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RESEARCH ARTICLE

A Multi-objective Home Health Care Fuzzy Green Vehicle Routing and Scheduling Problem with Different Types of Vehicles and Vehicle Trip Sharing Strategy

P. RATHINABHAGYA[1] AND J. MERLINE VINOTHA[2*]

PG and Research Department of Mathematics, Holy Cross College (Autonomous) (Affiliated to Bharathidasan University), Tiruchirappalli – 620 002, India.

E-mail: rathinabhagya20@gmail.com; merlinevinotha@gmail.com

***Corresponding Author: merlinevinotha@gmail.com**

ABSTRACT

Hospitals are facing problems due to the rapid growth of demand for services for ageing people, disabled people, people with fractured hips, different types of chronic diseases, mental illness patients, coma patients, etc. On account of this, the home health care service system is growing worldwide. In a natural-world scenario, CO_2 emission depends on some factors like traffic congestion, driver's driving behaviour, and road surface quality. Therefore, these factors create CO_2 emission that are uncertain in nature. The duration of the time window is uncertain in residential healthcare due to unexpected guests arriving, household duties, daily activities, and changes in previous appointments. In this paper, duration of time window and CO_2 emission are considered as fuzzy number. This work develops a mixed-integer linear programming model for home health care service routing and scheduling with the goal of minimising the total travel distance, travel cost, visiting cost, and CO_2 emission. The Enhanced Artificial bee colony algorithm and Enhanced Mutated cuckoo search algorithm are used to solve the home health care routing and scheduling problem. Owing to the competing nature of these objectives, these two heuristic algorithms use a normalised weighted-sum aggregated approach. A computational experiment has been conducted to test the performance of heuristic algorithms for the new modified instances, which are implemented using Python 3.12. The experiment results have shown that the Enhanced Artificial bee colony algorithm is more efficient than the Enhanced Mutated cuckoo search algorithm.

Keywords: *Home Health Care Routing and Scheduling, Single-valued Triangular Neutrosophic Fuzzy Number, Different Types of Vehicles, Vehicle Trip Sharing Strategy, weighted sum, Min-Max Normalization.*

INTRODUCTION

Home Health care (HHC) services have been developed as another method for regular clinical treatment that involves medical assessment, physiotherapist, some general hygiene care for the needed patients at their own home. In general, home health care services are essential for reducing hospitalization costs, frustrating environments, the necessity for longer stays in hospitals, and improving the satisfaction of patients. The home health care vehicle routing problem (HHC VRP) is used to find the best route for the fleet of vehicles with health care staff to serve all the assigned patient's homes within the preferred time while satisfying the objectives and considering various constraints. HHC service organizations were started in American countries and then in European countries. Home health care service system is facing a complex situation due to several factors, such as the increasing number of assigned patients and their needs, synchronization with other patients, and skills required of caregivers. Due to complexity of home health care

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system growing complexity provoke the researcher's interest to planning best suitable routing and scheduling for home health care system.

One of the earliest useful decision-support systems for everyday staff scheduling in home care organisations was presented by Eveborn et al. (2006). Various Swedish municipalities successfully implemented their LAPS-CARE system, which combined staffing, routing, and schedule planning. Bertels and Fahle (2006) solved the home health care problem by using a combination of linear and constraint programming and a heuristic approach to reduce transportation costs and increase patients and caregiver's satisfaction. Neda and Tonguc (2021) proposed new algorithm to minimize the transportation cost on Solomon instances for HHC VRP.

The aim of the multi-objective HHC VRP tends to determine routes for healthcare professionals who visit patients at their residence while simultaneously achieving a number of objectives, including minimizing travel time and costs, enhancing service quality, and balancing staff workload. Fathollahi-Fard et al. (2021) developed a bi-objective optimization model with a time window, route balancing and working time balancing and the objectives are to minimize both the cost and total service time. Decerle et al. (2019) discussed pareto-based multi-objective optimization for handling the minimum of total working time, maximum of service quality, minimum of maximum workload of caregivers and auxiliary caregivers and taking penalties for overtime working of caregivers during simultaneous service. Fathollahi Fard et al. (2020) examined a bi-objective robust optimization model and used keshtel algorithm to solved for home health care routing and scheduling problem (HHCRSP) with stochastic travel time, duration of service and gas emission.

Each vehicle in HHC-VRP faces a distinct seating or capacity limit, which affects how many employees it can accommodate. When multiple staff members travel together in the same vehicle, this is known as trip sharing. These two elements have a direct impact on route planning and the effectiveness of home healthcare services. Divsalar et al. (2023) addressed a mixed-integer nonlinear model for HHC routing service with a focus on minimising the total cost, sustainability, workload balance, and maximising service level quality. The authors proposed a multi-objective variable neighborhood search algorithm to test the instance and real-time data with different types of vehicles and different types of nurses. Sangeetha and Srinivasan (2021) investigated a new model multi-objective dynamic vehicle routing problem for simultaneous visits within preferred time slots for home health care system, and they proposed a mutated cuckoo search algorithm and tested it on randomly generated data instances with different types of vehicles.

Christian and Patrick (2015) investigated trip sharing, geographically distribution of patient's locations with different objectives concepts in HHCRSP. Yong et al. (2021) investigated a real-world case study of transportation resource sharing strategy with multi period and bi-objective model for 2-Echelon multi-period location routing problem. Ming et al. (2020) examined shared vehicle issue for two stages model problem under IoT in green logistics.

For the combined practice in HHC-VRP, synchronized visits require two or more healthcare providers to arrive at the same patient's residence at the same moment. Each staff member is required to take a specified amount of time during their shift for lunch. For schedules to remain practical and effective, both limitations must be incorporated into the routing strategy. Liu et al. (2021) tackled the situation of simultaneous care with lunch period, where caretaker begin their work from their home or HHCC for home health care service routing and scheduling problems with the help of proposed algorithm. Sohaib et al. (2016) proposed a SA-ILS for *VRP* with a time window and synchronization to test the benchmark instances. Briseida and Karl (2021) proposed a strategy of self-imposed time windows for vehicle routing problem synchronization at the delivery location to tackle this problem. Nasir and kuo (2020) addressed the challenges of synchronization, multiple visits, and multiple routes of delivery vehicle visits in routing and scheduling plan for home care problem. Liu et al. (2019) proposed an efficient adaptative large neighborhood search algorithm for home care *VRP* with synchronized visits. Andrea and Hirsch (2014) discussed HHC problems with break time, weekly rest time, and maximum working time. Coelho et al. (2016) developed a mixed-integer linear programming model for furniture delivery industry with lunch time using a multi-star randomized local search algorithm.

Uncertainty in HHC-VRP refers to unplanned events like fluctuating travel times, unexpected patient delays, urgent demands, or modifications to the time required for services. Because schedules may need to be adjusted in real time due to these uncertainties, route planning becomes more complicated. Effective approaches make an effort to manage these variations while maintaining efficient and consistent patient care. Shi et al. (2017) explore the *VRP* with a time window in home health care system and the problem of minimising the transportation cost

with uncertainty in the situation of need drugs demand. Shiri et al. (2023) proposed a multi-objective two-stage model that minimizes the cost of hhc centers while maximizing job opportunities with uncertain service times. Fariba et al. (2021) addressed the route allocation for therapists and minimising the transport and travel cost in the fuzzy environment of home health care problems. The author developed a model and solved this different size model by using MOICA, NSGA-II, and MOSEO. Shi et al. (2019) proposed a robust model for routing and scheduling problem of home health care service with uncertain travel time and service time. The authors used SA, TS, and VNS in Gurobi Solver to get the objective values. Fathollahi-Fard et al. (2020) examined jimenez's method to deal with the uncertainty in the travel time, period of service, and patient's satisfaction with multi-period, multi- depot HHCRS model problem. Adnen et al. (2022) proposed a new model for integrating home care routing and scheduling problem with uncertain travel time, dynamic behavior of patients, caregiver team. Cisse et.al (2017) describe nowadays how the home health care system frequently faces uncertainty and uncertainty parameters such as service time and travel time between two patient's locations, vehicle availability, and patient's demand.

In the past decade, HHC service system has faced numerous difficulties, and their increasing complexity has attracted many researchers to do research in the health care system. One of the earliest standard VRP frameworks with time windows, synchronisation, and precedence conditions for home healthcare visits was created by Bredström and Rönnqvist (2008). Decerle et al. (2018) examined a HHCRSP with hard and soft time-window constraints and the necessary synchronisation. To effectively manage parallel visits and different nursing skills, the authors created a memetic algorithm with unique crossover operators and a mixed-integer programming model. Their findings on benchmark and real-world French HHC data showed that the suggested algorithm produces excellent results for various kinds of instance types. An SA-ILS heuristic was created by Afifi et al. (2016) for the VRP with Time Windows and Synchronised Visits, where certain patients need multiple carers to serve them at the same time. To effectively manage both timing and synchronisation constraints, their method combines intensive local improvement techniques with simulated annealing. On benchmark datasets, their algorithm performed very effectively, achieving all known optimal outcomes and outperforming a number of previous best results. Euchi et al. (2020) create a hybrid AI-based approach that uses time windows, single-depot routing, and synchronized visits to address the HHC VRP. Their method creates effective healthcare provider plans by combining clustering and the Ant Colony System (ACS). The authors demonstrate how the hybrid approach enhances patient service and lowers overall time of completion for real HHC management.

The majority of the existing HHC-VRP research uses homogeneous vehicles and fixed parameters, neglecting real-world uncertainty and sustainability considerations. The studies Afifi et al. (2016), Bredström and Rönnqvist (2008), Decerle et al. (2018) and Euchi et al. (2020) solve healthcare routing with synchronised visits using predefined benchmark instances, and these focus on homogenous vehicles and deterministic parameters. They do not investigate how routing and staff scheduling are impacted by various vehicle sizes (small, medium, and large) with varying capacities and costs, as well as how planning quality is impacted by uncertain time-window duration. The extended HHC-VRP, which considers multiple healthcare providers and vehicles, unpredictable time duration, synchronised visits, service-level preferences, economic effectiveness, and environmental impact, which is still significantly lacking. The rest of this work is organized as follows: In section 2 discuss preliminary definition for fuzzy number. In section 3 presents the notations and description of the problem. In section 4, explains methodology. In section 5 discuss experiment result and in section 6 describe the conclusion.

METHODOLOGY

Preliminaries

Neutrosophic number

Let X is said to be a non-empty set. A Neutrosophic set $B \in R$ has the following form

$B = \{(r, T'_B(r), I'_B(r), F'_B(r)) : r \in R\}$, where the functions $T'_B, I'_B, F'_B : R \to [0,1]$ explains

the degree of truth membership, the degree of indeterminacy membership and the

degree of falsity membership as every element $r \in R$ to the corresponding set B, that is which a subset of R.

$$0 \leq T'_B(r) + I'_B(r) + F'_B(r) \leq 3$$

In specific, If X has only one element, then B as a neutrosophic number, that can be

expressed by, $B = (T'_B(r), I'_B(r), F'_B(r))$

Single-valued triangular neutrosophic fuzzy number

The single-valued triangular neutrosophic fuzzy number defined as $b =$

$((b_1, b_2, b_3); \alpha'_b, \beta'_b, \gamma'_b)$ is a neutrosophic set that is on R, the membership functions that are truth, uncertainty and falsity is defined as below,

$$T'_b(r) = \begin{cases} \alpha'_b\left(\frac{r - b_1}{b_2 - b_1}\right) & \text{for } b_1 \le r \le b_2 \\ \alpha'_b & \text{for } r = b_2 \\ \alpha'_b\left(\frac{b_3 - r}{b_3 - b_2}\right) & \text{for } b_2 \le r \le b_3 \\ 0 & \text{for otherwise} \end{cases}$$

$$I'_B(r) = \begin{cases} \frac{b_2 - r + \beta'_b(r - b_1)}{b_2 - b_1} & \text{for } b_1 \le r \le b_2 \\ \beta'_b & \text{for } r = b_2 \\ \frac{r - b_2 + \beta'_b(b_3 - r)}{b_3 - b_2} & \text{for } b_2 \le r \le b_3 \\ 1 & \text{for otherwise} \end{cases}$$

$$F'_B(r) = \begin{cases} \frac{b_2 - r + \gamma'_b(r - b_1)}{b_2 - b_1} & \text{for } b_1 \le r \le b_2 \\ \beta_a & \text{for } r = b_2 \\ \frac{r - b_2 + \gamma'_b(b_3 - r)}{b_3 - b_2} & \text{for } b_2 \le r \le b_3 \\ 1 & \text{for otherwise} \end{cases}$$

where $\alpha'_b, \beta'_b, \gamma'_b \in [0,1]$, $b_1, b_2, b_3 \in R$ and $b_1 \le b_2 \le b_3$.

Score function

The following score function is used to transform the neutrosophic data into crisp data

$SF'(b) = \frac{1}{2}\left((b_1 + 2b_2 + b_3)(2 + \alpha'_b - \beta'_b - \gamma'_b)\right)$,where $b = ((b_1, b_2, b_3); \alpha'_b, \beta'_b, \gamma'_b)$. The single-valued triangular fuzzy neutrosophic number where $\alpha'_b, \beta'_b, \gamma'_b \in [0,1]$, $b_1, b_2, b_3 \in R$ *and* $b_1 \le b_2 \le b_3$.

PROBLEM DESCRIPTION

This study examines an extension of the Home-Healthcare Routing Problem, in which healthcare providers visit patients in various locations within a restricted daily scheduling horizon by travelling from an organising service centre. Each healthcare worker begins the working day at the depot and is required to return when their designated visits have been completed. Every patient needs medical care that is specified by a time window and length of service. To achieve the required level of care, the provided service must start within the given window. Furthermore, healthcare staff members possess varying levels of service qualifications to cater to the diverse service needs of patients. Patients want different services from the healthcare staff members; some patients want small household services with cooking and cleaning, some bedridden patients want bathing and dressing services, some want a physiotherapist, and some want medical services. Some patients require simultaneous care due to their illness. In certain situations, synchronised care is necessary, which means that two qualified nursing staff are required to arrive at the same particular patient and begin providing care at the same moment. The travel time between HHC and the patient's home, from the patient's home to the patient's home, is denoted by $TT_{i'j'k'}$. The working schedule for the healthcare staff member is allotted as the entire day, and the lunch break is not considered a working hour. So, the lunch break duration for each healthcare staff member is assumed to be 1 hour. In this work, the capacity of the healthcare vehicle is according to the number of seating capacity of the vehicle, in addition to the driver. The different types of health care vehicles available to carry the health care staff members between HHC and the patient's home do not exceed a capacity limit.

In many studies, the healthcare staff member is allotted to the vehicle according to their service qualification level, but in this paper, some relaxation is given to this condition. Using a vehicle-sharing strategy, staff are allotted to the same or a different healthcare vehicle for synchronised visits to the locations that are geographically close to each other. This shared conveyance strategy provides that each of the patient visits is finished within the allotted time windows and synchronisation constraints while ensuring the effective use of the existing vehicle resources. Each healthcare staff member should use a single allowance and not change the good-condition allowance type during the trip. The service level of the healthcare staff member is considered by the patient satisfaction level.

In a real-world scenario, the time duration of the patient is uncertain because of the travel time and the waiting time of the healthcare staff member for simultaneous care. CO_2 emissions are also vague due to the driver's driving skill condition, road gradient, traffic congestion, using a lot of old vehicles, and varying speeds from vehicles. In this paper, the different types of time duration and emissions are considered a single-valued neutrosophic triangular fuzzy number. This problem is solved through instances with randomly generated data, some of which is real-world data, using two metaheuristic algorithms.

MATHEMATICAL MODEL

***Notations*:**

ABC - Artificial bee colony

MCSA - Mutated cuckoo search algorithm

EABCA – Enhance Artificial bee colony algorithm

EMCSA – Enhance Mutated cuckoo search algorithm

HHC – Home Health care

HHCC - Home Health care company

HHCRS - HHC routing and scheduling

HHCRSP – HHC routing and scheduling problem

i', j' – patient's node

$i', j' \in V$ – set of patient nodes including patient's home and depot

$k' \in K$ - set of different health care vehicle types

$sm' \in N$ - set of health care staff member's type

avs_1 - Average speed of the health care small vehicle

avs_2 - Average speed of the health care medium vehicle

avs_3 - Average speed of the health care large vehicle

Parameters and Their Description:

$d_{i'j'}$ - distance between depot to patient's home and patient's home to patient's home

$TC_{i'j'k'}$ - Traveling cost from patient i' to patient j' using health care vehicle type

$VCC_{sm'}$ - Staff member visiting cost of each patient for health care staff member from HHC Company

$\tilde{e}m_{i'j'k'}$ - Single-valued triangular neutrosophic CO_2 emission from health care vehicle type while traveling from patient i' to patient j' and depot to patient's home

$A_{sm'}$- capacity of the small health care vehicle

$B_{sm'}$ - capacity of the medium health care vehicle

$C_{sm'}$ - capacity of the large health care vehicle

$SL_{sm'}$ - Staff member service level

$OPT_{i'}$ - Earliest opening time of time window for patient i'

$CLT_{i'}$ - Latest Closing time of time window for patient i'

$ST_{i'}$ - Service time of patient i'

$NSM_{i'}$ - Number of sm' required at patient i'

$S_{j'}$ - Service start time at patient j'

$S_{i'}$ - Service start time at patient i'

$TT_{i'j'k'}$ - Traveling time from patient i' to patient j' and depot to patient's home by using health care vehicle type

$N_{syn\ v}$ - Set of synchronized visits

$i', j' \in N_{syn\ v}$ - every pair of synchronized visits i' and j' correlated with same locations, time windows, service time durations, service qualification level

$S_{i'}^{sm'_1}$ - Simultaneous care Start time of sm'_1

LD - lunch break duration for health care staff members

LDOT - Lunch break duration Opening time

LDCT - Lunch break duration Closing time

M' - large positive value

Decision Variables

$x_{i'j'sm'k'}$ - 1 if the health care staff member ds' of type sm' visits patient j' immediately after visiting patient i' by using health care vehicle type

- 0, otherwise

$S_{i'sm'}$ - Service starting time of sm' at patient i'

$l_{sm'}$ - lunch break starting time of sm'

Mathematical formulation for fuzzy multi-objective HHCRSP

***Objective function*:** A multi-objective optimisation model that minimises travel distance, travel cost, visiting cost, and emission is examined in this study. Min–Max normalisation is used to normalise each individual goal, and a weighted sum method is used to combine them.

Objective 1: Total Travel distance

$$Z_1 = \sum_{i' \in V} \sum_{j' \in V} \sum_{k' \in K} \sum_{sm' \in N} d_{i'j'} * x_{i'j'sm'k'} \quad ----$$

(1)

(Eqn. 1) minimizing the total travel distance on each route,

Objective 2: Total Travel cost

$$Z_2 = \sum_{i' \in V} \sum_{j' \in V} \sum_{k' \in K} \sum_{sm' \in N} TC_{i'j'k'} * x_{i'j'sm'k'} \quad ---$$

(2)

(Eqn. 2) minimizing the total travel cost on each route,

Objective 3: Total visiting cost

$$Z_3 = \sum_{i' \in V} \sum_{j' \in V} \sum_{k' \in K} \sum_{sm' \in N} VCC_{sm'} * x_{i'j'sm'k'} \quad ----$$

(3)

(Eqn. 3) minimizing health care staff visiting cost on each route,

Objective 4: Total CO_2 emission

$$Z_4 = \sum_{i' \in V} \sum_{j' \in V} \sum_{k' \in K} \sum_{sm' \in N} \tilde{e}m_{i'j'k'} * x_{i'j'sm'k'} \quad --(4)$$

(Eqn. 4) minimizing the total fuzzy CO_2 emission on each route,

Normalization Weighted sum Objective function

$$\text{Min } Z = W_1 Z_1^{norm} + W_2 Z_2^{norm} + W_3 Z_3^{norm} + W_4 Z_4^{norm} \quad ---(5)$$

Where normalization is applied

$$Z_{Objective}^{norm} = \frac{Z_{Objective} - Z_{Objective}^{min}}{Z_{Objective}^{max} - Z_{Objective}^{min}}$$

Subject to the constraints

$$\sum_{j' \in V} x_{i'j'sm'k'} = 1, \forall\, i' \in V, \forall\, k' \in K \quad ---(6)$$

$$\sum_{i' \in V} x_{i'j'sm'k'} = 1, \forall\, j' \in V, \forall\, k' \in K \quad ---(7)$$

$$\sum_{sm' \in N} \sum_{i' \in V} x_{i'j'sm'k'} = \sum_{sm' \in N} \sum_{j' \in V} x_{i'j'sm'k'} = 1, \forall\, k' \in K \quad ---(8)$$

$$\sum_{i' \in V} x_{i'j'sm'k'} = \sum_{j' \in V} x_{i'j'sm'k'}, \forall\, sm' \in N, \forall\, k' \in K \quad ---(9)$$

$$\sum_{i' \in V} NSM_{i'} \sum_{j' \in V} \sum_{sm' \in N} x_{i'j'sm'k'} \leq A_{sm'}, \forall\, k' \in K \quad ---(10)$$

$$\sum_{i' \in V} NSM_{i'} \sum_{j' \in V} \sum_{sm' \in N} x_{i'j'sm'k'} \leq B_{sm'}, \forall\, k' \in K \quad ---(11)$$

$$\sum_{i' \in V} NSM_{i'} \sum_{j' \in V} \sum_{sm' \in N} x_{i'j'sm'k'} \leq C_{sm'}, \forall\, k' \in K \quad ---(12)$$

$$\sum_{sm' \in N} x_{i'j'sm'k'} \leq 1 \;\; \forall\, i', j' \in V, \forall\, k' \in K \quad ---(13)$$

$$\sum_{j' \in V} \sum_{k' \in K} \sum_{sm' \in N} x_{i'j'sm'k'} = 2 \;\; \forall\, i' \in N_{syn\,v} \quad --(14)$$

$$OPT_{i'} \leq S_{i'} \leq CLT_{i'}, \forall i' \in V, \forall sm' \in N \quad ---(15)$$

$$S_{j'sm'} \geq S_{i'sm'} + ST_{i'} + TT_{i'j'k'} - M'(1 - x_{i'j'sm'k'}), \forall i', j' \in V, \forall sm' \in N, k' \in K \quad ---(16)$$

$$S_{0sm'} = 0 \;\; \forall sm' \in N \quad ---(17)$$

$$LDOT \leq l_{sm'} \leq LDCT \quad \forall sm' \in N \quad ---(18)$$

$$S_{j'sm'} \geq l_{sm'} + LD - M'(1 - x_{i'j'sm'k'}), \forall i', j' \in V, \forall sm' \in N, k' \in K \quad ---(19)$$

$$S_{i'sm'_1} = S_{i'sm'_2} \;\; \forall i' \in N_{syn\,v} \quad ---(20)$$

$$x_{i'j'sm'k'} \in \{0,1\}, \forall i', j' \in V, \forall sm' \in N, k' \in K \quad ---(21)$$

(Eqn. 6) and (Eqn. 7) states each vehicle start from the depot and returns to the depot after visiting the allotted patients exactly once. (Eqn. 8) indicates that each vehicle completes its route. (Eqn. 9) determine that if a vehicle serves a patient, it must also leave that patient. (Eqn. 10), (Eqn. 11), (Eqn. 12), ensure the different type of health care vehicle cannot to load more health care staff member than its capacities. (Eqn. 13) represents a vehicle may be shared by several sm′, but every move is given a distinct assignment to prevent unnecessary duplication, ensuring that each nurse can efficiently complete their tasks without overlap in responsibilities. (Eqn. 14) means every synchronised patient has a pair of sm′ assigned to them. (Eqn. 15) ensures every patient must start receiving care within the allotted time frame.

(Eqn. 16) makes sure that service at patient j′ doesn't begin until after service at node i′ is finished and it has travelled from patient i′ to patient j′. (Eqn. 17) indicates that all sm′ service starting time at HHCC are set to be zero. (Eqn. 18) guarantees that the lunch break takes place within the allocated lunch window. (Eqn. 19) confirms that the next patient will only receive care after the lunch break is over. (Eqn. 20) By enforcing the same service starting times, this constraint guarantees that synchronised patients needing several sm′ to receive simultaneous care. (Eqn. 21) describe binary variable indicating whether staff member sm′ visits patient j′ immediately after patient i′ using vehicle type k′.

ENHANCED ARTIFICIAL BEE COLONY ALGORITHM

The Artificial Bee colony algorithm is nature-inspired optimization algorithm based on foraging behaviour of honeybees. This algorithm is introduced by Karaboga (2005) [17]. The algorithm imitates how the real honeybees search for food sources and share information within a hive. ABC falls under the category of swarm intelligence algorithms and is commonly used for solving optimization problems. The artificial Bee colony algorithm which has 3 major stages is used in this work. Employer stage is redefining food sources according to neighbors nearby. Onlooker stage is updates solutions based on randomly selected sources. Scouts stage is creating random new solutions to a wide range search. In this work, ABC algorithm is enhanced by integrating the 2-OPT, multiple conflict objectives using normalization and weighted sum approach, fuzzy parameter to handle the uncertain situations of different type of time duration and CO_2 emissions in complex situation. This enhancement ABC algorithm is structured as follows:

Step 1: Initialization:

- Describe all input parameters of this problem.
- Convert the Neutrosophic triangular fuzzy data of different time duration and CO_2 emission into Crisp data by using score function.

- Initial solutions (food sources) are generated randomly. Every food source is a potential solution made up of customer-assigned priority values.
- The customers' visiting order is determined by these priority values.

Step 2: Fitness evaluation

- The customer visiting order is used to calculate the objective values for every food source, which include an overall travel distance, carbon emissions, travel cost, and visit cost. The Min-Max normalisation approach is used to scale these objective values between 0 and 1.
- Min–max normalization is used to make sure that various objective scales are related.

$$S_{no} = \frac{S - S_{o\,min}}{S_{o\,max} - S_{o\,min}}$$

where S_{no} – the objective's normalized value, S – actual value of objective, $S_{o\,min}$ – the objective's minimum value, $S_{o\,max}$ – the objective's maximum value.

- Following normalization, a weighted-sum aggregation technique is used to combine the various objectives into an aggregate scalar fitness value.

$$F_f = W_1' D_n' + W_2' TC_n' + W_3' VC_n' + W_4' E_n'$$

where F_f – Fitness function, D_n' - Normalized distance value, TC_n' - Normalized Travel cost value, VC_n' - Normalized visiting cost value, E_n' - Normalized emission value, W_1' , W_2' , W_3' , W_4' - weight parameter values. In this study, $W_1' = 0.25$, $W_2' = 0.10$, $W_3' = 0.10$, $W_4' = 0.55$.

Step 3: Employed Bee stage:

- By adding random perturbating to the current solution to generate the neighbor solution for each employed bee. Evaluating the fitness of the new solution.
- If the new solution is better, update the solution and its fitness value.

Step 4: Onlookers Stage:

- Select each solution based on its fitness value to evaluate the probability.
- Select a solution according to the calculated probability.
- Generating a new neighbor solution to evaluate the new solution.
- Update the solution along with its fitness value, if the new solution is improved.

Step 5: Scouts Stage:

- For several number of iterations, solution does not upgrade then replace the solution with new randomly generated solution.
- Update the fitness value according the new solution.

Step 6: 2-OPT

- Once the 3 bee stages are finished, the produced routes are refined using the 2-opt method.
- By eliminating overlapping routes and decreasing the needless travel distance, the 2-opt algorithm increases routing efficiency.
- To create the shortest route structures, it works by reversing specific route sections. An improved solution is retained, and its overall performance is improved if an ideal fitness value is found.

Step 7: Optimization:

The algorithm program runs for certain number of iterations to find optimal solution through the above 3 stages.

Step 8: Best solution:

The outcome with the lowest fitness value is chosen as the best solution once all iterations have been completed. The best customer priority order is represented by this solution.

Step 9: Priority Sorting

The priority values derived from the best answer are used to sort the customers. This arranged sequence establishes the customers' visiting order.

Step 10: Synchronized Visit

To ensure certain patients need synchronized visits, these visits are randomly selecting the patients and are included in the routes.

Step 11: Constructing Routes

Forming routes starting from depot and end at depot, staff member in each vehicle does not exceed vehicle's capacity limit and time window constraints.

***Step 12*:** The final outcome shows the optimised routes as well as all related outcomes.

ENHANCED MUTATAED CUCKOO SEARCH

The cuckoo search algorithm is a nature-inspired metaheuristic algorithm and it is mimics the behaviour of cuckoo bird. This algorithm is developed by Xin and Deb (2009). The 3 main rule for CS implementation and they are a single egg is laid by each cuckoo at time and it is placed in randomly chosen nest, the best nest with the highest-quality eggs will be promoted to the new generation, the number of available host nest is fixed and host bird identifies cuckoo eggs with probability $P_a \in (0,1)$. The new variant called mutated cuckoo search algorithm was introduced by Sangeetha and Srinivasan (2021). In this mutated cuckoo search algorithm, host nest is

selected randomly. The present study enhances the mutated cuckoo search algorithm through the incorporation of normalized weighted sum technique for multi-objective function and fuzzy parameters to deal with complex scenarios involving varying types of time duration and CO_2 emissions. The conceptual framework of this enhanced Mutated cuckoo search algorithm is as follows:

Step 1: Initialization

- Define input parameter and also some of the input data are generate random.
- Apply the score function to transform the Neutrosophic triangular fuzzy data with varying time durations and CO_2 emissions into Crisp data.
- A list of patient nodes should be shuffled randomly to create a variety of possible routes for population.

Step 2: Evaluation of fitness function:

- For every route, multiple objectives are calculated, such as distance, travel expenses, visiting costs, and emissions.
- The fitness function solutions that are used in this algorithm are determined using the same normalisation and weighted sum technique as in the Enhanced ABC algorithm.

Step 3: Neighborhood Local search 2-Opt

- Initialize a host nest. Choose a host nest to deposit fresh cuckoo egg.
- Find a nest at random from the population to serve as the host. Perhaps a new and improved solution will occupy the place of this nest.
- The 2-opt method reverses (swapping) the order of patient nodes in a particular section of the route in order to decrease the total distance and enhance initial solution quality and route efficiency.

Step 4: Levy flight

- Levy flight facilitates an investigation of the search space by avoiding local minima through the use of larger jumps.
- The existing route is modified to create a new route.

Step 5: Path relinking

- The process evaluates intermediate solutions as it progressively converts from one route to another.
- To find solutions between two routes by using path relinking. This process combines Diversification and local search.

Step 6: Inversion mutation

Routes can be mutated to produce new solutions by flipping a section of the routes.

Step 7: Abandon nest

- Worse solutions are handled by the abandon nest function, which replaces them with new routes created by inversion mutation.
- This guarantees that, in order to preserve population diversity, less than ideal solutions are eliminated and replaced with new ones.

Step 8: Merge route

By modifying routes to include any missing patients and allocating the number of routes to correspond with the number of vehicles, it provides that every patient is visited.

Step 9: Synchronized visit

Synchronized visit are incorporated for selected patients randomly and indicate this on the routes in order to verify that certain patient's simultaneous requirement. Each staff member does not exceed vehicle capacity and time window constraints.

Step 10: Update Best Solution

The best solution is updated if the currently generated solution yields a smaller fitness value than the best solution that had already been saved.

$$S_{Cur} < S_{Best}$$

Step 11: Termination Condition

All optimisation steps are continuously performed by the algorithm until the desired number of generations is attained. The best routes are listed as the final optimal solution once each iteration has been completed.

COMPUTATIONAL EXPERIMENTS

From the literature review, the instances were taken from Euchi et al. (2020), then the instance was modified and tested with randomly generated data. This experiment has been solved for more than 1000 patients. In this work, the dataset is organized into three categories, specifically small, medium, and large healthcare vehicles, which denote various instance classifications developed for computational testing. To evaluate the implementation of the suggested model under distinct levels of routing difficulty, different problem sizes, including 20, 50, and 80 patients, are considered for every data set type. To analyse the health care staff members sharing health care small, medium, and large vehicles with their capacities for trips to serve the patients and synchronised visits, include them in the route plan.

To investigate and handle the uncertainty in different types of time duration and CO_2 emission, they are taken as a single-valued neutrosophic fuzzy number. It is transformed into a crisp number by using the score function. This study's

fuzzy numbers and score function were taken from Srinivas & Prabakaran (2023). The datasets have been modified to incorporate different types of vehicles and uncertainty data because these parameters are absent from existing benchmarks. This experiment is considered for a one-day trip, including a lunch break in the route plan. Table 1 explains the modified set of instances, heterogeneous vehicles, fuzzy time duration used in this study and Table 2 describes the required parameters for this specific problem. To the best of our knowledge, there are no existing modified instances like this for the HHC scheduling and routing problem.

Table 1: Modified Instance Dataset

Vehicle Type	Instance	Number of patients	Number of health care staff members	Synchronized visits	Time windows		
					Small Time Duration	Medium Time Duration	Large Time Duration
Small Vehicle	1	20	4	2	[1.4,1.5,1.7; 0.98,0.05,0.03]	[1.8,2.1,3.1; 0.89,.12,0.09]	[2.6,2.9,3.8; 0.91,0.04,0.02]
	2	20	4	2	[1.5,1.8,2.8; 0.88,0.1,0.05]	[2.6,2.9,3.8; 0.95,0.06,0.04]	[3.6,3.9,4.8; 0.98,0.07,0.02]
	3	20	4	2	[1,1.6,2.5; 0.9,0.09,0.07]	[2.3,2.5,3.4; 0.79,0.02,0.01]	[3.1,3.4,4.2; 0.91,0.02,0.01]
	4	20	4	2	[1.2,1.5,2.3.; 0.73,0.02,0.01]	[2,2.4,3.2; 0.95,0.4,0.3]	[2.6,3.0,3.9; 0.9,0.04,0.01]
	5	20	4	2	[1.2,1.6,2.5; 0.81,0.02,0.01]	[2.2,2.5,3.4; 0.89,0.04,0.02]	[3,3.4,4.3; 0.94,0.04,0.01]
	6	50	10	5	[1.1,1.4,2.2; 0.76,0.03,0.01]	[2,2.3,3.1; 0.89,0.04,0.01]	[2,3.1,3.9; 0.93,0.03,0.02]
	7	50	10	5	[1.2,1.5,2.3; 0.82,0.1,0.02]	[1.9,2.2,3.0; 0.09,0.06,0.01]	[2.7,3.0,3.9; 0.87,0.4,0.01]
	8	50	10	5	[1.3,1.6,2.4; 0.78,0.04,0.01]	[2.2,2.5,3.4; 0.9,0.06,0.03]	[3.1,3.4,4.3; 0.88,0.05,0.04]
	9	80	16	8	[1.2,1.5,2.3; 0.72,0.01,0.01]	[2,2.3,3.1; 0.88,0.02,0.02]	[2.6,2.9,3.9; 0.84,0.02,0.01]
	10	80	16	8	[1.2,1.5,2.3; 0.8,0.03,0.02]	[2,2.3,3.2; 0.83,0.01,0.01]	[2.6,2.9,3.8; 0.88,0.02,0.02]
Medium Vehicle	11	20	4	2	[1.4,1.7,2.6; 0.8,0.09,0.01]	[1.9,2.2,3.1; 0.83,0.06,0.01]	[2.7,3,3.9; 0.9,0.04,0.03]
	12	20	4	2	[1,1.3,2.1; 0.8,0.05,0.01]	[1.8,2.1,2.9; 0.91,0.04,0.04]	[2.8,3.2,4.1; 0.96,0.04,0.04]
	13	20	4	2	[1.1,1.5,2.4; 0.85,0.1,0.05]	[2.1,2.4,3.3; 0.9,0.05,0.03]	[2.9,3.2,4.2; 0.89,0.03,0.02]
	14	20	4	2	[1.5,1.8,2.7; 0.83,0.05,0.02]	[2.6,2.9,3.8; 0.9,0.05,0.02]	[3.6,3.9,4.8; 0.97,0.05,0.02]
	15	20	4	2	[1.2,1.5,2.3; 0.77,0.04,0.04]	[2.1,2.4,3.1; 0.94,0.03,0.03]	[2.9,3.2,4.1; 0.9,0.02,0.02]
	16	50	10	5	[1.2,1.6,2.6; 0.79,0.05,0.05]	[2.2,2.5,3.6; 0.88,0.06,0.03]	[3,3.4,4.4; 0.89,0.02,0.01]
	17	50	10	5	[1.3,1.7,2.7; 0.79,0.03,0.02]	[1.7,2.1,3.0; 0.86,0.03,0.03]	[2.5,2.9,3.9; 0.89,0.03,0.03]
	18	50	10	5	[1.1,1.5,2.4; 0.8,0.1,0.01]	[2,2.4,3.2; 0.88,0.01,0.01]	[2.8,3.2,4.2; 0.88,0.03,0.02]
	19	80	16	8	[1.3,1.6,2.5; 0.77,0.1,0.01]	[2.3,2.6,3.5; 0.85,0.02,0.02]	[3.3,3.6,4.4; 0.93,0.03,0.03]
	20	80	16	8	[1.4,1.8,2.9; 0.9,0.09,0.09]	[2.2,2.6,3.6; 0.87,0.03,0.03]	[3.0,3.4,4.5; 0.9,0.03,0.03]
Large Vehicle	21	20	4	2	[1.2,1.5,2.5; 0.79,0.06,0.06]	[2.1,2.4,3.4; 0.89,0.07,0.06]	[2.7,3.0,4; 0.9,0.06,0.04]
	22	20	4	2	[1,1.4,2.3; 0.8,0.03,0.03]	[1.9,2.3,3.2; 0.94,0.07,0.04]	[2.8,3.1,4.0; 0.92,0.08,0.02]
	23	20	4	2	[1.4,1.7,2.8; 0.8,0.06,0.06]	[1.8,2.2,3.2; 0.79,0.02,0.02]	[2.6,3.0,4.0; 0.86,0.03,0.02]
	24	20	4	2	[1,1.3,2.2; 0.75,0.05,0.02]	[1.8,2.1,3.1; 0.87,0.08,0.07]	[2.9,3.2,4.3; 0.88,0.04,0.03]
	25	20	4	2	[1.4,1.7,2.9; 0.69,0.02,0.01]	[1.9,2.2,3.3; 0.78,0.05,0.04]	[2.7,3.0,4.2; 0.86,0.05,0.04]
	26	50	10	5	[1.3,1.5,2.5; 0.6,0.02,0.02]	[2.2,2.4,3.4; 0.83,0.04,0.04]	[3.0,3.2,4.4; 0.87,0.06,0.06]
	27	50	10	5	[1.1,1.4,2.4; 0.8,0.09,0.09]	[2,2.3,3.3; 0.89,0.06,0.05]	[2.8,3.1,4.1; 0.9,0.04,0.04]
	28	50	10	5	[1.2,1.4,2.4; 0.79,0.09,0.09]	[2.1,2.3,3.3; 0.9,0.07,0.07]	[2.9,3.1,4.1; 0.9,0.05,0.05]

	29	80	16	8	[1.5,1.7,2.9; 0.78,0.08,0.08]	[2.3,2.4,3.4; 0.87,0.08,0.08]	[3.3,3.5,4.4; 0.94,0.06,0.05]
	30	80	16	8	[1.4,1.6,2.6; 0.8,0.08,0.08]	[2.3,2.5,3.6; 0.87,0.07,0.07]	[3.5,3.8,4.7; 0.88,0.05,0.03]

Table 2: Parameter Setting

Parameters	**Surfaces**
(X_j, Y_j)	U|3,9|
d_{ij}	$\sqrt{(Y_i - Y_j)^2 + (Z_i - Z_j)^2}$
opt_i	(8,10)
clt_i	(14,17)
svc_{ij}	(250,650)
avs_1	40
avs_2	50
avs_3	60
$A_{sm'}$	(3+1) seaters
$B_{sm'}$	(5+1) seaters
$C_{sm'}$	(9+1) seaters
travel cost for small vehicle	(13, 20)
travel cost for medium vehicle	(20, 30)
travel cost for large vehicle	(25, 40)
sl_s	(0, 1)
Lunch duration	1 hour
Service time	(0.4, 1.4)
CO_2 emission of vs_1	[(0.1159,0.1161,0.1170; 0.99,0.01,0.01)]
CO_2 emission of vs_2	[(0.1211,0.1213,0.1225; 0.99,0.01,0.01)]
CO_2 emission of vs_3	[(0.145,0.147,0.157; 0.98,0.01,0.01)]

RESULT AND DISCUSSION

This study's computational results are based on the healthcare routing and scheduling model described in Euchi et al. (2020), which takes synchronised visits, healthcare providers' routing, and time window constraints into account to reduce the total time. The Euchi et al. (2020) study's benchmark instance structure is derived from standard datasets presented in Bredström and Rönnqvist (2008), where time window classifications for small, medium, and large were established. To make improvements that reflect variations in operation across the real world, the initially developed instances were expanded in the current work by adding uncertain time window durations and randomly generated travel distances, service time, travel cost, and visiting cost parameters. To improve allocating resources efficiently and representing actual healthcare transporting environments, predetermined vehicle capacity limitations and heterogeneous vehicle arrangements—such as vehicle size, seating capacity, and staff vehicle-sharing techniques—were also included. The outcomes produced by algorithms EABCA and EMCSA show that both approaches were successful in producing effective routes that met time window limitations, prescribed vehicle capacity restrictions, and synchronization requirements. Meanwhile, by reducing an inefficient travel distance and increasing scheduling effectiveness in an unpredictable operating environment, EABCA constantly outperformed EMCSA in terms of routing efficiency. These results are consistent with previous research, including Afifi et al. (2016) and Decerle et al. (2018), where improved outcomes for healthcare routing environments were attributed to improvements in planning adaptability and routing effectiveness. Since direct numerical comparison with deterministic Euchi et al. (2020) study results was not possible due to the incorporation of uncertainty, heterogeneous vehicles, and additional operational factors in the current work, performance analysis was conducted according to route performance, travel distance, travel cost, visiting cost, CO_2 emission is minimised, scheduling effectiveness and capacity usage.

In this paper, a mathematical model is incorporated into the EMCSA and the EABCA and the computational experiments were performed by Python 3.12. For every benchmark instance, EABCA and EMCSA have been executed several times separately, and the optimal objective values from each run was noted. The weighted sum approach is used to address the problem's multiple objectives. Tables 3-5 present each objective value in the original units of ABC algorithm, while tables 6-8 show each objective value along with the corresponding units of MCS algorithm for heterogeneous vehicles.

Table 3 Enhancing ABC Algorithm Result for small vehicle

Instance	Distance (km)	Travel Cost	Visiting Cost for all staff members	Travel time for all staff members (hrs)	Service time for all staff members (hrs)	Service level for all staff members	CO_2 emission (kg)	CPU (Sec)
1	61.984	867.933	4905.395	1.549	13.35	3.122	7.196	0.000
2	64.259	926.225	4863.95	1.605	13.23	1.88	7.459	0.0051
3	65.404	925.92	4723.5091	1.626	11.33	2.77	7.594	0.0469
4	58.954	833.317	4686.378	1.477	14.69	1.68	6.84	0.000
5	56.117	768.098	5205.179	1.4027	11.25	1.457	6.515	0.0312
6	61.795	877.697	5121.479	1.545	13.85	2.67	7.175	0.000
7	69.716	1050.817	14083.727	1.918	35.17	2.05	8.907	0.0625
8	60.54	825.394	5056.56	1.5	13.94	1.78	7.018	0.0156
9	84.423	1213.77	7738.901	2.09	20.95	3.185	9.78	0.000
10	86.883	1201.107	7316.784	2.171	21.71	4.63	10.086	0.0156

Table 4 Enhancing ABC Algorithm Result for medium vehicle

Instance	Distance (km)	Travel Cost	Visiting Cost for all staff members	Travel time for all staff members (hrs)	Service time for all staff members (hrs)	Service level for all staff members	CO_2 emission (kg)	CPU (sec)
11	57.696	1215.946	1494.101	1.154	23.66	2.61	6.998	0.0312
12	35.604	786.401	1652.54	0.712	16.65	1.365	4.318	0.000
13	33.267	800.544	1833.502	0.6653	13.2	0.874	4.035	0.0156
14	32.6337	702.574	1956.336	0.653	13.83	0.704	4.026	0.000
15	37.859	778.615	1868.78	0.7573	12.41	0.675	4.592	0.000
16	59.836	1263.403	2910.68	1.197	26.12	1.612	7.257	0.0469
17	78.606	1689.718	2608.787	1.571	24.73	2.258	9.535	0.0625
18	63.034	1336.165	8188.992	1.26	25.99	2.109	7.645	0.0156
19	93.802	2103.623	12267.761	1.876	40.22	4.717	11.377	0.0469
20	99.706	2275.338	11713.513	1.994	38.5	2.395	12.099	0.0469

Table 5 Enhancing ABC Algorithm Result for large vehicle

Instance	Distance (km)	Travel Cost	Visiting Cost for all staff members	Travel time for all staff members(hrs)	Service time for all staff members (hrs)	Service level for all staff members	CO_2 emission (kg)	CPU (sec)
21	37.838	974.388	7015.231	0.632	12.519	1.225	5.562	0.0312
22	40.817	1176.167	6346.726	0.68	31.15	1.701	6.001	0.0156
23	37.278	1065.382	6569.635	0.622	28.54	1.276	5.48	0.0156
24	36.165	953.618	6366.042	0.603	24.4	0.677	5.316	0.000
25	41.091	1157.573	6910.528	0.685	27.92	1.105	3.041	0.000
26	80.463	2067.698	14451.881	1.348	59.18	1.8	11.828	0.0469
27	73.556	2069.171	14132.791	1.226	61.869	2.038	10.811	0.0938
28	78.191	2040.53	14431.354	1.302	63.15	2.159	11.494	0.0625
29	123.624	3353.658	21693.88	2.06	69.06	3.615	18.171	0.0625
30	114.428	3278.102	21140.1486	1.904	87.52	2.137	16.807	0.0469

Table 6 Enhancing MCSA Result for small vehicle

Instance	Distance (km)	Travel Cost	Visiting Cost for all staff members	Travel time for all staff members(hrs)	Service time for all staff members (hrs)	Service level for all staff members	CO_2 emission (kg)	CPU (sec)
1	64.192	868.949	5054.82	1.6046	12.36	1.25	7.454	0.0156
2	66.031	933.545	4980.3026	1.649	14.94	2.64	7.6651	0.0156
3	68.561	1018.277	5021.416	1.713	13.72	1.376	7.955	0.0151
4	63.177	949.182	4898.72	1.580	15.44	1.287	7.334	0.0312
5	59.958	852.772	5259.105	1.499	11.82	0.947	6.96	0.0469
6	61.795	923.332	5227.13	1.632	14.3	2.331	7.587	0.1250
7	79.952	1296.891	14256.596	1.999	36.18	2.098	9.282	0.2031
8	60.542	825.394	5606.272	1.514	16.75	2.322	7.028	0.000

9	88.865	1289.152	7738.901	2.221	20.95	3.774	10.3173	0.0312
10	95.889	1369.746	7995.954	2.39	22.55	3.983	11.133	0.0938

Table 7 Enhancing MCSA Result for medium vehicle

Instance	Distance (km)	Travel Cost	Visiting Cost for all staff members	Travel time for all staff (hrs)	Service time for all staff members (hrs)	Service level for all staff members	CO_2 emission (kg)	CPU (sec)
11	64.96	1823.107	6738.6	1.29	27.5	1.51	7.885	0.0156
12	82.688	2346.234	3976.899	1.65	18.61	1.54	10.024	0.0938
13	74.201	2025.242	1833.502	1.477	25.68	1.377	9.03	0.0469
14	83.441	2448.782	3728.977	1.668	24.68	1.386	10.121	0.0625
15	87.094	1953.402	3944.223	1.742	21.52	1.033	10.566	0.000
16	67.321	1587.411	8869.272	1.346	29.3	1.738	8.167	0.2031
17	79.213	1741.073	8086.856	1.58	32.93	1.989	9.608	0.2344
18	63.099	1402.88	8504.28	1.26	29.68	1.909	7.655	0.0166
19	102.793	2209.225	12716.725	2.056	46.11	3.393	12.469	0.0469
20	104.611	2446.93	11754.653	2.093	40.72	2.168	12.689	0.0625

Table 8 Enhancing MCSA Result for large vehicle

Instance	Distance (km)	Travel Cost	Visiting Cost for all staff members	Travel time for all staff (hrs)	Service time for all staff members (hrs)	Service level for all staff members	CO_2 emission (kg)	CPU (Sec)
21	39.557	1220.692	7236.038	0.659	25	1.301	5.815	0.0625
22	43.914	1221.326	7196.916	0.732	29	1.388	6.456	0.0156
23	41.267	1118.433	7235.804	0.687	28.6	0.264	6.066	0.0625
24	37.002	1119.209	7083.707	0.617	29.7	0.988	5.439	0.03 12
25	41.741	1225.203	7034.939	0.695	28.81	1.087	6.137	0.0412
26	80.805	2244.636	14639.2098	1.337	60.88	2.453	11.878	0.1250
27	77.659	2368.193	14218.359	1.294	65.61	2.778	11.416	0.1094
28	78.194	2110.835	14966.602	1.303	64.2	2.541	11.494	0.0938
29	131.643	3959.928	21815.994	2.192	76.2	2.168	19.36	0.0938
30	123.02	3445.162	21366.741	2.051	89.47	3.131	18.082	0.1719

To describe the algorithm's performance, the best values from each instance were used to calculate the overall mean μ′ and standard deviation σ′, and the Tables 9,10 and 11 display the normalised weighted sum values (Z), which serve as a common metric for comparing the algorithms overall objective values. Both the EABCA and EMCSA are solved and provide their output values for multi-objective functions such as distance, health care staff visiting cost, travel cost, and CO_2 emission. The normalization weighted-sum aggregation method is used to solve the multi-objective function. The EABCA gives better results in comparison to the EMCSA for small, medium, and large vehicle types.

Table 9 Comparison table for small vehicle

Enhance ABC Algorithm			Enhance Mutated Cuckoo Search Algorithm	
Instance	**Z**	**CPU (sec)**	**Z**	**CPU (sec)**
1	0.3605	0.000	0.3687	0.0156
2	0.4248	0.0051	0.4348	0.0156
3	0.4014	0.0469	0.4152	0.0151
4	0.3871	0.000	0.3989	0.0312
5	0.3837	0.0312	0.4451	0.0469
6	0.1164	0.000	0.1719	0.1250
7	0.2166	0.0625	0.2232	0.2031
8	0.1627	0.0156	0.1649	0.000
9	0.1376	0.000	0.1393	0.0312
10	0.1386	0.0156	0.1453	0.0938

Mean μ′	0.2729	0.0176	0.2907	0.0577
SD σ′	0.1219	0.0211	0.1251	0.0609

Table 10 Comparison table for medium vehicle

Enhance ABC Algorithm			Enhance Mutated Cuckoo Search Algorithm	
Instance	**Z**	**CPU (sec)**	**Z**	**CPU (sec)**
11	0.4151	0.0312	0.4232	0.0156
12	0.2074	0.000	0.2192	0.0938
13	0.2217	0.0156	0.2721	0.0469
14	0.2205	0.000	0.2382	0.0625
15	0.2273	0.000	0.2441	0.000
16	0.1635	0.0469	0.1782	0.2031
17	0.1807	0.0625	0.1836	0.2344
18	0.1662	0.0156	0.1727	0.0166
19	0.1542	0.0469	0.1645	0.0469
20	0.1554	0.0469	0.1664	0.0625
Mean μ′	0.2112	0.0266	0.2262	0.0782
SD σ′	0.0732	0.0222	0.0747	0.0752

Table 11 Comparison table for large vehicle

Enhance ABC Algorithm			Enhance Mutated Cuckoo Search Algorithm	
Instance	**Z**	**CPU (sec)**	**Z**	**CPU (sec)**
21	0.2766	0.0312	0.2826	0.0625
22	0.2946	0.0156	0.3176	0.0156
23	0.2744	0.0156	0.2895	0.0625
24	0.296	0.000	0.3001	0.0312
25	0.3026	0.000	0.3145	0.0412
26	0.2025	0.0469	0.2228	0.1250
27	0.2091	0.0938	0.2235	0.1094
28	0.2351	0.0625	0.2372	0.0938
29	0.2045	0.0625	0.2092	0.0938
30	0.1994	0.0469	0.2026	0.1719
Mean μ′	0.01769	0.0375	0.05775	0.08069
SD σ′	0.0211	0.0289	0.0609	0.0452

CONCLUSION

This work presents multi-objective HHC vehicle routing and scheduling problems in uncertain situations, along with synchronised visits and vehicle sharing strategies. In this work, a mixed-integer mathematical formulation was created, and two existing heuristic algorithms were combined with a normalization weighted-sum technique to address this multi-objective problem. The numerical experiment was solved by enhanced ABCA and enhanced MCSA for the modified instances. The outcomes of the computational experiment with enhanced ABCA provide better performance compared to enhanced MCSA. Comparison of objectives shows that better routing and distribution choices can lower travel distance, travel expenses, visiting costs and emissions without affecting service quality. The benchmark instances were extended and modified because the existing benchmark did not contain the required information. The extensions presented in this paper offer home healthcare organisations a more effective and efficient planning framework. In the future, the work can be extended to IoT technology, multi-modal, real-life case studies, dynamic planning with time synchronization, and AI and ML optimisation techniques for home health care management systems.

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