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ORIGINAL ARTICLE

Multiobjective problem modeling of the capacitated vehicle routing problem with urgency in a pandemic period

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Abstract
This research is based on the capacitated vehicle routing problem with urgency where each vertex corresponds to a medical facility with a urgency level and the traveling vehicle could be contaminated. This contamination is defined as the infectiousness rate, which is defined for each vertex and each vehicle. At each visited vertex, this rate for the vehicle will be increased. Therefore time-total distance it is desired to react to vertex as fast as possible- and infectiousness rate are main issues in the problem. This problem is solved with multiobjective optimization algorithms in this research. As a multi-objective problem, two objectives are defined for this model: the time and the infectiousness, and will be solved using multiobjective optimization algorithms which are nondominated sorting genetic algorithm (NSGAII), grid-based evolutionary algorithm GrEA, hypervolume estimation algorithm HypE, strength Pareto evolutionary algorithm shift-based density estimation SPEA2-SDE, and reference points-based evolutionary algorithm.

Keywords Vehicle routing problem · Multiobjective optimization algorithm · Many objective optimization algorithm · Optimization

1 Introduction

This research is based on vehicle routing problems (VRPs) and this problem can be changed/improved for a specific real-life engineering challenge. Therefore, there are many variants of these problems (Appendix 1). These variants are based on the formulation and definition of the specific problem/challenge. Although it can be categorized in different ways, in general, the VRP (and its variants) can be categorized based on the number of objectives: single-objective and multiobjective problems. In single-objective problems, generally the traveled distance (minimization problem) is the objective in VRPs. In addition, VRPs are proposed/changed as multiobjective optimization problem with many different objective definitions; in [51], a collaborative multicenter vehicle routing problem with resource sharing and refrigerated vehicles with temperature control constraints (CMCVRP-RSTC) is proposed (biobjective mixed-integer linear model) with the objectives of minimizing the total cost and minimizing the number of vehicles. Therefore, a hybrid heuristic algorithm that combines the k-means clustering-based tabu search into NSGA (TS-NSGA-II) is proposed and used to solve the problem. Similarly, in [49], a metaheuristic algorithm called the NSGA-large neighborhood search (NSGA-LNS) is proposed to solve the model. Many optimization algorithms have been proposed: the distributionally robust equilibrium optimization (DREO) method [57] and the membrane-inspired multiobjective algorithm (MIMOA) (as a biobjective problem where business interests and customer satisfaction are objectives of the study and are compared with the NSGA-II, SMG-MOMA, and MIMOA algorithms) [33]. As stochastic (stochastic customer requests), a multiobjective and time window problem named the dynamic vehicle routing problem with time window (DVRPTW) is investigated in [48], and a dynamic multiobjective optimization evolutionary algorithm

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(DMOEA) based on an ensemble learning (EL) (EL-DMOEA) algorithm is proposed to solve this problem.

Real-life problems are modeled as single- and multi-objective VRPs engineering applications, solid waste management is investigated in [32] with many objectives that are based on financial, environmental, and social considerations. These problems are solved by a new algorithm named the adaptive memory social engineering optimizer (AMSEO), which performs better than simulated annealing (SA) and the social engineering optimizer (SEO) for the solid waste management problem. A stochastic VRP team of mobile police units in Brussels is considered such that the team acts on urgent conditions such as accidents, violence, or alarms [39]. Emergency water trucking (EWT) is an important problem for large-scale water distribution to drought-affected areas [47]. This problem is modeled as a CVRP. It is solved by a new algorithm that hybridizes ant colony optimization metaheuristic with random variable neighborhood descent (MACS-RVND) [47]. The biomass supplies logistic problem [8, 9] is critical for sustainable development. In [9], the two-echelon biomass resource location and routing problem (2E-BRLRP) was discussed, where the location of the biomass resources and corresponding routes were evaluated to obtain the best biomass collection facilities. A hybrid heuristic algorithm (H-HA) that embeds variable neighborhood search (VNS) into the framework of tabu search (TS) is proposed in [9]. Railway maintenance management is discussed as a VRP with respect to the traveling cost in [16]. To solve the problem, a branch-and-bound approach based on a partition and permutation model is proposed for the railway maintenance management problem. The battery manufacturing industry is one of the application areas for VRP (as a two-echelon problem), and in [41], the green transportation problem for this area is considered a two-echelon problem. At the first echelon, the green transportation with inventory problem is discussed, and at the second echelon, the simultaneous pickup and delivery of capacitated multidepot (distribution and collection center) heterogeneous green vehicle routing problem (MDHVRPSPD) is the main focus (heterogeneous vehicles for the multidepot routing problem are discussed in [34] with a definition of open location (MD-OLRP), and in [26], the multidepot open vehicle routing problem (MDOVRP) is analyzed with state-of-the-art formulations). Three objectives are selected and integrated in the problem: carrying cost, transportation cost and carbon emission cost (as a single-objective problem). The simulated annealing algorithm (SAA) with the swap neighborhood solution method is evaluated to solve the problem (the simulated annealing algorithm with the insertion method is also considered) [41]. Transportation of the valuable items, also called The Cash-in-Transit (CIT), is the application of the VRP in real-life, in [45]. CIT is selected as the main topic (time-dependent CIT routing problem (TD-CITRM)) of the study such that the time dependency, stochasticity, nonlinearity, and multigraph structure problem is solved with respect to the travel speeds: deterministic (TD-CITRM-DT) and stochastic (TD-CITRM-ST) [45]. Urban transportation is perhaps the fundamental application area of VRP in such a way that the travel time, trips per vehicle, and loading time (constants are time, vehicle capacity, and trip duration) are important criteria of the problem where in [36] multi-trip time-dependent vehicle routing problem with time windows (MT-TDVRPTW) is proposed and solved with hybrid meta-heuristic algorithm adaptive large neighborhood search (ALNS) and variable neighborhood descent (VND). Transporting military personnel is aVRP in [24] and named the vehicle routing problem, and it considers reconnaissance and transportation (VRPCRT) for wartime troop movements. Additionally, an ant colony optimization (ACO) algorithm is developed and used to solve the problem. The problem of gas field sewage recycling is modeled as the period vehicle routing problem (PVRP) in [19], where customers have an uncertain frequency of service. Therefore, customers' sewage data are initially predicted, and a two-stage preoptimization and real-time optimization model is proposed by using five single-objective optimization algorithms: jDE-niche, jDE, DE, GA, and ACO. As another interesting application of machine learning algorithms to VRP, in [54], a deep reinforcement learning framework was used to solve CVRP, and deep reinforcement learning was also used for the pickup and delivery problem (PDP) in [27]. Also, deep reinforcement learning methodology is applied to mobile edge computing (MEC) network problem [23], where distributed resource scheduling is considered [22]. In [5], human preferences are evaluated for the optimization of taxi fares in the network during the COVID-19 pandemic, where in that study, a network optimization problem to optimize taxi fares is formulated and solved. Heath care is the most critical application area. Vaccine distribution is one of the critical application areas of VRPs, similar to the motivation of the research in [18] under epidemic conditions, distribution of vaccines requires special vehicles (with refrigeration). In [18], a central depot has the vaccine doses, and they are distributed from this depot. There are different priority groups that are distributed to locations with temporary housing. It is clear that there are limited numbers of vaccines and trucks with refrigerated compartments and related healthcare workers. In [18], a novel hybrid solution procedure that merges the augmented ϵ-constraint method, optimal control theory, and dynamic programming is used to solve the developed biobjective VRP model. In [35], home healthcare (HHC) logistics as a real-life problem is discussed as a cumulative vehicle routing problem (CCVRP) in such a way that the times (especially the arrival time to the vertex for this problem minimizing the system's delayed latency by satisfying mandatory visit times) are minimized, unlike the distance with many nonfixed depots, and travel from the depots and vertexes is inside that problem.

The observations obtained because of examining the relevant studies in the literature can be briefly summarized as follows: *There are many VRP models exists in the literature; however, these models are insufficient to solve the problems of the pandemic period and a new model/ framework is needed. *Modeling VRP (or the proposed model in this research) only as a single-objective problem prevents solution diversity and detailed examination of the problem. Therefore, VRP should be modeled as a multi-objective optimization problem (minimum total traveled distance may not enough to investigate the problem and solution). *The objectives of multiobjective in VRP problems are generally minimizing the total cost, minimizing the number of vehicles. However, these objectives are not sufficient for the medical distribution problem in pandemic period. A set of new variables and objectives are needed. *From the results of the hybrid heuristic algorithms for VRP, it can be inferred that hybrid algorithm may present promising performances; however, their necessity is not clear because there is not any paper presented to give overall performances of the algorithms. *Two-phase problems (for example two echelon) can be generalized as many phases system which can be useful for evaluating the proposed model where urgency level is defined to give priority for the vertexes. Therefore, an improved encoding scheme is needed to integrate on optimization algorithms.

1.1 Motivation of the research

This research uses capacitated vehicle routing problem with urgency (CVRP-U) as a variant of VRP. Different models of problems related to routing are given in the literature—as given in the literature. When different variations in VRP are compared with the problem proposed in this study, the following points can be made:

- CVRP-U has no time window; during the pandemic, all medical units—vertexes—can be accessible without a strict working time (can be reached/ worked 24/7); however, the important property is the urgency of the desired product (urgency value at the vertex). It is desired to deliver the medical products as fast as possible to the higher urgency vertex.
- CVRP-U has no multidepot and/or multicompartment, and it is not desirable to visit other depots by the vehicle because it could cause spread of the virus to other depots and also to other vehicles and units. If multiple depots are needed, then a separate route planning problem will be considered (vehicle routing problem). Similarly, multicompartments means that different types of products are delivered with the same vehicle, and it is assumed that all necessary products are combined into one package for sterilization.
- CVRP-U is an open system, which means that the vehicles do not return to the depot; after they deliver to the vertex, they must be cleaned.
- CVRP-U has vehicles that are of the same type; this problem is assumed to be inside a limited region, and therefore, the vehicles have almost the same category, with similar capacity. It is important to deliver products quickly during the pandemic, and it is recommended to prefer vehicles of similar categories that best meet the transportation and parking features of the distribution area. Thus, the disinfection of these vehicles, loading of products, and maintenance of vehicles are easier (and less expensive) for the same types of vehicles. In addition, when there are more vehicles than are necessary, the extras can easily be used interchangeably in the case of accidents. However, in future studies, heterogeneous vehicles (properties and their types as in two-echelon problems) will be considered.
- CVRP-U has distance constraints with the infectiousness constraints; not only the maximum distance but also the maximum infectiousness is considered to terminate the vehicle's job.
- CVRP-U is a vehicle routing problem, not an arc problem that considers the edges (vertexes). However, it is possible to consider all vertexes to be a residence, and that problem can be considered an arc problem. For a future study, it could be considered an arc problem for the distribution of daily products—food and medicine—in a pandemic distribution with vehicles with multicompartments.
- CVRP-U is a multiobjective optimization problem. In this way, it is possible to select one solution from many. Thus, it is possible to select the solution for the different periods of a pandemic.

The problem is considered to be a multiobjective problem in this research, and the NSGA-II, GrEA, HypE, SPEA2SDE, and RPEA algorithms are applied to the problem. The problem described in this research is modeled as a multiobjective optimization problem. The most important purpose of doing so is to be able to offer a more general solution. Measures can be taken according to different risk levels in cases to be taken in pandemic or similar situations. Accordingly, the infectiousness rate can be taken into consideration. If the spread of the disease is more important than the urgency of the product, then a solution can be sought for small infectiousness rates. In a similar situation, in the case of spreading the disease, it can be desirable to make the product distribution fast. This presentation of the possible options between these two extreme situations is the motivation of this research.

Therefore, in this research, a model with new datasets is proposed and solved with multiobjective optimization algorithms. To examine this proposed model, different cases (implementations) have been considered, and the datasets have been updated under these situations.

This paper is organized as follows. Section 2 givens the definitions for the algorithm, Sect. 3 gives the operators and the encoding scheme used in this study with a brief definition of the multiobjective optimization algorithms. Then, in Sect. 4, the implementation is given with the definition of the dataset, implementation results and their discussion. In the last section, the future work, advantages and disadvantages of the research and some missing links are emphasized, and a benchmark is defined for the researchers.

2 Problem Definition

In Fig. 1, the position of the vertex on the CMT1C problem dataset is presented - datasets will explain at the implementation section- (The presentation of the CMT1C problem only is for illustrative purposes. The same is true for all datasets in the research.). The whole dataset is composed of vertex sets with different urgency values. The urgency situation is one of the important parameters in the pandemic and the distribution of medical products according to this urgency is of critical importance. Since urgency is an important issue for the problem under study, it is clear that we should start with the vertexes with the highest level of urgency. For this reason, it is important to make preliminary preparations before starting to solve the problem in order to understand the problem and to produce solutions accordingly. For this, the problem can first be divided into different urgency levels as shown in the figure. The reason for this is to observe whether the problem solution has the necessary resources for the highest urgency level. These resources are the number of vehicles, vehicle capacity and contamination levels. These are the parts that make problem solving easier or harder (In this section, different urgency levels are shown in order to analyze the problem). Therefore, the distribution network can be divided into subsets according to Urgency (as shown in Fig. 1). Subsets created due to urgency situations should be combined in succession. After visiting the vertex with the highest urgency subset, current vehicle can move to the next subset. However, the most accurate decision for this transition is to make it between the closest vertexes in the subsets that are neighbors of each other. This situation constitutes one of the difficulties in this research and it is expected that the optimization algorithm will find the most suitable solution. In case the number of vehicles exceeds the specified number of emergency levels, more than one vehicle serves the units in the same emergency situation. This can be observed in each sample in this study. In this case, some vehicles may skip the next emergency and try to reach other units with the lower emergency level. Similarly, as examined in this study, any node can suddenly change the emergency level (dynamic situation) and at this stage, it is expected that the most appropriate vehicle will serve this situation. In this dynamic case, it will be solved by the optimization algorithm. For all these reasons, the urgency situation proposed in this study, which is important in the pandemic, complicates the VRP.

Considering all of these new variables and the traditional CVRP problem, the problem in this study is described below.

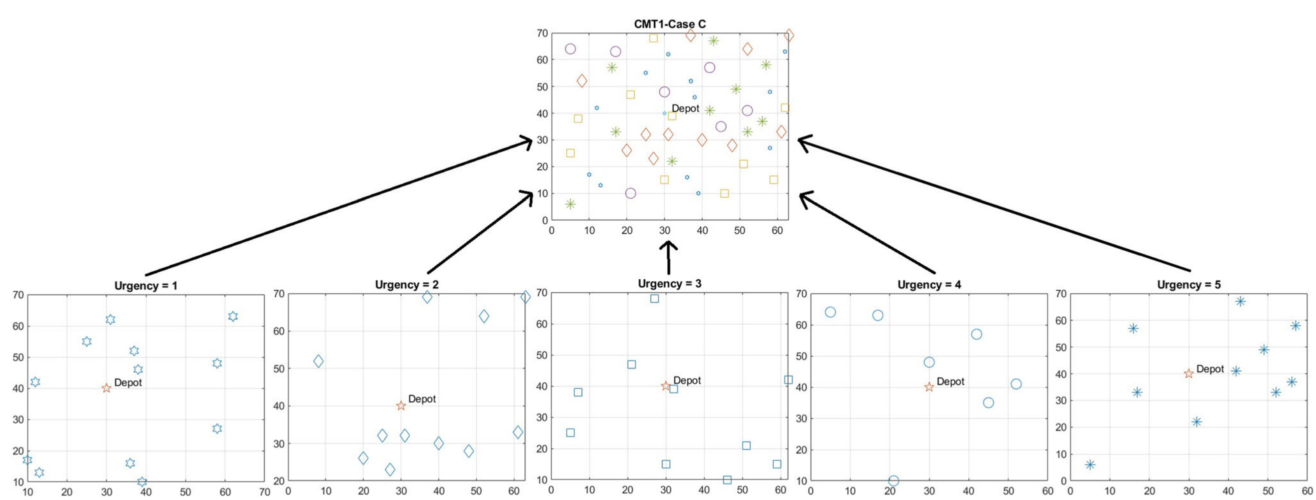

Fig. 1 The subsets of the CMT1C dataset, as an example

$$f_1 = \sum_{j=1}^{Pk} \left(\sum_{m,l \in P_k,} d_{m,l} \times x_{m,l} \right) \quad (1)$$

$$f_2 = max\left(exp\left(c \sum_{j \in P_k} i_j \right) \right) \quad (2)$$

where f_1 and f_2 are objectives, $d_{m,l}$ is the distance between vertex m and vertex l in the path j where P_k is the path of vehicle k which is the number of paths (or similarly number of vehicles), x is the binary decision variable, c is the scaling factor, i_j is the infectiousness rate of node j. In this research, two objective functions (f_1 and f_2, respectively) are defined. The first objective function (f_1) is to follow the shortest path in the desired total. The shortest route also corresponds to the fastest delivery. The second goal (f_2) is the highest infectiousness value among the paths. Thus, it is desired to minimize the possibility of transmitting the disease. If both objectives are aimed at minimization, these two objectives can be combined with the help of the penalty function. So why should be address the multiobjective problem? The answer depends on the decision making. Periods of pandemics can demand different requirements and needs. The transport of medical products as soon as possible at the onset of a pandemic could be more important than other criteria. In contrast, if medical supplies are in a manageable condition, preventing the spread of the epidemic can stand out more than the delays that could occur from product distribution. Therefore, the decision maker is asked to choose one of the possible solutions. For this reason, the problem mentioned in this study has been considered and analyzed as a multiobjective optimization problem. However, the problem must meet some basic criteria. These criteria are as follows: (i) Each vertex in the entire vertex must be visited only once, (ii) all vertexes must be delivered, (iii) the vehicle does not return to the warehouse after completing its deliveries, (vi) the capacity of each vehicle must be greater than the sum of the capacities of the vertexes that it visits, and (vii) the order of the vertexes is given with respect to the urgency u.

3 Coding/Encoding

An encoding scheme is an efficient way to represent decision variables. It is possible to encoding decision variables in binary, real or permutation, where decision variables are represented as a set of binaries, real or non-repeated integer values, respectively. Since in VRPs (like traveling salesman problem) the order of the vertex is the decision variables and it is not desired to travel the same vertex, permutation encoding is the most appropriate method to present decision variables. However, directly creating permutational encoded variables (decision variables, which are the members of the population) and processing them (for example crossover methods, mutation methods etc.) may not be possible or efficient through the optimization algorithm. Therefore, the most basic method is to use real numbers and then sorting them. In addition, number of decision variables are increased with the number of vehicles because the decision variable set is divided/distributed into the vehicles. The index of these sorted values became the desired encoding scheme, and optimization algorithm process only real valued decision variables. However, the VRP uses index of the sorted decision variables. This sorting-based encoding methodology is generally preferred for optimization algorithms. However, in this research a new parameter for pandemic period is defined: urgency. For this reason, it is not possible to use conventional sorting-based encoding methodology. For this reason, an improved encoding methodology is proposed and an example of this operation is given in Fig. 2.

The proposed/improved encoding scheme begins with the pre-definite/known information about number of urgency levels and corresponding vertexes with the number of vehicles. The size of decision variable set is equal to sum of number of vertexes with number of vehicles - 1. Therefore, the decision variable can be divided into vehicles. For example (in Fig. 2), two levels of urgency are given so that vertexes 3, 4, and 6 belong to urgency level A and 1, 2, 5, and 7 belong to urgency level B; with two vehicles. Then, the real numbered decision variable set is generated (either randomly at the initialization phase or from the generations of the optimization algorithm). For example the decision variable is generated as [0.2, 0.8, 0.5, 0.7, 0.4, 0.9, 0.3, 0.1, 0.6]. Next, it is divided into the urgency level as [0.2, 0.8, 0.5, 0.7] and [0.4, 0.9, 0.3, 0.1, 0.6] with respect to the vehicle

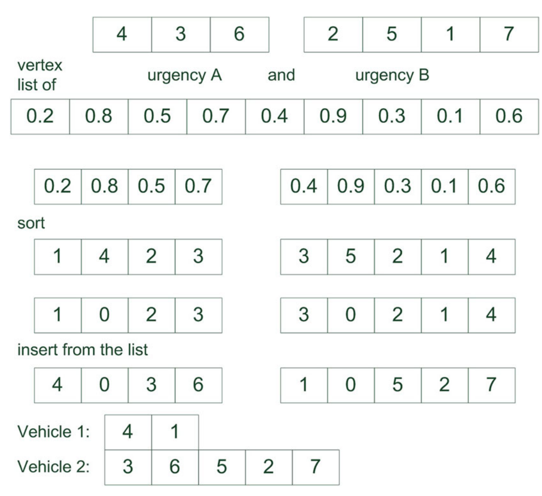

Fig. 2 An example of the preferred levels of encoding

numbers. Then, this variable set is sorted and their index is recorded as [1, 4, 2, 3] and [3, 5, 2, 1, 4]. The higher index is replaced by zero which means it is the point to divide/distribute sorted decision variable to the vehicles. Finally the indexes indicated vertexes are become a new sets as [4, 0, 3, 6] and [1, 0, 5, 2, 7], and then they are distributed to the vehicle with respect to the zero value. The encoding scheme—given in Fig. 2—can be summarized as follows. (1) The vertex of each urgency level is found. (2) The decision variable is created. (3) This decision variable is divided into parts by the urgency number. (4) Each piece is sorted, and its rank index is kept. (5) Values exceeding the data size are replaced with 0. Thus, it is divided into vehicles. (6) Vertexes are determined according to these indexes. (7) The vertex is distributed to vehicles, and a route is determined for each vehicle.

The size of the encoded decision variable depends on (i) the number of urgency level, (ii) the number of vehicles, and (iii) the number of vertexes. At the problem given in Fig. 2, there are 2 urgency level 2 vehicle and 7 vertexes. Therefore, the size of the decision variable is selected as 9. The size of decision variable is divided into two because of the number of vehicles. This division must not be equal like the example in Fig. 2. Also, each part is divided into number of urgency level. For this reason, each level needs and additional variable size (+1) (if the size of part is larger than two for this example because there is two urgency level). In Fig. 2 (at the sort part line 4) the higher index is the indicator to divide these sub-sequences (indexes 4 and 5, in Fig. 2 line 4). It is also noted from Fig. 2, it is showed that (from line 5 to line 6) the sorted and indexed sequence is applied to the urgency-vertex set (first line) to get the id of the vertexes. Therefore for each vehicle at first the higher urgency level units are visited and the next urgency level and goes on until all vertex are visited. By this way, asynchronously (with respect to the vehicle), it is guarantees that (if there are enough resources) same urgency levels are visited sequentially by each vehicle, and after that vehicle moves to the next urgency level; and it continues until all vertex are visited.

4 Implementation

In this section, the methods and results of the research are given. For this purpose, first of all, the dataset used in this research is explained. A total of 24 different datasets were used for 4 different situations and 6 datasets in total. After the dataset is explained, the optimization algorithms used in this research, the parameters of these algorithms, and the operators of the algorithms will be explained. Finally, the solutions obtained as a result of applying the optimization algorithms to the datasets and the connections between these solutions and the algorithms will be presented as the Sect. 4.3.

4.1 Dataset

In this research, the dataset from [11] is selected as the basis of the used dataset. Table 1 gives the properties for the dataset (meta-dataset).

Three features of each dataset (in total six dataset are selected) are given in the table. Vertex corresponds to the units within the dataset (corresponding to the medical centers in this research); vehicle corresponds to the number of vehicles selected for that dataset; and capacity corresponds to the unit load that each vehicle can carry. In this research, different datasets will be derived based on this dataset.

Six dataset are selected from the study of [11]. These datasets are changed to be useful for the current research. Therefore for every dataset, 4 different variants are formed, and labeled as A, B, C, and D, for example CMT1B or CMT12D. The variants are; Case A: only one vertex with highest urgency and other vertexes have the lowest urgency level. Case B: similar to Case A but other vertexes have random urgency levels in [1, 5]. Case C: All vertexes have the random urgency. Hence, number of vertex with urgency=5 is larger than the number of vehicles. Case D: almost 5% of vertexes are chosen with urgency = 5. The other vertex urgency levels are assigned randomly.

4.2 Optimization algorithms

In this study, the problem is discussed as multiobjective, and five multiobjective evolutionary algorithms are used for problem solving. These algorithms are the nondominated sorting genetic algorithm (NSGAII) [12], grid-based evolutionary algorithm GrEA [55], hypervolume estimation algorithm HypE [3], strength Pareto evolutionary algorithm shift-based density estimation SPEA2SDE [28], and reference points-based evolutionary algorithm (RPEA) [29]. In this section, these algorithms are defined only

Table 1 Dataset properties [11]

Dataset	Vertex	Vehicle	Capacity
CMT1	50	5	160
CMT2	75	10	140
CMT3	100	8	200
CMT4	150	12	200
CMT5	199	17	200
CMT12	100	10	200

briefly, and important differences are indicated when the results are discussed at the next section. The reader can find detailed information about the algorithms in the given references (however, the proposed operators are investigated).

NSGA-II is a nondominated sorting algorithm such that the domination of the solutions is used with respect to their position in the objective space, where each solution is compared with every other solution with respect to the domination principle. Then, these sorted solutions are nominated to the next generation with respect to their rank and distances between the neighborhood solutions by using the operator to maintain their diversity, which is called crowding the distance. As evolutionary algorithm NSGA-II uses tournament selection operator with SBX crossover and polynomial mutation so that simulated binary crossover and polynomial mutation with both distribution indexes of 20 with crossover and mutation probabilities are 1.0 and $1/n$, respectively. Crowding distance operator and dominance idea are used to sort the solution candidates and the best members are selected by using the ranking.

In GrEA (simulated binary crossover and polynomial mutation with both distribution indexes of 20 with crossover and mutation probabilities are 1.0 and $1/n$, respectively), the new operators are defined as grid dominance and grid difference. The solutions are located on a grid, and the performance of each solution is evaluated with this position. The distance and grid dominance idea are used to distinguish the better solutions. Three properties related to the grid are defined in the algorithm which are grid ranking, grid crowding distance, and grid coordinate point distance, which are defined in both the mating selection and environmental selection processes. In addition to the three operators, grid setting is defined as a new operator. At the grid, each solution has a location on it, and performances is estimated by their location at the grid with respect to the number of solutions with identical or similar grid locations. At each generation lower and upper boundaries of the grid are determined from the current population and this range is divided to form a grid (grid division $div = 50$). The performance of the member of the population is measured as the sum of the coordinates at the grid, and it is used in tournament selection operator. Finally, the difference between grid locations of the member's objective values with respect to each other is used to select best candidates to the next generator.

HypE (hypervolume estimation algorithm for multiobjective optimization with crossover and mutation are selected as simulated binary crossover and polynomial mutation with both distribution indexes of 20 with crossover and mutation probabilities are 1.0 and $1/n$, respectively) is another algorithm that proposed a new domination idea called the hypervolume (the indicator-based performance assessment). Hypervolume is a good indicator; however, it requires more time to calculate. Therefore, in HypE, a fast approximate (uses Monte Carlo simulation) hypervolume calculation is proposed. HypE algorithm has three operators mating selection (crossover), variation (mutation), and environmental selection (selection) operators. For mating selection binary tournament selection is used in the algorithm the only difference is to calculate hypervolume instead of objective value, and this value is evaluated in tournament selection. After the mutation of the offspring, environmental selection aims to select best members with respect to the hypervolume value-based domination.

Strength Pareto evolutionary algorithm with shift-based density estimation (SPEA2-SDE) is another estimator used in multiobjective algorithms. This estimator is directly used to distinguish the solution performance. The SDE operator is used to estimate the density (both the distribution and convergence of individuals) in order to make Pareto-based algorithms applicable to many-objective optimization problems. The density of the surrounding area of an individual is estimating by shifting the position of other individuals/members with respect to the proximity to the Pareto approximation. In brief the aim of SDE is to drag individuals at poor convergence from crowded regions.

Finally, the RPEA algorithm is a reference point-based algorithm with nondominated individuals to solve many-objective optimization problems. There are two important operators in RPEA, which are generation of reference points and selection of individuals. The reference points are applied to the selection operator to drag the solution candidates towards the Pareto front. The individuals who are survived to the next generator are selected among the generated population based on the by calculating the distances between the reference points and the individual in the objective space by a modified/weighted Euclidean distance (weighted Euclidean distance measure where weight value is selected as $1/(numberofobjectives)$). A set of reference points is generated based on the combined population with parents and offspring that genetic operators (crossover and mutation are simulated binary crossover and polynomial mutation with both distribution indexes of 20 with crossover and mutation probabilities are 1.0 and $1/n$, respectively) are performed to obtain an offspring population. A reference point may be a local ideal point. Therefore, initially all the non-dominated individuals are sorted based on the crowding distances, and then $\alpha = 0.4$ rate of individuals with the largest crowding distances of this sorted and combined population is chosen. Finally, the $\gamma = 0.05$ multiplied local nadir points are generated and selected as the reference points for the algorithm.

In additional to these algorithmic parameters, all these multiobjective optimization algorithm uses the proposed uniquely encoding scheme which presents and applies real valued sequences. The implementations are repeated 30 times and statistical properties are recorded on tables as numerical metric values (metrics are explained in the next section). These statistical results are both mean and standard deviation of these independent run results. In addition Wilcoxon rank sum test is used to compare the algorithms at a significant level of 0.05.

4.3 Results

In this section, the results of the multiobjective optimization algorithms are reported and compared/discussed by using numerical and graphical results. In this research six benchmark test suits are selected and altered (four different cases from static to dynamic problems are also considered) to make them suitable to be used as an example for pandemic period. Figure 3 gives these datasets and their known best solutions where the datasets and their corresponding best results present in [11] which are demonstrates both complexity of these datasets and their best solutions. In this research these problems are altered and they became harder (also not possible) to be solved by using conventional methods reported in [11].

As the multiobjective part of the evaluation of the CVRP-U model, in this research, five multiobjective optimization algorithms (all of these algorithms use same basic genetic operators to alter and generate offspring solution candidates) have been applied to these problems, and two metrics are selected to evaluate the performance of the algorithms. These metrics are hypervolume [53] and spread metrics [40, 52]. The hypervolume metric is an area measurement technique (in 2D objective space it is the measurement of the area with respect to the solution candidates on objective space) such that as the solutions are closer to the optimal position and distributed well enough, a larger value for the hypervolume metric is obtained with respect to the reference point. This metric provides general information about the distribution and convergence of the solutions when the exact Pareto front is not known. However, additional metric is needed to clearly present the distribution of the solutions. It is important for this research because the main motivation of the study is to give options to the decider. Therefore, it is desired from the algorithm to give uniformly spaced (if possible) solutions on the objective space to cover the entire Pareto approximation set (almost) uniformly. Therefore, a spread metric is preferred and used to compare the solutions. This spread metric is defined as;

$$\Delta = \frac{d_f + d_b + \sum_{i=1}^{N} |d_i - d'|}{d_f + d_b + Nd'} \quad (3)$$

where d_f and d_b are the Euclidean distances between the extreme solutions and the boundary solutions, and d' is the average Euclidean distance. The results are investigated from case A to case D. The results for each case, the

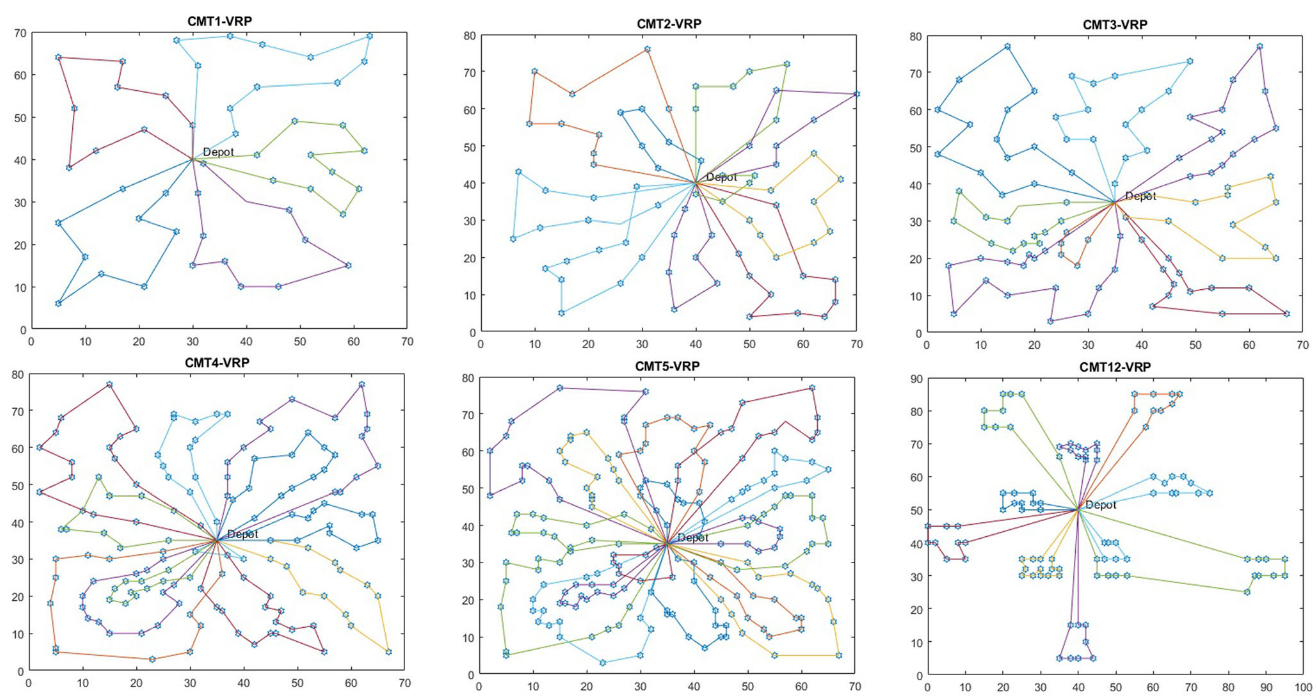

Fig. 3 Solutions for the minimum distance of VRPs applied to CMT problems [11]

datasets and corresponding performances of the algorithms will be investigated.

Initially, for all datasets with case A (CMTxA) is considered in the Tables 2, 3, 4 and 5 give the results with respect to the hypervolume, and spreading metrics are considered. For Case A, only one vertex with highest urgency and other vertexes has the lowest urgency level. Therefore, case A may be considered as the basic case among other three cases. For this case the vertex with the highest urgency will be the permanent member at every decision variable. In addition to this information, the number of vertexes is increased in number for CMT1-CMT5, in other words the CMT1 relatively easier problem than CMT5. For CMT12 problem, even the number of vertex equal to CMT3, since the vertex are located in groups in CMT12. The definition of the urgency will make it harder to travel between any different urgency level vertex that are located relatively faraway. When the results on tables are investigated, the HypE algorithm gives the best hypervolume value among the obtained results. The HypE algorithm is a hypervolume based algorithm so that the selection operator is based on hypervolume indicator. It is also indicated/concluded that for a more static problem—case A—the calculation of hypervolume metric is easier and more accurate, for this reason HypE algorithm gives the best hypervolume metric performance for both small or large decision space dimension. However, the same is not true for the distribution of solutions. The HypE algorithm showed the worst performance with the RPEA algorithm for the spreading metric [29], which gives the distribution performance of the solutions to the purpose space and cannot provide a better solution for any dataset compared with the other algorithms. The main reason that HypE could not present good results for the distribution is mainly because of there is not any efficient method to drag the solution candidates to the Pareto approximated front. The only mechanism is the selection of the solutions to create reference points. However, as the solutions moves to each other the generated reference points also come close to each other. While the HypE algorithm obtained one of the best performance outcomes for the hypervolume metric value, it did not yield acceptable results in the distribution stage. This situation can be understood when assessing how the algorithm works. The algorithm uses the hypervolume metric as the dominance method as the motivation for development. When the study in which the HypE algorithm

Table 2 Hypervolume metric statistical results for CMT1-D, CMT2A-D, and CMT3A-D

Problem	D	NSGAII	GrEA	HypE	SPEA2SDE	RPEA
CMT1A	54	6.8852e−1 (3.25e−3) +	6.8932e−1 (3.23e−3) +	6.9301e−1 (2.48e−3) +	6.8509e−1 (4.39e−3) ≈	6.8249e−1 (5.74e−3)
CMT1B	65	6.5287e−1 (5.89e−3) +	6.4941e−1 (4.88e−3) +	6.4569e−1 (6.25e−3) ≈	6.4410e−1 (7.66e−3) ≈	6.3915e−1 (5.69e−3)
CMT1C	70	6.4539e−1 (6.27e−3) ≈	6.4820e−1 (5.95e−3) ≈	6.4955e−1 (3.88e−3) +	6.4626e−1 (5.80e−3) ≈	6.4165e−1 (8.74e−3)
CMT1D	63	6.4569e−1 (7.14e−3) ≈	6.4652e−1 (5.41e−3) +	6.4472e−1 (7.85e−3) ≈	6.4489e−1 (4.27e−3) ≈	6.3932e−1 (7.94e−3)
+/ − / ≈		2/0/2	3/0/1	2/0/2	0/0/4	
CMT2A	84	7.1413e−1 (8.21e−3) ≈	7.1799e−1 (6.00e−3) +	7.3348e−1 (5.60e−3) +	7.0866e−1 (6.38e−3) ≈	7.0916e−1 (6.48e−3)
CMT2B	110	6.7557e−1 (9.13e−3) ≈	6.8754e−1 (6.98e−3) +	6.8156e−1 (5.04e−3) ≈	6.8423e−1 (7.96e−3) +	6.7305e−1 (1.16e−2)
CMT2C	120	6.7834e−1 (8.90e−3) +	6.8193e−1 (8.22e−3) +	6.8155e−1 (9.49e−3) +	6.8281e−1 (4.18e−3) +	6.6792e−1 (9.57e−3)
CMT2D	107	6.7426e−1 (8.15e−3) ≈	6.8210e−1 (5.28e−3) +	6.8306e−1 (7.06e−3) +	6.7934e−1 (6.28e−3) +	6.6532e−1 (8.30e−3)
+/ − / ≈		1/0/3	4/0/0	3/0/1	3/0/1	
CMT3A	107	6.3371e−1 (9.06e−3) ≈	6.4351e−1 (1.13e−2) +	6.6786e−1 (9.81e−3) +	6.2583e−1 (7.60e−3) ≈	6.2775e−1 (1.30e−2)
CMT3B	127	5.9294e−1 (1.17e−2) ≈	6.1284e−1 (1.09e−2) +	6.1719e−1 (1.05e−2) +	6.0332e−1 (1.02e−2) ≈	5.9229e−1 (1.32e−2)
CMT3C	135	5.9037e−1 (7.05e−3) ≈	6.0263e−1 (1.26e−2) +	6.0069e−1 (1.08e−2) +	5.9644e−1 (1.08e−2) ≈	5.8278e−1 (1.56e−2)
CMT3D	123	6.0122e−1 (1.64e−2) ≈	6.0479e−1 (1.21e−2) +	6.0321e−1 (1.09e−2) +	5.9769e−1 (1.09e−2) ≈	5.8925e−1 (1.20e−2)
+/ − / ≈		0/0/4	4/0/0	4/0/0	0/0/4	

Table 3 Spacing metric statistical results for CMT1-D, CMT2A-D, and CMT3A-D

Problem	D	NSGAII	GrEA	HypE	SPEA2SDE	RPEA
CMT1A	54	4.4707e+0 (2.13e+0) ≈	1.3829e+1 (1.97e+1) ≈	1.3517e+1 (7.29e+0) ≈	9.4228e+0 (1.14e+1) ≈	1.1872e+1 (1.59e+1)
CMT1B	65	1.0015e+0 (2.27e+0) ≈	5.1824e−1 (9.21e−1) +	9.9550e+0 (1.55e+1) ≈	4.0118e−1 (1.13e+0) +	2.7407e+0 (3.16e+0)
CMT1C	70	2.9685e−1 (5.02e−1) +	2.4032e−1 (7.60e−1) +	4.1866e+0 (2.47e+0) ≈	1.0798e+0 (2.94e+0) +	3.0864e+0 (4.10e+0)
CMT1D	63	1.5785e−1 (2.76e−1) +	6.9772e−1 (1.80e+0) ≈	1.1421e+1 (1.96e+1) −	1.7369e+0 (3.64e+0) ≈	1.5910e+0 (1.65e+0)
+/ − / ≈		2/0/2	2/0/2	0/1/3	2/0/2	
CMT2A	84	1.1070e+1 (3.37e+0) ≈	1.5524e+1 (6.51e+0) ≈	2.4197e+1 (2.36e+1) ≈	1.5798e+1 (7.76e+0) ≈	2.3951e+1 (3.61e+1)
CMT2B	110	3.0470e+0 (7.02e+0) ≈	2.9731e+0 (5.19e+0) ≈	9.4570e+0 (1.79e+1) ≈	1.5214e+0 (2.74e+0) ≈	3.0039e+0 (4.25e+0)
CMT2C	120	1.5939e+0 (1.74e+0) ≈	1.8752e+0 (2.11e+0) ≈	7.9732e+0 (6.63e+0) ≈	2.0396e+0 (2.00e+0) ≈	6.1387e+0 (1.13e+1)
CMT2D	107	1.3247e+0 (1.99e+0) ≈	1.4407e+0 (2.39e+0) ≈	4.8709e+0 (4.55e+0) ≈	1.6396e+0 (2.20e+0) ≈	2.7664e+0 (2.39e+0)
+/ − / ≈		0/0/4	0/0/4	0/0/4	0/0/4	
CMT3A	107	2.7457e+1 (1.62e+1) ≈	2.4061e+1 (2.62e+1) ≈	3.3316e+1 (3.37e+1) ≈	2.8344e+1 (3.79e+1) ≈	3.2854e+1 (2.02e+1)
CMT3B	127	1.9737e+0 (1.06e+0) ≈	2.3127e+0 (2.94e+0) ≈	6.9867e+0 (9.76e+0) ≈	5.3523e+0 (6.07e+0) ≈	6.0778e+0 (5.91e+0)
CMT3C	135	8.5709e−1 (1.18e+0) +	1.6317e+0 (2.86e+0) ≈	9.8284e+0 (1.69e+1) ≈	1.1166e+1 (2.18e+1) ≈	1.9667e+1 (4.13e+1)
CMT3D	123	1.9009e+0 (1.92e+0) ≈	1.7261e+0 (2.11e+0) ≈	3.6689e+0 (3.31e+0) ≈	3.0585e+0 (3.30e+0) ≈	4.0594e+0 (4.37e+0)
+/ − / ≈		1/0/3	0/0/4	0/0/4	0/0/4	

is proposed is examined, it is applied to 2-, 3-, 5-, 7-, 10-, 25-, and 50-purpose DTLZ problems to show the performance of the algorithm [3]. Within this framework, hints about the performance that can be obtained for two-purpose problems, as in this study, are encountered. However, information about the distribution of the solutions produced by the algorithm proposed in the study is not available. The results were compared considering only the hypervolume metric. Since it is also in the study here, it has been shown that it performs better for some test problems than the NSGA-II, SHV, IBEA, RS, SPEA2 algorithms for which the algorithm is compared for biobjective problems [3]. However, overall, it could not be concluded that it is better than the other algorithms. However, for the DTLZ2 and DTLZ4 problems, better results are obtained than those from the NSGA-2 algorithm [3]. However, there was no detailed discussion with regard to the distribution of the results. To evaluate this concern, the working focus of the algorithm should be understood. The algorithm basically realizes superiority among solutions with approximately one equivalent of hypervolume calculation. However, when the number of objectives is two, the real hypervolume calculation is used (not the estimation) due to the lack of difficulties in the calculation. Even though it is thought to be caused by an estimate hypervolume calculation at first glance, it is obvious that this approach is not valid since the study in this study is for two purposes. The main purpose of the problem in the distribution is that the solutions converge over generations. In other words, no measures have been taken for the distribution of the solutions. Solutions can become groups close to each other, including in the Pareto front corners. In this case, solutions grouped with solutions at the boundaries of the objective space can increase the value of the hypervolume metric, while grouped solutions cause an increase in the distance between them. Therefore, while good values were obtained for the hypervolume metric, a good solution was not obtained for the distribution. The distribution of the solutions is an important criterion for this research and the spread metric is the indicator for the distribution of the solutions. From all the algorithms NSGA-II gives the best distributed solutions. Also, GrEA algorithm gives almost same performance with the NSGA-II algorithm with respect to the distribution of the solutions. The main reason

Table 4 Hypervolume metric statistical results for CMT4-D, CMT5A-D, and CMT12A-D

Problem	D	NSGAII	GrEA	HypE	SPEA2SDE	RPEA
CMT4A	161	5.1887e−1 (2.27e−2) ≈	5.3401e−1 (1.27e−2) ≈	5.8515e−1 (7.52e−3) +	5.0586e−1 (1.30e−2) ≈	5.1848e−1 (1.74e−2)
CMT4B	193	5.3477e−1 (1.41e−2) +	5.3301e−1 (1.67e−2) +	5.3418e−1 (1.11e−2) +	5.1042e−1 (2.62e−2) ≈	5.0548e−1 (1.81e−2)
CMT4C	205	4.9285e−1 (2.64e−2) ≈	5.2779e−1 (9.78e−3) +	5.3232e−1 (1.46e−2) +	5.0155e−1 (1.73e−2) ≈	4.9391e−1 (1.73e−2)
CMT4D	187	5.1375e−1 (7.61e−3) ≈	5.2582e−1 (2.88e−2) ≈	5.3913e−1 (1.73e−2) +	5.0544e−1 (1.37e−2) ≈	5.0940e−1 (1.96e−2)
$+/-/\approx$		1/0/3	2/0/2	4/0/0	0/0/4	
CMT5A	215	4.0318e−1 (1.30e−2) ≈	4.0259e−1 (1.53e−2) ≈	4.7486e−1 (1.42e−2) +	3.7096e−1 (1.32e−2) −	4.0035e−1 (1.68e−2)
CMT5B	262	4.2418e−1 (1.46e−2) ≈	4.3130e−1 (1.64e−2) ≈	4.6331e−1 (1.47e−2) +	4.2738e−1 (4.39e−2) ≈	4.2705e−1 (2.30e−2)
CMT5C	279	4.0970e−1 (2.08e−2) ≈	4.2669e−1 (2.64e−2) ≈	4.4239e−1 (8.35e−3) ≈	4.1454e−1 (3.91e−2) ≈	4.1629e−1 (3.12e−2)
CMT5D	253	3.9413e−1 (1.89e−2) ≈	4.3315e−1 (3.13e−2) ≈	4.4526e−1 (1.69e−2) ≈	3.9558e−1 (2.51e−2) ≈	4.1849e−1 (2.01e−2)
$+/-/\approx$		0/0/4	0/0/4	2/0/2	0/1/3	
CMT12A	109	6.5708e−1 (5.97e−3) +	6.4925e−1 (1.41e−2) ≈	6.8792e−1 (1.23e−2) +	6.3411e−1 (1.20e−2) ≈	6.4052e−1 (1.82e−2)
CMT12B	135	6.0975e−1 (1.36e−2) ≈	6.1657e−1 (1.84e−2) ≈	6.2008e−1 (1.82e−2) ≈	6.0766e−1 (1.46e−2) ≈	6.0449e−1 (1.33e−2)
CMT12C	145	5.8812e−1 (1.58e−2) ≈	5.9827e−1 (1.56e−2) +	6.0763e−1 (1.65e−2) +	5.8587e−1 (1.26e−2) ≈	5.7497e−1 (2.05e−2)
CMT12D	126	5.9627e−1 (2.37e−2) ≈	6.0869e−1 (1.65e−2) +	6.0461e−1 (1.53e−2) +	5.9219e−1 (1.38e−2) ≈	5.8650e−1 (1.45e−2)
$+/-/\approx$		1/0/3	2/0/2	3/0/1	0/0/4	

that these two algorithms give the best distributes results is the crowding distance operator that is common for NSGA-II and GrEA algorithms. This method helps the algorithm to obstruct solutions to from groups, come closer to each other.

Table entities are for the results of CMTxB problems with respect to the hypervolume, and spreading metrics are considered. The case B is similar to case A but other vertexes have random urgency levels in [1, 5]. This problem set is relatively harder than case A with respect to the different urgency levels on the vertexes. Even a similar comment can be made for the CMTxB dataset with respect to the hypervolume metric, NSGA-II and GrEA algorithms also presents better/similar (very close) results statistically. HypE gives the best result in overall due to the same reason as explained in case A. Another similarity is obtained for the distribution property of the algorithms so that the NSGA-II and GrEA algorithms produced better distributed solutions, while the HypE algorithm produced better hypervolume values in general. While not obviously performing well, GrEA, with its acceptable performance, performed particularly well for problems with relatively small decision variable dimensions and even better than the other algorithms. The largest reason for result is the grid definition. It is the determination of the purpose space that is dominant according to this grid by dividing the grid. In the proposed study, the performance was evaluated over the 4-, 5-, 6-, 8- and 10-purpose DTLZ problems [55]. However, no investigation has been made for dual-purpose problems. However, in the study for DTLZ5, it is seen that the performance of the algorithm decreases when the number of objectives is small (for example, 3 and 4) [55]. Another inference appears to be in comparison with the HypE algorithm. As expected, DTLZ1, DTLZ3, DTLZ5, and DTLZ6 have been shown to converge better than the HypE algorithm. Although some discussions were made for the distribution feature, comparative results were not given. From the results given in the study and the tables in this research, it is shown that the GrEA algorithm is not better than the other algorithms, but better solutions can be obtained for some datasets. Although these results say that its performance is only acceptable, the two-objective problem performance is sufficient for the many-objective optimization algorithm.

Table 5 Spacing metric statistical results for CMT4-D, CMT5A-D, and CMT12A-D

Problem	D	NSGAII	GrEA	HypE	SPEA2SDE	RPEA
CMT4A	161	1.9829e+1 (6.79e+0) ≈	1.4021e+1 (3.08e+0) ≈	3.5873e+1 (1.92e+1) ≈	3.3170e+1 (1.64e+1) ≈	1.9337e+1 (5.13e+0)
CMT4B	193	1.5803e+0 (1.47e+0) ≈	2.8447e+0 (2.69e+0) ≈	7.5232e+0 (7.85e+0) ≈	5.7540e+0 (5.25e+0) ≈	9.7930e+0 (1.15e+1)
CMT4C	205	4.6337e+0 (4.35e+0) ≈	1.7576e+0 (1.13e+0) +	7.3111e+0 (5.19e+0) ≈	6.6013e+0 (7.02e+0) ≈	9.7100e+0 (7.41e+0)
CMT4D	187	2.7342e+0 (2.86e+0) ≈	5.2667e+0 (5.43e+0) ≈	5.8602e+0 (2.74e+0) ≈	7.1918e+0 (7.66e+0) ≈	8.1336e+0 (7.88e+0)
$+/-/\approx$		0/0/4	1/0/3	0/0/4	0/0/4	
Problem	D	NSGAII	GrEA	HypE	SPEA2SDE	RPEA
CMT5A	215	2.8980e+1 (2.50e+1) ≈	1.7209e+1 (4.50e+0) ≈	5.1331e+1 (4.45e+1) ≈	2.3154e+1 (7.02e+0) ≈	2.6512e+1 (1.93e+1)
CMT5B	262	1.0923e+1 (1.12e+1) ≈	8.1653e+0 (8.52e+0) ≈	9.8718e+0 (5.86e+0) ≈	4.2663e+0 (1.25e+0) +	1.1569e+1 (4.24e+0)
CMT5C	279	4.6598e+0 (3.64e+0) ≈	5.9879e+0 (3.31e+0) ≈	1.1095e+1 (1.36e+1) ≈	4.5891e+0 (4.03e+0) ≈	6.3916e+0 (3.59e+0)
CMT5D	253	4.7829e+0 (4.52e+0) ≈	6.8720e+0 (8.02e+0) ≈	1.2405e+1 (1.94e+1) ≈	7.6219e+0 (4.59e+0) ≈	5.9965e+1 (1.11e+2)
$+/-/\approx$		0/0/4	0/0/4	0/0/4	1/0/3	
CMT12A	109	2.4093e+1 (1.00e+1) ≈	1.6897e+1 (9.73e+0) ≈	2.2360e+1 (1.04e+1) ≈	2.5573e+1 (1.52e+1) ≈	1.8480e+1 (1.06e+1)
CMT12B	135	3.6280e+0 (6.67e+0) +	3.8240e+0 (3.13e+0) ≈	2.8340e+1 (6.36e+1) ≈	6.5996e+0 (3.66e+0) ≈	2.5250e+1 (3.02e+1)
CMT12C	145	4.4516e+0 (5.92e+0) ≈	4.6346e+0 (6.94e+0) ≈	5.5363e+0 (2.79e+0) ≈	8.8254e+0 (1.72e+1) ≈	1.1497e+1 (1.57e+1)
CMT12D	126	3.1996e+0 (4.56e+0) ≈	4.2630e+0 (6.26e+0) ≈	5.0732e+0 (5.40e+0) ≈	1.5659e+1 (2.29e+1) ≈	8.0584e+0 (5.02e+0)
$+/-/\approx$		1/0/3	0/0/4	0/0/4	0/0/4	

For case C, CMTxC, where all vertexes have the random urgency where number of vertexes with urgency=5 is larger than the number of vehicles; and for case D, CMTxD, almost 5% of vertexes are chosen with urgency = 5. The other vertex urgency levels are assigned randomly are two hardest cases in the research. However, the optimization algorithms can handle the get solutions for the cases. As explained reasons and with the proposed coding scheme, similar results are obtained for all cases even case C and case D. The best solutions are obtained from HyPE algorithm where for all cases the size of the decision space remains almost same with respect to the proposed coding scheme. Also, NSGA-II and GrEA algorithms give the better distributed solution sets due to the crowding distance operator. Therefore, as a suggestion an improved HyPE algorithm with crowding distance operator may improve the distributed property of the algorithm

Next, we consider a review over the dataset. Tables 2 and 3 give the results for the CMT1 dataset. When the results and statistical information are analyzed, it is seen that the NSGA-II and HypE algorithms give similar results in terms of more hypervolume metrics. In the case of convergence, NSGA-II was able to produce results with a better distribution than the other algorithms. The most important reason for NSGA-II's performance is that the number of decision variables is the smallest for the CMT1 problems. This algorithm, compared to the relatively older algorithm, produced more acceptable results for a smaller number of decision variables. Tables 2, 3, 4 and 5 have been evaluated together because they are close to each other and are therefore algorithms that produce approximately similar performance. The HypE algorithm is the hypervolume metric, and the NSGA-II algorithm has become prominent in the distribution of solutions. When considering the hypervolume metric of the performance of the NSGA-II algorithm, the CMT3-CMT5 dataset is observed. Despite this consideration, this algorithm gave good results for the distribution due to the crowding distance and nondominated sorting operators. As shown in Tables 2, 3, 4 and 5, the performance of the NSGA-II algorithm has decreased due to the explanation reason, and it could not exhibit its superiority as in CMT1. However, with the HypE algorithm, the GrEA algorithm resolved this gap and became a rival to HypE for CMT3. Nevertheless, as the number of variables increases, its performance decreases. However, it has been observed that the GrEA algorithm gives acceptable results for all of the CMT datasets.

Tables 2, 3, 4 and 5 demonstrate the performance of the algorithms on all the datasets considered and discussed in this research. When all the results obtained and the connection of these results with the dataset are examined, the first output obtained is the inadequacy of the effect of the RPEA algorithm on the problem examined. The RPEA algorithm is a many-objective optimization algorithm based on the reference point set definition idea that is the main theme for many similar optimization algorithms [29]. As stated in the RPEA study, the performance of the method is focused on many-objective problems. In the study on DTLZ problems [13], its performance for 6.8- and 15-dimensional objective spaces was examined [29]. Although it has been shown from the results that better results are obtained for DTLZ2 and DTLZ4, it is not discussed how the algorithm can perform for a small number of objectives [29]. An adaptive method is preferred to find reference points in the algorithm. Accordingly, dominated individuals in the combined population are chosen as the reference point. The basis of the algorithm is to determine reference points adaptively in every iteration and calculate the distance according to these reference points. The selection of reference points as nondominated individuals in each iteration causes less distance between them and the other solution and distortion of the distribution of solutions in the objective space. Since the motion of the solutions in the objective space depends on these reference points (Tchebychev), the convergence of the solutions will slow down, and the distribution will be distorted. In this study, the RPEA algorithm did not produce good results for any dataset compared to the other algorithms. The problem examined in this study has two objectives. While the small number of objectives is an advantage for the multiobjective optimization algorithm, it has been observed that it also creates a disadvantage in algorithms designed for many-objective problems. Therefore, the NSGA-II and SPEASDE algorithms, which are older than the other algorithms in this study, give similar results for the hypervolume metric. The NSGA-II algorithm, which was developed to provide a uniform distribution of solutions in the objective space, gave better results for spreading metrics on many datasets.

4.4 Research development opportunities and future studies

In this research, while discussing a new model for product distribution in a pandemic period, the system was modeled as static, a dynamic model and a multiobjective problem to present solution candidates to a decision maker for possible situations. The development of the CVRP-U model proposed in this study should be seen as a futuristic study in terms of examining the problem. In this model, the situations where products such as vaccines that must be stored and distributed under certain conditions must be brought to the nodes within a certain period of time. In this case, there should be changes in the vehicles; even high-cost helicopter transportation should be a problem, and certain products should be distributed within the specified time. It should even be proposed when it cannot be distributed in certain situations.

In addition to these improvements, the requirement for the dataset is obvious. Although 24 datasets were produced with 3 different datasets for dynamic cases used in this study, the number of datasets should be increased only for this study or similar studies since this dataset was created with an existing dataset update. One of the most important problems is the dynamic case. In this research, the urgency of the vertexes is changed. The problem environment (number of vertexes, number of vehicles, and parameters) can also vary. This change can occur after the product distribution has started. In these cases, the vehicles must communicate with each other, and similar to in this research, a centralized solution is distributed to the vehicles in such a way that their routes are changed. However, for the problems in which communication is limited, a decentralized problem and solution are required. The decentralized problem is considered to be an important problem that should be discussed in the future.

Additionally, during pandemic periods, it is necessary to carry necessities in homes. Thus, the problem can be turned into an arc problem. In the case of high virus contagion during the pandemic period, the transportation of drugs to each household can be modeled as an arc problem. In this case, it is necessary to ensure that these products are distributed within a day (approximately 18 h). In this case, the number and capacity of the vehicles are another study that must be examined.

In addition to these discussions, vehicles rented with many possible roads should be considered in such a way that not only the type of vehicle but also the road (or different possible routes) can be selected and considered to be the decision variable.

5 Conclusion

In this study, the distribution of important medical products in the case of a pandemic or similar disaster was modeled as CVRP-U and developed with two new definitions. These definitions are the urgency and the infectiousness rate. The definition of urgency affects the decision variables and the operators associated with them, and the definition of the infection rate, on the other hand, increases the number of objectives and reveals the nature of the problem. CVRP-U model was modeled as a biobjective problem, and solved by using optimization algorithms. The definition of urgency became the definition of a sequence for the vertexes. Therefore, the crossover and mutation operators have been updated with this new definition. Since there is no related dataset in the literature, a new dataset was created by updating the existing dataset. Thus, the definition of the problem, the tools necessary to solve the problem and the environment where the problem will be tested have been created. The problem has been solved through this dataset using five different optimization algorithms. It has been shown that the operators proposed from the results can be applied in more than one algorithm. In addition, it was observed that the NSGA-II algorithm gave better results in terms of convergence in the results examined from two different frames in terms of the convergence and distribution, while the HypE algorithm gave better results for the hypervolume metric.

Appendix 1

A vehicle routing problems and variants

Vehicle Routing Problems are one of the important problem set in real life engineering challenges. Many real-life applications and corresponding problems can be considered inside special applications of the VRP. As the engineering problem defines more detailed, the conventional VRP needs to improved to became a new form/variant. In the literature, there are many variants have been proposing to solve these problems. In Appendix 1, these variants are briefly presented to support not only the impact and important of the proposed research but also the authors believes that these variants may help the researcher to solve their investigated problem.

Delivery problems are one of the case for the variants of the VRP. Online retailer deliveries are most likely the most frequently used indirect application for the VRP. The indirect problem is generally that the shipping company manages the distribution of goods to the customers. However, occasionally, retailers distribute their own products, and that problem is considered to be a vehicle routing problem with time windows (VRPTWs) [25, 38]. As a different point of view, that problem is considered and solved in terms of a case-based reasoning (CBR) methodology in [38] (an experience-based problem-solving technique based on artificial intelligence). In the discussion in [38], the experience and metrics of the previous drivers along the same path are recorded and used to obtain the best solution for the VRP. Additionally, these metrics are the objectives of the problem, which maximizes the number of lengthy historical customer chains and minimizes the total cost.

The dial-a-ride problem (DARP) is a delivery problem in such a way that the aim is to transport customers from the origin to the destination locations [30]. In [30], single-depot and multidepot DARPs are considered with respect to the heterogeneous fleet of vehicles, and the problem is solved with a multistart hybrid algorithm that combines the iterated local search (ILS) and set partitioning (SP) approaches. The evacuation of people by buses and cars is the VRP problem discussed in [59]. The bidirectional multilane conflict-eliminating cell transmission model (BCECTM) with the split delivery vehicle routing problem (BCECTM-SDVRP) is proposed in [59], where a genetic algorithm with a chromosome coding scheme is constructed to solve the evacuation optimization model. The aim is to generate an optimal vehicle traveling trajectory in this way to improve the evacuation performance. As a delivery and pickup case, the multiproduct vehicle routing problem with simultaneous pickup and delivery (VRPSPD) is the main problem in [37, 43, 60]. A waiting strategy (WS) based on a re-routing indicator (RI) (the threshold to decide) for the vehicle routing problem is proposed with a genetic algorithm (GA) with a meta-heuristic method.

The capacitated vehicle routing problem with alternative delivery, pick-up and time windows is considered in [42] (based on postal and courier delivery). Alternative delivery points and parcel lockers are innovations for the VRP, and a hybrid approach that integrates CP (constraint programming), GA (genetic algorithm) and MP (mathematical programming) was proposed for the optimization of the problem. In delivery problems in real life, the participation of ordinary people in the logistics of products helps the company reduce the delivery costs, and in this way, ordinary drivers can be hired to deliver with their own vehicles. This problem is called the vehicle routing problem with occasional drivers (VRPOD), which is discussed in [31]. To solve this problem, a multistart ILS algorithm where a greedy randomized constructive method with an extended neighborhood is proposed.

Two-echelon problems consider the additional (intermediate) unit (vertex or depot) that connects the transportation units. Two-echelon problems can be considered to be two-phase problems; in this point of view, the line-haul feeder vehicle routing problem (LFVRP) can be evaluated in this category. In [6], LFVRP is discussed where two types of vehicles, small and large, are used in the research. Therefore, their parking lines only provided service for both of them, and the other provided service only for the small vehicles. As suggested in [6], large vehicles can be considered to be depots (virtual depots); therefore, both vehicles must be at the same place and at the same time, and thus, the problem becomes a synchronization problem (actually a time window problem, as in line-haul feeder vehicle routing problem with time windows (LFVRPTW)).

Two-echelon problems are suitable for transfering goods to the vertex in urban deliveries [1]. These two-echelon ideas are considered to be the inner and outer areas of the urban area in [1], where the gray zone is defined as the border of the inner city and outer area. Therefore, a three objectives which are the total transportation cost, total GHG emissions and total disturbance) is the two-echelon vehicle routing problem (2eVRP) with vehicle synchronization and gray zone customers is discussed in [1], and it is solved by using heuristics based on a large neighborhood search into a heuristic cuboid splitting integrated LNS into a multiobjective method. Similar to two-echelon problems, it is possible to consider the time window to be two layers. In [20], the vehicle routing problem with two-layer time window assignment and stochastic service times (2 L-TWAVRPSST) is formed by using this idea, and it is solved with the progressive hedging algorithm. These two windows are formed based on the customers' choice and assigned a flexible width of time where the time window is decided with a combination of stochastic demand and service time [20]. The motivation of the study is to serve more customers with a smaller number of vehicles [20] (the objectives are the minimization of the traveling costs, penalty costs and vehicle fixed costs), where adding new vehicles is more costly in terms of penalties to customers. Similar to the study in [20], a two-echelon collaborative multidepot multiperiod vehicle routing problem (2E-CMDPVRP) is proposed as a multiobjective integer programming model where the objectives are the minimization of operational costs, waiting times, and number of vehicles [50]. Collaboration is a means to form pseudosynchronization among multiple facilities and transportation times. Three-dimensional k-means clustering and NSGA-III (IR-NSGA-III) are merged as a hybrid algorithm to solve 2E-CMDPVRP [50].

In addition to all of these problems, environmental studies have emerged, such that reducing the emission or route planning of electrical vehicles are discussed, over the past decade (as a part of green engineering, these studies are named green vehicle routing problems G-VRPs). Electrical vehicles and the corresponding environmental (carbon) emissions are also considered by the study [32, 57]. G-VRP can be divided into two groups: electrical vehicles and emission reduction problems. The aim of emission reduction (minimization)-based studies is to decrease the total pollution from vehicles. Various types of optimization algorithms and models are proposed and discussed, such as in the [14] whale optimization algorithm (WOA) algorithm combined with the tabu search algorithm and local search procedures; and in [21] grey wolf optimizer is prefered. In [4], the multipath (multiple possible arcs for traveling between two vertexes) map on an urban area of Berlin is considered with randomly generated demands (orders). Historical information about the traffic of the road (arc) is a parameter of the problems for a green VRP, and in [17], the time-dependent multidepot green vehicle routing problem with time windows (TDMDGVRPTW) is considered based on the historical traffic information of the network. Connected and automated vehicles (CAVs) use the technologies of communication and control to accelerate and break the vehicle without (or very little) driver intervention, and a hybrid particle swarm optimization (HPSO) algorithm is developed to solve this problem.

Localization and routing problems are joined in [2] and are called the green stochastic open (stochastic customers' location) location-routing problem (GSOLRP), where different vehicles are assigned with respect to the demand and road limitations with uncertainty (Taguchi's method is applied for parameter estimation). A hybrid metaheuristic method joining the imperialist competitive algorithm (ICA) and variable neighborhood search (VNS) was developed in [2]. The multiobjective multidepot heterogeneous vehicle capacitated arc routing problem (CARP) is solved for G-VRP in [10], where four objectives are given for the problem: total cost, emission, span and load utilization rate. For this problem, a memetic algorithm based on Two Arch2 (MATA) is proposed and compared with the D-MAENS, MDILSMA/D, and IACO algorithms. The usage of electrical vehicles makes the emissions zero (carbon-free); however, the charging time and charging frequency are the reasons for the VRP problem for electrical vehicles. Charging stations are considered to be vertexes on the map [44]. In [46], a day-ahead scheduling framework is proposed as the electrical vehicle routing problem, and it is solved by using the salp swarm algorithm (SSA) on a real-life case from San Francisco.

The time window property of the VRP is inserted into the electrical VRP in [61], where the elitist genetic algorithm addresses the electric vehicle routing problem with a time window, and it is applied to the simulation of a postal service system problem. In [58], the VRP named the green mixed fleet vehicle routing problem with realistic energy consumption and partial recharges (GMFVRPREC-PR), which contains three important aspects (realistic energy consumption, partial recharging policy, and carbon emissions) is discussed, and an adaptive large neighborhood search heuristic is developed to solve the problem. In [56], an electric vehicle routing problem with mixed back-hauls, time windows, and recharging strategies (EVRPMBTW-RS) is proposed in such a way that the total travel cost is minimized as an objective of the problem and is solved. Similar to stochastic (dynamic) VRP, electrical vehicles are also considered for dynamic cases. In [48], a dynamic electric vehicle routing problem (DEVRP) is proposed, where the demand from customers, battery capacity and load degree change with respect to time while minimizing the total driving distance. The adaptive memetic algorithm (MA) for DEVRP is proposed, and the alternating direction method of the multipliers (ADMM) solution algorithm is developed to solve the applied problem. Carbon emissions minimization is one of the aims of CAV technologies [7]. Therefore, in [7], the speed of the vehicle is selected as the decision variable for low-carbon VRP for CAVs. As some of the electrical vehicles, drones (or UAVs) are used for delivery to specific areas in such a way that they can pick up from a center (depot) and deliver to specific locations with a defined flying time with respect to the battery power. These problems are named VRP-drones (VRPDs). In [15], in VRPDs, vehicles (drones) make deliveries as long as the capacity and constraints are not exceeded. A hybrid approach to improve the combination of sweep and genetic algorithms is proposed for VRPD [15].

Data availability The datasets generated during and/or analyzed during the current study are not publicly available due to the research on these datasets still going on but are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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