Mutated cuckoo search algorithm for dynamic vehicle routing problem and synchronization occurs within the time slots in home healthcare

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Abstract The advancement and development of technologies promote more interest in exploring Dynamic Vehicle Routing Problems (DVRP), especially in Home Healthcare. Home healthcare (HHC) has gained more attention from researchers in recent years due to its increasing demand. There are certain cases where some patients may require one or more care services concurrently. In such a situation, synchronization of vehicles within specific time slots is necessary. The inclusion of dynamic patients and synchronization of vehicles without disregarding the time window will transform into a formidable task for HHC organizations. Hence, the investigation of the Dynamic Vehicle Routing problem where Synchronization occurs within the Time Slots (DVRPSTS) becomes a remarkable model in the context of HHC. This paper proposed one such complex endeavour considering multi-objectives such as (i) minimize the total travel time and the number of vehicles utilized (ii) maximize the number of new patients visits in HHC. The accuracy and efficiency of the proposed algorithm Mutated Cuckoo Search Algorithm (MCSA) are validated by comparing its results with existing methods in the literature. Thus, this algorithm outperforms most of the randomly generated test instances. To the best of our knowledge, the proposed MCSA has not yet been modelled for the DVRPSTS in HHC.

Keywords Dynamic vehicle routing problem · Synchronization · Time slots · Mutated cuckoo search algorithm · Home healthcare

1 Introduction

According to the “World Population Ageing (2019)” report, there is a constant rise in the ageing population. It is predicted that by 2050, the elderly population (65 years or more) will project up to 16 per cent and their proportion of the world population will be one in six (1:6). As a result of an increase in the elderly population, the growing cost of in-patient hospitals, traffic congestion, rise in chronic (like diabetes) and contagious diseases (like coronavirus), etc. would produce high demand for home healthcare among different healthcare service delivery systems (Landers 2016). Home Healthcare (HHC) provides a set of care services to patients at their respective homes using suitable caregivers. In this realistic world, innovations in technologies like Global positioning systems (GPS), Radio Frequency Identification (RFID) tags, smart mobile updates etc., create a significant impact on logistics and transportation services. These advancements in technologies help to perform fleet management effectively and proficiently (Liao 2016; Nasir 2020). Hence, many researchers have been attracted to investigate more about the Dynamic Vehicle Routing Problem (DVRP) (Larsen 2002; Euchi 2015; Fikar 2017; Demirbilek 2019; Sangeetha 2020a).

Planning and routing the appropriate professional caregivers' vehicles to the patients according to their demands and preferences within the time window is a crucial job for HHC. In our HHC system, the process of DVRP begins

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when the new patients' requests arrive after the execution of the route plan. Indeed, the new patients are included in a suitable route path and synchronization of vehicles happens within the time slots whenever it is required. The introducing two simultaneous real-time scenarios in the HHC service system are (i) introducing the vehicle routing in a dynamic environment (ii) synchronization of visits within the specific time slots has made this problem more challenging. This proposed and unique model is called Dynamic Vehicle Routing Problem, where Synchronization occurs within the Time Slots (DVRPSTS). Since this model is an NP-hard problem (Fikar 2017; Sangeetha 2020a). Solving it within a specific time frame is notoriously difficult by using exact algorithms. Despite the fact that contemporary optimization techniques such as metaheuristic algorithms can generate high-quality solutions, they cannot produce exact solutions. But it has the capability of producing the most appropriate solutions. Such types of algorithms are profoundly reasonable to solve a real-time problem like DVRPSTS of HHC. Only a few researchers have used nature-inspired metaheuristic algorithms for solving DVRP in the literature of HHC (Fikar 2017; Sangeetha (2020a, 2020b); Borchani 2019). The Cuckoo Search Algorithm (CSA) has received much attention from researchers in various optimization areas (Yang 2009; Ouaarab et al. 2014; Xiao et al. 2018; Alsager et al. 2020; SwathyPriyadharsini 2021). Therefore, this research proposed a novel Mutated Cuckoo Search Algorithm (MCSA) to solve this new variant of DVRPSTS in HHC.

Our proposed variant focused on multi-objectives such as minimizing the total travel time of caregivers and the number of vehicles utilized for the routing and maximizing the number of patient visits in each route plan. To address this model, an MCS Algorithm has been developed to execute the numerical analysis by comparing with two incredible metaheuristic algorithms like the Genetic Algorithm (GA) and Discrete Cuckoo Search Algorithm (DCSA). Hence, this research work shows that the proposed algorithm is very promising and outperforms the other two competing algorithms like GA and DCSA in most cases.

The rest of this paper is organized as follows: In Sect. 2, a detailed literature review on static, dynamic and synchronization visits and application of the CS algorithm in VRP. In Sect. 3, describes the DVRPSTS of HHC and its mathematical formulation. Section 4 presents the pseudocode and flowchart of the MCSA. Section 5 contains the experimental analysis and its outputs. Finally, Sect. 6 concludes the study.

2 Literature review

Innovations and advancements in technology transform and improve the monitoring and managing skills of the healthcare system by using wireless sensor networks (Li 2009; Kateretse 2013; Yaghmaee 2013; Prakash 2019), IoT (Kore 2020; Kadhim 2020), mobile healthcare (Jeong 2014), tele homecare system (Dinesen 2009), RFID technology (Liao 2016), U-Health platform (Jung 2013), and sensing technology (Khawaja 2017; Simik 2019), etc. The impact of covid-19 infections, patients preferred to be treated at home by their healthcare services rather than hospitalised. Hence, the integration of advanced technology with the health care system will help in handling the pandemic effectively. It has further increased the demand for HHC services significantly. Therefore, it is crucial in optimizing the routing plan of heterogeneous vehicles with limited resources of the HHC organization. It creates a vast interest in finding a Suitable Action Planner (SAP) for constructing the complex scheduling and routing of caregivers, taking into account various constraints in a static, dynamic environment and synchronization visits of caregivers etc.

The various planned management in static circumstances is examined by Nickel (2012), constructed constrain programming, Adaptive large neighbourhood search (ALNS) and Tabu search regarding benefits of cost and time. Sangeetha (2020b) proposed enhanced elitism in Ant Colony Optimization (E-ACO) to solve Heterogeneous VRP to maintain workload balance among various caregivers to maintain continuity of care in HHC.

In the dynamic environment of VRP in HHC, various types of action planners have been discussed and developed by Demirbilek (2019) and examined two different variants such as the Daily Scenario-Based Approach (DSBA) and Weekly Scenario-Based Approach (WSBA) for anticipating future demands by multiple nurses. Nasir (2018) proposed an integrated model of scheduling and routing for daily planning in HHC. It is solved using mixed-integer linear programming (MILP), and two heuristic methods are incorporated, Initial heuristic solution and self-correcting variable neighbourhood search algorithms. Euchi (2015) demonstrated artificial Ant Colony (AC) with a 2-opt local search to solve the Dynamic pick-up and delivery vehicle routing problem (DPDVRP) to reduce the total cost. Haitao (2018) proposed Enhanced Ant Colony Optimization (E-ACO) for the homogeneous vehicle. Here, ACO combined with K-means and crossover operation to extend search space and avoid falling into local optimum.

Developed suitable techniques for vehicle routing with synchronization visits by Rabeh et al. (2012) displayed the

problem as a Synchronized VRP with Time Window (SVRPTW) and proposed a MILP and solved, using the LINGO_11.0 solver for reducing the total time. Parragh (2018) demonstrated the first problem as VRPTW with pairwise Synchronization and the second problem as the service technician routing and scheduling problem (STRSP). They were designed using ALNS to reduce the total cost. Nasir (2020), under Synchronization requirements between HHC staff and Home Delivery Vehicles (HDVs) visits, a MILP model is developed to characterize the optimization problem for minimizing the total cost. A Hybrid Genetic Algorithm (HGA) presented to suggest HHC planning decisions. Mankowska (2013) constructed Home Health Care Routing and Scheduling Problem (HHCRRSP) to minimize the total cost using the Adaptive variable neighbourhood search algorithm. Borchani (2019) defined a variant of VRPTWSyn in HHC. A hybrid Genetic Algorithm with a Variable Neighborhood Descent search (GA-VND) is proposed for reducing the difference in service time of different vehicles and providing the workload balance. David Bredström (2008) presented a mathematical programming model for the combined vehicle routing and scheduling problem with time windows and additional for imposing pairwise synchronization and pairwise temporal precedence between customer visits, independently of the vehicles. It is solved using CPLEX Branch and Bound. Rousseau (2002) developed the Synchronized Vehicle Dispatching Problem (SVDLP). The solution method proposed in this paper relies on the subsequent insertion of customers using the greedy procedure.

Application of Cuckoo Search Algorithm (CSA) in VRP, initially introduced by X. Yang and Suash Deb (2009), stated that CSA works well when dealing with multimodal and multi-objective optimization problems. Ouaraab et al. (2014) initially modelled Improved CS (ICS); this model is mainly adapted to solve the symmetric travelling salesman problem (TSP). Local perturbations are introduced as 2-opt and double-bridge in their proposed Discrete CSA. Xiao et al. (2018) discussed the patient transportation problem to reduce transport emissions formulated for the CVRP model. Also, a 'split' procedure has been implemented to simplify the individual's representation. Astute cuckoos are introduced to improve the ICS's searchability. Alssager et al. (2020) developed a hybrid CS with Simulated Annealing (SA) algorithm for the CVRP, consisting of three improvements—the investigation of 12 neighbourhood structures, three selections strategies and hybrid it with the SA algorithm. Therefore, from the above survey, very few papers have been discussed on both dynamic and synchronization constraints. No work has been modelled for CSA combined with different local search methods for solving the DVRP in the literature of

HHC. Thus, it is worthwhile to examine this remarkable SAP model of MCSA is proposed for DVRPSTS in HHC.

3 Problem description

This study proposed a dynamic HHC model, which initially does not possess the complete data of all patients. Each patient must be visited in a preferable time window. Assuming that the number of caregivers, vehicles in each type and number of care activities to be performed are known before the route plan begins. Meanwhile, many new patients' demands are constantly emerging over time. A working day is divided into four different time slots $S = \{S1, S2, S3, S4\}$ as mentioned in Table 8. The new arrival of patients is scheduled for any one of these time slots based on their demands and should be allotted to the respective vehicles existing in a shift. During the execution of the route path, typically, some patients have been visited, with few new patients waiting to be serviced at any moment in the same working day. Hence, DVRPSTS is divided into a set of standard VRP in every time slot and then solving them in order of instances using the meta-heuristic MCS algorithm.

3.1 Measuring dynamism

The levels of dynamism are varied for different types of DVRP. Usually, dynamism is categorized based on the ratio of some dynamic requests relative to the total. They are (i) degree of dynamism, (ii) effective degree of dynamism and (iii) effective degree of dynamism with time window. This paper recognizes the DVRP model in Haitao Xu (2018) and interprets DVRP as a set of static CVRP in each time slot. Therefore, this paper selects the metric, degree of dynamism (dod), which is the ratio of the known to unknown patients before the route plan starts to visit:

$$dod = \frac{\text{no. of known patients nodes}}{\text{total no. of patients nodes}}$$

If dod is 1, all patient demands are known in prior, and the problem is entirely static, while if dod is 0, then there exist no patient demands are known in prior. Hence, this model problem of HHC is a partial-dynamic problem.

The above Fig. 1 illustrates clearly the working process of the system DVRPSTSP in HHC. The red node of the system indicates the HHC depot where all the vehicles start and end. Three different capacitated vehicle route paths are shown in Fig. 1. All three heterogeneous vehicles would accept the request of known and unknown patients and visit them within a specific time horizon. Green nodes indicate visited and known patient requests; white nodes indicate unvisited and known patient requests; yellow nodes

Fig. 1 Illustration of DVRPSTSP in HHC

indicate new and unknown patient requests. Triangular nodes indicate the synchronization of route paths of two different vehicles. The dash-dotted lines represent the completed routes, straight lines represent the planned routes but not yet visited, whereas dotted lines indicate the unplanned routes or newly formed routes. Each time a patient request arises during the route plan, it must be inserted into the appropriate route plan without violating the vehicles capacity and time limit constraints. But, in real-time situations, the insertion of new patients into a specific time window will be a significantly more complicated task. Hence, it is necessary to reschedule the order of visits for the remaining nodes in the route plan after each new node is added. This rescheduling process provides a sustainable balanced workload among the caregivers and makes them reach the HHC depot within their working time horizon. Thus, the action planner of MCSA uses a decision-making technique in which the new patient's requests are dynamically assigned to suitable vehicle route paths as demonstrated in Fig. 2.

3.2 Problem formulation

In this study, the locations of patients are scattered randomly or semi-clustered. The total travel time is evaluated and given as an input source. Consider the various professional and non-professional caregivers working under the HHC organization, like physicians, nurses, therapists, nurse assistants, etc. This set of caregivers have been assigned to three different capacities of vehicles. Every vehicle should allocate a single route plan for visiting a group of pre-assigned patients. Each patient must visit in their preferred time window. Our idea is to provide a suitable action planner (SAP) for this complex dynamic

Fig. 2 Process of suitable action planner

routing and synchronization within the time slot. The working process of SAP is explained clearly in Fig. 2. Synchronization of vehicles is performed based on the patient's requirements. As a result, vehicles with different capacities should be coordinated so that sync vehicles should not overlap in their respective time slots. So, this problem is initially formulated using the MILP. Hence, specifications, notations and mathematical formulation for this proposed model are discussed below:

3.3 Specifications and notations

The specifications and notations of DVRP can be formally defined as follows:

Graph: Consider an undirected graph $G = (N, E)$, where $N = \{0, 1, 2, \dots, n, n+1\}$ is the set of nodes and E is the set of all possible links between two nodes.

Depot: In this graph, nodes 0 and $n+1$ represent the depot where routes begin and complete at the same node.

Patient nodes: There are n patients. Each patient's home is represented by nodes $1, 2, \dots, n$. Each node requires q demand to perform a set of care activities.

Total Time ts_{ij} : In this problem, ts_{ij} means the sum of time taken for travel from node i to node j and time taken for care service s_i performed at node i . That is, t_{ij} represents the travel time from node i to node j and s_i represents the care service time of node i (i.e., $ts_{ij} = t_{ij} + s_i$).

Synchronized node: Node i requires synchronization of vehicles based on their demand for care services corresponding to different capacities of vehicles sync each other within the specific time slot.

Route: Each route must start and end at the depot. It is assigned to be a sequence order of n nodes with the same

demand capacity to deliver during their working time limit Q_i^{wt} .

Dynamic Route: A dynamic route is designed for a type of vehicle to serve a set of known patients and allow new patients' requests during the execution of the planned route.

DVRPSTS: To deal with three different types (type 1, type 2, type 3) of vehicles with limited capacities $Q = \{Q_1, Q_2, Q_3\}$. Dynamic nodes of patients are assigned with different vehicle capacities so that patients' demand q_i must coincide with the vehicle capacity Q_i and provide the services within their total working time horizon Q_i^{wt} . Synchronization of vehicles happens whenever there is a need for synch vehicles achieved within the specific time slots. Hence, each vehicle can probably serve known or unknown patients and synchronization visits whenever it is necessary.

N^k = set of patients to be visited by vehicle type k
 w_i^k =set of new patients' arrival with respective to their demand required = $\{w_i^1, w_i^2, w_i^3\}$
 ts_{ij} = travel time of caregivers from node i to node j and service time taken at node i are included
 d_i = number of demands required at patient node i
 r_i = set of routes available for each shift.
 I^k = idle time of vehicle type k ,
 $[a_m^k, b_m^k]$ = starting and ending time horizon for m^{th} vehicle of type k such that $a_m^k < b_m^k$
 t_{total}^k = total working time for m^{th} vehicle of type k .
 S_t = number of time slots in a day = $\{S_1, S_2, S_3, S_4\}$
 $S_t^{kk'} = \cup_{i=1}^4 S_i^{kk'}$ $k \neq k', \forall k, k' \in K$, are the time slots for the synchronized vehicles at the required patient's node within the specific time slot.

3.5.1 Decision variables

$$x_{ij}^k = \begin{cases} 1, & \text{if a vehicle } k \text{ travels from node } i \text{ to node } j \\ 0, & \text{Otherwise} \end{cases}$$

$$y_i^k = \begin{cases} 1, & \text{if the capacity of the vehicle } k \text{ and demand of node } i \text{ are suitable, then assign them in their respective route path} \\ 0, & \text{Otherwise} \end{cases}$$

$$z_{mi}^k = \begin{cases} 1, & \text{if the } m^{th} \text{ vehicle of type } k \text{ visits the new patient node } i \text{ within the specific time slot} \\ 0, & \text{Otherwise} \end{cases}$$

3.4 Mathematical formulation

It is mainly focused on multi-objectives such as (i) to minimize the total travel time, idle time, and the number of vehicles utilization without exceeding the time window and (ii) to maximize the number of patient visits during each route plan. Present the proposed model DVRPSTS in a MILP formulation. The following are the assumptions and notations made to formulate this model for further clarification.

3.5 Parameters

N = set of patient's homes or nodes = $\{0, 1, 2, \dots, N, n+1\}$
 K = set of different types of vehicles= (type 1-SV, type 2-MV, type 3-LV)
 Q^k = set of capacitated vehicles = $\{Q^1, Q^2, Q^3\}$
 m =maximum available number of vehicles in each type= $\{1, 2, 3, \dots, n\}$

3.6 MILP formulation

Our proposed model is formulated as

$$\text{Min} \left\{ \sum_{i=0}^n \sum_{j=1}^{n+1} ts_{ij} x_{ij}^k + \sum_{i=0}^n I^k y_i^k \right\} \forall k \in K \quad (1)$$

$$\text{Max} \sum_{(i=0)}^n w_i z_{mi}^k \forall k \in K \& m = 1, 2, \dots, n \quad (2)$$

Subject to constraints

$$\sum_{i=0}^k x_{ij}^k = 1 \quad \forall j = 1, 2, \dots, n+1 \& k \in K \quad (3)$$

$$\sum_{i=0}^k x_{ij}^k - \sum_{i=0}^n x_{ji}^k = 0 \quad \forall j = 1, 2, \dots, n+1 \& k \in K \quad (4)$$

$$\sum_{j=1}^{n+1} x_{0j}^k \leq 1 \quad \forall k \in K \quad (5)$$

$$\sum_{j=1}^{n+1} x_{jn+1}^k \leq 1 \quad \forall k \in K \quad (6)$$

$$\sum_{j=1}^{n+1} d_j x_{ij}^k \leq 1 \quad \forall i = 1, 2, \dots, n \text{ \& } k \in K \quad (7)$$

$$a^k \leq x_{ij}^k \leq b^k = 1 \quad \forall i = 1, 2, \dots, n; j = 1, 2, \dots, n+1; i \neq j; \text{ \& } k \in K \quad (8)$$

$$b_m^k - a_m^k \leq t_{total}^k \quad \forall m = 1, 2, \dots, n \text{ \& } k \in K \quad (9)$$

$$S_{ts_i}^k = S_{ts_i}^{k'} \quad \forall i = 1, 2, \dots, n; \forall k, k' \in K; t = 1, 2, 3, 4 \quad (10)$$

$$S_{r_i}^k \cap S_{r_j}^{k'} = \emptyset, \exists i \neq j \quad \forall k, k' \in K \quad (11)$$

$$b_m^k - a_m^k < t_{total}^k = I^k \quad \forall m = 1, 2, \dots, n \text{ \& } k \in K \quad (12)$$

$$x_{ij}^k \leq |M| - 1 \quad \forall M \subseteq \{1, 2, \dots, n\}; j = 1, 2, \dots, n+1 \text{ \& } k \in K \quad (13)$$

$$x_{ij}^k \in \{0, 1\} \quad \forall i = 0, 1, 2, \dots, n; j = 1, 2, \dots, n+1; i \neq j \text{ \& } k \in K \quad (14)$$

$$y_i^k \in \{0, 1\} \quad \forall i = 0, 1, 2, \dots, n; m = 1, 2, \dots, n; \text{ \& } k \in K \quad (15)$$

$$z_{mi}^k \in \{0, 1\} \quad \forall i = 0, 1, 2, \dots, n \text{ \& } k \in K \quad (16)$$

The objective functions are (1) minimizing the total travel time and idle time of vehicles. (2) maximizing the number of new patients visited in a time window. Constraint (3) Each vehicle visits the node only once. Constraint (4) Each vehicle enters and leaves the node. Constraint (5) & (6) Every vehicle starts and ends at the depot. Constraint (7) demand required at node j must be less than or equal to the capacity of vehicle k . Constraints (8) & (9) are time window constraints. Constraint (10) & (11) are the synchronization constraints. Constraint (12) the idle time of vehicles must be less than the scheduled time horizon. Constraint (13) sub-tour elimination. Final constraints (14), (15) & (16) describe the nature of decision variables.

4 A standard cuckoo search algorithm

The standard Cuckoo Search Algorithm (CSA) was initially developed by Yang and Deb (2009). It is a meta-heuristic algorithm inspired by the interesting feature of parasitism in cuckoo species and originally developed to address multimodal functions. CSA can be summarized as three ideal rules: (1) The egg, laid by each cuckoo in the randomly selected nest, represents a random solution; (2) Towards the end of each iteration, the optimum nest with an egg of good quality is saved for the future generation. In other words, the best fitness of solution is retained; (3) there is a fixed number of host bird nests and where $P_a \in [0, 1]$ is a specific probability of finding the cuckoo's egg in the nest by the host bird. Suppose a host bird discovers the cuckoo's egg, then it would throw out the egg or abandon the nest. So that the egg is further would not be incubated. In the CSA, this phenomenon can be described in an easier way that a fraction of P_a of the current set of solutions is replaced by randomly generated solutions. A solution X_i^{t+1} is generated from the solution X_i^t of cuckoo i as given in the Eq. (i) by performing a Lévy flight:

$$X_i^{t+1} = X_i^t + \alpha \oplus \text{Levy}(s, \lambda) \quad (i)$$

where $\alpha < 0$ is the step size, which should be associated with the scales of the problem of interest and $\alpha = 1$ is the most regularly used value in most cases. The significant characteristic of Lévy flights is to intensify the search around a solution and to take occasionally long steps that can minimize the probability of falling into local optima. The levy flight is based on a power-law tail with a probability density function, and its step length mainly depends on the value generated by levy flight trajectories. Both step length and step size s are randomly drawn from the Lévy distribution as given below Eq. (ii):

$$\text{Levy}(s, \lambda) \sim s^{-\lambda}, (1 < \lambda \leq 3) \quad (ii)$$

4.1 Discrete cuckoo search algorithm

Ouaarab et al. (2014) modelled a new variant of the CSA which is known as the Discrete Cuckoo Search Algorithm (DCSA), which considers a new set of cuckoos that perform Lévy flights. The proposed algorithm is mainly adapted for solving combinatorial problems like the Travelling Salesman Problem (TSP) using 2-opt and double bridge moves.

4.2 Pseudocode of DCSA

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1: Initially generate the population of host bird nest  $x_i, i=1,2,...,n$ 
2: while ( $t < \text{MaxGen}$ ) or (stop condition) then do
3:   Select the host bird nest randomly and improve the solution by generating a new solution by using Levy flights
4:   Smart cuckoos' evolution with a small portion ( $P_c$ )
5:   Calculate the fitness value ( $F_i$ ) of newly generated solution
6:   Randomly select a next nest among  $n$  nests (say  $j$ ) and find its fitness Value ( $F_j$ )
7:   if ( $F_i > F_j$ ) then
8:     replace  $j$  with the newly generated solution;
9:   end if
10:  A small portion ( $P_a$ ) of the low-quality nests are abandoned and modified by new ones
11:  Hold the optimal solutions (or nests with greater quality solutions);
12:  Sort the solutions and find the current best solution
13: end while
14: Postprocess outcomes

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This algorithm is fascinated by three key components such as: (1) a simple method of selection approach; (2) the lesser number of parameters are used; (3) more diversity in search space by using levy flight strategy, which controls the step length by small and large perturbations, so that there exists stability between exploration and exploitation. Hence, the CS algorithm brings out emerging results and fits a wide-ranging scope of optimization problems.

4.3 Mutated cuckoo search algorithm for DVRPSTS in HHC

This research proposed a modified version of swarm intelligence that is inspired by a cuckoo's brood parasitism called Mutated Cuckoo Search Algorithm (MCSA) in order to address this new variant DVRPSTS in HHC. It is mainly based on enhancing the selection process with mutated strategies for each iteration. Below are the key terms of MCSA.

4.4 Key terms of MCSA

4.4.1 Nest

An individual in the population. Here, assume that a cuckoo bird lays only one egg in a nest.

4.4.2 Egg

A solution of the algorithm is generally represented as the survival of an egg in a nest.

4.4.3 Host nest initialization

In the proposed model, initialize the individuals randomly to make the problem more realistic.

4.4.4 Selection of host nest to lay a new cuckoo egg

The classic CSA uses a random selection approach. Cuckoo birds do not follow this selection approach since it applies a mimic strategy based on the most similar eggs: in the pattern, colour and shape to increase the egg's survival. The imitation character of the cuckoo bird enhances the performance of MCSA, which incorporates a more

Table 1 Neighbourhood structures (Xiao et al. 2018; Alssager et al. 2020)

S. No	Name	Category	Description
1	2-opt	Intra-route	Two nonadjacent arcs are deleted and added to a route so that it gives a new initial solution
2	OR-opt	Intra-route	Two adjacent nodes are deleted and added in a route so that it gives a new initial solution
3	3-opt	Intra-route	Three nonadjacent arcs are deleted and added to a route so that it gives a new initial solution
4	Double-bridge	Intra-route	Four arcs are deleted and added that need not be successively adjacent in a route to produce a new initial solution

Fig. 3 Neighbourhood structures (Alssager et al. 2020)

Fig. 4 Inverse mutation—abandoned nests (Ouaarab et al. 2014)

advanced selection strategy based on neighbourhood structures. The selection of the best initial route is performed by applying four neighbourhood structures such as 2-opt, OR-opt, 3-opt and double bridge as described in Table 1. Hence, the selection process of the best nest plays a vital role in this algorithm.

Generate and sort the initial solutions, then select the current best initial solution. This current best initial solution predicts the high-quality solution will emerge in a relatively small number of generations. Thus, the algorithm highlights the unique mutated strategy to make more intensify and diversify in the search space (Fig. 3).

Table 2 Levy Flights moves using path relinking strategies carried by cuckoos (P_c) (Ouaarab et al. 2014)

Levy flights (Step length)	Path relinking strategies	Description
If $LF \geq 2$	Cross over	The arc between two adjacent nodes i and j belonging to route one and the arc between two adjacent nodes i' and j' belonging to route two are both removed. Next, an arc is inserted connecting i and j' and another is inserted linking i' and j
then $LF < 2$	Inter-route	Swap one node from one route with one node from another route

Fig. 5 Path relinking strategies (Alssager et al. 2020)

Fig. 6 Algorithm of Levy flight (Husselmann and Hawick 2013)

1. Set u and v to double value type
2. Set $u = \pi^*(U(0,1]-0.5)$
3. if $\alpha = 1$ the //When $\alpha = 1$, // the distribution simplifies to Cauchy
4. return $(c \tan u)$
5. end if
6. Set $v = 0$
7. While $v = 0$ do
8. $V = -\log(U(0,1])$
9. end while
10. if $\alpha = 2$ then //When $\alpha = 2$, // the distribution defaults to Gaussian
11. return $(2c\sqrt{v} \sin(u))$
12. end if
13. Return $\frac{c(\cos(\frac{u(1-\alpha)}{v}))^{1-\alpha} \sin(\alpha u)}{\cos(u)^{1/\alpha}}$ // {The following is the general Levy case}

4.4.5 Abandon nest P_a

When an egg is abandoned, a new one is replaced in the population. The abandoned routes are rebuilt by using the inversion mutation process (Fig. 4).

4.4.6 The step

The step length is proportionate to the cross over or inter-route move on a solution.

4.4.7 Levy flights

To increase the cuckoo bird's chances of survival, it needs to improve its skills. As they move from step to step via Levy flights, they look for the best solution in each step without stagnating in a local optimum. Moreover, smart cuckoos are introduced to improve the existing solution. Levy flight is performed in MCSA by using Path Relinking Strategies (PRS). Path Relinking is a diversifying strategy that is used as a way of exploring routes between selected initial solutions. By exploring trajectories that associate high-quality

solutions with the original solution, this strategy generates a path in the neighbourhood space that leads to the final solution. The paths between these two solutions are explored using crossover or inter route techniques, as shown in Table 2. If this process results in a new best solution, then the current best solution is replaced with the new one. Otherwise, it continues with the current best solution (Fig. 5).

The above moves are linked with the step length generated by the Lévy flight. Usually, Lévy flight is generated by a probability density function that has a power-law tail. Cauchy distribution is commonly used for this purpose (Alssager et al. 2020). According to Husselmann and Hawick (2013), random numbers are generated from a Lévy distribution as shown in the algorithm below (Fig. 6).

The steps associated with the path relinking strategy are set without any prior knowledge. However, it is performed based on experimental knowledge to identify the most appropriate moves that significantly impact the solutions. Therefore, an experimental investigation of these strategies has been carried out to identify their effectiveness in improving the solution.

4.4.8 Fitness evaluation

MCSA calculates the total travel time for each route and determines if it is feasible and exceeds the overall working time. Every feasible route between two nodes is denoted as an arc (i, j) . The fitness value is calculated as the total travel time of each vehicle. The schematic representation of DVRPSTS's solution using MCSA is displayed clearly in Fig. 7.

4.5 Pseudocode of MCSA

Initialization

- (1) Set initial population size N
- (2) Set the $MaxGen$.
- (3) Set the small portion of smart cuckoos P_c
- (4) Set the small portion of worst nest abandoned P_a
- (5) Calculate the initial host nest fitness value
- (6) Calculate the abandoned worst nest, $aband = P_a * n$
- (7) $i=0$

Main Algorithm

- (8) While the stop condition is not satisfied, do
 - for nest i , ($t \leq MaxGen$) do
 - (9) Sort and select the best nest i using neighbourhood structures
 - evaluate its fitness value
 - 2-opt
 - evaluate its fitness value
 - 3-opt
 - evaluate its fitness value
 - OR-opt
 - evaluate its fitness value
 - double-bridge
 - end for
 - (10) Generate a New Solution (NS) by taking a levy flight from the Selected Best Solution (SBS)
 - (11) If $LF \geq 2$, then
 - Perform Cross-over
 - else
 - Perform Inter-route
 - end if
 - (12) Calculate the fitness solution for the NS
 - (13) If $f(NS) < f(SBS)$
 - $NS = SBS$
 - $f(NS) = f(SBS)$
 - end if
 - (14) for all eggs to be abandoned $< aband$ do
 - Generate new cuckoo solution from the selected host nest egg by using inverse mutation process
 - end for
 - (15) Calculate the fitness value of new eggs and sort all the solutions.
 - (16) end while

Thus, the new mutated selection process is performed by P_c cuckoos, which play an important role in controlling the balance between intensification and diversification in the search space. Introduce the two main criteria for avoiding infeasible situations, such as checking the

capacity of the vehicles with patients' demand and also checking synchronized time slots for the vehicles. As far as the authors are aware, there has not been any research carried out on MCSA for dynamic routing and synchronization in home healthcare.

5 Experimental study

The metaheuristic algorithm MCSA is coded for DVRPSTS in HHC. The algorithm's performance has been

tested and found to be better than GA and DCSA. In this numerical experiment, run the test instances for three different capacity vehicles as given in Table 3. The day is divided into two shifts. Each shift has a time window of 270 min. Since the caregiver's work is based on shift (half day), lunch break is not included in the route plan. Once the

Fig. 7 Schematic representation of DVRPSTS in HHC using MCSA

shift is over, all vehicles return to their depots. This experimental study has done several numerical analyses using different test instances.

5.1 Problem test instances

The algorithm investigated using randomly generated test instances for three different capacities of vehicles that are small vehicles (SV), medium vehicles (MV) and large vehicles (LV). Based on real-time situations, consider the small type of vehicle requires a greater number of demands than the medium and large types of vehicles. The problem test instances are displayed in Table 3.

5.2 Experimental analysis

The experimental analysis for the proposed algorithm is implemented using python 3.9 version and configuration Intel inside 1.33 GHz and 8 GB of RAM operating windows 10 with 64 bits. Table 4 represents the parameter settings of the experimental setup.

Initially, investigate the performance of MCSA using randomly generated test instances and the same is compared with other two popular algorithms, GA and DCSA. This process has been repeated 10 times and finds the best solution for all three metaheuristic algorithms as shown below in Table 5.

Table 5 reveals that MCSA finds the optimal route path, giving the least total travel time in all test instances.

Thus, the performance of the proposed algorithm is achieved and shown in above Fig. 8. Furthermore, the proposed algorithm MCSA is fitted to a unique combinatorial problem in HHC. The insertion of dynamic nodes in each route plane is carried out without violating the following constraints like total working time of caregivers, synchronized constraints, demands of patients, etc. This proposed algorithm has been executed in a dynamic environment with the synchronization of vehicles using randomly generated test instances for further checking its efficiency. While investigating the results, it computes the number of dynamic nodes included, the total number of nodes visited and the percentage of utilized vehicles in a

Table 3 Test instances (Fathollahi-Fard et al. 2019)

S. No	Vehicle's type	Instances	Route Path
1	Small vehicles	SV1	01,04,06,09,77
2		SV2	55, 92, 20, 33, 96
3		SV3	72, 51, 79,41, 39
4		SV4	98, 16, 17,65, 63,57
5		SV5	21, 84, 52, 99, 18
6		SV6	15, 93, 27, 73,53,59
7		SV7	68,25,40, 94, 67
8		SV8	50,38,75,74,97
9		SV9	90,83,05,81,88
11	Medium vehicles	MV1	08, 11, 14, 02,91
12		MV2	45, 48,77,86,09
13		MV3	26, 30,43,89
14		Mv4	80,31,82,24
15		MV5	34,47,63, 65
16		MV6	36,49,60,58
17		MV7	69,71, 66,62
18		MV8	38,74, 61,29
19		MV9	92,96, 37,44,12
20	Large vehicles	LV1	03,07, 81, 05
21		LV2	42,14,23,11
22		LV3	43,100, 56,89
23		LV4	87,40,35,25
24		LV5	32,95,13, 85
25		LV6	78,22,19,60,58
26		LV7	10,76,51, 79
27		LV8	70,64,54,46, 28

whole working day. The results of MCSA have been compared with those of two other algorithms GA and DCSA, in Table 6.

It is realized from Table 6 that the computational results of MCSA outperform GA and DCSA in most of the test instances.

Table 4 Parameters setting (Ouaarab et al. 2014)

S. No	Parameters	Values
1	Initial population size (n)	100
2	MaxGen	40
3	Intelligent cuckoo (P_c)	0.6
4	Abandon of worst nest (P_a)	0.2
5	Execution time	10 s

Table 5 Comparison of three algorithms DCSA, GA and MCSA

S. No	Instances	DCSA Best Sol	GA Best Sol	MCSA Best Sol
1	SV1	226	204	174
2	SV2	181	182	151
3	SV3	215	235	142
4	SV4	237	194	175
5	SV5	174	186	170
6	SV6	269	274	177
7	SV7	211	200	124
8	SV8	243	257	175
9	SV9	223	222	157
11	MV1	246	254	208
12	MV2	198	200	172
13	MV3	176	166	155
14	Mv4	193	172	161
15	MV5	187	154	125
16	MV6	183	139	130
17	MV7	156	169	134
18	MV8	207	164	125
19	MV9	263	221	182
20	LV1	198	157	157
21	LV2	229	196	185
22	LV3	189	167	135
23	LV4	178	189	137
24	LV5	148	154	128
25	LV6	195	189	176
26	LV7	206	166	135
27	LV8	221	213	132

Bold values represent the optimal solutions for each instance

5.3 Results of accepting rate of dynamic nodes

Table 7 illustrates the dynamic nodes acceptance rate for three meta-heuristic algorithms. This experiment found out that MCSA incorporates the maximum number of dynamic nodes within the number of available vehicles for each shift. The proposed algorithm comparatively performs well and helps to reduce the number of vehicles utilized to visit them. It would increase the continuum of care and overall cost-benefit for the HHC organization. It is demonstrated in the below table.

Also, present a graphical representation of the inclusion of new nodes in Fig. 8, which quickly helps to compare and identify the performance of MCSA, GA and DCSA. Figure 9 illustrates MCSA's superior performance in each type of vehicle.

Fig. 8 Displays the efficiency of MCSA with GA and DCSA

Table 6 Computational results of MCSA with GA and DCSA for the dynamic routing problem

Instances	DCSA			GA			MCSA		
	No. of dynamic nodes included	Total no. of nodes visited	Utilization of vehicles (%)	No. of dynamic nodes included	Total no. of nodes visited	Utilization of vehicles (%)	No. of dynamic nodes included	Total no. of nodes visited	Utilization of vehicles (%)
SV1	1	6	93.7	1	6	82.9	2	7	94.4
SV2	2	7	90.7	2	7	98.1	3	9	88.5
SV3	1	6	86.6	1	6	97.4	2	6	90.7
SV4	2	8	93	2	8	90	4	9	97
SV5	2	7	89	2	7	98.8	2	7	82
SV6	0	6	99.6	0	6	100	2	8	90
SV7	1	6	94.8	1	7	85.9	1	7	99.2
SV8	1	6	97	0	5	95.1	3	8	99.2
SV9	1	6	98.1	0	5	82	2	7	84
MV1	0	5	91.1	0	5	94	1	6	95.1
MV2	1	6	85.9	1	6	88.1	1	6	96.2
MV3	2	6	91.1	2	7	95.1	2	7	100
MV4	3	7	92.9	2	6	90.3	2	6	86.6
MV5	2	6	90	3	7	83.7	4	8	86.2
MV6	2	6	96.2	3	7	94.8	4	7	96.6
MV7	1	5	92.2	2	6	100	2	5	83.3
MV8	2	6	86.7	2	6	88.8	3	7	96.2
MV9	0	5	97.4	1	6	94.4	2	7	98.5
LV1	1	5	87.4	3	7	98.8	3	7	99.2
LV2	1	5	95.1	2	6	97.4	2	7	93.7
LV3	1	5	91.1	2	6	90.7	3	7	91.1
LV4	2	5	99.6	2	6	92.9	3	7	92.5
LV5	2	6	91.4	2	6	94.4	3	6	98.5
LV6	1	6	93.7	2	7	96.6	2	7	95.5
LV7	2	6	93.7	2	6	96	4	8	96.6
LV8	2	7	89.6	1	6	89.6	2	7	90.3
Total	36	155		41	163		64	183	

Bold values represent the optimal solutions for each instance

Table 7 Expresses the acceptance rate of dynamic nodes for each type of vehicle

Algorithms	Vehicles type	Total no. of Dy-nodes	No. of Dy-nodes accepted	Acceptance rate (%)	No. of Dy-nodes not accepted	No. of extra vehicles required
MCSA	SV	21	21	100	Nil	0
	MV	21	21	100	Nil	0
	LV	22	22	100	Nil	0
GA	SV	21	9	43	12	2
	MV	21	16	76	5	1
	LV	22	16	73	6	1
CSA	SV	21	11	52	10	2
	MV	21	12	57	9	2
	LV	22	12	55	10	2

Fig. 9 Inclusion of new nodes for SV, MV and LV vehicles

5.4 Synchronized nodes

The total working time of the caregivers (vehicles) in a day is divided into four time slots. Synchronization of vehicles (Rabeh et al. 2012) is done at the nodes according to time slots, $S = \{S_1, S_2, S_3, S_4\}$. A day has a total of 540 min, and each time slot ranges from 0 to 135 min. Almost 20 per cent of nodes have been synchronized for both known and new patients in test instances of the problem (Table 3).

The synchronization required for patients based on their demands in the specific time slot. The patient's node which is needed to be synchronized may be performed in shift I (i.e., slot 1 or slot 2) or shift II (i.e., slot 3 or slot 4) are given below:

Table 8 Synchronize time slot (Rabeh et al. 2012)

Slots	Time range (mins)
S_1	0–135
S_2	136–270
S_3	271–405
S_4	405–540

Sync nodes = [5,9,11,14,25,38,40,43,51,58,60,63,65,74,77,79,81,92,96,101,104, 121,129, 146,154].

- Shift I

- (i) Slot 1 = {9,92,79,65,25,5,104}
- (ii) Slot 2 = {77,96,51,63,40,81,101}

- Shift II

- (i) Slot 3 = {146, 74, 121,60,14,43}
- (ii) Slot 4 = {154, 38,129,58,11,89}

Table 9, illustrates the allocation of different capacities of vehicles for the sync nodes (sync patients) based on their time slot.

5.5 Optimal output

Thus, the optimal route is achieved for dynamic routing instances implemented by the proposed MCSA with the available number of vehicles in each shift as shown below in Table 10.

Table 9 Allocation of vehicles to the sync node as in a requested time slot

Shifts	Slots	Sync nodes	SV	MV	LV		
Shift 1	Slot 1 (8 am—10.15 am)	9	SV1	MV2	–		
		92	SV2	MV9	–		
		79	SV3	–	LV7		
		65	SV4	MV5	–		
		25	SV7	–	LV4		
		5	SV9	–	LV1		
		104	SV5	–	LV8		
		77	SV1	MV2	–		
	Slot 2 (10.15 am—12.30 pm)	96	SV2	MV9	–		
		51	SV3	–	LV7		
		63	SV4	MV5	–		
		40	SV7	–	LV4		
		81	SV9	–	LV1		
		101	SV5	–	LV8		
		Shift 2	Slot 3 (12.30 pm—2.45 pm)	146	SV6	MV7	–
				74	SV8	MV8	–
121	–			MV4	LV5		
60	–			MV6	LV6		
14	–			MV1	LV2		
43	–			MV3	LV3		
Slot 4 (2.45 pm–5 pm)	154		SV6	MV7	–		
	38		SV8	MV8	–		
	129	–	MV4	LV5			
	58	–	MV6	LV6			
	11	–	MV1	LV2			
	89	–	MV3	LV3			

6 Conclusion

This paper discussed the novel model of DVRP along with synchronizing constraints in HHC. The purpose of this research work is to bring insight into vehicle routing problems under a unique dynamic strategy which uses an improved CSA. Due to the complexity of the problem, only a few papers have dealt with metaheuristic algorithms for the DVRP in HHC. In order to deal with such a complex model of DVRP with synchronization constraints in HHC, the most appropriate meta-heuristic algorithm has been developed called a Mutated Cuckoo Search Algorithm (MCSA). Thus, this is the first application in which HHC has been able to handle both dynamic situations and synchronize vehicles.

The problem is modelled based on practical scenarios of HHC, such as the inclusion of new patients' and synchronization visits. As a result, the proposed new variant, DVRPSTS, strives to minimize total travel time and idle time while maximizing the number of patients on each

Table 10 Optimal output for each instance

Shifts	Instances	Optimal Route path
Shift I	SV1	0–9–6–33–20–103–109–77–0
	SV2	0–92–98–16–17–147–57–107–108–96–0
	SV3	0–79–41–94–118–138–51–0
	SV4	0–65–112–113–73–59–140–1–151–63–0
	SV5	0–104–27–93–21–67–68–101–0
	SV7	0–25–84–97–88–50–148–40–0
	SV9	0–5–18–39–72–144–145–81–0
	MV2	0–9–91–47–115–26–77–0
	MV5	0–65–102–49–105–135–36–119–63–0
	MV9	0–92–82–37–24–133–155–96–0
	LV1	0–5–23–7–110–117–126–81–0
	LV4	0–25–136–76–56–130–152–40–0
	LV7	0–79–35–125–148–149–87–134–51–0
	LV8	0–104–70–64–95–85–100–101–0
Shift II	SV6	0–146–4–52–53–99–55–15–154–0
	SV8	0–74–75–83–90–141–142–153–38–0
	MV1	0–14–30–8–2–111–11–0
	MV3	0–43–86–106–45–48–127–89–0
	MV4	0–121–71–66–31–44–129–0
	MV6	0–60–62–143–29–128–114–122–58–0
	MV7	0–146–62–80–69–154–0
	MV8	0–74–34–12–131–124–139–38–0
	LV2	0–14–78–22–116–42–123–11–0
	LV3	0–43–46–28–150–156–157–89–0
	LV5	0–121–54–13–32–132–129–0
	LV6	0–60–3–120–137–19–10–58–0

route. Synchronizing of vehicles takes place during their respective time slots. MCSA is composed of a few unique approaches, such as path relinking in LF, inverse mutation, and mutated selection strategies. This approach of MCSA with SAP enables it to make prudent decisions in the planning of each route, especially when handling dynamic nodes.

The experimental study exhibits the approach compared with the most prominent algorithms like GA and DCSA for randomly generated test instances. Hence, the computational results observed and enhanced metaheuristic algorithm produced the optimal outputs for solving the DVRPSTS variants in HHC.

Thus, the outcomes of experimental analysis reveal the significance of these unique approaches built-in MCSA. The solution quality from the algorithm identifies that the proposed approach is a suitable action planner for dynamic routing problems with synchronization of HHC.

In future, the research work can be extended to schedule along with a dynamic routing plan and synchronization. Further, explore stochastic travel and service time of caregivers.

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