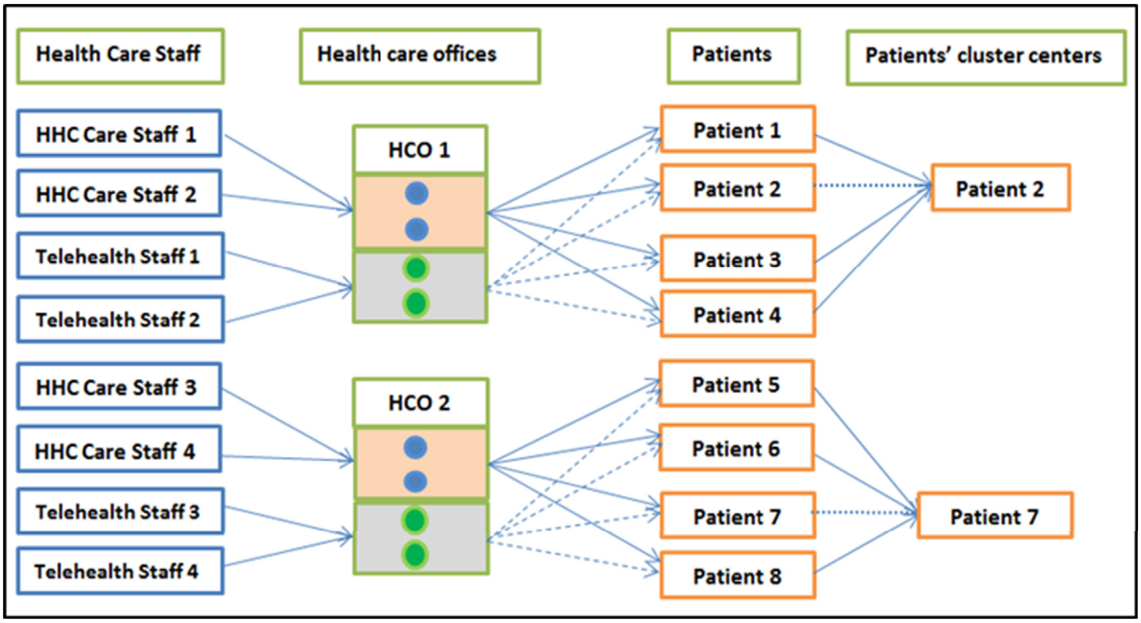

Fig. 1. An integrated HHC planning problem.

sort out better strategies and plans to cope these challenges. For instance, the integration of HHC services with other health care delivery services (e.g. telehealth, e-clinics and community care) and care mechanisms can enhance the cooperation among all the stake holders at different levels and improve the service quality.

Telehealth provides cost-effective and quality care through the use of telecommunication and information technologies to patients at a distance. Telehealth resembles HHC as health care staff connects to patients at their homes, although it is a virtual connection. The rapid growth in the information technology and easy access to the internet and smart phones played a critical role in bringing the telehealth into the limelight. The role of technology improvements (e.g. capturing health related data through sensor networks, data transmission, and data analysis based spontaneous actions and alarms) is also a reason for its popularity. A simple telehealth initiative includes patient monitoring through telephone calls. Whereas, digital, video or wireless devices can be used as an advanced intervention to monitor and transmit patient health information using computer softwares and mobile applications (Aikens et al., 2015; Mallow et al., 2014). Telehealth can also be useful in a variety of potential preventive care settings and training of health care staff. The availability and use of information and communication technology has swiftly boosted the telehealth based care and created new possibilities for the management of chronic diseases in the clinical and health care delivery services (Telemedicine, 2010). Thus, the appropriate application and combination of different health care services and technology improvements can provide health care to those segments of the society which need an alternative to the conventional hospital based care.

In addition, many patients who receive HHC are elderly or have a disability and they usually remain isolated from social circles and community gatherings. In order to enhance the home health care quality experience, social activities and patients group based preventive care lessons should also be considered as part of home health care plans. In an attempt to socialize and enrich the community care experience, district elderly community centres have been established in many developed countries. These community centres enable elderly people to interact with other people and remain in the community while leading a healthy, respectful, and dignified life. These facilities can also be used to provide preventive health care training, arranging healthy game competitions among the elderly and teaching social skills to isolated and disabled patients. Community health centres assist a part of the population that is disproportionally in poor financial health and that contains those people which are at higher risk for poor health (Hing et al., 2011). Community health centres offer services beyond the scope of traditional primary care, such as providing long term care plans and collaborate with other institutes to promote healthy life styles e.g., healthier pregnancies and families (Primary Health Care, 2008). Therefore, patients' group based health care activities and social interactions are essential to improve the quality of care for isolated segments of the society.

Hence, the importance of long term HHC and telehealth cannot be denied but the way these services are used still needs improvements. HHC firms and health care professionals should promote the combined use of HHC and telehealth to provide long term, sustainable, cost effective and high quality care. The presented research in this paper is an attempt to meet the above mentioned challenges. The HHC resource dimensioning problem determines the number of health care workers with the required set of skills and quantity of different physical/infrastructure resources to meet the patient demand. This research can be seen as a special case of home health care resource dimensioning problem, it integrates the concept of telehealth and patients group based care in the conventional setting of a home health care problem. An integer linear programming model is developed which not only integrates the HHC with telehealth based care but also incorporates the patient's group based care in the care plans. The present study focuses on a shared visit of a home health care nurse and a telehealth care staff where a HHC nurse physically visits the patient or patients' cluster, whereas, telehealth staff virtually interacts and supervise the whole care session. To the best of our knowledge, the present study is the first effort to integrate these three dimensions of health care delivery in a single mathematical model in the context of home health care literature. Fig. 1 presents the structure of the problem considered in this paper.

1.2. Contributions

Though a short version of this work (Nasir and Dang, 2017) has been presented before, however, this study includes many significant contributions to the literature. The integration of HHC, telehealth based care and patients' group/cluster based care in a mathematical model is among one of the main contributions of this work. The proposed mathematical model determines the optimal number of required HHC workers, telehealth care staff, health care offices, and patients' clusters to meet the given HHC patients' demand. Moreover, considering the locations of all the resources and patients, the model decides the optimal locations for the health care offices and best possible assignment among all the resources and patients. Additionally, the mathematical model makes time windows based schedules to provide health care at each patient location and patients' cluster centre. Taking into account the required services and available qualifications, the model creates a pair of a HHC worker and telehealth staff to conduct a health care delivery session for a patient or patients' cluster against a specific time window. Hence, the studied problem and the proposed model offers an added advantage to the health care organizations to make inclusive plans considering patients group-based care, home health care and telehealth based care.

The second contribution is associated to maintain the service quality and patient satisfaction. In this regard, the proposed mathematical model introduces penalties for violations of certain criteria with respect to the pairing of health care workers and forming patients' clusters. The consideration of these penalties in the mathematical model is an attempt to make more cohesive patients' clusters and maintain appropriate experience balance for the provision of health care staff for all the care sessions. The integration approach of this problem enables a HHC firm to successfully tackle the critical issues related to under skilled or inexperienced home health care staff through a proper combination and supervision of telehealth based care staff.

The third contribution is related to the validation of the appropriateness of the data used for the health care staff and patients' groups/clusters in the mathematical model. Since the main aim of the proposed model is to organize the HHC nurses and telehealth staff resources with respect to patient's requirement in a specific time window. Consequently, we evaluate the effectiveness of the proposed integrated plan via clustering the HHC nurses, telehealth staff, and patient information using the Fuzzy c-means. Though there are several clustering methods, however, it cannot be said which one is better than others (Alpaydin, 2010). For example, partitioning (K-means, K-medoids), hierarchical (Agglomerative and Divisive), model-based (Decision Tree, Neural Network), grid-based, density-based (DBSCAN, AUTOCLASS) and soft-computing (Fuzzy c-means) (Hussain et al., 2016, 2017). However, the main purpose of our third contribution is the use of Fuzzy c-means to classify HHC nurses, telehealth staff, and patient information without prior knowledge of their class labels (Bezdek et al., 1984). The purpose of Fuzzy c-means is to classify the objects (i.e. HHC nurses, telehealth staff, and patient information in our study) into clusters (e.g. closeness between nurses basis on their similarities) according to their membership degree values between 0 and 1.

Lastly, the sensitivity analysis explains the behavior of the mathematical model and cost components of objective function considering the variation in the values of some key parameters.

The rest of this paper is organised as follows. In Section 2, we present the related work. In Section 3, we introduce the problem description, mathematical formulation and Fuzzy c-means based effectiveness evaluation method. Computational experiments and data generation are explained in Section 4. The results and sensitivity analysis are discussed in Section 5. Finally, Section 6 presents the conclusion and future research.

2. Related work

The HHC resource dimensioning problem determines the number of care givers with the required set of skills and quantity of different material resources to meet the demand. These decisions are necessary to maintain a particular service level at the least possible cost. Busby and Carter (2006) designed a decision support method to quantitatively evaluate the trade-offs among cost, patient's satisfaction, and patient's waiting time. Blake and Shimla (2014) studied a problem related to blood collection system. They used the queuing model to employ the minimum staff while maintaining waiting time restrictions. Li et al. (2002) proposed a strategic operations hospital management model under the restrictions of location, size and medical teaching status. The model associates strategic equipment and service options, intermediary and operational decisions, and hospital performance. The findings help the hospitals to decide about the development of required capabilities and improve performance.

Most of the research literature in HHC addresses scheduling and routing problems. The HHC scheduling and routing problem was first studied by Begur et al. (1997) and Cheng and Rich (1998). Begur et al. (1997) developed a decision support system to plan the schedules and routes for care givers. The proposed work successfully reduced the cost considering manual paper work and travel expenses. Cheng and Rich (1998) investigated the HHC problem with respect to full time and part time nurses along with time windows based schedules for patients. The authors introduced two different mixed integer linear programming (MILP) formulations and a two phase heuristic solution method for the considered problem. Bertels and Fahle (2006), Thomsen (2006), and Eveborn et al. (2006) extended the research work on HHC problems by investigating operational and tactical decisions, exploring heuristic solution methods to solve scheduling and routing issues. More recently, the scheduling and routing problems have been studied by several authors Rasmussen et al. (2012), Mankowska et al. (2014), Yalçındağ et al. (2016) and Trautsamwieser and Hirsch (2014). A HHC scheduling and routing problem with dependent services was studied by Mankowska et al. (2014). The authors used variable neighborhood search (VNS) based heuristics methods to solve the problem. Yalçındağ et al. (2016) proposed a data driven method to estimate travel times before assignment of routes to caregivers. A medium term HHC planning problem was solved by Trautsamwieser and Hirsch (2014) through a branch-price and cut approach. Rasmussen et al. (2012) investigated the crew scheduling problem in the HHC domain in the perspective of preference-based visit clustering and temporal dependencies. The authors focused on the assignment of health care workers to patients with the objective of minimizing cost. Some of the uncovered visits in the problem were adjusted manually. Nasir and Dang (2018) proposed a more flexible HHC scheduling and routing problem by considering the patient and staff selection in the same mathematical model. The proposed model combines the new entrants with the existing patients and staff to determine the daily scheduling and routing plans, whereas, a VNS based heuristic solution method and its variant are used to solve the studied problem.

Lanzarone et al. (2012) proposed a set of mathematical models with the aim to balance the workload and maintain the continuity of care for the HHC assignment problem. These models take into account different types of health care provider characteristics. Variability of patient's demands is considered for the efficient and robust planning by the HHC firms. The objective of perfect continuity of care and better workload balance is accomplished in the numerical experiments. Research work on the political districting problem and HHC districting problem has been addressed by several authors. Hess et al. (1965) and Hojati (1996) proposed location allocation problem based mathematical formulations for the districting problem. They also developed heuristic solution methods to solve the large problem instances. More recently, Ricca and Simeone (2008) developed a multi-criteria set partitioning formulation for the political districting problem. They considered indivisibility of basic units, contiguity, population equality, compactness and conformity to administrative boundaries as the criteria in the proposed formulation. The authors used heuristic methods to solve the model. The districting problem in the HHC domain is also addressed in the literature, with some authors exploring the HHC districting problem along with typical scheduling and routing issues of the HHC problem (Blais et al., 2003; Benzarti et al., 2013; Bashir, 2013). The health care problem considered by Benzarti et al. (2013) is formulated as an integer linear programming problem with the objective of workload balance and minimizing travel times. Although several studies have been conducted to address various types of HHC problems (e.g. HHC resource dimensioning and assignment problems, HHC scheduling and routing problems, HHC districting problems), the integration of HHC services with other related services (e.g. telehealth and community care) did not get the attention of the researchers.

The utilization of community health care facilities for the aging citizens in Taiwan was studied and evaluated by Chang et al. (2013). It was observed that the more skillful and experienced health care staff should be employed to meet the requirements of elderly population. Lin et al. (2016) explored the timetabling issues at an elderly day care centre. The authors developed a particle swarm optimization based algorithm and compared the findings against other metaheuristic algorithms.

Erickson et al. (2015) studied the integration of telehealth into the graduate nursing syllabus. The authors registered seventy two nurse practitioner students from a college and implemented the project by providing classroom and clinical practices. Results show that the integration experience improves students' knowledge of telehealth as a method of delivering care to the underserved segments of the society. Considering the early design process, Lilholt et al. (2015) evaluated the serviceability of the telehealth system, named Telekit and designed for the Danish TeleCare, to estimate possible problems which could prevent the effective implementations. The authors used heuristic evaluation method and uncovered many potential issues with respect to the associated design. Telehealth has been also used to discuss and consult the treatment possibilities with a specialist for the management of pain and related complexities (McGeary et al., 2012). Pekmezaris et al. (2012) investigated the effect of remote patient monitoring on heart failure patients. The study reveals that the remote monitoring can be used as an economical and conveniently adaptable method to manage the heart failure patients. The tele-ICU and other related telehealth programs promise quality oriented and cost effective care to the communities by facilitating the small health care facilities to manage the careful treatment for patients without moving them to the big hospitals (Lowery et al., 2014).

Though the utilization of telehealth and community health care facilities to serve the marginalized segments of the society is impressive, the decentralized planning approach and isolated application of these services limit the capability of the health care planning system to get the maximum advantage. The mathematical models presented in the existing HHC literature do not provide centralized planning approach to HHC, telehealth and patients' group based care. Similarly, the research literature in the perspective of community health care and telehealth also lacks the integration of these services with the HHC service through consideration of common issues and development of mathematical planning models.

In order to meet the above-mentioned challenges, this study proposes an integrated planning approach by considering three types of health care services: (1) HHC service, (2) telehealth, and (3) patients' group based care. The presented approach and the mathematical model developed in this study not only offer the integrated planning scheme to these three health care services but also contribute significantly to the existing health care related literature as mentioned in detail in section 1.2.

3. Problem description

3.1. Mathematical formulation

The set of patients and health care offices (HCO) are denoted as P and G respectively. These health care offices are used by telehealth nurses to connect to patients and study the patient health records while HHC nurses collect their schedules, feedback and training materials from these offices. $N = Hn \cup Tn$, is defined as the set of HHC nurses Hn and telehealth nurses Tn. The terms health care worker and nurse will be used interchangeably in this paper. S and T represent the set of services being offered by the health care organization and set of time windows respectively. Maximum work load capacity for each HHC office $j \in G$ and every nurse $i \in N$ is shown as H_j and M_i respectively. The considered problem offers four types of health care services and the service duration for a service at each patient $k \in P$ is represented as d_k. The binary parameters o_{si} and p_{sk} denote the qualification of each nurse and requirement of each patient for a service $s \in S$ respectively. The distance between a health care office $j \in G$ and a health care worker $i \in N$ is given as do_{ji}. dh_{nk} represents the distance between a HHC nurse $n \in Hn$ and a patient $k \in P$

The parameters c_k, g, e and f are used to model the patients' cluster centres. c_k and g represent the number of patients at each patient location and desired number of patients at each patients' cluster centre respectively. The lower and upper limits for the total number of patients at each patients' cluster centre are fixed through parameters e and f respectively. Whereas, the distance between two patients $k, l \in P$ in the perspective of patients' cluster is represented as df_{kl}. The patients are assigned to each other to sort out the best location as patients' cluster centre. The constraints (16)–(19) to model the patients' clusters in this model are impressed by the political districting work of Hess et al. (1965).

The integer linear programming model contains two binary coverage variables, five binary assignment decision variables, and one positive integer variable. The binary coverage variables z_i and v_j cover the recruitment and selection decisions of potential health care workers and health care offices respectively. Whereas, the binary assignment variables x_{ji}, and y_{ik} determine the assignment of health care offices and health care workers to health care workers and patients respectively. The binary assignment variables u_{kl} and qr_{il} are used to model the patients' clusters. The assignment of patients to patients' cluster centres and allocation of health care workers to patients' cluster centres are controlled through these two variables respectively. The binary assignment variable rt_{hnt} integrates the HHC with telehealth based care and schedules the care sessions with respect to a set of time windows. It sorts out the right pair of a HHC nurse $n \in Hn$ and telehealth nurses $h \in Tn$ to conduct a health care session at a patient home or patients' cluster centre against a specific time window $t \in T$. The positive integer variable w is used to determine the optimal number of patients' clusters.

Moreover, the mathematical model assigns penalties for the violation of patients' preferences and other related parameters. D and I represent the set of districts and set of interests for the patients respectively. A penalty cost incurs if a patient and the cluster centre assigned to that particular patient do not belong to same district. dt_{dk} shows the residence of a patient $k \in P$ in a district $d \in D$. The considered problem also penalizes if patients with mismatching interests are grouped in a cluster. it_{rk} denotes the interest of a patient for an activity $r \in I$. The experience gap matrix Bt_{hn} as given in equation (1), is used in the objective function (2) to calculate the penalty cost considering experience gap in a pair of HHC nurse and Telehealth nurse assigned to a patient. The current experience in terms of number of years for each nurse $i \in N$ is denoted as Ex_i. The experience gap matrix Bt_{hn} and penalty cost discourage the similar experience for both type of nurses during a shared assignment. Hence, it encourages the pairing of experienced and fresh nurses for a care session. Whereas, a pair of both fresh nurses or both highly experienced nurses will incur more penalty cost.

$$Bt_{hn} = \frac{1}{(|Ex_h - Ex_n| + 1)} \quad \forall\, n \in Hn, \forall\, h \in Tn \tag{1}$$

The objective function aims to minimize the total cost which comprises of travel costs, fixed costs and penalty costs. A summary of all the notations along with different cost parameters is presented in Table 1.

Table 1
Notations.

Notation	Definition
Indices	
P	Set of patients
S	Set of services to be provided by the health care organization
G	Set of candidate locations for health care offices
T	Set of time windows
Hn	Set of HHC nurses
Tn	Set of Telehealth nurses
N	Set of total health care workers ($N = Hn \cup Tn$)
D	Set of patient districts
I	Set of patient interests
Parameters	
M_i	Maximum workload limit for a health care worker $i \in N$
H_j	Maximum workload capacity of a health care office $j \in G$
c_k	Number of patients at each patient location $k \in P$
g	Average number of patients desired at each patient cluster
e	Lower limit parameter for the number of patients desired at each patient cluster
f	Upper limit parameter for the number of patients desired at each patient cluster
d_k	Duration of a service offered to a patient $k \in P$
Ex_i	Experience of a nurse $i \in N$
it_{rk}	Interest of a patient $k \in P$ for an activity $r \in I$
dt_{dk}	Current residence district $d \in D$ for a patient $k \in P$
do_{ji}	Distance from a health care office $j \in G$ to a health care worker $i \in N$
dh_{nk}	Distance from a nurse $n \in Hn$ to a patient $k \in P$
df_{kl}	Distance from a patient $k \in P$ to a patient $l \in P$
o_{si}	1 if a health care worker $i \in N$ is qualified for the service type $s \in S$
p_{sk}	1 if a patient $k \in P$ requires a service type $s \in S$
a_i	Cost to hire a health care worker $i \in N$
b	Cost to open a health care office
c	Travel cost per unit of distance
m	Penalty cost for district violation and interests mismatch considering patients' cluster
F	Penalty cost to discourage similar experience for shared Telehealth and HHC nurse visits
Decision Variables	
z_i	1 if a health care worker $i \in N$ is hired by the health care organization, 0 otherwise
v_j	1 if a health care office location $j \in G$ is selected for opening, 0 otherwise
x_{ji}	1 if a health care office $j \in G$ is allocated to a health care worker $i \in N$, 0 otherwise
y_{ik}	1 if a health care workers $i \in N$ is assigned to patient $k \in P$, 0 otherwise
u_{kl}	1 if a patient $k \in P$ is assigned to another patient $l \in P$ at cluster centre, 0 otherwise
rt_{hnt}	1 if a Telehealth nurse $h \in Tn$ and a HHC nurse $n \in Hn$ are assigned to a time window $t \in T$, 0 otherwise
qr_{il}	1 if a health care worker $i \in N$ is assigned to a patient cluster centre $l \in P$, 0 otherwise
w	patient clusters variable

$$\begin{aligned}\min \textstyle\sum_{i\in N}\sum_{j\in G} cdo_{ji}x_{ji} + \sum_{n\in Hn}\sum_{k\in P} cdh_{nk}y_{nk} + \sum_{(k,l)\in P} cdf_{kl}u_{kl} \\ + \textstyle\sum_{n\in Hn}\sum_{l\in P} cdh_{nl}qr_{nl} + \sum_{i\in N} a_i z_i + \sum_{j\in G} bv_j \\ + \textstyle\sum_{(k,l)\in P} mu_{kl}((1-\sum_{d\in D} dt_{dk}dt_{dl}) + (\sum_{r\in I} it_{rl} - \sum_{r\in I} it_{rk}it_{rl})) \\ + \textstyle\sum_{h\in Tn}\sum_{n\in Hn}\sum_{t\in T} Frt_{hnt}Bt_{hn}\end{aligned} \tag{2}$$

Subject to:

$$\textstyle\sum_{j\in G} x_{ji} = z_i \quad \forall\, i \in N \tag{3}$$

$$x_{ji} \le v_j \quad \forall\, i \in N,\ \forall\, j \in G \tag{4}$$

$$y_{ik} \le z_i \quad \forall\, i \in N,\ \forall\, k \in P \tag{5}$$

$$\textstyle\sum_{h\in Tn} y_{hk} = \sum_{n\in Hn} y_{nk} \quad \forall\, k \in P \tag{6}$$

$$\textstyle\sum_{i\in N} y_{ik} = 2 \quad \forall\, k \in P \tag{7}$$

$$rt_{hnt} \le \textstyle\sum_{k\in P} y_{hk} \quad \forall\, n \in Hn,\ \forall\, h \in Tn,\ \forall\, t \in T \tag{8}$$

$$\textstyle\sum_{t\in T}\sum_{h\in Tn} rt_{hnt} = \sum_{k\in P} y_{nk} \quad \forall\, n \in Hn \tag{9}$$

$$\textstyle\sum_{n\in Hn} rt_{hnt} \le 1 \quad \forall\, h \in Tn,\ \forall\, t \in T \tag{10}$$

$$\textstyle\sum_{h\in Tn} rt_{hnt} \le 1 \quad \forall\, n \in Hn,\ \forall\, t \in T \tag{11}$$

$$rt_{hnt} = 0 \quad \forall\, n \in Hn,\ \forall\, h \in Tn,\ \forall\, t = t_5 \tag{12}$$

$$\textstyle\sum_{k\in P} d_k y_{ik} \le M_i z_i \quad \forall\, i \in N \tag{13}$$

$$\textstyle\sum_{i\in N} M_i x_{ji} \le H_j v_j \quad \forall\, j \in G \tag{14}$$

$$p_{sk} y_{ik} \le o_{si} z_i \quad \forall\, i \in N,\ \forall\, k \in P,\ \forall\, s \in S \tag{15}$$

$$\textstyle\sum_{l\in P} u_{kl} = 1 \quad \forall\, k \in P \tag{16}$$

$$\textstyle\sum_{l\in P} u_{ll} = w \tag{17}$$

$$eu_{ll}g \le \textstyle\sum_{k\in P} c_k u_{kl} \quad \forall\, l \in P \tag{18}$$

$$\textstyle\sum_{k\in P} c_k u_{kl} \le fu_{ll}g \quad \forall\, l \in P \tag{19}$$

$$qr_{il} \ge y_{il} + u_{ll} - 1 \quad \forall\, i \in N,\ \forall\, l \in P \tag{20}$$

$$qr_{il} \le y_{il} \quad \forall\, i \in N,\ \forall\, l \in P \tag{21}$$

$$qr_{il} \le u_{ll} \quad \forall\, i \in N,\ \forall\, l \in P \tag{22}$$

$$\begin{aligned}x_{ji}, y_{ik}, u_{kl}, z_i, v_j, rt_{hnt}, qr_{il} \in \{0{,}1\} \quad \forall\, j \in G, \forall\, i \in N, \forall\, n \in Hn, \\ \forall\, h \in Tn, \forall\, (k, l) \in P\end{aligned} \tag{23}$$

The objective (2) is to minimize the total cost, which comprises eight components. The first component include the travel cost of the hired health care workers to the selected health care offices. The second component represents the travel cost incurred by HHC nurses for visiting patients at their homes. The third and fourth component cover the travel cost of the patients to the patient cluster centres and travel cost of the HHC nurses to the patient cluster centres respectively. The fifth and sixth components are the fixed cost of hiring the health care workers and opening health care offices respectively. The seventh component incurs the penalty cost for including those patients in a cluster whose residence districts and interests are not similar to the patient at the center of the cluster. The eighth component defines the penalty cost if both the nurses included in a pair are fresh or highly experienced. Constraints (3) show that each hired nurse must be assigned to only one health care office. Constraints (4) and (5) guarantee that only selected HHC offices and hired health care workers are available for assignment to the health care workers and patients respectively. Constraints (6) ensure that an equal number of HHC and Telehealth nurses are assigned to each patient. Constraints (7) show that only two nurses can be assigned to each patient at maximum. Constraints (8)–(9) implement the shared visit of a HHC nurse and Telehealth nurse for each patient at a specific time window. Constraints (10)–(11) guarantee that each nurse can be assigned only once for a single time window. Constraints (12) implement the break time window. Constraints (13)–(14) ensure that the hired health care workers and selected HHC offices will not be overloaded during the assignment process. Constraints (15) guarantee the service compatibility between the health care workers and patients. Constraints (16) show that each patient must be assigned to only one patients' cluster. Constraints (17) determine the number of patient cluster centres selected for opening. Constraints (18) and (19) determine the minimum and maximum patients for a patient cluster centre with parameters $e < 1$ and $f > 1$. Constraints (20)–(22) are used to implement the decision variable qr_{il} and find the distance covered to access the patient cluster centers.

3.2. Fuzzy c-means based effectiveness evaluation method

Since the proposed model integrates HHC nurses, telehealth staff and patients' group based care through the formation of patients' groups, pairing of health care staff and corresponding assignment tasks among all the entities. Hence, an independent evaluation is essential to assess the effectiveness of the proposed integrated plan based on the data set used to solve the model. Therefore, considering the parametric data associated with the proposed model an implementation of Fuzzy c-means was performed to classify the HHC nurses, telehealth staff, and patient information. We used FCM clustering approach (Bezdek et al., 1984) to achieve our objective that is to classify the required data accordingly. The objective of fuzzy approach is to classify the objects into clusters according to their membership degree values between 0 and 1.

$$X = \begin{bmatrix} x_{11} & x_{12} & - & x_{1N} \\ x_{21} & - & - & - \\ - & - & - & - \\ x_{n1} & - & - & x_{nN} \end{bmatrix} \tag{24}$$

$$x_k = [x_{1k}, x_{2k}, \ldots\ldots, x_{nk}]^T,\ x_k \in \mathbb{R}^n \tag{25}$$

$$X = \{x_k | k = 1,2,\ldots,N\} \tag{26}$$

Like other clustering techniques, FCM uses some notations to describe the functionality of the algorithm, which we have grouped into three categories. First, in order to describe the structure of the data set, notations shown in equations (24)–(26) are used. Equation (24) shows that data set consists of n observations and each observation include N measure variables which are grouped in form of n-dimensional column vector as shown in equation (25). Similarly, a data set with N observations can be represented by equation (26). Second, in order to describe the minimization of the objective function of FCM algorithms, notations shown in equation (27)–(29) are used.

$$J(X; U, V) = \sum_{t=1}^{c} \sum_{k=1}^{N} (\mu_{tk})^m \left\| x_k - v_t \right\|_A^2 \tag{27}$$

$$U = [\mu_{tk}] \in M_{fc} \tag{28}$$

$$V = [v_1, v_2, \ldots., v_c],\ v_i \in \mathbb{R}^n \tag{29}$$

Where U is the fuzzy partition matrix of data set X as shown in equation (28) and V is the vector of cluster prototypes that are centres as shown in equation (29). Third, in order to compute the squared inner-product distance norm, notations shown in equation (30) and (31) are used.

$$D_{tkA}^2 = \|x_k - v_t\|_A^2 = (x_k - v_t)^T A (x_k - v_t) \tag{30}$$

$$m \in [1, \infty) \tag{31}$$

The fuzziness of the resulted clusters that is cost function can be determined by using equation (31) and it can be measured through the total variance of x_k from v_t.

4. Computational experiments

4.1. Data generation

Being mindful of real life situations, a random data set was generated considering 100 patients, 40 nurses (HHC and telehealth nurses) and 14 health care offices. Twenty different sized problem instances were created with this data set. Table 2 provides the features of these instances. The number of patients, potential nurses and health care offices against each instance are shown in Table 2.

The distance matrix data for the assignment of health care workers, HHC offices and patients is computed through Euclidean distance matrix. The randomly selected coordinates are used as the location for each entity. A set of 8 time windows is used to plan the schedules for nurses in the given planning horizon and the fifth time window is defined as the mandatory break for all the health care staff. Out of four health care services being offered, every patient demands one service and each nurse should be skilled for at least two services. Maximum capacity for each nurse and health care office is 420 min and 4200 min respectively. Each patient can specify his residence in one district out of a set of seven districts. Similarly, each patient must specify at least two interests out of a set of four common interests. The experience of nurses varies between 1 and 7 years. The nurse qualifications, nurse experience, patients' service demand, patients' interests and patients' districts are randomly assigned with respect to associated criteria. The residence location for every patient contains only one patient and four patients are desired at each patient cluster. The lower limit e and upper limit f parameters for the desired number of patients at each patients cluster are set at 0.7 and 1.3 respectively. The duration of each service is 60 min for both HHC nurses and telehealth nurses. The service duration time includes the travel time for HHC nurses and patient's health record study time for telehealth nurses. The travelling cost depends on the distance covered. The fixed cost and travel cost per unit distance are similar to local costs for such facilities in Hong Kong. The salaries of telehealth nurses are kept relatively higher as compared to HHC nurses. The penalty costs for violation of patient preferences and nurse experience gap violation are set at 7 and 9 Hong Kong dollars (hkd) respectively, whereas, travelling cost is kept at 5 hkd per unit of distance.

4.2. Test environment

The integer linerar programming formulation is implemented in Optimization Programming Language (OPL). The mathematical model is solved with ILOG CPLEX 12.6. Subsequently, the effectiveness evaluation of the proposed integration plan is performed using R tool[1] and its package "e1071". All the experiments are performed using a machine with Intel Core i5 (3.20 GHz) and 4 GB of RAM.

5. Results

Table 3 shows the results obtained through the solution of the mathematical model using CPLEX. CPLEX could only deliver a solution for the first fourteen instances owing to the computational difficulty of our mathematical model. The presence of a large number of binary decision variables make it very difficult to compute large scale problems in a reasonable time. In the perspective of this difficulty, the instances (11)–(14) were solved by relaxing the constraints (15) and (20)–(22). Consequently, the results for these four instances do not contain the cost component TCNC. Therefore, we will present the analysis on the basis of first ten instances as these instances contain all the cost components and constraints.

The results reported here are based on 5 runs of each instance. The run time is measured in seconds, while cost is calculated in hkd. The second column in Table 3 shows the computational time, whereas 3rd and 4th column show the total cost (TC) and total travelling cost (TTC) respectively. The columns 5–8 show the breakup of total travelling cost. The terms TCNO, TCNP, TCNC, and TCPP represent the travelling cost from the nurses' homes to health care offices, nurses' homes to patients, nurses' homes to patients' clusters and travelling cost of patients to patients' clusters respectively. The ninth column shows the fixed cost (FC) as a sum of nurse recruitment and health care office opening cost, whereas, the last two columns show the penalty costs for patients' preferences violation and experience gap violation for paired nurses respectively.

The results shown in Table 3 indicate that the mathematical model has successfully tackled all the aspects considered in this problem. A close examination of the results shows that the total cost increases with the increase in the size of the problem from the first to the 10th instance but the increase in cost only incurs to hire the most necessary resources and bear the essential traveling cost. The model only hires optimal

[1] https://cran.r-project.org/bin/windows/base/

Table 2
Characteristics of the set of Instances.

Instance	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Patients	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95	100
Nurses	4	4	8	8	12	12	16	16	20	20	24	24	28	28	32	32	36	36	40	40
HCO	2	2	2	4	4	4	6	6	6	8	8	8	10	10	10	12	12	12	14	14

Table 3
Computational results for the mathematical model.

Instance	Time	TC	TTC	TCNO	TCNP	TCNC	TCPP	FC	PrefCost	ExpCost
1	9	99329	4280	1620	1965	305	390	95000	28	21
2	9	127537.50	7420	2355	3820	715	530	120000	77	40.50
3	10	169992.30	9830	3330	4805	905	790	160000	126	36.30
4	10	172291.20	12080	3300	6590	1095	1095	160000	168	43.20
5	11	214434.74	14215	3970	7570	1365	1310	200000	175	44.74
6	11	257324.45	17060	5150	8860	1605	1445	240000	210	54.45
7	11	258674.95	18340	4990	9925	1785	1640	240000	273	61.95
8	19	340888.20	20490	5375	11215	2070	1830	320000	322	76.20
9	28	383492.80	23040	6235	12465	2320	2020	360000	364	88.80
10	26	426308.35	25860	7300	13775	2580	2205	400000	357	91.35
11	75	424459.60	24080	6915	15235	–	1930	400000	280	99.60
12	1200	466914.55	26530	8145	16295	–	2090	440000	273	111.56
13	1980	508776.20	28375	8560	17515	–	2300	480000	280	121.20
14	1985	510363.65	29930	8545	18925	–	2460	480000	294	139.65

Table 4
Percent increase in costs.

Instance	TC (%)	TTC (%)	FC (%)	PrefCost (%)	ExpCost (%)
1	–	–	–	–	–
2	28.40	73.36	26.32	175	92.86
3	33.29	32.48	33.33	63.64	−10.37
4	1.35	22.89	0	33.33	19.01
5	24.46	17.67	25	4.17	3.56
6	20	20.01	20	20	21.70
7	0.52	7.50	0	30	13.77
8	31.78	11.72	33.33	17.95	23
9	12.50	12.45	12.50	13.04	16.54
10	11.16	12.24	11.11	−1.92	2.87

resources and optimal assignment among all the entities ensures the lowest possible travelling costs and penalty costs. The findings presented in Table 4 along with Figs. 2 and 3 will further affirm these observations. Table 4 shows the percent increase in the TC, TTC, FC and penalty costs (PrefCost and ExpCost) with the increasing instance number.

Fig. 2 compares the percent increase in the total cost, total travelling cost and fixed cost with respect to the ascending instance numbers. One can see that the percent increase in the total travel cost is decreasing over the increasing size of the considered problem. Moreover, the change in total travel cost shows the consistent trend as compared to the total cost and fixed cost. This consistency means that with the increasing size of the problem, the mathematical model gets more and better choices for assignment among the considered entities with the objective of cost minimization, although this increase in problem size also adds to the computational difficulty of the problem. In case of fixed cost, the percent increase does not show consistency. In few cases, it retains previous values and there is zero increase against the larger size of the problem in the next instance. This can be observed for the 4th and 7th instance. The observed inconsistency and higher percent increase in some instances can be attributed to the recruitment of the most essential health care workers and setting up health care offices against the large size of the problem and higher demand. Whereas, the zero or very small increase for the 4th, 7th, and some other instances uphold the observation that the mathematical model attempts to minimize the cost as much as possible even with the increasing size of

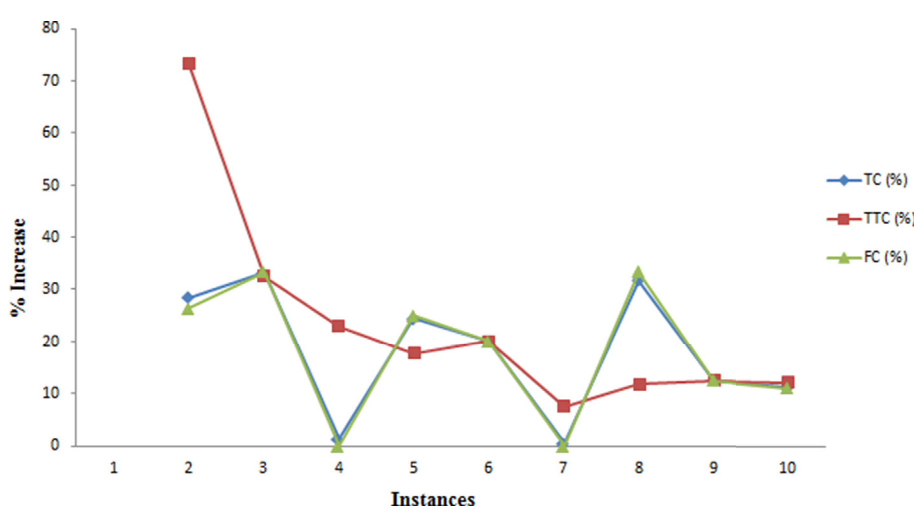

Fig. 2. Comparison of percent increase in cost for TC, TTC and FC.

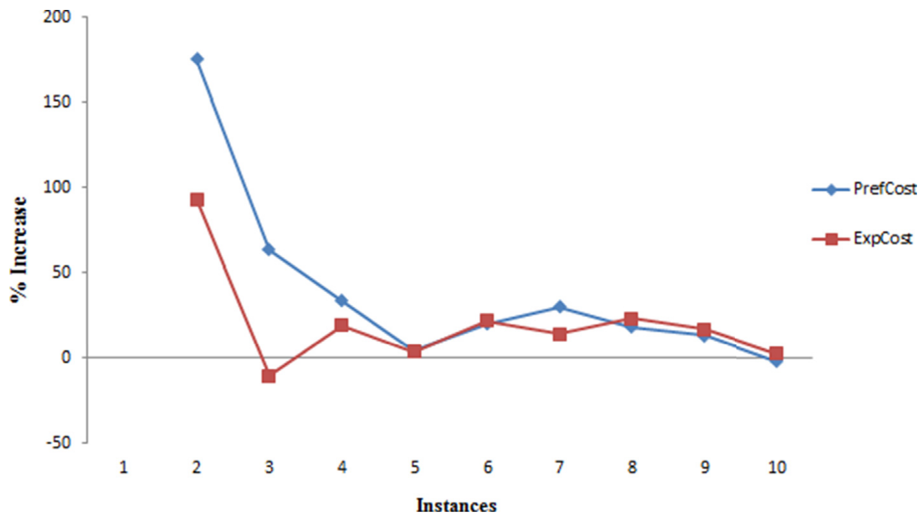

Fig. 3. Comparison of percent increase in cost for PrefCost and ExpCost.

the problem. The total cost shows a similar trend as the fixed cost. The similarity between these two costs is understandable as the fixed cost contributes the major portion of the total cost. The percent increase in penalty costs, experience gap cost, and patients' preference violation cost, is shown in Fig. 3. It can be seen that both the costs do not contribute significantly to the total cost due to the low value of penalty cost parameters as mentioned in section 4. Furthermore, the percent increase is also witnessing the decreasing or somehow consistent trend for both types of penalty costs. Such behavior can be associated with the availability of a large number of patients and nurses in the large sized problems which assists in making good matches. Thus penalty costs do not rise significantly with the increasing size of the problem.

Table 5 shows the results regarding the number of resources selected through the solution of the mathematical model. The second column of Table 5 presents the data about the number of health care workers hired against each instance of the considered problem. The third and fourth column show the breakup of the values observed in the second column in terms of HHC nurses and telehealth nurses. The fifth column presents the number of health care offices selected for opening considering all the requirements. Whereas, the sixth and seventh column show the number of patient clusters and the total number of health care workers assigned to these clusters respectively. The resource selection results as shown in the Table 5 complement the results of Table 3. These results also support the discussion about the costs shown in Table 3 and 4 as these costs are associated with these fixed resources. It is pertinent to mention here that the health care workers assigned to patients' clusters HNAC, as shown in the seventh column, are also the sum of both HHC nurses and telehealth nurses.

Table 5
Mathematical model results for resources selection.

Instance	N	Hn	Tn	HCO	Clusters	HNAC
1	3	2	1	1	1	2
2	4	2	2	1	2	3
3	6	3	3	1	3	4
4	6	3	3	1	4	5
5	8	4	4	1	5	6
6	10	5	5	1	6	8
7	10	5	5	1	7	9
8	12	6	6	2	8	10
9	14	7	7	2	9	12
10	16	8	8	2	10	12

5.1. Fuzzy c-means based effectiveness evaluation results

In order to evaluate the effectiveness of the proposed integrated plan to cluster the nurse, nurse-patients, and patients data, we employed two measures, Fuzzy Silhouette coefficient and Kappa (k) measure, to evaluate the classification results of FCM technique. The relevant distance matrices, nurses' qualification matrix, patients' demand matrix and other associated data values were used. The first measure fuzzy silhouette coefficient is used to judge the quality of a cluster or entire clustering scheme. The interpretation of Fuzzy Silhouette coefficients is shown in Table 6.

The fuzzy silhouette coefficient of nurse, nurse-patients, and patients with an optimal number of clusters is shown in Fig. 4. In terms of Nurse clustering, we observe four clusters (i.e. N = 4) with some noise in the data as shown in Fig. 4-a. Similarly, in terms of Nurse-Patient clustering, we observe two clusters (i.e. N = 2) with a minor difference. Finally, in terms of Patient clustering, we observed five clusters (i.e. N = 5) with some noise in the data. Like other measures such as Precision, Recall, and F1, Kappa is used to extract the information from the confusion matrix of a learner and evaluate the effectiveness of the classification. In case of sample Nurse, Patient-Nurse, and Patients' groups data collection, we found k = 0.64, k = 0.67, and k = 0.61 which refer to substantial agreement for the performance of Fuzzy c-means to classify the relevant data. These results indicate the effectiveness of proposed integration plan for clustering the Nurse and other staff members, and patient data which can aid a decision maker to effectively plan and group the available resources.

5.2. Sensitivity analysis

Sensitivity analysis is performed for some important parameters in order to evaluate the effects of variations in the parameter values on the cost components included in the objective function of our mathematical model. Although, most of the parameters used in this mathematical

Table 6
Interpretation of Kappa Test.

Kappa (k)	Agreement
< 0.00	Poor
0.00–0.20	Slight
0.21–0.40	Fair
0.41–0.60	Moderate
0.61–0.80	Substantial
0.80–1.00	Almost Perfect

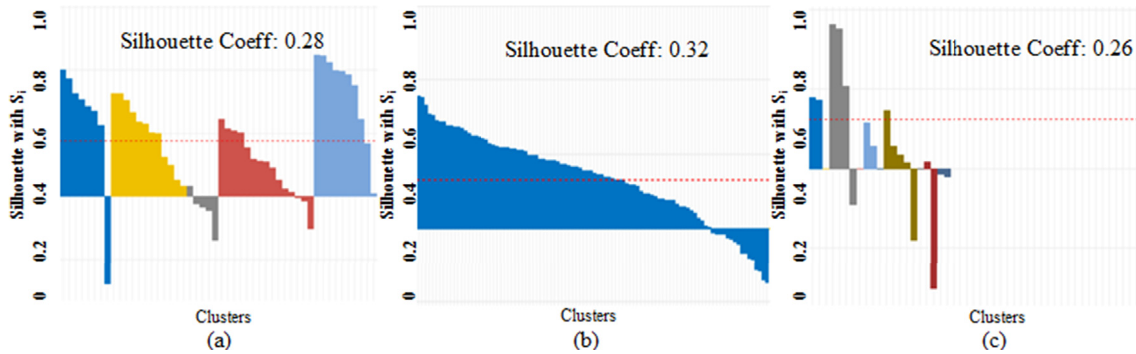

Fig. 4. Silhouette Coefficient for a) Nurse, b) Patient-Nurse, and c) Patient Clustering.

model (e.g. capacity, distance and cost related parameters) depend on the real life situation, some key parameters must be fine-tuned before practical implementation of this study. The parameters *e* and *f* are assessed in this analysis as these parameters are used as lower and upper limits for the total number of patients at each patients' cluster centre in the model. For this analysis, we used 6th, 7th and 8th instance as these instances are large enough and similarly, these instances can also be solved in a reasonable time through CPLEX. In the previous experiments, the values for *e* and *f* were set at 0.7 and 1.3 respectively. The sensitivity analysis is accomplished in three phases.

First, the upper limit parameter *f* is kept fixed at 1.3 and lower limit parameter *e* varies from 0.1 to 1. Then, the lower limit parameter *e* is kept fixed at 0.7 and upper limit parameter *f* varies from 0.8 to 1.7 in the second phase. The results obtained through these experiments show a similar trend for all the considered instances. Thus, we only reported results against one instance in Table 7. The variation in the values of *e* and *f* only effected the cost components TCNC, TCPP, and PrefCost. Whereas, the cost components TCNO, TCNP, FC, and ExpCost remained unchanged and did not show any sensitivity with respect to the variation in the values of *e* and *f*. Therefore, Table 7 only includes the cost information about those cost components which are sensitive to the parameters considered in this analysis. First four columns in Table 7 show the results considering the variation in the value of *e* and fixed value for *f*. Whereas, columns 6–9 show the results with respect to variation in the value of *f* and a fixed value for *e*. The 5th and 10th column represent the total cost for these sensitive cost components. Figs. 5 and 6 show the associated changes in the cost components for the variation in the values of *e* and *f* respectively. Fig. 5 shows that the cost components experience only very small change during the variation of *e*. It can be seen that value of TCPP observes slight increase while the value of TCNC and PrefCost observe slight decrease or remain consistent with the increasing value of *e* from 0.1 to 1. Whereas, in case of *f* the cost component TCNC show a significant decrease while cost components TCPP and PrefCost show a substantial increase as the parameter value changes from 0.8 to 1.7. This observation is clearly depicted in Fig. 6.

It is evident from the results that there are certain parameter values for both *e* and *f* which show the lowest total cost. These parameter values are shown in bold in Table 7. In order to further confirm these best parameter values, we performed experiments with the simultaneous variation in the values of both the parameters *e* and *f* in the third phase. The results obtained through these parameters are shown in columns 11–16. The cost components show similar results as observed during the variation of *f* in the second phase. Thus, the results presented in the columns 11–16 and Fig. 7 affirm our earlier findings related to best parameter values. We can conclude that the best parameter values for *e* and *f* vary from 0.8 to 1 and 1.5 to 1.7 respectively. Hence, the sensitivity analysis assists to sort out best parameter values and shows the behavior of the model considering the variation in parametric values.

Taken together, the considered problem and the mathematical model enable the successful integration of telehealth and patients' group based care to the HHC dimensioning problem. Results obtained through integer linear programming model solution and sensitivity analysis indicate the successful implementation of the integration approach and show the behavior of the model with respect to different circumstances. The proposed model successfully determines the required optimal resources, patients' groups and staff pairing along with best assignment decisions considering the objective of cost minimization. Additionally, Fuzzy c-means based approach affirms the effectiveness of the integration approach against the associated data used in this study. Health care managers can improve operations through the utilization of well-defined integration approach and detailed analysis provided in this study. Moreover, service quality, employee satisfaction,

Table 7
Sensitivity analysis results.

e = 0.1 to 1.00, f = 1.3					e = 0.7, f = 0.8 to 1.7					e = 0.1 to 1.00, f = 0.8 to 1.7					
e	TCNC	TCPP	PrefCost	Total Cost	f	TCNC	TCPP	PrefCost	Total Cost	e	f	TCNC	TCPP	PrefCost	Total Cost
0.1	1615	1435	217	3267	0.8	2675	1180	161	4016	0.1	0.8	2675	1180	161	4016
0.2	1615	1435	217	3267	0.9	2675	1180	161	4016	0.2	0.9	2675	1180	161	4016
0.3	1605	1445	210	**3260**	1.0	2120	1305	175	3600	0.3	1.0	2120	1305	175	3600
0.4	1605	1445	210	**3260**	1.1	2120	1305	175	3600	0.4	1.1	2120	1305	175	3600
0.5	1605	1445	210	**3260**	1.2	2120	1305	175	3600	0.5	1.2	2120	1305	175	3600
0.6	1605	1445	210	**3260**	1.3	1605	1445	210	3260	0.6	1.3	1605	1445	210	3260
0.7	1605	1445	210	**3260**	1.4	1605	1445	210	3260	0.7	1.4	1605	1445	210	3260
0.8	1605	1450	210	3265	**1.5**	1330	1510	231	**3071**	**0.8**	**1.5**	1330	1510	231	**3071**
0.9	1605	1450	210	3265	**1.6**	1330	1510	231	**3071**	**0.9**	**1.6**	1330	1510	231	**3071**
1.0	1605	1450	210	3265	**1.7**	1330	1510	231	**3071**	**1.0**	**1.7**	1330	1510	231	**3071**

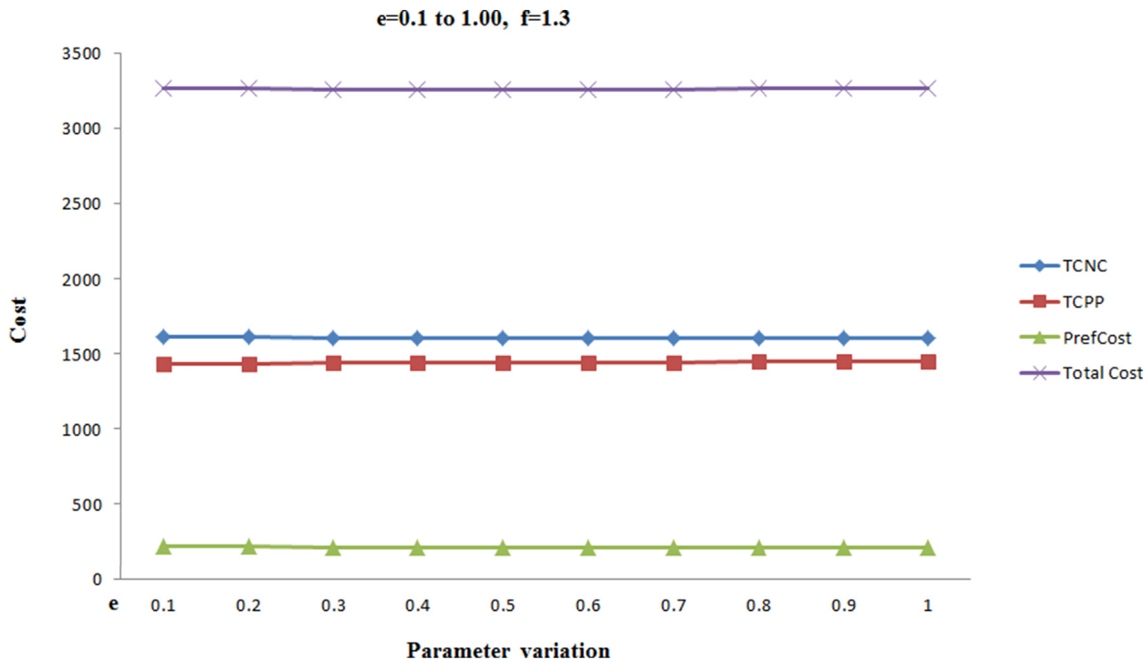

Fig. 5. Sensitivity on the variation of *e*.

and operational efficiency can be enhanced through simultaneous consideration and integration of health care aspects considered in this problem. Specifically, the HHC, community care and telehealth organizations confronting the issues related to inexperienced staff, poorly qualified health care workers, care staff absenteeism and dissatisfied patients can adopt such models to improve the quality of service and to maintain cost effective operations.

5.3. Threats to validity

The results obtained through this integrated approach and proposed model are promising and encourage us to investigate other related issues of this challenging planning problem in the future. However, healthcare planners may find some difficulties with respect to the proposed approach as given below:

1. We used simulated data set to perform the experiments owing to unavailability of real data set. In the existing HHC literature, the addressed problems and experimental data sets are based on the specific work environment and background of considered HHC organizations, thus not suitable for this particular problem. Moreover, to the best of our knowledge, the proposed integrated approach is the first study to integrate HHC, telehealth and patients group based care. Therefore, the absence of benchmark testing data can be addressed through real implementations in the future studies.
2. The real implementation and results may differ to some extent depending upon the work environment of the considered organization and related data set. Nonetheless, the real implementation will provide more detailed insights to further improve the proposed approach.

6. Conclusion

There are convincing arguments for undertaking long term care to improve and sustain the quality of life. Home Health Care and telehealth are very well suited for patients who are unable or unwilling to

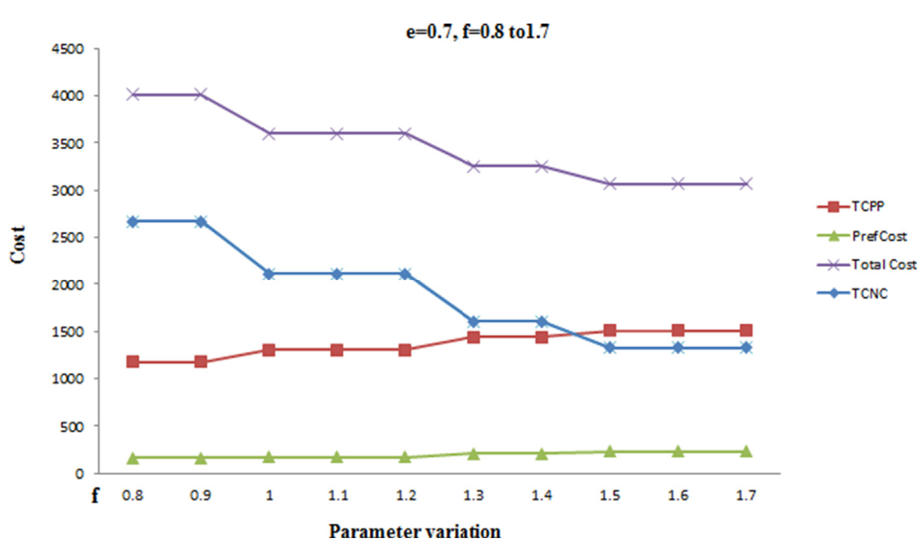

Fig. 6. Sensitivity on the variation of *f*.

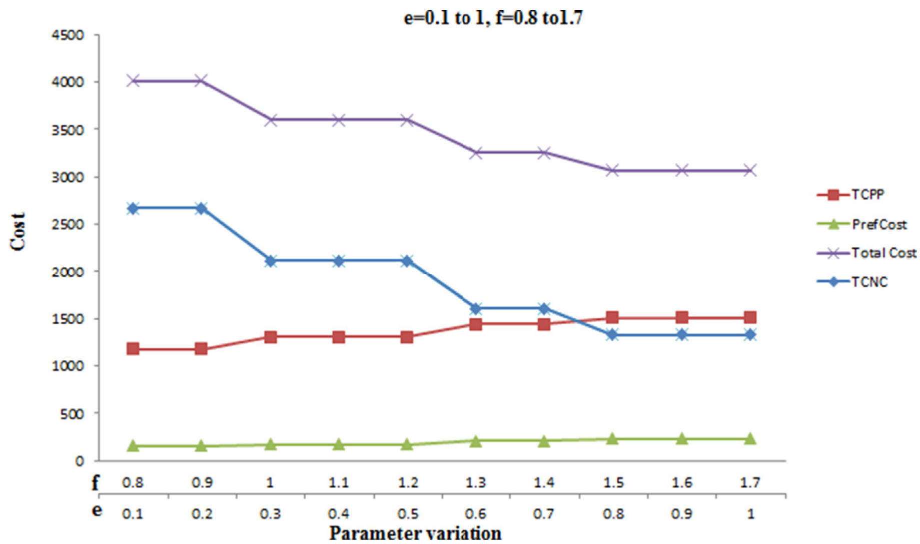

Fig. 7. Sensitivity on the simultaneous variation of *e* and *f*.

avail conventional health care facilities. However, the elderly population and HHC patients may develop negative behaviors and adverse health effects because of isolation from social circles. The studied problem integrates HHC resource dimensioning problem with telehealth based care and patients' group based home health care. A mathematical model is developed to integrate the HHC resource dimensioning problem with the telehealth based care and patients' group-based health care services. The mathematical model not only selects the optimal number of health care workers, health care offices and patients' clusters based on their location but also performs the assignment tasks. Additionally, the model pairs a HHC nurse and telehealth nurse together to conduct a health care session. Each pair is assigned to a patient or patients' cluster for the required health care session which is scheduled against a specific time window. Moreover, the mathematical model attempts to meet the patients' preferences and provide properly experienced nurses to all patients by incorporating the penalties in the objective function against the violation of associated criteria. The model successfully solves the considered issues and delivers optimal results. The performance of the model against different types of cost components and meaningful sensitivity analysis with respect to variation in values of some key parameters provide a deep insight into the model behavior. Subsequently, the validation of the effectiveness of the proposed integration approach in order to cluster the nurse, telehealth staff, and patient data is performed using Fuzzy c-means.

Future research could extend the mathematical model to incorporate the staff training and learning characteristics in the integration plan. It is also necessary to explore the efficient and effective algorithms and heuristic methods to solve the large scaled problems.

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