Integrating Machine Learning and Evolutionary Algorithms for Optimized Scheduling and Routing in Home Healthcare Logistics

Zayd Elbassri, Khalil Bouramtane, Said Kharraja, Omar El Beqqali, and Jamal Riffi

Abstract— **In this paper, we introduce a global framework integrating predictive analytics and multi-objective optimization for the purpose of home healthcare logistics optimization. First, several machine learning approaches such as Multinomial Logistic Regression, Support Vector Machines, Random Forest, AdaBoost, and Gradient Boosting are implemented to predict and classify patients' care requirements. This categorization not only separates professional-grade nurses from primary-grade nurses but also decides whether one caregiver or two caregivers are to be deployed depending on the condition of the patient (bedridden or semi-dependent). Secondly, we create a Multi-Objective Vehicle Routing Problem with Time Windows (MOVRPTW) to schedule the caregivers efficiently and reduce transport costs. Since the corresponding optimization problem is NP-hard, we take two advanced genetic algorithms Non-dominated Sorting Genetic Algorithm II (NSGA-II) and Strength Pareto Evolutionary Algorithm 2 (SPEA2) to find good-quality solutions. To solve the problems of bedridden patient care with multiple visits per day, our model incorporates synchronization constraints to ensure continuity of care and coordination among single-caregiver teams in case dedicated double teams are not possible. By combining predictive analytics with strong optimization techniques, our framework not only improves resource allocation effectiveness and facilitates timely service delivery but also decreases operating expenses, thus providing a holistic solution to the changing needs of home healthcare logistics.**

Keywords: Home healthcare problem; Machine learning; Evolutionary algorithm (EA); Synchronization and Continuity of Care; Vehicle Routing Problem with Time Windows (VRPTW).

I. Introduction

Home health care (HHC) is increasing exponentially because of a rising population, technological innovation, policy reform, and increasing preference for aging in place. It also saves healthcare expenses and decreases hospital pressures. As per Bridge Market Research [1], the European HHC market is predicted to expand at a CAGR of 8.3% during 2024-2031, valued at USD 135.4 billion. This is in line with WHO recommendations for community-based care [2].

HHC is an essential source of care for disabled, chronically ill, and elderly individuals, whose needs has increased manifold since the COVID-19 pandemic [3]. New providers are simplifying logistics, providing care coordination, specimen procurement, and medical deliveries [4], all things being equal, even with scattered patients in rural settings.

Home healthcare (HHC) generally involves four phases: (1) collecting patient data; (2) predicting care needs via machine learning; (3) optimizing schedules and routes, with synchronization for multi-visit or two-caregiver cases [6]; and (4) delivering care based on planned paths to ensure continuity and efficiency.

This work applies machine learning and operations research to two key HHC challenges: predicting care needs (single vs. dual caregiver) and optimizing routing. The goal is to reduce wait times and transport costs while improving schedule efficiency. Our system employs machine learning algorithms like Support Vector Machine (SVM), Random Forest (RF), AdaBoost, and multinomial logistic regression (MLR) with L2 regularization, which are trained on Electronic Health Records (EHRs) [5]. EHR systems ensure effective care through patient data centralization.

The optimization module minimizes transportation costs and vehicle utilization by bundling several visits as a single visit. We use Evolutionary Algorithms (EAs) [7], NSGA-II, and SPEA2, to find trade-offs among conflicting goals that are opposing each other. These algorithms are appropriate for dynamic and complicated scheduling in HHC problems.

Synchronization constraints ensure continuity of care for two-caregiver visits, even without dedicated teams. While ML models predict care needs accurately, performance may degrade with noisy or imbalanced data [8]. Hybrid and adaptive methods like

Zayd ELBASSRI is with University Sidi Mohamed Ben Abdellah, Faculty of science Dhar El Mahraz, Laboratory of Computer Science, Innovation and Artificial Intelligence (L3IA); Fez, Morocco; e-mail: zayd.elbassri@usmba.ac.ma).

Khalil BOURAMTANE is with University of Jean Monnet Saint-Etienne, IUT of Roanne, LASPI, RU, F-42300, ROANNE, FRANCE; e-mail: khalil.bouramtane@univ-st-etienne.fr).

Said KHARRAJA is with University of Jean Monnet Saint-Etienne, IUT of Roanne, LASPI, RU, F-42300, ROANNE, FRANCE; e-mail: said.kharraja@univ-st-etienne.fr).

Omar EL BEQQALI is with University Sidi Mohamed Ben Abdellah, Faculty of science Dhar El Mahraz, Laboratory of Computer Science, Innovation and Artificial Intelligence (L3IA); Fez, Morocco; e-mail: omar.elbeqqali@usmba.ac.ma).

Jamal RIFFI is with University Sidi Mohamed Ben Abdellah, Faculty of science Dhar El Mahraz, Laboratory of Computer Science, Innovation and Artificial Intelligence (L3IA); Fez, Morocco; e-mail: jamal.riffi@usmba.ac.ma).

memetic-adaptive Neighborhood Search help manage same-day service variations without delaying schedules [9][10].

Unlike previous works that combine machine learning and optimization for routing problems, our study targets the unique challenges of home healthcare by integrating care-need prediction with synchronization and continuity-of-care constraints. We also build a hybrid dataset combining clinical and logistical data, allowing realistic simulation. This dynamic linkage between ML outputs and routing decisions enhances both care quality and operational efficiency.

II. Problem Statement

A. Predicting Patient Care Needs

Care need prediction is very important in-home care. Incorrect designation of patients as having low or high needs can cause a waste of resources or insufficient preparation. The heterogeneity of patient data, which can be biased on geo-graphic or socio-economic axes [9], is another factor exacerbating this challenge. In addition, class-imbalanced data with significant cases being under-sampled complicates model generalization [12]. It requires strong data preprocessing, careful model evaluation, and regular updates to support new trends. B. Routing and Scheduling Optimization.

B. Optimizing Routing and Scheduling

Home care routing is compounded with real-world constraints such as caregiver skills, patient preference, and unexpected same-day requests [14]. These all contribute to making VRPTW particularly challenging. Multi-objective optimization is required to balance travel time, waiting time of patients, and workload fairness [15]. Classical approaches lack here, and this calls for adaptive, hybrid solutions combining real-time optimization and predictive analytics.

III. METHODOLOGY

This research combines three main modules: data collection, machine learning (ML) for care need classification, and a multi-objective optimization framework with caregiver synchronization and continuity-of-care constraints. Through the enrichment of publicly available datasets with expert VRPTW features, we provide a rich foundation for predictive analytics and route planning.

A. Data collection

Healthcare data are constrained by tight privacy regulations on Electronic Health Records (EHRs) [11]. We got around this by utilizing semi-real public data sets from Kaggle [12], which contain patient characteristics such as age, gender, and ICD-10 diagnoses for predicting care needs. They do not possess routing-specific information such as coordinates, time windows, and repeated visit information.

To supplement this shortage, we merged the Kaggle data with Solomon Benchmark VRPTW data [13], a logistics benchmark of 56 instances of (R-, C-, and RC-types). This more diverse dataset contains geographic coordinates, service demands, time windows, and other attributes such as *visit_purpose*, *required_caregivers*, and *expected_visits*. These attributes support realistic modeling of multi-visit schedules and coordinated two-caregiver tasks in home healthcare.

This integration allowed us to enrich the patient records (from Kaggle) with spatial and scheduling constraints (from Solomon VRPTW), resulting in a synthetic but realistic dataset for simulating home healthcare operations. By linking clinical needs with routing logistics, we were able to test how ML-driven care classifications impact downstream scheduling and resource allocation in a spatial context.

By merging and augmenting both datasets on our side, we gained a more informative set of features (see Table I), such as *care_need_level* (predicted by our ML models), *visit_purpose*, *required_caregivers* (1 or 2), and *expected_visits* (number of visits per day). Our more informative dataset allows us to test our solution under more realistic circumstances, so that synchronization and continuity-of-care constraints can be addressed correctly.

TABLE I. DATASET STRUCTURE

customer_ id	coordinates		demand	due_ time	ready_ time	service_ time	care_ need_ level
	x	y					
0	x0	y0	e0	e0	l0	s0	c0
1	x1	y1	e1	e1	l1	s1	c1
…	…	…	…	…	…	…	…
100	x100	y100	e100	e100	l100	s100	c100

Additional Attributes (Not Shown):

- visit_purpose: Indicates visit type, such as "assessment" or "follow-up".
- required_caregivers: Determines how many caregivers.
- patient_classification: A label (e.g., “semi-dependent” or “bedridden”) distinguishing patient groups and influencing the complexity of required care.
- expected_visits: Indicates how many times per day the same patient needs service, facilitating continuity-of-care constraints.

Fig. 1 illustrates the Geographical Distribution of Patients, in which the spatial distribution of semi-dependent and bedridden patients is depicted. Every point identifies a patient's location. Service demand is denoted by bubble size, and tooltips provide prominent attributes such as *patient_classification*, *visit_purpose*, and *service_demand*. Clustering patterns are identified with this visualization, and high-density patient distribution areas are determined, which are of utmost importance for caregiver route optimization.

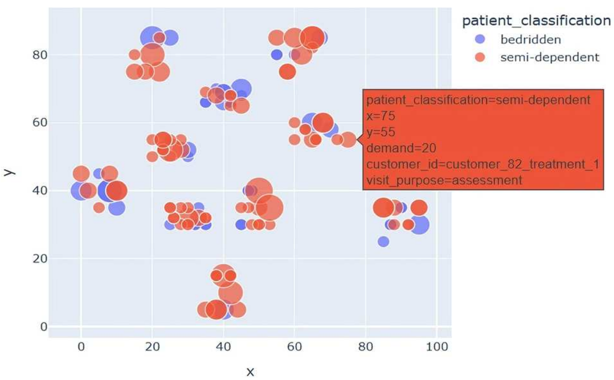

Figure 1. Geographical Distribution of Patients

B. Machine learning models

Before routing optimization, our model predicts the number of cars per patient (one or two caregivers). We utilized machine learning models with preprocessing techniques such as feature selection, hyperparameter optimization, and class balancing. We applied an 80/20 train-test split to evaluate model performance. To reduce overfitting and improve generalization, we used 5-fold cross-validation during training. Hyperparameters for each model were selected using grid search to optimize classification performance based on F1-score.

The models used demographic information, diagnosis, reason for visit, and other features to forecast care as low or high. These include Multinomial Logistic Regression (MLR), which generalizes logistic regression with softmax and L2 regularization [14]; Support Vector Machine (SVM), which separates care levels using kernel-based decision functions; Random Forest (RF), an ensemble of decision trees with majority voting; AdaBoost, which improves weak learners by focusing on misclassified instances [17]; and Gradient Boosting, which builds successive trees to correct prior errors through additive modeling.

The result of these models is expressed in the *care_need_level* field and is used to represent whether a patient would potentially need single or double coverage. Wherever the predicted level is 2 caregivers, this can initiate synchronization opportunities and determine multi-visit continuity patients if *expected_visits* greater than 1.

C. Caregiver Team Composition and Synchronization

We have 25 caregivers, 25% of whom are in permanent two-nurse teams, and 75% who are single (individual) teams. When the bed patients need concurrent treatment but a two-nurse team is not available, two solo caregivers schedule their visits (see Eq. (13) and Eq. (14)) for combined service. The two solo teams then proceed individually after the combined visit. Since patients in bed will probably require multiple visits a day, continuity-of-care constraints (Eq. (15)) necessitate the same group or at most two distinct groups per patient per day, which provides consistent, good-quality service and maximizes overall use of resources.

D. Multi-Objective Optimization Approaches

A balance of several goals is required in such complex issues as home care scheduling and vehicle routing. Multi-objective optimization methods seek to find Pareto-optimal solutions and effective trade-offs among the competing goals. Related layout and scheduling problems have been extensively studied in other contexts as well [18].

Evolutionary algorithms like the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and the Strength Pareto Evolutionary Algorithm 2 (SPEA2) are especially suited, with population-based search and diversity-maintaining methods but differing in fitness assignment and selection.

1) Non-Dominated Sorting Genetic Algorithm II (NSGA-II)

The NSGA-II was introduced by Deb et al. and is also referred to as the elitist nondominated sorting genetic algorithm [19]. It is nowadays a common method for finding multiple Pareto solutions of multi-objective optimization problems. NSGA-II partitions the population into Pareto fronts utilizing dominance relations. It is an elitist method that preserves diversity and non-dominated solution-oriented. Its computational complexity is O(MN^2) with *M* objectives and *N* population size. This is less than its previous version.

In NSGA-II, each solution is encoded as a numeric chromosome. Depot nodes are excluded from the chromosome but considered during fitness evaluation. Workload balancing constraints guide patient allocation, while genetic operators (crossover, mutation, selection) produce the next population. Crowding distance ranks solutions within each Pareto front, prioritizing those in lower-ranked fronts like PF_1 over PF_2.

Crowding distance of every solution x_i over several objectives *M* is given by:

$$CD_i = \sum_{m=1}^{M} CD_{im}$$

Where:

$$CD_{im} = \frac{f_m(x_{i+1}) - f_m(x_{i-1})}{f_m(x_{max}) - f_m(x_{min})}$$

Here, $f_m(x_i)$ represents the value of the *m-th* objective for the solution x_i, while x_{max} and x_{min} are the maximum and minimum values for that objective in the population.

NSGA-II begins by combining parent and offspring populations, then identifies Pareto fronts. It builds the next generation by adding solutions from these fronts until the population limit is reached. Crowding distance is used to rank solutions within each front, and new offspring are generated through crowded tournament selection, crossover, and mutation. In multi-objective optimization, selecting efficient algorithms is essential for balancing conflicting goals, especially in complex tasks like HHC routing. While methods like VEGA, DEMO, and SPEA have gained attention, NSGA-II and SPEA2 stand out for their superior performance. NSGA-II uses elitist selection and crowding distance to build diverse Pareto fronts, making it effective for minimizing vehicles and transport cost. SPEA2 improves on this with enhanced fitness evaluation and an external archive, offering greater diversity and adaptability for HHC routing challenges.

2) Strength Pareto Evolutionary Algorithm 2(SPEA2)

Zitzler et al. presented the Strength Pareto Evolutionary Algorithm 2 (SPEA2). The original SPEA algorithm [15] was improved in [16]. Non-dominated solutions are stored in an empty external archive at first in SPEA2 and a fixed population size. It ensures diversity and optimality in the Pareto front by calculating each solution's fitness by taking into account both its density and dominance strength.

A strength value *S(i)* which indicates the number of solutions it dominates is given to each solution iii in the combined population P_t (current population) and Q (archive).

$$S(i) = |\{j | j \in P_t + Q \wedge i \succ j\}|$$

Where $|\cdot|$ denotes the size of a set, and $\succ$ represents the Pareto dominance relation. The raw fitness $R(i)$ of a solution i is then computed as:

$$R(i) = \sum_{j \epsilon P_t + Q, j \succ i} S(j)$$

A solution i is considered non-dominated if $R(i)$=0; otherwise, a higher $R(i)$ value indicates greater domination by other solutions.

To maintain diversity, SPEA2 introduces a density metric $D(i)$, defined as:

$$D(i) = {}^{1}\!/_{(\sigma_i^k + 2)}$$

where σ_i^k is the distance to the *k-th* nearest neighbor of solution i in the objective space. The overall fitness $F(i)$ of a solution, i combine its raw fitness and density:

$$F(i) = R(i) + D(i)$$

In selection, solutions with F(i)<1 are passed to the archive for the next generation. However, when the archive size is greater than its limit, solutions are deleted step by step based on the minimum distance criterion. Conversely, when the archive size is less than its limit, dominated solutions with higher fitness are added until the desired size is obtained.

SPEA2's fitness consideration worst-case complexity is of $O(M^2 \log M)$. While archive truncation has a worst-case complexity of $O(M^3)$ such that M is the population size and archive size.

IV. *MATHEMATICAL FORMULATION*

This subsection presents HHC-MOVRPTW, a bi-objective model to solve the Home Healthcare Routing and Scheduling Problem (HHCRSP) [15]. In contrast to the traditional Vehicle Routing Problem with Soft Time Windows (VRPTW) [16], HHCRSP includes patient-preferred time windows in a manner that arriving early or late incurs a penalty.

The model attempts to reduce two goals: the vehicles and total cost of transport along with penalties. For this reason, the model includes some sets, parameters, and decision variables under large restrictions.

Sets and Indices

- C: Set of caregivers
- P: Set of patients
- D: Set of depots (typically, one depot)
- T: Set of time periods
- V: Set of vehicles

Parameters

- $Dist_{ij}$: Distance between location i and location j
- t_{ij}: Travel time between location i and location j
- Q_v: Capacity of vehicle v
- q_i: Demand of patient i
- e_i: Earliest start time for service at patient i
- l_i: Latest start time for service at patient i
- M: A sufficiently large constant
- G_i: Maximum offset for synchronization at task $i \in NB$
- CgT: Maximum number of teams allowed per patient (for continuity)
- H: Maximum route length (shift length) that a caregiver team can work (e.g., 8 hours).
- α, β: Cost factors to penalize earliness or lateness if soft time windows are used.
- W_k: service duration at task i

Decision Variables

- x_{ij}^{v}: Binary variable that is 1 if vehicle v travels from location i to location j, and 0 otherwise
- y_{iv}: Binary variable that is 1 if patient i is assigned to vehicle v, and 0 otherwise
- z_v: Binary variable that is 1 if vehicle v is used, and 0 otherwise
- s_i: Start time of service at patient i
- u_i: Auxiliary variable used for subtour elimination
- $\tau_i \geq 0$: A synchronization start time for tasks with multi-caregiver requirements.

Bi-Objective Functions

- Minimize the number of vehicles:

$$Minimize\ f1 = \sum_{v \epsilon V} z_v \tag{1}$$

- Minimize the transportation cost:

$$Minimize\ f2 = \sum_{v \epsilon V} \sum_{i \epsilon P \cup D} \sum_{j \epsilon P \cup D} dist_{ij} x_{ij}^{v} \tag{2}$$

$$+\alpha \sum e_i + \beta \sum l_i$$

Constraints

- Each caregiver visits the HHC depot at the start and end of their route:

$$\sum_{i \epsilon P \cup D} x_{i0}^{v} = 1 \qquad \forall v \epsilon V \tag{3}$$

$$\sum_{j \epsilon P \cup D} x_{0j}^{v} = 1 \qquad \forall v \epsilon V \tag{4}$$

- Total quantity of drugs requested does not exceed the vehicle's capacity:

$$\sum_{i \epsilon P} q_i y_{iv} \leq Q_v \qquad \forall v \epsilon V \tag{5}$$

- Service within specified time window:

$$e_i \leq s_i \leq l_i \qquad \forall i \epsilon P \tag{6}$$

- Ensure that the following service cannot begin until after the completion of the leading service:

$$s_j \geq s_i + t_{ij} - M\left(1 - x_{ij}^{v}\right) \ \forall i, j \epsilon P \cup D, \forall v \epsilon V \tag{7}$$

- Ensure that each caregiver's route both begins and ends at the home healthcare depot:

$$\sum_{j \epsilon p} x_{ij}^{v} = y_{iv} \qquad \forall i \epsilon D, \forall v \epsilon V \tag{8}$$

$$\sum_{i \epsilon p} x_{ij}^{v} = y_{jv} \qquad \forall j \epsilon D, \forall v \epsilon V \tag{9}$$

- Subtour elimination to prevent sub-tours:

$$u_i - u_j + |P| x_{ij}^{v} \leq |P| - 1 \quad \forall i, j \epsilon P, i \neq j, \forall v \epsilon V \quad \text{(u is an auxiliary variable)} \tag{10}$$

- Vehicle usage constraint:

$$x_{ij}^{v} \leq z_v \qquad \forall i, j \epsilon P \cup D, \forall v \epsilon V \tag{11}$$

- Maximum route length (shift constraint): ensuring no route exceeds allowable working time H:

$$s_k + W_k + t_{k0} \leq H \qquad \forall v \in V \tag{12}$$

Synchronization and Continuity of Care (constraints)

- Synchronization of Single Teams:

For tasks $i \in NB$ requiring two caregivers simultaneously, define $x_{ik}, x_{il} \in \{0,1\}$ to indicate which teams *k*, *l* are assigned. Let s_{ik}, s_{il} be their service start times. Enforce:

$$s_{ik} - s_{il} \leq G_i + M(2 - x_{ik} - x_{il}) \tag{13}$$

$$s_{il} - s_{ik} \leq G_i + M(2 - x_{il} - x_{ik}) \tag{14}$$

If G_i=0, arrivals must be simultaneous; otherwise, teams arrive within G_i time units.

- Continuity of Care (Multiple Visits):

For patient *i* with tasks R_i, define $y_{R_i k}$=1 if team k handles at least one visit of i's set R_i. Then:

$$\sum_{k \in v} y_{R_i k} \leq CgT \qquad , \forall i \epsilon P \tag{15}$$

V. RESULTS

Here, five machine learning models (Gradient Boosting (GB), Multinomial Logistic Regression (MLR), Support Vector Machines (SVM), Random Forest (RF), and AdaBoost) were learned to predict whether a patient would need basic (one caregiver) or critical (two caregivers) home healthcare. Table II summarizes the performance of the five machine learning models based on accuracy, precision, recall, and F1-score. Gradient Boosting achieved the best balance of predictive performance, particularly in identifying high-need patients, which is essential for optimizing downstream caregiver assignment.

TABLE II. PERFORMANCE METRICS FOR MACHINE LEARNING

Model	*Accuracy*	*Precision*	*Recall*	*F1-score*
Gradient Boosting	92.11%	0.93	0.90	0.91
Random Forest	91.92%	0.91	0.89	0.90
SVM	91.53%	0.90	0.88	0.89
AdaBoost	91.74%	0.91	0.88	0.89
Multinomial LogReg	84.00%	0.82	0.78	0.80

The multi-objective algorithms SPEA2 and NSGA-II were tested on 100 patient instances for optimizing caregiver resources. SPEA2 showed better performance in reducing vehicle usage, with an average of 29.995 vehicles (range: 29–30) over 400 generations, compared to 30.9875 for NSGA-II (range: 30–32). In terms of transportation cost, SPEA2 also performed better, with a mean cost of 3,890.77 versus 4,227.44 for NSGA-II. Despite the computational complexity due to large instance sizes, SPEA2 consistently yielded more efficient, Pareto-optimal solutions.

TABLE III. VEHICLE USAGE RESULT

Instance	**Algoritms**	**Gen.**	**Avg**	**min**	**max**	**Fitness _best _one**
C.100	SPEA2	400	3890.7718	3890.2956	3985.5475	3985.5475
	NSGA-II	400	4227.4424	4152.0182	4288.8306	4288.8306

TABLE IV. TRANSPORTATION COST RESULT

Instance	**Algorithms**	**Gen.**	**Avg**	**min**	**max**	**Fitness _best _one**
C.100	SPEA2	400	29.995	29	30	29
	NSGA-II	400	30.9875	30	32	30

We evaluated two additional metrics: the standard deviation (SD) of results across runs, and the average execution time. These metrics provide insights into algorithm stability and computational efficiency. As shown in Table V, SPEA2 not only achieved lower costs and fewer vehicles, but also showed more consistent results (lower SD) and faster convergence on average.

TABLE V. PERFORMANCE STABILITY AND RUNTIME COMPARISON

Algorithm	***Vehicle SD***	***Cost SD***	***Time (s)***
SPEA2	0.40	28.31	13.5
NSGA- II	0.68	36.95	15.2

VI. DISCUSSION AND CONCLUSION

This research presents a system which integrates machine learning–based care need forecasting and multi-objective home healthcare logistics optimization. The Gradient Boosting gave the most accurate result (92.11%), correctly categorizing patients as single- or double-caregiver classes. This assisted in optimizing route scheduling, particularly for bedridden patients requiring synchronized or repeated visits, where accurate classification helped activate continuity constraints only when needed.

The application of NSGA-II and SPEA2 revealed vehicle number versus cost trade-offs for minimizing and demonstrated that focus on diversity as well as domination strength in SPEA2 was best for optimizing route balancing as well as coordinating caregivers. SPEA2 also showed lower variability and faster convergence, making it a more stable and efficient choice. The continuity-of-care restrictions also bettered the care quality for such patients requiring several visits a day. Despite these promising results, the framework is limited by the use of synthetic data and static scheduling assumptions. In conclusion, our method demonstrates the power of optimization and predictive models in addressing actual HHC scheduling issues. Future directions cover more data, real-time scheduling, and the increased constraints that will meet changing care conditions, including integration with GIS/EHR systems and support for dynamic decision-making.

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