Real-Time IoMT-driven Optimisation for Large-Scale Home Health Care Planning

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Abstract: The number of home caretakers is rising rapidly due to an increasing number of elderly people, recent pandemics, and the advancement of home health care facilities. Wearable medical devices and the Internet of Medical Things (IoMT) help health care managers monitor patients in real-time and provide remote medical care. This reduces home visits and helps Home Health Care (HHC) companies plan their resources. The paper addresses the HHC planning problem of allocating the optimal number of experts to patients while minimising the delay in visiting the patient, matching medical expertise with patient needs, and identifying the patient's visit sequence. To tackle this, a new mixed-integer mathematical problem is proposed to reduce the total visit time for patients. This paper makes three key contributions towards tackling this plan, including (i) providing a formal definition of the problem and putting it in context with related work, (ii) proposing multiple problem instances varying in complexity, and (iii) an initial analysis of several heuristics and an exact solver (CPLEX) on these problem instances. The results indicated that the application of computational intelligence combined with IoMT can reduce patient visitation time significantly in a daily plan and therefore lead to 3.7 percent improved care for HHC patients.

1 INTRODUCTION

Supply chain management is an important component of sustainable development and plays a key role in optimising various systems. The Home Health Care (HHC) system has recently attracted the attention of various systems and settings since it deals with human lives and supply chain considerations (Reddy et al., 2022). Inefficiencies in home health care systems and their supply chain operations have significant impacts on human lives worldwide. In the context of home health care, research has shown that nurses spend a considerable amount of time on non-clinical supply chain duties, indicating inefficiencies in the system (De Vries and Huijsman, 2011; Vervoort et al., 2021). This system could save a human life, especially when patients with traumatic diseases need timely and justified services from the comfort of their homes (Nikzad et al., 2021). Hence, efficient use of supply chain networks (including expert home carers, patients, and HHC organisations) could improve the effectiveness of HHC systems, since the daily demand for home care is increasing.

Nowadays, patient monitoring and care are crucial to recovery. Some organisations offer real-time patient monitoring and data recording by employing applications to both reduce their costs and face the challenges of meeting the growing demands of patients. Technologies used to monitor patients with HHC have shown significant benefits in reducing mortality rates (Polisena et al., 2010). Athelas is a leading provider of patient monitoring systems (Athelas, 2003). Patients carry sensitive data about their health, which requires more layers of protection. Therefore, a new form of IoT (Internet of Things) for health care has emerged: IoMT (Internet of Medical Things). If any results are beyond the normal range, the patient immediately receives an alert from the nursing staff for further follow-up medical treatments (Dwivedi et al., 2022).

The motivations behind using the IoMT concept are to perform real-time patient monitoring and plan patient visits. A real-time device is attached to the patient's body according to their chronic diseases. This device not only monitors patients daily, but can also perform certain health care activities, such as remote

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monitoring of the patient's heart rate and administering certain types of medicine. In contrast to earlier research on HHC supply chain network planning (see, e.g., (Ait Haddadene et al., 2019; Goodarzian et al., 2021; Fathollahi-Fard et al., 2022)), IoMT responds quickly to changes in the schedule and can reschedule the current plan as needed.

The contributions of the study include a new mathematical model considering allocating skill-based nurses to HHC patients based on different service menu, developing multiple metaheuristic algorithms suitable to solve the problem, and considering real-time changes to verify the applicability of the IoMT plan.

Therefore, in this study, a methodology for IoMT wearable devices is first proposed. The problem aims to assign an optimal number of experts to various patients requiring service while minimising the total visitation time, determining the daily plan and visitation intervals. The term "threshold intervention level" is used to identify patients with conditions of the highest severity. Finally, several metaheuristics that depend on different concepts are adapted to the problem and benchmarked on several realistic problem instances that vary in complexity.

The proposed mathematical problem considers various inputs and settings, such as using constraints considering the patient's time window, multiple choices to assign nurses, the Patient's Service Menu (PSM), and the uncertain nature of the proposed IoMT plan. In contrast to previous studies, each patient has its own unique time window for the visit and requires specific services among the range of services. First, we adapt the well-established Simulated Annealing (SA) and Particle Swarm Optimisation (PSO) to tackle the problem and serve as baselines. We then introduce a new co-evolutionary Particle Swarm Optimisation (CPSO) algorithm to explore if a more sophisticated approach translates into better performance (measured in terms of solution quality). Several problem instances, varying in size, are introduced to validate the performance of the three search algorithms and an exact solver (CPLEX).

The organisation of the paper is as follows. The next section provides the reader with a comprehensive literature review of related works. The proposed IoMT methodology and mathematical modelling are presented in Section 3. Section 4 includes the optimisation strategy and the experimental results of the metaheuristics. Finally, Section 6 concludes the paper and discusses future work.

2 LITERATURE REVIEW

The research field on HHC management is not new. However, there is a growing trend in HHC research to consider decision-making and management science approaches.Most HHC supply chain papers have focused on creating a strategic framework. According to (Landers et al., 2016), 52 percent of patient transactions are conducted online, virtual or through an app. As a result, more studies are needed to fill this gap and address the transition from traditional care to HHC. This section represents an overview of the relevant literature on HHC followed by a discussion of research gaps in HHC.

Routing and Scheduling Problems. Most current studies in the field of HHC supply chain network design employ new algorithms or introduce new methodologies to solve their proposed mathematical modelling. The study of Fard et al. (Fathollahi-Fard et al., 2018) addressed a green HHC vehicle routing problem by using a mixed-integer linear programming model to reduce expenses and green emissions. Using the Lagrangian relaxation procedure, Decerle et al. (Decerle et al., 2018) solved HHC routing and scheduling for many time windows using a memetic algorithm. The results of the problems were promising. Shi et al. (Shi et al., 2019) proposed a robust optimisation problem for an HHC plan and compared the results in a deterministic setting. Mathematical programming was used to minimise vehicle route logistics expenses per visitation. Bahadori et al. (Bahadori-Chinibelagh et al., 2022) addressed multi-depot routing programming for HHC optimisation to reduce transportation costs. The study assumed that routing rates must be limited. The model was flexible and effective under different conditions due to two constructive algorithms. The scheduling of HHC staff under uncertain conditions was investigated in (Restrepo et al., 2020). The objective was to minimise work shift costs by achieving optimal allocation, reducing shift-changing penalties, and expecting recourse. Having an optimised routing and scheduling plan can be most beneficial when having access to the required resources. Therefore, allocation models are needed to overcome problems such as nurse workloads, time window, and fair distribution of resources. However, assigning the optimal number of resources based on the patient's condition has been overlooked.

Allocation Problems. The use of location-allocation problems can be seen in the design of recent HHC supply chain networks. For instance, in (Rodriguez-Verjan et al., 2018; Lin et al., 2018) a location-allocation problem is proposed to both locate the

HHC centres and reduce the total cost of resources and facilities. The authors used mixed-integer linear programming, as in (Xiao et al., 2018), to address the HHC problem. However, the utilised time window is not able to address real-time changes as it is assumed to be fixed. The application of location-allocation problems is quite limited in the literature of HHC. In addition, allocating nurses to patients based on the PSM is ignored in this sense.

Metaheuristics for HHC Applications. The application of metaheuristics has been highlighted in previous studies. Erdam et al. (Erdem and Koç, 2019) addressed HHC patients with electronic vehicle routing challenges and their limitations. The problem was to optimise travel time and the number of nurses. In the analysis, metaheuristics based on genetic algorithms and variable neighbourhood search performed better. Other studies (eg (Decerle et al., 2019b; Decerle et al., 2019a)) considered using metaheuristics such as non-dominated sorting genetic algorithm II (NSGA-II) and an evolutionary approach like multi-directional local search (MDLS) to optimise working time and quality of service, respectively.

Bi-objective programming could reduce routing time and reduce costs in an HHC system, according to (Khodabandeh et al., 2021). The epsilon-constraint method verifies the results of the problem. In (Erdem and Koç, 2022) a hybrid algorithm is proposed to address the problem of HHC with electronic vehicles. Promising results were reported for complex routing problems. In (Xiang et al., 2023) a routing and scheduling HHC problem that accounts for the patient's preference was considered. The cost objective is minimised using hybrid NSGA-II, which proved to be better than the e-constraint method.

In summary, there is a research gap in that the application of IoMT and real-time changes has not yet been considered in the existing literature (Fikar and Hirsch, 2017; Emiliano et al., 2017; Dwivedi et al., 2021). This study first proposes a dynamic and real-time plan using IoMT in a smart platform environment to enable online and instant decision-making during an unexpected patient emergency scenario. Previous studies insisted on routing and scheduling, such as (Di Mascolo et al., 2021), or defined a new solution strategy to address HHC problems, such as (Liu et al., 2021). Only a few studies have used an allocation strategy to assign the optimal number of nurses to each patient. Furthermore, this work is the first to propose (and account for in optimisation) a combination of different time windows, patient service menus, and service levels for experts.

3 FORMAL PROBLEM DEFINITION

HHC monitors and improves patient care using medical records, such as age, sex, symptoms, vital signs, trauma, and others. HHC technologies, including wearable devices, allow real-time patient monitoring, medical data storage, and remote care (McGillion et al., 2020). Therefore, HHC resources are allocated when needed and patients are served more efficiently. Each patient starts the day with the expectation of certain services. The HHC sector has many experts that can be assigned to these patients, but each expert can only provide specific medical care.

In summary, the proposed methodology has the following steps:

- Phase one - System installation: The phase is centred on using the HHC system with IoMT, which calls for the mobilisation of actual industry 4.0 systems—computers, software, and wearables—for patient programming, monitoring, and analysis.
- Phase two - Diagnosis: Wearable Internet of Things (IoMT) devices can diagnose symptoms, monitor patient status, and provide remote medical treatment, therefore saving time and money. They are able to forecast when to intervene and alert medical staff before the patient's condition deteriorates. A specified Threshold Intervene Level (TIL) enables the wearable device to proactively assess and store real-time patient conditions in a cloud-based data centre. With expert designations for every patient, this system uses past data, real-time diagnosis, and patient observation to identify and forecast urgent conditions.
- Phase three - Provide healthcare: Depending on TIL, the IoMT wearable devices distinguish between patient severity levels. The technology tracks and saves real-time data if the level is less than TIL. Patients can also push a button to request assistance if it goes beyond TIL, and an experienced home health carer is dispatched.

  Considering the proposed methodology, IoMT in HHC is a network of connected devices in which patient monitoring is done using secured network based on internet. This provides online and instant monitoring of each patient. On the other hand, TIL is a critical parameter in which determines the health condition of each patient separately. IoMT and TIL are interconnected in the proposed HHC problem since IoMT alerts the HHC staff based on instant changes of patient's condition given the TIL level. Current study only focuses on the scheduling aspect of the HHC as the main problem that HHC companies dealing with specially in Canada. Therefore, this study considers scheduling for the HHC patient without taking into account machine learning or triggering mechanism. However, these will be a part of future development of the current study. Given the current nature of the problem and considering the IoMT changes in a real-time manner, this setup can be utilised in US and UK considering their challenges in the HHC sector (Statista, 2020).

The objective of the HHC planning problem is to assign experts to HHC patients based on their service requirements. Patients expect the HHC system to provide home medical care, and accordingly the HHC manager matches experts who possess a particular medical expertise with patients requiring that specific medical care. In other cases, interventions such as prompt visits to patients in extreme cases are allocated by the HHC system. The HHC system provides remote medical care in specific cases, thereby reducing patient visit costs and time.

Following discussions with carers and medics, we have developed the following (formal) problem statement to capture the essence of the problem: In this problem, two factors determine the number of home health carers to be assigned per day based on the patient's service requirement and time window. The objective is to reduce the visitation time associated with the experts serving the patients. It should be noted that the assignment of experts takes place only if they have the required skills to serve patients. In addition, only a limited number of resources are available each day. Therefore, based on the structure of the proposed HHC, the following assumptions can be considered:

- Each patient has a specific service menu that must be served during the day.
- Only one expert home carer must be assigned to each patient.
- An expert would be assigned to a patient only if the person has the required medical skill to serve the patient.
- An expert is sent to a patient only if the threshold severity level goes beyond the real-time severity level.
- The number of experts available is fixed and limited each day.

Table 1 provides an overview of the problem parameters: Lim_{Tr} is based on time and signifies the travel time that has to be bounded due to the suppositions of the problem. Furthermore, INT_i defines the threshold intervention level of the patient by a number (derived from the IoMT system and wearable devices in real-time). If its value goes above λ_i, an expert must be sent to visit the patient. Considering 1, the proposed objective function and constraints of the HHC problem can be expressed as below:

Table 1: Problem parameters and definitions.

Notations	Definition
$e = 1,\dots,E$	Set of expert home caregivers
$i,j,h = 1,\dots,P$	Set of patients
$k = 1,\dots,K$	Set of all periods (days)
$\varphi = 1,\dots,j$	Set of all visits
Parameters	**Definition**
$\mathrm{Tr}T_{i,j}$	Travel time visits of patients i and j
ViT_i	The time duration in which patient i must be visited
PT	The penalty time
EV_i	The earliest visit of patient i
LV_i	The latest visit of patient i
Ne_i	The total number of experts
SE_{ei}	The skill of the expert caregiver e to visit patient i
Lim_{Tr}	Distance parameter to limit the travel time
$DU_{\max}$	Maximum available time for expert home caregivers
λ_i	The real-time severity level of patient i
INT_i	$INT_i \geq \lambda_i, 1$ Otherwise, 0
VB	A very big number (without dimension)
Variables	**Definition**
$A_{e,i,j,k}$	1, if expert home caregiver e is assigned to patient j after visiting patient i in period k
$ST_{e,i}$	Starting time of in-home patient i for visitation
$AT_{e,i,k}$	The arrival time of an expert home caregiver e

$$\mathrm{Min}\,Z = \textstyle\sum_{e\in E}\sum_{i\in P}\sum_{j\in P-i}\sum_{k\in K} A_{e,i,j,k} * (\mathrm{Tr}\,T_{i,j} + ViT_i) + \sum_{e\in E}\sum_{i\in P} ST_{e,i} \tag{1}$$

Equation 1 defines the objective function, which minimises visit time based on the patient's time window. Expert home carers must adhere to the patient's schedule.

$$AT_{e,j,k} \leq LV_j \quad \forall e \in E, j \in P, k \in K \tag{2}$$

$$EV_j \leq AT_{e,j,k} \quad \forall e \in E, j \in P, k \in K \tag{3}$$

Constraints 2– 3 highlight that the unique time window for a patient needs to be taken into consideration while performing the allocation of HHC experts to the respective patient.

$$\sum_{e\in E}\sum_{i\in P}\sum_{j\in P-i}\sum_{k\in K} A_{e,i,j,k} = Ne_i \quad \forall e \in E, i \in P, k \in K \tag{4}$$

$$\sum_{e\in E}\sum_{i} A_{e,i,j,k} * SE_{ei} \geq 1 \quad \forall j \in P-i, k \in K \tag{5}$$

Constraint 4 requires all skilled expert workers to organise and comply with expert plan visits. Whilst Constraint 5 ensures that all skilled home carers are assigned based on their competence and the PSM.

$$AT_{e,i,k} + ViT_i + \mathrm{Tr}\,T_{i,j} + \left(A_{e,i,j,k} - 1\right) * VB \leq AT_{e,j,k} \quad \forall e \in E, i \in P, k \in K \tag{6}$$

$$AT_{e,j,k} - AT_{e,i,k} - ViT_i \leq \mathrm{Lim}_{Tr} + \left(1 - A_{e,i,j,k}\right) * VB \quad \forall e \in E, i \in P, k \in K \tag{7}$$

$$AT_{e,i,k} + ViT_i + TrT_{i,0} \leq DU_{\max} \quad \forall e \in E, i \in P, k \in K \tag{8}$$

Constraint 6 determines the time it takes an experienced home carer to reach a patient requiring medical service. It is necessary to divide expert home carers by time gap to assign them to patient homes. Thus, expert home carers must maintain a time between visits. It must be noted that this is not a routing constraint and it only divides experts using time; Constraint 7 accounts for this. Constraint 8 requires expert home carers to work a certain number of hours each day.

$$\sum_{e \in E} \sum_{i \in \varphi} A_{e,i,j,k} = \sum_{e \in E} \sum_{j \in \varphi} A_{e,j,h,k} \quad \forall k \in K, h \in \varphi \tag{9}$$

$$\sum_{e' \in E'} \sum_{i \in \varphi} A_{e',i,j,k} = \sum_{e' \in E} \sum_{h \in P} A_{e',j,h,(k+1)} \quad \forall k \in K, i, j \in P \tag{10}$$

Here, the set $\varphi = \{0, 1, \ldots, n+m\}$ is defined to show the total number of visits n and visit breaks from one home to another m. If we consider patients from the set $\{0, 1, \ldots, i, j, h, \ldots, m\}$, it is important for an expert home carer to finish his/her work at a patient's home before visiting another patient. Hence, Constraint 9 is utilised to overcome this issue. Constraint 10 is shaped to ensure the continuity of the assigned home care to all the expert home caregivers.Once an expert is assigned and served a patient, it must continue the service to other patients if possible.

$$\sum_{i \in P} A_{e,i,0,k} = 1 \quad \forall e \in E, k \in K \tag{11}$$

$$\sum_{J \in P} A_{e,0,j,k} = 1 \quad \forall e \in E, k \in K \tag{12}$$

$$ST_{e,1} = \sum_{i \in P} \sum_{j \in P} \mathrm{Tr}\,T_{0,1} * A_{e,0,1,k} * INT_1 \quad \forall i, j = 1 \tag{13}$$

$$A_{e,i,j,k} \in \{0, 1\} \quad \forall e \in E, \forall i, j \in P, k \in K \tag{14}$$

$$AT_{e,i,k} \geq 0 \quad \forall e \in E, \forall i \in P, k \in K \tag{15}$$

Constraints 11– 12 ensure that experts must return to the HHC centre after visiting their patients. Constraint 13 defines the start time of the plan. Finally, Constraints 14– 15 indicate binary and non-negative decision variables, respectively.

The following methodology addresses real-time changes in the proposed HHC planning problem: First, the model initialises by setting the values of $\mathrm{Tr}\,T_{i,j}$, ViT_i, PT, EV_i, LV_i, Lim_{Tr}, and $DU_{\max}$. In each search, it sets $i = P$ if $INT_i \geq \lambda_i$. The model is then optimised based on λ_i to achieve an efficient assignment. However, if λ_i changes, the problem sets $i = P$ and $e = E$ to their new values. Then the input value of the model will be updated and solved.

4 EXPERIMENTAL SETUP

This section motivates and defines the experimental setup pertaining to optimisation algorithms, their parameter settings, and test problems as used for the subsequent experimental study.

4.1 Optimisation Strategies

To tackle the IoMT-based HHC planning problem proposed in Section 3, we consider four different algorithms: two established metaheuristics used as a baseline, Simulated Annealing (SA) and Particle Swarm Optimisation (PSO); a more recent method, Co-evolutionary PSO (CPSO), used to understand if we can achieve improved performance; finally, an exact optimizer, CPLEX, will be used to understand the applicability and limits of exact optimisation to the problem.

We would expect the exact solver to do well on small and medium-sized versions of the problem but to be computationally intractable for larger problems, providing a sweet spot for metaheuristics. The implementation of algorithms, test problems, and visualisations can be downloaded at xxx.[1]

SA and PSO Algorithms. The complexity of problems in the HHC domain means that there is scope for the application of metaheuristics (Liu et al., 2021; Hiermann et al., 2015; Goodarzian et al., 2021). We consider the application of two well-known and widely used algorithms to solve problems of the type considered here, SA and PSO (Kennedy and Eberhart, 1995). SA has shown to be a promising approach for discrete mathematical problems (Yuan et al., 2009), while PSO was originally proposed for continuous problems but has been adapted to different types of problems since then. In our case, each discrete variable is represented by a binary string, which means that our PSO algorithm searches over a binary space. In solving the problem, these algorithms use the same approach to create an initial solution. The results of these two metaheuristics are then compared with the

[1]The link will be made available upon acceptance of the paper.

baseline using the GAMS CPLEX solver in terms of the improved performance of the proposed HHC plan. Penalization is used as the constraint-handling strategy with the penalty term simply counting the number of violated constraints; more advanced strategies are part of future research.

CPSO Algorithm. CPSO (He and Wang, 2007) is a multi-population version of classic PSO aimed at tackling complex multi-modal problems more efficiently. This is addressed for the first time in (He and Wang, 2007). CPSO uses multiple populations of particles, allowing the algorithm to explore the search space more thoroughly and find a better balance between exploitation and exploration. The chromosome design is shown below:

According to Figure 1, a chromosome represents a set of patients who must be served by an expert with a corresponding service level. This will form a set of patients (P) followed by experts (E), in which they must be served according to their service menu (S). To form this, a heuristic method based on the staircase method is applied using the north-west corner. Based on this method, suppliers (experts) and customers at demand points (patients) form a matrix in which their demands must be met given their required services (Holmberg and Ling, 1997). This method guarantees the feasibility of the HHC plan and assigns each expert to a patient based on their daily needs (Bazaraa et al., 2011). Therefore, multiple rows are formed based on the total number of patients and experts in the HHC, as shown in Figure 1. To simplify services and differentiate them, services 1 through 3 are denoted by A,B, and C. Consequently, a corresponding value of 0 and 1 is assigned to show whether a patient needs a certain service or not (for example, AB equals (1,1,0), showing that the patient requires services one and two). Based on the north-west corner method, experts are assigned to patients to fully meet their demands. The north-west corner method works as follows: A matrix is created in which rows responsible for experts and columns are responsible for patients. each cell of the matrix represents the allocation of experts to patients. The method begins with the north-west corner of the matrix and allocates the units as much as possible, then it moves to the next row, this process is continues until the resources are exhaust in each row and assignments are done. Given an hour to complete each task, the assigned patients and their required time for treatment form the right-hand side of the expert column. Finally, the assignment of each expert is shown. Once allocated (red brackets) using the north-west corner, the required skills are assigned and therefore deducted from the PSM. This process will continue until every patient has an assigned expert to visit.

	P1	P2	P3	P4	P5	P6	P7	P8	EE
E1								(1,0,0)	(1,0,0) (P8,1)
E2	(1,1,1)				(1,1,1)				(1,1,1) (P1,3), (P5,2)
E3		(0,1,1)				(0,1,1)			(0,1,1) (P2,2), (P6,1)
E4			(1,1,1)	(1,1,1)			(1,1,1)		(1,1,1) (P3,1), (P4,2), (P7,2)
PSM	~~(1,1,1)~~, 0	~~(0,1,1)~~, 0	~~(0,0,1)~~, 0	~~(1,0,1)~~, 0	~~(1,1,0)~~, 0	~~(0,1,0)~~, 0	~~(1,0,1)~~, 0	~~(1,0,0)~~, 0	

Figure 1: Representation of chromosome and allocation of experts using heuristic staircase method (P: Patients; E: Experts; PSM: Patient's Service Menu (a tuple consisting of 0 and 1 digit, representing three services); EE: Expert's Expertise, (eight patients, four experts, and three services)).

Table 2: Parameter setting for SA, PSO, and CPSO algorithms.

Alg.	Parameter	Setting
SA	Maximum iteration *MaxIt*	100
	Sub iteration *SubIt*	50
	Initial Temperature	15000
	Rate of reduction	0.99
PSO & CPSO	Population size N	100
	Interia weight W	1
	Weight Damping Ratio $Wdamp$	0.99
	Accelaration coefficient c_1	1.3
	Accelaration coefficient c_2	1.3
	Internal swarm value (CPSO) w_1	0.22
	External swarm value (CPSO) w_2	0.42

4.2 Test Problems

To better understand the complexity of the problem and the performance of the solution methods, we propose case studies (problem instances) of varying problem sizes and parameter values, including small, medium, and large problems; in practice, this could translate to HHC services of varying size (eg due to geographical differences) (AlayaCare,). In addition, the following setting in Table 2 is used for algorithm parameters:

SA uses a reduction rate of 0.99. The reduction rate signifies the reduced value of the initial temperature (15000) in each iteration. In each iteration, a new solution is found and if the new solution is inferior to the best solution, then it will be retained as the best solution discovered. Otherwise, $exp(-\delta/temperature)$ is solved, where δ is the difference between the current solution and the best solution. The parameters values are derived from (Kirkpatrick et al., 1983) as one of the best practices for this problem. For the CPSO algorithm, the settings have been taken from (Kou et al., 2009). It must be noted that, to consider the same condition when evaluating the proposed metaheuristics, the number of function evaluations is set to 1000 as stopping criteria.

The values of the problem parameters can vary within a range in practice; however, following (AlayaCare,) we set the parameters as follows: $\text{Tr}\,T_{i,j} = 25$, $LV_i = 18$, $\text{ViT}_i = 65$, $\text{Lim}_{Tr} = 75$, $PT = 300$, $DU_{\max} = 45$, $EV_i = 10$, and λ_i is verified by our IoMT. The experimental study presented in the next section will initially use these settings to evaluate the performance of each metaheuristic used.

5 EXPERIMENTAL RESULTS

This section evaluates the proposed HHC network for different problem sizes using various parameter values and settings. Table 3 displays the mean of the best objective score (BOS), computational time, and the standard deviation over 50 runs of the solution methods. For CPLEX we use the lower bound obtained by using GAMS.

Table 3 Column 1 contains the problem instance's identifier, in which the first number is patients, the second and third are the number of internal and external experts, and the fourth number is the number of required services. Column 2 presents the lower bounds for the problem instances that arise from solving the model using the CPLEX solver in GAMS.The best results over 50 trials of each algorithm is taken. The CPU time is in seconds, and the mean standard deviation is the amount of variation between problem solutions. It is observed that CPLEX was able to solve the problem with up to 45 patients, 15 internal and 8 external caregivers within the time limit of 7200 seconds. No significant improvement was observed by increasing the time limit or employing additional RAM and CPU (the initial computation is performed on Windows OS 10, 16 Gigabyte RAM, and 4 Gigabyte GPU). However, SA was able to solve the problem faster, especially for larger problems. PSO needed more CPU time and achieved a lower BOS when compared to SA. However, in the case of CPSO, the results are more promising. For problems in which 15 and 10 internal and external home caregivers we employed to serve 35 and 45 patients, CPSO showed better results compared to both SA and PSO. Moreover, the mean CPU time to find the best solution and the standard deviation for CPSO is significantly shorter compared to the SA algorithm.

Figure 2 shows the variance of the BOS obtained in 50 runs for the metaheuristics (CPLEX is deterministic). For small problems (Samples 1-4) (Figure (a)), both the SA and CPSO algorithm work well in terms of the optimal solution. Furthermore, PSO presented a good solution and, with a slight difference, placed itself after SA and CPSO. For medium-sized problems (Samples 5-10) (Figure (b)), the SA algorithm is statistically the best performing algorithm among meta-

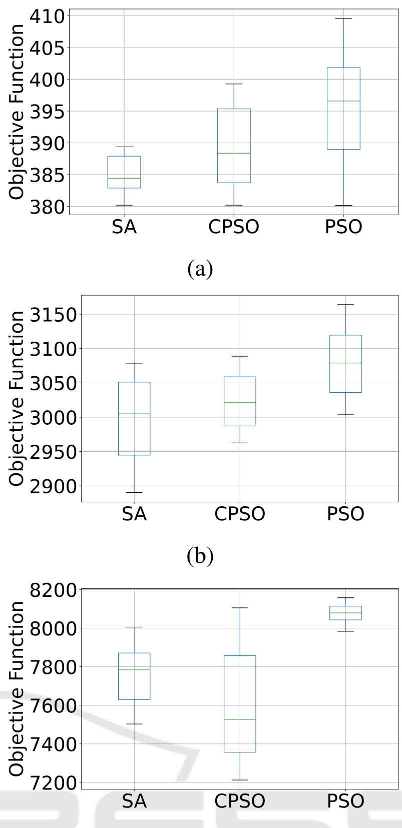

Figure 2: Box plot of the different metaheuristics (a) small (Samples 1-4), (b) medium (Samples 5-10), (c) large (Samples 11-16).

heuristics and in some samples close to the CPLEX results. It is interesting to note that the CPSO algorithm provides the second-best solution. However, for large problems (Samples 11-16) (Figure (c)), CPSO is able to obtain a good objective function solution with a relatively lower standard deviation value compared to SA and PSO. It might be noted that the CPSO takes slightly higher computational time than SA and PSO, due to the additional operators which CPSO employs for obtaining a good solution in every test run. The additional operators helps to obtain a better solution in every test run, and hence the standard deviation is higher for 50 trials compared to SA and PSO. In three larger problem instances, CPLEX was unable to obtain a result in the given 7200 seconds (as indicated by '-' in the table). Also, the convergence plot in Figure 3 indicates that all algorithms have a similar convergence behaviour with SA converging slightly faster than others.

The current study uses three metaheuristics, which are compared in a paired fashion, and performance outputs do not follow a normal distribution. Therefore, we can use the Friedman's test (Marusteri and

Table 3: Summary of the average result obtained from different algorithms for set_1 instance over 50 runs (Instance ID, respectively: Number of patients, internal experts, external experts, required services; CPLEX: The lower bound from GAMS; BOS: Best objective score; Std.dv: The standard deviation; Time: Computational time in seconds.)

Instance ID	CPLEX	SA			PSO			CPSO		
		BOS	Std.dv	Time	BOS	Std.dv	Time	BOS	Std.dv	Time
6_2_2_5	311.2	323.2	1.1	25.3	323.7	4.1	32.5	317.7	4.8	24.1
6_3_3_5	331.4	350.6	2.2	37.3	359.9	2.1	41.1	353.8	2.6	35.1
10_2_2_5	350.3	363.7	4.2	39.6	374.8	4.3	51.1	369.4	5.4	40.1
10_3_3_5	371.4	380.1	2.8	35.3	382.8	5.1	64.1	368.7	9.9	38.1
15_10_5_5	2264.8	2149.5	51.4	437.7	2252.9	26.4	512.6	2248.1	11.5	412.7
15_15_8_5	2353.9	2333.2	45.1	354.5	2395.1	27.4	408.9	2357.8	35.6	418.1
25_10_5_5	2430.8	2437.8	46.7	323.4	2467.4	47.5	503.2	2458.3	52	400.4
25_15_8_5	2562.6	2568.4	38.3	447.7	2588.9	26.9	506.7	2586.5	27.9	423.1
35_10_5_5	2704.2	2718.3	17.9	444.2	2759.8	40.8	478.8	2757.1	37.6	443.1
35_15_8_5	2956.5	2965.9	52.2	451.3	2990.4	51.9	504.3	2962.8	55.3	521.1
45_10_5_5	8099.1	6237.1	59.4	439.6	6280.1	87.9	401.5	6285.9	72.6	420.8
45_15_8_5	-	6132.3	101.6	455.6	6143.1	96.9	549.3	6142.8	105.4	513.5
65_10_5_5	10033.3	6830.7	34.7	424.5	6882.1	38.7	554.2	6876.6	32.5	418.4
65_15_8_5	-	6822.5	49.1	490.3	6891.1	58.8	497.5	6932.3	47.7	478.1
85_10_5_5	19092.8	7023.1	97.5	486.2	7307.1	47.7	507.3	7300.6	52.1	462.9
85_15_8_5	-	7838.4	50.3	438.5	7903.9	89.7	472.5	7907.2	44.9	487.1

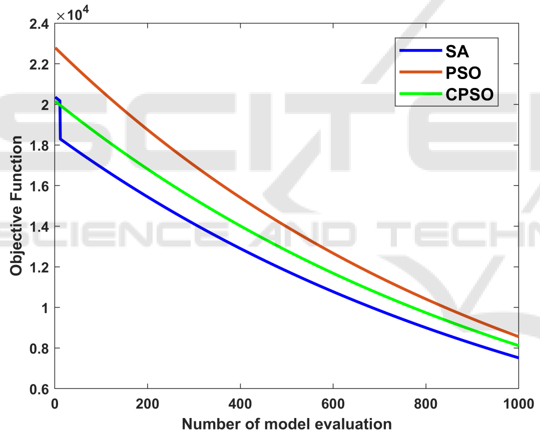

Figure 3: Convergent level of the metaheuristic algorithms based on objective function and number of model evaluation for large (85-15-8-5 problem).

Bacarea, 2010) to determine whether there are statistically significant differences among the performances of these algorithms. Table 4 shows the result of the Friedman's test for the metaheuristics considering the large problem (to evaluate the performance of the algorithms in real-world-size problems), which had the greatest impact on algorithm performance, consisting of 85 patients, 15 internal and 8 external experts, with a significance level equal to 0.05. Since the $p-value$ is less than the significance level, the result implies that there is a significant difference in the performance of these algorithms.

Table 4: Friedman's ANOVA for significance level 0.05.

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	171.04	2	85.52	48.87	2.44526e-11
Interaction	98.96	48	2.0617		
Error	167.5	75	2.2333		
Total	437.5	149			

Table 5: Sensitivity analysis on PSM (Before the IoMT plan).

Scenario A (Before)	Visit time
Before any changes (A-a)	734
Changes four hours before IoMT plan starts (A-b)	734
Changes three hours before IoMT plan starts (A-c)	760
Changes two hours before IoMT plan starts	760
Changes one hour before IoMT plan starts	760
Changes one hour without IoMT plan	789

5.1 A More in Depth Analysis of a Single Case Study

The HHC centre service menu is shown in Table 6. In addition, Expert's skills can be summarised as follows: Expert 1 (S1,S2,S4), Expert 2: (S2,S4,S5), Expert 3: (S1,S2,S3,S4), Expert 4: (S2,S3,S4,S5), Expert 5: (S5), Expert 6: (S1-S5), Expert 7: (S2,S4,S5), Expert 8: (S5), Expert 9: (S1,S2,S3,S4), Expert 10: (S1-S5). S1-S5 defines their ability to perform a service.

Table 6 assumes that patients (1–15) are chosen from a group of patients with $INT_i \geq \lambda_i$. The real-life

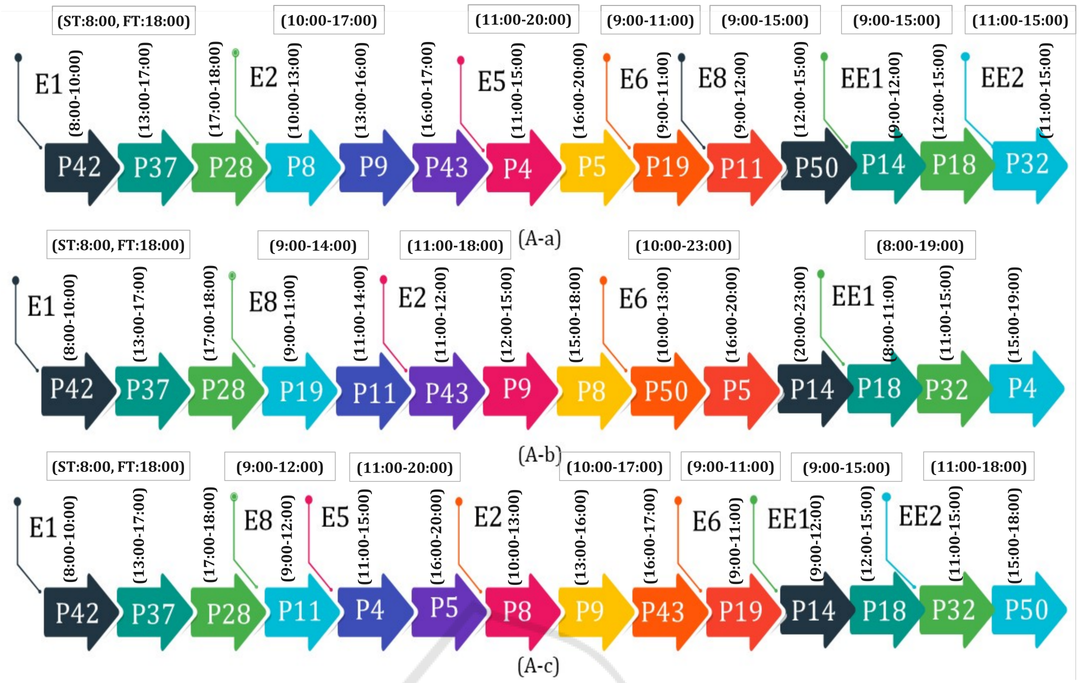

Figure 4: Patient's visitation sequence and assignments of experts to patients in scenario A; A-a: Before any change; A-b: Changes four hours before the start of IoMT plan; A-c: Changes three hours before the start of IoMT plan (E: Internal experts; EE: External experts; P: Patients; ST: Start time; FT: Finish time).

experience of similar HHC companies (AlayaCare,) combined with available resources motivated this article to use current settings.

Table 6: PSM; P:Patients; S: Services; λ: Current condition of each patient.

ID	λ	S1	S2	S3	S4	S5	Time Window
P1	0.86	1	1	0	1	0	(11:00-16:00)
P2	0.95	0	0	1	1	0	(16:00-22:00)
P3	0.92	1	1	1	0	1	(10:00-15:00)
P4	0.99	1	0	1	1	0	(9:00-22:00)
P5	0.94	0	0	0	0	1	(9:00-17:00)
P6	0.78	0	0	1	0	0	(9:00-15:00)
P7	0.99	0	0	0	1	0	(15:00-19:00)
P8	0.78	0	1	1	0	0	(9:00-12:00)
P9	0.93	0	0	0	0	1	(13:00-16:00)
P10	0.82	0	0	1	1	0	(11:00-21:00)
P11	0.98	0	1	0	1	0	(13:00-20:00)
P12	0.95	1	0	0	1	0	(8:00-19:00)
P13	0.78	1	0	0	1	0	(11:00-20:00)
P14	0.76	0	0	1	1	0	(10:00-21:00)
P15	0.84	0	1	0	0	1	(13:00-22:00)

Using the large problem settings and CPSO algorithm, the scheduling plan and optimal solutions are presented in Table 7. It shows the expert's allocation to the patients alongside their intervals. In addition, the visitation time of each expert for the entire day (including start and finish times for each expert; 10 experts, 15 patients, and 5 services) is provided.

Table 7: The IoMT plan and assignment of experts for E:10, P:15, and S:5.

Assignments	Visitation	Intervals
Expert 9	(11:00-16:00)	$P1 \rightarrow P13$
Expert 6	(10:00-18:00)	$P3 \rightarrow P2$
Expert 3	(9:00-12:00)	$P4$
Expert 10	(9:00-18:00)	$P5 \rightarrow P8 \rightarrow P11 \rightarrow P12 \rightarrow P14$
Expert 4	(9:00-13:00)	$P6 \rightarrow P10$
Expert 2	(15:00-20:00)	$P7 \rightarrow P15$
Expert 7	(13:00-14:00)	$P9$

Given the skill level and time window of both patients and experts, it is clear that expert 10 visits most of the patients, while other experts are only eligible to visit either one or two patients within the considered plan.

5.2 Sensitivity Analyses Based on IoMT Real-Time Changes

The proposed IoMT plan considers three phases, including service installation, diagnosis, and performing home care for patients. System installation is performed using wireless wearable sensors and the condition of the patients is monitored in real time. The plan is dynamically responsive to changes and offers a new plan rapidly when a change occurs. Here, scenario A is defined as follows: In scenario A, we consider that a change has occurred in the PSM before the plan starts. In this scenario, it is assumed that patient 4 ($P4$) has changed their service plan from (10110) to (11110), which means that this patient changed his services from services 1, 3, and 4 to services 1, 2, 3, and 4 before the start of the IoMT plan.

Based on Figure 4 and Table 5, the sensitivity analysis is conducted on the original plan, considering the change in PSM for patient 4. Changes are observed four to one hour before the IoMT plan starts. In addition, the original plan (A-a), changes four hours before the start of the IoMT plan (A-b), changes three hours before the start of the IoMT plan (A-c), changes two hours before the start of the IoMT plan, and changes one hour before the start of the IoMT plan are identified in this table. Four hours before the plan starts, the assignments are distributed with more flexibility and a reduction in total visitation time is observed. Last but not least, the problem shows a 3.7 percent difference from the original IoMT plan, considering one hour before changes and no IoMT plan is implemented ((788-760)/760=0.037).

By tightening this time to three and two hours, fewer options remain to assign experts to care for patients; therefore, an increase in total visitation time is predictable (see Figure 4 (A-b)). Here, the model avoided ignoring patient 11 and tried to assign it to an expert. Since the model assigned E8 to this patient in Figure 4 (A-c), the patients previously assigned to internal experts now must be assigned to external experts for visitation; therefore, an increase in total visitation time has occurred here. One hour before the start of the IoMT plan, the total visitation time remains constant since there is no flexibility to change the sequence of assignments based on the patient's service menu and time window. It is observed from this figure that even a slight change in PSM can ultimately result in allocation of different experts or utilisation of more external experts, which may result in an increase in the total number of visitation hours in a daily HHC plan. Another interesting point to mention here is the CPSO's role to respond (re-solve) the problem when having immediate changes. The algorithm updates the input according to the current changes and solves the new problem in the least possible time. This shows the adaptability and responsiveness of the proposed algorithm and the suggested IoMT plan to any real-time changes.

6 CONCLUSIONS AND FUTURE WORK

The proposed IoMT methodology controls, monitors and records the real-time condition of patients. A structured plan by IoMT is suggested to assign the optimal number of experts to a set of available home carers. Real-time monitoring of a patient's condition is a crucial tool for HHC managers to identify current and real-time conditions and decide accordingly how to react. If changes occur before the plan, the changes can be made only three hours in advance. However, applying instant changes is more challenging during the final hours, when many patients are scheduled to be visited by experts.

The experiments carried out revealed that the HHC planning problem is difficult due to the large number of variables and constraints. In addition, using multiple metaheuristics allowed us to evaluate the efficiency of the methods under various conditions and settings. SA and CPSO both proved to be efficient when faced with medium-sized problems. In terms of dealing with large problems, CPSO has been statistically proven to be better. In terms of objective function of the problem, both SA and CPSO have similar results, with SA slightly working better; however, by the means of the overall time spent to reach their best solutions, CPSO performed better when CPLEX was bound to 7200 seconds in large-size problems. This result can be meaningful, especially when working with patients with more serious symptoms.

The current results of the problem enable managers to make better decisions in severe conditions. Considering real-time changes, it adds another layer of credibility and reliability among the patients and the HHC's medical staff. This study sets the groundwork for future research to evaluate optimal experts for the IoMT plan. Future work will look at finding a more efficient way to optimise the HHC problem. In addition, the mathematical formulation can be extended to include external experts, risk-related elements, and algorithm's parameter adjustments.

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