A Hybrid Genetic Algorithm Approach based on Patient Classification to Optimize Home Health Care Scheduling and Routing

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ABSTRACT

This study aims to solve the multi-objective problem of home healthcare scheduling and routing. The former's objectives are to upgrade the travel distance, the workload balance, and the waiting time of caregivers. A novel approach was proposed based on patient and caregiver clustering with the K-means++ algorithm in the first step and a hybrid genetic algorithm to optimize the global operation in the second step. The problem was solved regarding the deterministic and the uncertain aspect. The uncertain parameter investigated is the number of patients. A numeric study was conducted to prove the performance of the recommended approach using the Solomon Benchmark.

Keywords-home healthcare; scheduling; routing; clustering; genetic algorithm

I. INTRODUCTION

The recent home health care growth primarily stems from its association with the elderly, whose number has increased during the recent decades. An estimation of Home Health Care (HHC) service revenue is about $96.9B, with many HHC companies exceeding 35,000 and giving more than 600 million visits annually to serve 15 million patients [1]. Scientific growth, technical advancement, and improving life conditions are the primary factors driving this development. Advancements in information technology have enabled individuals in need of assistance to receive the necessary help in the comfort of their own homes. With telemedicine tools, caregivers can monitor the patient's health state and any change in his health condition. This important type of progress in the particular industry sector generated a significant interest among researchers. The problem of HHC Scheduling and Routing (HHCSR) has been addressed in several studies and has been modeled in various extensions depending on the problem criteria and constraints considered each time. Two aspects of this problem have been presented in the literature: the deterministic aspect, which is solved by most studies, and the uncertain aspect. The deterministic aspect consists of solving the problem in advance. Before the workday begins, caregivers will receive the proposed scheduling solution. Each caregiver has a set of patients to visit. Any change in the patient's state is not considered. The uncertain aspect can affect more than one parameter. The number of patients may increase or decrease depending on the patients' state, the number of caregivers may decrease depending on their availability, and the availability of routing paths may vary depending on the state of the road network. Despite its importance and relevance to the real word situation, this aspect is less studied in the literature. Another important parameter of this problem is the variety of a patient's needs and the limited number of the caregivers who offer each service.

This study aims to solve the HHCSR problem based on patient and caregiver clustering in a deterministic environment in the first step and an uncertain environment in the second step. The clustering of patients and caregivers was used to guide the Genetic Algorithm (GA) approach to assign a caregiver to each patient.

II. LITTERATURE REVIEW

Researchers have conducted numerous studies to address the HHC system and its various versions. The problem has been studied with multi-depots, time windows, and caregiver skills to optimize caregiver and patient preferences. The relevant studies can be classified into three categories: literature reviews [2-7], models, and applications. Several versions of this problem have been proposed, most of them have suggested a deterministic solution. This multi-objective problem has been solved with the use of various approaches. Many studies recommended a Pareto approach solution. A green home healthcare routing and scheduling problem was addressed in [8]. The authors considered physician-patient satisfaction and sustainability. They proposed an improved adaptive reference point-based NSGAIII algorithm to solve the problem and conducted a comparison study to demonstrate the effectiveness of the suggested approach. To minimize the tardiness of soft services and caregivers' workload, authors in [9] introduced a mixed integer linear programming model. Two Pareto and decomposition-based approaches with multi-objective evolutionary algorithms are recommended. The memetic algorithm NSGA-LS was developed to trade-off exploration and exploitation. The scheduling and routing problem of minimizing the travel distance, the vehicle cost, and the caregiver wage were considered in [10]. The authors presented a mathematical formulation considering the service time window and patient preferences and integrating the lunch break and flexible departure depot for caregivers. The problem of HHC service routing with multiple depots and a time window was studied in [11]. To organize the caregiver visits according to the patients' locations, this study adopted the clustering technique k-means. The problem was considered a pickup and delivery problem and solved with the Tabu Search approach. Authors in [12] analyzed HHC with a time window. They suggested a bi-objective mathematical formulation minimizing the total service duration.

A bi-objective optimization problem for HHCSR in an uncertain environment was suggested in [13] with the consideration of optimizing caregiver skills and workload balance. Mixed-integer programming formulation and the Adaptive Large Neighborhood Search Embedded Approach for uncertain patient service times were proposed. Authors in [14] studied the stochastic version of HHCSR optimizing stochastic demand, service, and travel time. They recommended a two-stage mathematical model and a hyper heuristic approach based on Tabu Search metaheuristic and Variable Neighbourhood Search. Authors in [15] explored the HHCSR problem for high population density. The proposed mathematical model was based on the Markov decision process and chance-constrained programming, optimizing travel, waiting time, life quality, and the empowerment of the elderly. The suggested approach to solve this problem was based on Q-learning and Ant Colony Optimization. The stochastic HHCSR problem with multiple synchronized services was investigated in [16]. The authors recommended a stochastic programming model that considers caregivers' travel time and service time with service synchronization. The introduced approach employed CPLEX, GA, and General Variable Neighborhood Search (GVNS) to solve the deterministic problem. GA and Monte Carlo simulation were utilized to solve the stochastic programming problem. Authors in [17] examined the impact of uncertainty on the time of patients' appointments. A model was developed to address the uncertainty of travel and service time in the HHCSR problem. The researchers employed Gurobi Solver, simulated annealing, tabu search, and variable neighbourhood techniques to solve the proposed model. A novel clustering approach based on k-means, reducing the k-means limitations, and using a hypercube of constraints and weighted Euclidian distance as a similarity criterion was provided in [18]. In [19], a new method was presented for customer classification based on shopping cases and financial information, enhancing the accuracy of traditional methods. The method uses GA to ensure similarity and quality function. Authors in [20] provided a dynamic, adaptive controller for healthcare service deployment using hybrid bio-inspired multi-agents, optimizing energy costs, and maintaining high performance for fog cloud computing between fog servers. The scheduling of paratransit vehicles, focusing on the Dynamic Response Area (DRA) approach was explored in [21]. The study developed an agent-based simulation model to evaluate its proposed strategy.

Clustering is one of the least integrated methods in the HHCSR problem-solving process, particularly in the uncertain aspect. Only a limited number of studies have explored the method of clustering patients and caregivers to address this problem. This research aims to solve the HHCSR problem in both deterministic and uncertain environments. To facilitate the assignment step, the proposed approach uses K-means++ clustering to efficiently group patients and caregivers. The patient classification is based on service qualification requirements and patients' locations, while the caregiver classification considers their qualifications and locations. Furthermore, this approach was extended to accommodate new patient requests and ensure an effective scheduling and routing process.

III. PROBLEM DESCRIPTION

The HHCSR problem is considered as an extension of the common Vehicle Routing Problem (VRP) with a time window. It has been classified as an NP-hard problem [22]. The problem consists of assigning a set of caregivers to a set of patients to give them a set of services. Each caregiver must depart every workday from the hospital, visit all the patient locations associated with him, and return to the hospital after finishing their tour. Each service has a required qualification and time window. The caregiver providing a service must meet the required qualifications. Each service has a time window and overdoing it will cause a penalty to the system. The mathematical model of this problem can be seen in [10].

IV. THE PROPOSED APPROACHES

This study proposed two approaches: The first approach named HGKS (Hybrid Genetic Algorithm with K-means for Static environment) solves the HHCSR problem in a deterministic environment, and the second called HGKD (Hybrid Genetic Algorithm with K-means for Dynamic environment) suggests a solution if a new patient request arrives during the approach's execution.

A. The HGKS Approach

This approach consists of solving the HHCSR problem in advance using K-means++ as a first step, to cluster patients and caregivers. The clustering of patients is based on their locations and the qualifications required for the service needed. The caregiver's clustering is based on their locations and their qualifications. A heuristic was utilized to assign caregivers to patients, and GA to optimize the whole operation.

B. HGKD Approach

HGKS is an extension of the previous approach with the ability to support new arriving patient requests. During the generations of GA, new requests can be added, the approach will update the assignment process, and a novel population will be created. The crossover and mutation will be performed with the new individual. The algorithim steps of the HGKD approach can be seen below:

```
Algorithm 1: Initial_population ( )
Output: Initial Population
Begin
K_means_clustering ( );
  While (List_Patients ≠ Ø)
       Choose_a_random_patient ( );
       Choose_random_caregiver ( );
       Choose_random_Path ();
       Compute_travelled_distance ( );
       Compute_waiting_time();
       Update_caregiver_position();
   EndWhile
End
Algorithm 2: HGKD
Result: Best_Solution
Generate_initial_population();
While (Iteration ≤ Nb_iterations)
If (A Given generation)
Update_List_patients();
K_means_clustering();
Update_population_Insert_Patients_requests
();
Select_for_crossover();
Crossover();
Select_for_Mutation();
Mutation();
Iteration ← Iteration + 1;
EndIf
EndWhile
```

C. Solution Coding

The GA solution is represented by a matrix, as portrayed in Table I. Letters P, C, and S represent patients, caregivers, and services, respectively.

TABLE I. SOLUTION CODING

P1	P2	P3	P4	P5	P6	P7	P8
C1	C2	C3	C1	C2	C3	C1	C2
S1	S2	S3	S1	S2	S3	S4	S4

V. NUMERIC STUDY

A. Experimental Environment

The numerical tests were performed on a computer equipped with 16 GB of RAM and a processor speed of 2.4 GHZ. The application was developed in C++. The numeric data were extracted from the Solomon Benchmark with some modifications to be adaptable to the studied problem. After several tests, the GA parameters utilized in the research were: number of population members = 30, selection probability for people in each population for crossover = 0.95, and probability for individuals to be picked for mutation = 0.1. The objective function was an aggregation of three sub-functions: The travel distance, the workload balance, the waiting time, and the skills penalty. The sub-functions have corresponding coefficient values of 0.3, 0.2, 0.2, and 0.3, respectively (chosen after several tests). The number of iterations was 1000. Each test was repeated 15 times, and the average value was taken. The Kmeans++ algorithm was tested with five clusters for patients and two clusters for caregivers for 500 iterations.

The proposed approaches were tested with several Solomon Benchmark instances observed in Table II. The instances were classified into three groups: small-size instances (25 patients and 4 caregivers), medium-size instances (50 patients and 6 caregivers), and large-size instances (100 patients and 16 caregivers). The uncertain event was created at iteration number 200 by adding 10 new patients to the initial patient list. The new patients were selected from the instance r201 (the 10 first patients). Table III shows a comparative study between the two proposed approaches in this study, HGKS and HGKD, and the HGGVNS approach proposed in [10].

B. Numeric Results

Figures 1-9 present the results provided in the numeric studies.

TABLE II. EXPERIMENTAL RESULTS OF STATIC AND DYNAMIC APPROACHES

Instance	HGKS		HGKD		Gap
	AVG	T(s)	AVG	T(s)	
c105-25-4	159.81	19.00	144.16	26.85	-9.79
c107-25-4	160.04	17.00	144.43	19.00	-9.75
c108-25-4	160.48	16.45	144.21	16.00	-10.13
r201-25-4	204.72	17.00	282.31	18.00	37.90
r205-25-4	207.43	17.90	274.90	17.00	32.53
r210-25-4	204.91	16.50	282.31	18.00	37.77
rc201-25-4	162.11	17.50	114.34	18.00	-29.47
rc206-25-4	161.13	16.80	114.55	15.00	-28.91
rc208-25-4	161.78	16.00	118.15	17.00	-26.97
c107-50-6	323.14	44.42	292.04	46.23	-9.62
c108-50-6	322.01	41.13	292.50	29.00	-9.16
c109-50-6	323.37	43.20	292.06	42.00	-9.68
r206-50-6	429.76	48.06	510.55	51.00	18.80
r207-50-6	427.03	46.33	291.17	32.00	-31.82
r208-50-6	425.96	49.66	511.90	54.00	20.18
rc202-50-6	422.59	45.33	358.27	40.00	-15.22
rc203-50-6	423.24	41.30	377.48	49.00	-10.81
rc204-50-6	424.24	44.93	388.52	39.00	-8.42
c104-100-16	1041.8	129.57	1003.1	112.0	-3.72
c108_100-16	1050.3	134.33	1011.3	88.00	-3.72
c109_100-16	1059.9	129.64	1009.0	120.0	-4.80
r208_100-16	918.30	158.13	1010.9	121.0	10.09
r210_100-16	916.29	103.27	1010.6	109.0	10.30
r211_100-16	913.45	108.40	1011.6	118.0	10.75
rc203_100-16	1085.8	120.2	1069.5	102.0	-1.50
rc204_100-16	1093.9	121.01	1089.9	93.00	-0.37
rc208_100-16	1094.8	126.91	1084.2	120.0	-0.97

TABLE III. COMPARISON OF THE EXPERIMENTAL RESULTS WITH THE HGGVNS APPROACH

Instances	HGGVNS	HGKS		HGKD	
	AVG	AVG	Gap	AVG	Gap
c105-25-4	437.89	159.81	-63.51	144.16	-67.08
c107-25-4	409.75	160.04	-60.94	144.43	-64.75
c108-25-4	398.35	160.48	-59.71	144.21	-63.80
r201-25-4	693.17	204.72	-70.47	282.31	-59.27
r205-25-4	577.65	207.43	-64.09	274.90	-52.41
r210-25-4	622.20	204.91	-67.07	282.31	-54.63
rc201-25-4	715.74	162.11	-77.35	114.34	-84.02
rc206-25-4	672.37	161.13	-76.04	114.55	-82.96
rc208-25-4	614.76	161.78	-73.68	118.15	-80.78
c107-50-6	858.36	323.14	-62.35	292.04	-65.98
c108-50-6	815.99	322.01	-60.54	292.50	-64.15
c109-50-6	791.43	323.37	-59.14	292.06	-63.10
r206-50-6	1032.15	429.76	-58.36	510.55	-50.54
r207-50-6	1015.67	427.03	-57.96	291.17	-71.33
r208-50-6	928.77	425.96	-54.14	511.90	-44.88
rc202-50-6	1274.23	422.59	-66.84	358.27	-71.88
rc203-50-6	1210.13	423.24	-65.02	377.48	-68.81
rc204-50-6	1149.19	424.24	-63.08	388.52	-66.19
c104-100-16	1318.26	1041.86	-20.97	1003.13	-23.91
c108_100-16	1365.87	1050.38	-23.10	1011.31	-25.96
c109_100-16	1327.15	1059.95	-20.13	1009.05	-23.97
r208_100-16	1292.13	918.30	-28.93	1010.94	-21.76
r210_100-16	1619.10	916.29	-43.41	1010.66	-37.58
r211_100-16	1398.76	913.45	-34.70	1011.65	-27.68
rc203_100-16	1617.25	1085.83	-32.86	1069.50	-33.87
rc204_100-16	1407.15	1093.97	-22.26	1089.97	-22.54
rc208_100-16	1476.29	1094.84	-25.84	1084.25	-26.56

VI. RESULTS AND DISCUSSION

Figure 1 displays the patient clusters of centroids with the new requests inserted through the parameters of location and required qualification. It demonstrates a good distribution of the initial patients and the newly inserted ones, as well as the centroids of patient clusters. Figure 2 represents the cluster centroids in the static case (before new request insertion). Figure 3 demonstrates the new repartition (X and Y) of new patients after insertion. This figure depicts the different locations of patients depending on the clusters presented by their centroids.

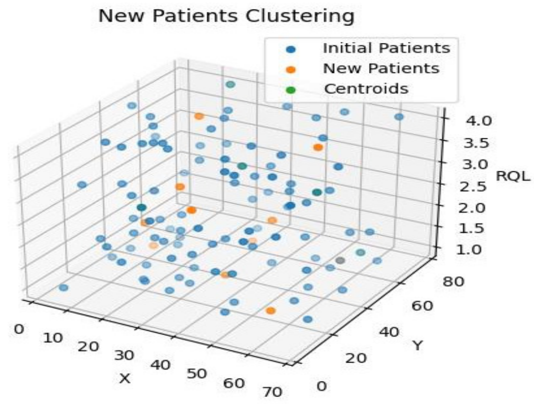

Fig. 1. New patient clustering.

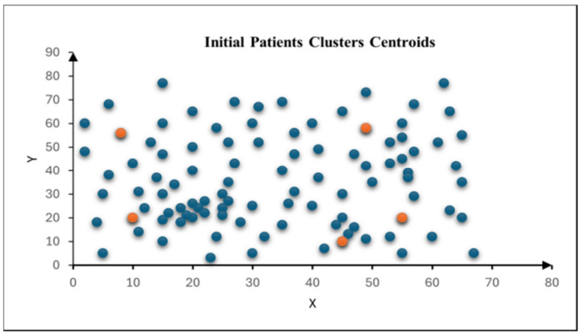

Fig. 2. Initial cluster centroid locations.

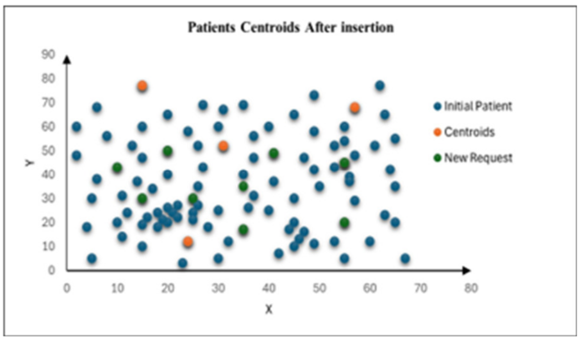

Fig. 3. Final patients cluster centroids locations.

Figure 4 illustrates the penalty skill level with variations. It manifests a variation in the first iterations. In iteration 200, it shows a small increase, and after that, a stability. Figure 5 discloses the caregiver's workload balance. The plot displays a decrease (the difference between the maximum load and the minimum load of caregivers). In iteration number 200, it decreased and then increased again to be stable.

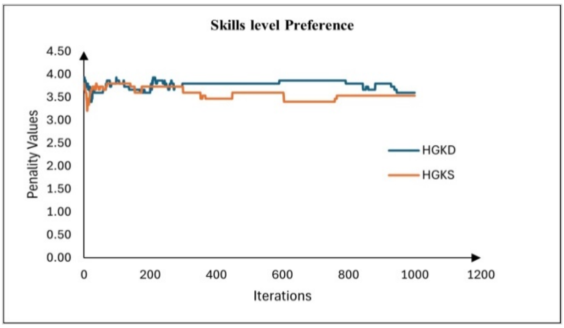

Fig. 4. Skill preference penalty.

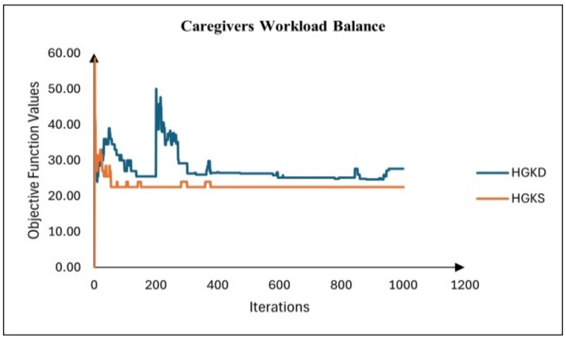

Fig. 5. Caregiver workload balance.

Table II presents the numeric results of several tests of the two approaches, HGKS and HGKD. It portrays the average total cost and the computational time of each test. Despite introducing new patients (10 per test), in many cases (19 out of 27 tests), the dynamic approach finds a better solution than the static approach. After new requests were inserted in generation 200, the clustering ameliorated the diversity of the GA population. This improvement guided the GA to find better solutions. The numeric results show a comparable solution value for the two proposed approaches, HGKS and HGKD, with HGGVNS (Table III) [10]. In all cases, the objective function value for our approaches is better than the objective function value of HGGVNS. This difference is certainly in part due to the difference in parameters and metric values, but also to the performance of the proposed approach, including the k-means clustering. To confirm this comparison, p-value and t-value calculation was performed between the two proposed approaches and HGGVNS**.** The results are significant at $p < 0.05$ for the two approaches compared to HGGVNS. For HGKS, the t-value is 4.63452, and the p-value is 0.000012. For HGKD, the t-value is 4.58629 and the p-value is 0.000014. These statistical results exhibit a significant difference between HGKS and HGGVNS and between HGKD and HGGVNS, supporting the conclusion that there is a meaningful and non-random distinction between them. Figure 6 provides the variation of the HGKS and HGKD objective function values with the different instances. The total cost increases with the instance size. For the two approaches, the variation is almost equal and the two plots are approximately superposed.

Figure 7 represents the computational time variation for a small instance. The two plots are almost superposed and the variation is slight due to the small size of the instances. Figure 8 displays the computational time variation for medium-sized instances. The variation in this Figure is more substantial due to the augmentation of instance size compared with Figure 8.

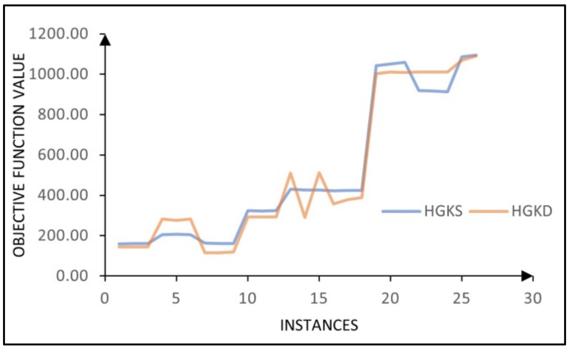

Fig. 6. Objective value variation with instance size.

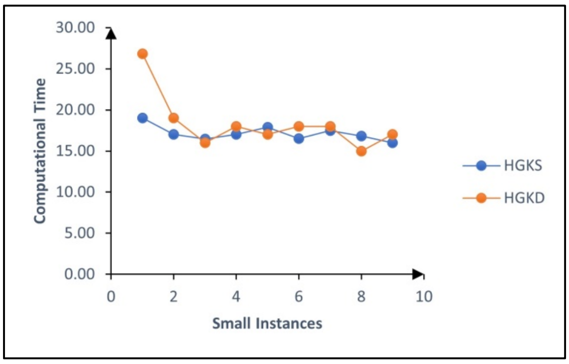

Fig. 7. Small instance computational time.

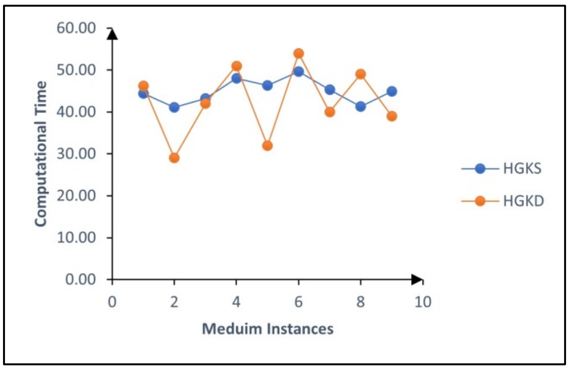

Fig. 8. Medium instance computational time.

In Figure 9, the variation between the two approaches for large instances becomes more essential due to their size. The running time increased and decreased in parallel for the two approaches, depending on the instance's size. This result improves the robustness of the HGKD approach to reach a good convergence in an acceptable time, despite the insertion of new requests during the approach execution. The insertion of new requests did not cause an observable computational time increase owing to the small number of new inserted requests (10 requests), specifically for medium (50) and large (100) instances.

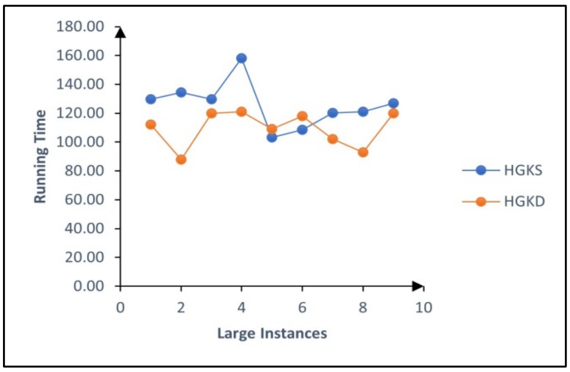

Fig. 9. Large instance computational time.

VII. CONCLUSION AND FUTURE WORK

This study addressed the problem of home health care scheduling and routing in both deterministic and uncertain environments. Two approaches were proposed. The HGKS approach is based on patient and caregiver clustering, which refers to location as well as the required qualifications. The HGKD approach extends the HGKS approach to accommodate uncertain events and the arrival of new patients during its execution. The numeric results show a good convergence of the two approaches. The comparison study demonstrates an advancement in the HGKD approach. The numeric tests exhibit the efficiency of integrating the clustering method after inserting the new requests. It helps the genetic algorithm improve the diversity of its population. The running time did not increase significantly, which proves the robustness of the proposed approach for new requests' insertion. This work can be extended to be applied to real-world data. A learning approach in inserting new requests can enhance its performance. Additionally, the Pareto approach, such as NSGAII or NSGAIII, can provide more efficient results concerning this multi-objective problem.

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