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IMPROVED WATER FLOW-LIKE ALGORITHM FOR CAPACITATED VEHICLE ROUTING PROBLEM

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ABSTRACT

The capacitated vehicle routing problem (CVRP) has many applications in different domains seeking ways to minimize the total traveled distance. Although the CVRP has been widely investigated in the literature, it is facing ongoing operational challenges. Moreover, despite various metaheuristics that have been proposed to solve this problem, its optimal solution is still not achieved. Thus far, the water-flow-like algorithm (WFA) has obtained a reasonable solution for this problem, with room for further improvement. The WFA has strategies for diversification (in the precipitation operation). This study aims to enhance the WFA for solving the CVRP by providing a good solution in terms of diversity and quality. The basic WFA is capable of solving the CVRP, however, it has problems in terms of slow convergence and the tendency of being trapped in the local optimum. Therefore, an improved WFA (IWFA) is proposed in this study to overcome this weakness by increasing the diversity of solution search in the precipitation operation using constructive heuristics (i.e., nearest neighbor, random method, and greedy randomized adaptive search procedure). Constructive heuristics aim to construct new solutions instead of duplicating existing ones. Computational results show that the IWFA outperforms the basic WFA with a solution quality improvement of up to 76.92% and is better than other state-of-the-art methods by up to 74.55%. This finding indicates that the IWFA is a promising approach for solving instances of CVRP.

Keywords: *Capacitated Vehicle Routing Problem, Metaheuristics, Constructive Heuristics, Water-Flow-Like Algorithm.*

1. INTRODUCTION

Efficient distribution of goods is of paramount importance, not only for the survival of many logistic service providers, but ultimately for the competitiveness of a region's economy by lowering the cost of goods to consumers. Cost savings can be achieved, in particular, through the use of high quality routes and schedules for the fleet of vehicles that performs distribution tasks.

The capacitated vehicle routing problem (CVRP) is a complex combinatorial optimization problem (COP), which is categorized as a nondeterministic polynomial-time (NP)-hard problem [1]. The CVRP is a combination of two NP-hard problems, namely, the traveling salesman problem (TSP) and the bin packing problem (BPP) [2]. First proposed by [3], the CVRP is described as the problem of designing the shortest route from a central depot to a set of scattered points with identified demands [4]. As an NP-hard problem, numerous optimization methods have been proposed to solve the CVRP, and such methods vary in terms of their complexity, efficiency, and capability to fulfill their tasks [5]. The development of efficient optimization algorithms is an exploratory research field because numerous real-world problems can be modeled as an optimization problem and should be solved to optimality or near-optimality within a reasonable time. In this respect, the algorithm design literature has been growing continuously in two directions, that is, developing new search strategies and improving the performance of the existing search procedures by the modification or hybridization of one search procedure with other search procedures [6].

Optimization algorithms are classified into two groups, namely, exact and heuristic methods [7], [8]. Exact methods, such as dynamic, branch and bound [9], and mathematical [10] programming approaches, can guarantee the optimal solution of the problem. However, these methods require an

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excessive amount of time to identify the optimal solution as the problem size increases [11], [12], [6]. Therefore, heuristic algorithms are more widely used than exact solution procedures to obtain satisfactory solutions within an acceptable computation time [13]. Heuristic algorithms can be divided into two categories, namely, constructive heuristics and metaheuristics [2]. Constructive heuristics, such as the nearest neighbor (NN) [14], [15] and the saving heuristic of Clarke and Wright [11], are typically the fastest methods employed for constructing a feasible solution [4], [17]. The quality of the generated solutions contributes to determining the best solution for the problem. Therefore, these algorithms are seldom used as stand-alone algorithms to deal with the COP [18]. For additional information, the readers are referred to [19], [20], [21]. Metaheuristic algorithms can be classified into two main categories, namely, single-solution-based metaheuristics (S-metaheuristics) and population-based metaheuristics (P-metaheuristics) [22]. The S-metaheuristic algorithms, such as simulated annealing[23], [24] and greedy randomized adaptive search procedure (GRASP) [25], have the capability to exploit the search space in a short time, but have several weaknesses, such as weak exploration and the tendency to be trapped in the local optima [22], [26]. The P-metaheuristic algorithms, such as genetic algorithm (GA) [27], [28], particle swarm optimization (PSO) [29], cuckoo search (CS) [30], [31], and ant colony optimization (ACO) [32], [6], are more concerned with exploration, rather than exploitation, by dealing with a set of solutions. However, these are limited by premature convergence and low convergence speed. For additional information about metaheuristic algorithms, the reader is referred to [33]. Therefore, having an adequate combination of complementary algorithmic concepts can be the key for achieving good performance in solving many hard COPs [34], [35], [36].

A new metaheuristic called water-flow-like algorithm (WFA) has emerged in the literature. The WFA is based on the reproduction strategy of the natural behavior of water flowing from a high level to a low level with four base operations, namely, flow splitting and moving, flow merging, water evaporation, and water precipitation, as described by [37]. The WFA has been successfully applied to a wide range of optimization problems. [38] proved that the WFA outperforms other metaheuristic algorithms in terms of the speed and accuracy for solving the TSP. The motivations for using the WFA are as follows:

- The WFA is population based, such that it can dynamically address population size through the splitting and merging operations, in contrast to other metaheuristic algorithms, such as GA and ACO, whereby the number of solutions can increase or decrease during the optimization process.
- The WFA can use the important features of metaheuristic algorithms by being self-adaptive in addressing the other parameters during the algorithm iterative search process.
- The WFA can avoid being trapped in the local optima and can search within a large solution space using the evaporation operation.
- The WFA reduces the number of solutions when multiple solutions move to the same location (objective value) to avoid redundant searches that typically lead to wasted resources.
- The WFA is characterized as being simple and flexible, thus motivating scholars to perform several modifications to improve its performance.

The basic WFA for CVRP (WFA-CVRP) was proposed by [5]. The results of WFA-CVRP show that the WFA performs well in terms of solution quality. However, exploration process improvement is needed, because the WFA has the tendency to be trapped in the local optima. This finding can be attributed to the lack of diversity in the precipitation operation, which tends to duplicate the same current solution. Enhancing the diversity of population-based problems has been addressed by other scholars [39], [40], [41]. This is important because diversification is crucial to the performance of the population-based algorithm [42]. In the WFA, the precipitation operation has been shown to play an important role in increasing the diversity of the solution space in the WFA [26], [37], [43]. This precipitation operation often does not elicit adequate attention toward the WFA design. Enhancing such a strategy can increase the diversity of the solution to support the efficiency of finding the global minimum [26], whereby the same number of current solutions is being duplicated when performing this operation during the WFA process. However, this condition indicates that the WFA has a significant chance of being trapped in the local optima due to the lack of solution diversity. To solve this insufficiency, the WFA can be improved by constructive heuristics to create the solutions instead of duplicating them. In this study, we employ three of the most well-known constructive heuristics that are used in constructing the solutions for the CVRP. These heuristics are NN, random method (RM), and GRASP. The main research question of this work is, "What is the right constructive heuristic to construct an initial population instead of duplicating the same current solutions that can be enhanced in the WFA exploration to sufficiently cover the search space?". The answer of this research question will be found during the experiments.

The remainder of this paper is organized into sections. Section 2 provides a brief review of the literature on the WFA. Section 3 provides a description of the problem. Section 4 presents the WFA. Section 5 discusses the exploration of the WFA using the constructive heuristics in the precipitation operation for solving the CVRP. Section 6 presents the computational and analysis results that are used to select the most suitable constructive heuristics for the proposed WFA and compares the performance of the proposed improved WFA, which we call IWFA, with that of other state-of-the-art methods. Finally, Section 7 draws the conclusion and suggests areas for further research.

2. RELATED WORKS

Compared with other metaheuristics, such as GA and AC, the WFA has been successfully used to solve a variety of real-world problems. [37] proposed the WFA for the BPP and used a random solution to generate the initial solution to ensure solution diversity. They used the neighbor advancement method to determine the best neighborhood solution of the current solution. The results show that the WFA outperforms the GA, PSO, and electromagnetic-like mechanism. [44] improved the WFA through the WFACF model to solve the manufacturing cell fraction problem. The model utilizes the similarity coefficient and machine assignment methods, as well as part assignment, to generate an initial feasible solution in the first stage, whereas in the second stage, they used flow splitting and moving to improve the solution using machine shifting and insertion move. Both stages were completed to determine the best neighborhood of the current solution. The proposed WFACF performed better than the hybrid GA and simulated annealing. [43] applied the modified WFA (MWFA), which utilized the tabu search and gradient descent techniques for solving the recurrent fuzzy system, to obtain high-speed convergence and reduce the computational complexity. Their results showed the effective performance of the MWFA in solving the problem. [38] proposed the WFA for solving the TSP. The WFA-TSP used NN to construct the initial solution and applied the one-step insertion move with the two-opt neighbor search strategies for splitting and moving. The experimental results show that the WFA-TSP has outperformed the ACO in terms of the best solution and computation time for all datasets.

Meanwhile, [45] developed the WFA by combined with simulated annealing to construct an initial solution for later improvement, and the two-opt was used to find the best neighbor. The experimental results revealed the competitiveness of the proposed algorithm compared with other algorithms. [46] proposed a hybridized WFA with tabu search for the TSP. They used RM to construct the initial solutions and employed the two-opt and three-opt local searches after the splitting operation to improve the intensification characteristics of the algorithm. The aim of this hybridization is to provide a better balance of exploration and exploitation. The analysis result proved that the proposed algorithm provided a better balance of solution exploration and exploitation and possessed significantly better-quality solutions than the base WFA. [47] proposed a hybridized WFA with simulated annealing for the TSP to provide a better balance of exploration and exploitation. They used NN to construct the initial solutions and four local search methods, namely, random swap, two-opt, three-opt, and four-opt, as the improvement methods. The experimental results showed that the hybrid method improved the solution quality compared with the basic WFA. [48] proposed the FWFA, a hybrid between fuzzy logic and WFA methods, to construct the decision support system for selecting the objective strategy in road traffic engineering. The best decision was proposed to decrease the level of traffic congestion. [49] proposed the WFA for solving the wafer probing scheduling problem and combined the mutation strategy aims to explore solutions of unvisited regions through the precipitation operation [26]. [49] proposed the enhanced precipitation operation of the WFA for solving the wafer probing scheduling problem by using the mutation strategy to explore solutions of unvisited regions through the precipitation operation. Table 1 shows the summary of studies related to the WFA.

Table 1Summary of studies related to the WFA and their characteristics for different problems

Author	Proposed for	Enhanced method	Aims to
[37]	Bin packing problem	RM and advanceme nt method	Generate the initial solution with diversity

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			and find the best neighborhood solution.
[43]	Recurrent fuzzy system	Tabu search and gradient descent techniques	Obtain high-speed convergence
[49]	Wafer probing scheduling problem	Mutation strategy	Explore solutions of unvisited regions through the precipitation operation
[38]	TSP	NN Insertion move and two-opt	Improve the initial solution for more diversity
[45]		SA Two-opt	Improve the initial solution for more diversit
[46]		RM Tabu search, two-opt, and three-opt	Balance between diversification and intensification
[47]		NN SA, swap, two-opt, three-opt, and four-opt	Balance between diversification and intensification

3. THE CAPACITATED VEHICLE ROUTING PROBLEM

The CVRP is described as a graph theoretic problem. We let $G = (N, E)$ be a complete and undirected graph, where $N = (0, \ldots, n)$ is the node set and $E = ((i, j)\text{: } i, j \in N)$ is the edge set. Node set $N = (0, 1, 2, \ldots, n)$ corresponds to n customers, whereas node 0 corresponds to the depot that is the start and end node of the vehicles for their trips. The other nodes represent the customers having a nonnegative demand, di, and each customer must be served by exactly one vehicle. The traveled distance from node i to node j is defined as $dij > 0$, and each vehicle has a unique capacity of Q_k. The total demand of the customers assigned to a route must not exceed the capacity of the vehicle. The objective of this problem is to determine the routes that minimize the total cost (distance), that is, it aims to solve the problem of assigning customers to vehicles and determining customer visit sequences for each route to minimize the total traveled distance by the vehicles. In accordance with these explanations, the mathematical model for the CVRP can be written as [5].

3.1 Metaheuristic for the CVRP

Developing efficient optimization algorithms is an exploratory research field because numerous real-world problems can be modeled as an optimization problem and must be solved to optimality or near-optimality in a reasonable amount of time [6], [31]. In this respect, the algorithm design literature has been growing continuously in two directions: developing new search strategies and improving the performance of the existing search procedures by modification or by hybridization of one search procedure with other search procedures [6].

[28] proposed the improved GA based on the local mutation operator. A two-layer chromosome coding scheme is designed, which can improve the initial solutions. Their improved measures have considerable significance in suppressing the procedural intricacy degree to enable convergence. [27] combined the sweep algorithm with GA in order to enhance the exploration of the GA, thereby avoiding convergence in a limited region and enhancing the search capability of the GA in approaching a close-to-optimal solution. Other research proposed by [50], [51] have improve GA by using mutation to preserve the solution diversity. [15] proposed the enhanced ACO by using NN to overcome the shortcomings of the ACO, such as its slow computing speed and local convergence, to improve the performance of the algorithm and the quality of the solutions. [6] combined LNS with ACO and aimed to provide a satisfactory level of diversification. [52] proposed the ACO with scatter search to obtain the capability to explore different parts of the solution space and to find better solutions. [29] proposed the combinatorial expanding neighborhood topology particle swarm optimization (CENTPSO) method, which aimed to take advantage of the exploration capabilities of a global neighborhood structure.

4. WATER FLOW-LIKE ALGORITHM

The WFA was designed to mimic the natural behavior of water flowing from a high to a low level, which helps in the process of searching for an optimal solution. Flows can be split into subflows or merged into one flow according to the topography

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of the search space. Flowing water is regarded as problem solving. Hence, a flow is modeled as a solution, and the solution space of a problem is analogous to the geographical terrain. The objective function value is modeled as the flow altitude. The WFA has been applied to solve various COPs. The WFA consists of four base operations, namely, flow splitting and moving, flow merging, water evaporation, and water precipitation, which have been adopted to search for the global optimum.

5. WFA for the CVRP

[5] applied the WFA to solve the CVRP (i.e., WFA-CVRP). Therefore, the difference in applying the WFA-CVRP lies in its data representation. This shall be discussed in the subsequent paragraphs. As for the WFA-TSP, the solution is presented as one-dimensional array with a length M, where M is the number of cities in the original dataset. Each cell value in the array represents the number of cities selected in a specific order in the solution. Figure 1 shows a sample solution representation of a TSP solution. A feasible solution is represented as a sequence of nodes, where 1, 2, 3, …, M represents the indexed cities and 4, 3, 10, …, 7 represents the city numbers arranged in the sequence indicating a specific tour path. The initial solution is constructed using the NN.

City index	1	2	3	4	5	6	7	8	…	*M*
Cities	4	3	10	6	1	9	8	12	…	7

Figure 1: Example of the solution representation of the TSP in the WFA

In the WFA-CVRP, the solution is presented as a one-dimensional vector, where the numbers 1 to 8 represent the customers and 0 indicates the depot. The length of the solution represents the total number of customers. Each solution has a number of routes that can be counted based on the total number of 0 minus 1. The example of the solution representation, as shown in Figure 2, has three routes. The first route serves two customers (7 and 4), the second route serves three customers (5, 8, and 2), and the third route serves three customers (3, 6, and 1). The initial solution is generated by randomly selecting customers for the current route without violating the capacity of the vehicle. If a violation occurs, then a new route is created and this procedure is repeated until all the customers are routed.

Route 1	0	7	4	0	
Route 2	0	5	8	2	0
Route 3	0	3	6	1	0

0	7	4	0	5	8	2	0	3	6	1	0

Figure 2: Example of the solution representation of the CVRP in the WFA

Although the analysis of the experimental results shows that the WFA-CVRP has exhibited good performance, WFA can be easily trapped in the local optimum. Thus, the WFA lacks diversity in the precipitation operation, which tends to duplicate the same number of current solutions when performing the precipitation operation. [45] has increased the diversity of the WFA in the TSP by improving the initial solution using simulated annealing. Meanwhile, [43], [26] have improved the precipitation operation strategies using gradient descent techniques. The results showed significant improvement. Furthermore, the results were more consistent with the natural behavior of water flow, thus increasing the diversity of the solution. Several constructive heuristics can be used to ensure diversification in the precipitation operation, as discussed previously. The literature has shown that various constructive heuristics can be used. These constructive heuristics are ranked in order of popularity as follows: NN [15], [24], [53], [54], [55], RM [6], [8], [51], [56], [57], [58], [59], GRASP [60], [61], [62], [63], [64], saving heuristic of Clarke and Wright [16], [65], [66], and insertion heuristics [67], [68].

5.1 IWFA for the CVRP

The proposed IWFA has all of the components of the WFA proposed by [5], with the improved precipitation operation component. The role of the precipitation operation is to explore a wide area. Therefore, the proposed IWFA aims to increase the exploration of the solution space and prevents flows from stopping the search process. The precipitation operation handles two possible condition, namely, enforced precipitation and regular precipitation.

Enforced precipitation is used when no improvement is achieved for all of the solution searches after *a number of* iterations. In this case, all flows must evaporate and return to the ground as precipitation with the same number of current flows to prevent flows from stopping the search process. In the WFA-CVRP, when no improvement is achieved for all of the flows in the solution search after a number of iterations, random swapping is performed between two customers in the solution in order to reassign new locations randomly to flows.

Regular precipitation is applied after *t* iterations (same *t* values as those in evaporation) to return the evaporated water and to balance water evaporation. In the basic WFA, *N* new flows (solutions) are poured down, thus duplicating the same number of current flows (solutions) to increase the diversity of the solution. However, a possible drawback is that such a population would lack the diversity necessary to obtain near-optimal solutions when the same solutions are duplicated, because the current and newly poured solutions will still be searched in the same solution space.

Three constructive heuristics, namely, NN, RM, and GRASP, are proposed to construct the same number of current solutions instead of duplicating the same solutions, thus providing considerable opportunity to enhance the WFA-CVRP to diversify the solution space effectively because constructive heuristics construct different solutions to start the search. Figure 3 shows the pseudocode of the proposed IWFA using NN.

The NN algorithm used in this study was first introduced by [69]. First, for each vehicle, an unserved node *i* is randomly selected. Then, from among the unsequenced nodes, the NN algorithm selects node *j*, which minimizes the length between *i* and *j* (*if two or more nodes are at the same closest distance, then simply select one of them*) and iterates the same process on node *j* until a complete tour is constructed. The constructive heuristics is performed when the regular precipitation conditions is met.

```
Generate empty solution
repeat number of route
Initial empty route.
Select unvisited node i randomly;
insert i in the route;
    repeat the following until all costumers are visited
    Select unvisited point j that minimizes the distance
     between i and j;
     If the demand of j ≤ capacity of route
     insert j in the route;
     end
calculate route demand;
calculate route distance;
solution [count] = route;
end
return solution
```

Figure 3: Pseudocode of the NN

Figure 4 shows the proposed IWFA using RM. The RM generates the initial solution in many optimization problems. This method randomly generates an initial solution with uniform probability. The RM algorithm follows the algorithm proposed by [22]. The pseudocode of the WFA-RM is also shown in Figure 4.

```
Generate empty solution
repeat number of route
Initial empty route.
    repeat the following until all costumers are
           visited
        Select unvisited point i randomly;
        If total demand of i <= capacity of route
        insert i in the route;
    end
calculate route demand;
calculate route distance;
solution [count] = route;
end
return solution
```

Figure 4: Pseudocode of the RM

Figure 5 shows the IWFA using GRASP, which is an iterative process that uses a multi-start method where each iteration consists of the construction and improvement phases. As each initial solution is generated using one greedy randomized heuristic, the constructed solution is improved by a local search until the local optimal solution is obtained. However, the present work attempted to generate the initial solution in the construction phase. In the construction phase, one element at a time is iteratively constructed for a feasible solution. At each iteration, the subsequent element that can be inserted into the partial solution is then determined by arranging all of the elements in a candidate list. With a greedy function, the incremental cost is evaluated for each candidate element. The candidates are arranged based on their greedy value in a restricted candidate list (RCL). At each iteration, one candidate element is randomly selected from the RCL, after which the element is added to the partial solution (this step denotes the probabilistic aspect of the heuristic). The RCL is updated once the element has been added to the partial solution. This update is implemented by reevaluating the greedy value of the unvisited candidate elements (this step denotes the adaptive aspect of the heuristic) [70]. The pseudocode of the WFA-GRASP is illustrated in Figure 5.

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```
Generate empty solution
Repeat number of route
Initial empty route s.
  Repeat the following until all costumers are visited
  determine the feasible element i, and add it to
   the candidate list cl;
   generate a restricted candidate list (RCL)
   based on the greedy value of the cl;
   RCL ← g(i) ≥ gmin + α(gmax − gmin);
   randomly select element j from the RCL;
   insert j into the route;
   end
calculate the route demand;
calculate the route distance;
solution [count] = route;
return solution
```

Figure 5: Pseudocode of the GRSP

For the neighborhood structures, three neighborhood structures (i.e., swap, move, and two-opt operator) are selected randomly to generate a number of neighbors as subflows from the original solution, as presented in [5]. The new neighbors are generated randomly and added to the population. If the new neighbors are feasible, then the population is sorted. Flow movement is a solution search from the current solution to the new solution. The new solution will not be generated from the original solution if the momentum of the original solution is zero, and in this case, the original solution will be considered a stagnant solution.

6. RESULTS, COMPARISONS, AND DISCUSSION

The proposed algorithm was coded in Java platform JDK 1.6, a Windows environment, and a personal computer with an Intel core i7 (2.20 GHz CPU speed and 8 GB RAM). In this work, Java language is selected because it has the capability to deal with object-oriented and cross-platform programming and is widely used by many researchers. The performances of the IWFA variants were evaluated by testing them on 55 CVRP benchmark datasets from http://vrp.atd-lab.inf.puc-rio.br/. The tests were carried out to determine which of the methods can improve the exploration of the basic WFA and to evaluate the efficiency of the proposed IWFAs. The selected instances were distributed equally on each dataset based on the number of customers. In testing the improvement methods, this study used the same computer resources and programming languages employed by [5] to test the diversity measurement method. The minimum result (Min), average (Avg), and standard deviation (Std) values of 31 independent runs are then reported. The significance test for non-normal distributed results, called nonparametric test, is performed to verify that the results of these variants are statistically significant. Two types of nonparametric tests, namely, the Wilcoxon signed rank and Friedman tests, are used [22], [71].

6.1 Parameter Setting and the Number of Runs Performed

Several parameters should be assigned before the IWFA initiates the search process. The algorithm adjusts these parameters in a dynamic manner during the optimization process. We compared the results of different parameter values to set the appropriate values of the parameters of the IWFA in order to solve the CVRP. Table 2 shows the minimum distance result of the IWFA with different parameter setting values. The statistical analysis test was performed to determine whether any significant difference exists between these parameter values.

Table 2 Minimum distance result obtained by the standard WFA for different parameter setting values

Instance	Best solution for different parameter setting values		
	$W = 4$, $V = 3$, $T = 6$, $\max(n) = 2$	$W = 8$, $V = 5$, $T = 20$, $\max(n) = 3$	$W = 15$, $V = 10$, $T = 30$, $\max(n) = 5$
E-n22-k4	**375.28**	**375.28**	**375.28**
E-n23-k3	**568.56**	**568.56**	**568.56**
E-n33-k4	**837.67**	**837.67**	**837.67**
E-n76-k8	777.74	**774.41**	788.30
E-n76-k10	882.24	**876.78**	**876.54**
E-n101-k8	879.56	878.55	**874.62**
E-n101-k14	1,178.16	**1,144.11**	1,189.71
M-n151-k12	**1,147.87**	1,149.37	1,166.59

For the statistical analysis, the Wilcoxon test was used to evaluate the effect of different parameter values on the performance of the algorithm, as shown in Table 3. Although Table 2 shows that the parameter values W =8, V =5, T =20, and $\max(n)$ =3 are better than the other parameter values, no significant improvement can be observed between parameter values W =8, V =5, T =20, and $\max(n)$ = 3 and other parameter values, as shown in Table 3.

Table 3: Results of the Wilcoxon test for different parameter values

$W = 8$, $V = 5$, $T = 20$, $\max(n) = 3$ vs.	**$W = 4$, $V = 3$, $T = 6$,**	**$W = 15$, $V = 10$, $T = 30$,**

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	max(n) = 2	max(n) = 5
E-n22-k4	=	=
E-n23-k3	=	=
E-n33-k4	=	=
E-n76-k8	=	=
E-n76-k10	=	=
E-n101-k8	=	=
E-n101-k14	=	=
M-n151-k12	=	=

The parameters of the IWFA are set in our preliminary experiments, as shown in Table 4.

Table 4: Parameter settings of the WFA-CVRP

	Parameter	Value
1	Base momentum T	20
2	Initial mass W_0	8
3	Initial velocity V_0	5
4	Limit number of subflows max(n)	3

6.2 Results of the IWFA for the CVRP

The IWFAs were tested on the CVRP datasets with different levels of complexities to determine which of the proposed methods can improve the exploration of the basic WFA. The tests were done to evaluate the efficiency of the proposed IWFAs. The selected instances were distributed equally on each dataset based on the number of costumers. The same computer resources and programming languages used to test the diversity measurement method were used to test the improvement methods. The Min, Avg, Std, and median values of 31 independent runs are then reported.

6.2.1 Experimental results

This section presents the experimental results of three types of proposed IWFAs for the CVRP.

- WFA with NN.
- WFA with RM.
- WFA with GRASP.

The following types of experiments were conducted:

a. The first experiment aimed to investigate the performance of each IWFA variant in enhancing the exploration mechanism in the precipitation operation compared with the basic WFA;

b. The second experiment aimed to investigate the performance of each IWFA variant against one another; and

c. The third experiment aims to verify the efficiency of the winning IWFA variant compared with other state-of-the-art methods.

a. IWFA Variants compared with the basic WFA for the CVRP

In this experiment, the results of the basic WFA are compared with those of the IWFAs to identify which of the proposed methods is better in exploring the basic WFA. The performance of the proposed algorithms is tested on 13 instances, which represent the small, medium, and large instances. The best (Min) results are reported for each tested CVRP instance. The overall purpose of this comparison is to evaluate the effectiveness of NN, RM, and GRASP in the basic WFA in obtaining a solution with good quality.

Table *5* presents the results of the basic WFA versus WFA-NN, basic WFA versus WFA-RM, and basic WFA versus WFA-GRASP. The best results are shown in bold font. The experiment uses 13 datasets representing the small, medium, and large datasets.

Table 5: Comparison of the minimum solution (distance) and gap between the basic WFA and the proposed methods (i.e., NN, RM, and GRASP)

The last three columns show the differences between the solution results of the proposed IWFA and of the basic WFA. The first three dataset results show that the IWFA has reached the shortest path solution similar to the basic WFA. However, the results show negative values indicating the extent of the differences of the solutions between the IWFA and the basic WFA. The results show that all of the proposed IWFAs obtained better results than the basic IWFA. Thus, we can conclude that solution diversity can be enhanced and better results can be obtained by adding and/or constructing new solutions instead of duplicating the same number of current solutions during the precipitation operation. Furthermore, among all the proposed IWFAs, the IWFA using NN presented the best result. Moreover, the WFA-NN presented the best result among all the proposed IWFAs for all instances, and NN presented the largest difference value. The proposed IWFAs, namely, WFA-NN, WFA-RM, and WFA-GRASP,

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exhibited improved performance of up to 63.04%, 30.26%, and 31.46%, respectively, compared with the baseline.

b. Comparison among the IWFA variants

The performance and behavior of the proposed IWFA is further investigated based on the best solution (Min), Avg, and Std.

Table 6 shows the comparison of the results of all of the proposed IWFAs.

Table 6 shows that WFA-NN consistently obtained the most Min solution for all datasets. Furthermore, WFA-NN obtained better results in terms of low Avg and Std. This result proves that the WFA-NN presents a more robust and stable algorithm than the other proposed IWFAs. Next, to verify whether the results are different, the performance of the proposed algorithm has also been tested using the Wilcoxon test with a significance interval of 95% ($\alpha = 0.05$) critical level. Pairwise comparison was executed for the basic WFA and the other proposed algorithms. Table 7 presents the *p* value of the basic WFA versus those of other proposed algorithms for the CVRP instances. In Table 7, the symbol "+" denotes that the basic WFA is statistically better than the contending proposed algorithms (*p* value < 0.05), "–" denotes that the basic WFA is outperformed by the contending proposed algorithms (*p* value > 0.05), and "=" denotes that the basic WFA exhibits the same performance as the contending proposed algorithms (*p* value = 0.05).

Table 6: Comparison of the Min, Avg, and Std of all of the proposed constructive heuristics (i.e., WFA-NN, WFA-RM, and WFA-GRASP)

The results shown in Table 7 indicate that all of the proposed constructive heuristics are statistically better than the basic WFA in all of the instances, except for one instance, that is, "E-n22-k4," where the basic WFA exhibits the same performance as that of the WFA-RM. This result supports the fact that the modified precipitation operation component improves the performance of the basic WFA. Thus, the proposed methods obtain better results than the basic WFA. Finally, this experiment shows that the performance of the constructive heuristics is considerably better than that of the basic WFA. This is because the IWFA integrates the capabilities of constructive heuristics instead of duplicating the solutions in the precipitation operation of the basic WFA, which can enhance the diversity of the solution to explore different regions of the solution.

Table 7: The p value of each proposed constructive heuristic IWFA-CVRP variant against the WFA-CVRP

Basic WFA vs.	WFA-NN	WFA-RM	WFA-GRASP
Ins. Name	***p* value**	***p* value**	***p* value**
E-n22-k4	–	=	–
E-n23-k3	–	–	–
E-n33-k4	–	–	–
E-n51-k5	–	–	–
E-n76-k8	–	–	–
E-n76-k10	–	–	–
E-n101-k8	–	–	–
E-n101-k14	–	–	–
M-n101-k10	–	–	–
M-n121-k7	–	–	–
M-n151-k12	–	–	–
M-n200-k17	–	–	–
G-n262-k25	–	–	–

We conducted another statistical test, that is, the Friedman test. The Friedman test is a multiple comparison test that compares the proposed algorithm with the other proposed algorithms in the literature. In this statistical test, the average results are used as input data for comparison. The test is applied by testing the significant differences of all of the available algorithms (i.e., our proposed algorithm and the proposed algorithms in the literature). If the *p* value of the test is less than the critical level (i.e., 0.05), then the compared algorithms are ranked to determine the better performing algorithm (a lower value is better). For further statistical analysis, if the results obtained by the Friedman test is significant, then the post hoc methods (Holm and Hochberg statistical test) are applied to adjust the *p* value for each comparison of the best performing algorithms, which are called the controlling algorithms, and the other algorithms [71].

Table 8 presents the average ranking for each compared algorithm produced using the Friedman test. The algorithms are sorted in ascending order, where a lower ranking value indicates a better rank. Notably, the WFA-NN is ranked as the first. The Holm and Hochberg statistical test has also been conducted.

Table 9 presents the adjusted *p* values of the Holm and Hochberg statistical test for each comparison between the WFA-NN (the control method) and the other methods.

Table 9 shows that WFA-NN is statistically better than the other methods because its adjusted *p* value is less than 0.05. The results of the experiments show that the constructive methods can diversify the solution search process unlike the standard precipitation operation in the basic WFA. The results reveal that WFA-NN is able to obtain the results better than the other proposed methods. The NN produces new sol6+utions that maintain the diversity of the precipitation component. The main research question in section 1 (introduction) was answered in this experiment.

Table 8: Average ranks obtained using the Friedman test for each IWFA variant compared with the basic WFA

#	Algorithms	Ranking
1	WFA-NN	1.2143
2	WFA-GRASP	2.3571
3	WFA-RM	2.4286
4	Basic WFA	4

Table 9: Adjusted p value obtained by the Holm and Hochberg statistical test for the WFA-NN versus the other adopted algorithms

#	Algorithms	Unadjusted *p* value	*p* value, Holm	*p* value, Hochberg
1	Basic WFA	0	0	0
2	WFA-RM	0.012827	0.025653	0.019172
3	WFA-GRASP	0.019172	0.025653	0.019172

The results of the statistical tests shown in the previous tables indicate that the WFA-NN outperforms the other proposed algorithms on most tested instances. NN, which uses different starting cities, allows various final solutions to be obtained with better quality solution because NN selects the subsequent costumer, thus minimizing the length between the previous and current costumers. Thus, *n* different solutions may be obtained with this greedy procedure.

c. IWFA compared with other state-of-the-art methods

The results of the IWFA are compared with those of the basic WFA and other state-of-the-art methods. The following algorithms are selected from the CVRP literature. However, the comparison is only based on the Min and Avg. The computational time is also presented even if it cannot be used for comparison.

- CENTPSO: combinatorial expanding neighborhood topology particle swarm optimization [29].
- CS-Ouaarab: improved CS by adopting an extension of CS, called CS-Ouaarab [31].

Table 10 presents the best-quality solutions obtained from the application of IWFA, CENTPSO, and CS-Ouaarab on the CVRP benchmark datasets alongside the best-known results (BKR). The table indicates that the IWFA obtains better results than the other state-of-the-art algorithms for all of the reported instances, except for B-n43-k6. In terms of Avg, the IWFA obtains better results for all of the reported instances, except for E-n51-k5 and P-n50-k8. Notably, the compared methods did not report time. Although the IWFA results are inferior to the BKR for all of the instances, the obtained results for these instances are competitive. From the BKR, the IWFA results are observed to match the BKR for E-n22-k4 and E-n23-k3.

Table 10: IWFA against other state-of-the-art methods

Table 11 shows the percentage deviation and Std based on Min between the IWFA and other state-of-the-art methods with BKR. As can be seen, the percentage deviation for IWFA has a small value compared with the CS-Quaarab and CENTPSO for all datasets, except for B-n43-k6. Such a result indicates that the IWFA has obtained the best algorithm solution for the CVRP. Hence, the IWFA has outperformed the other state-of-the-art algorithms for the CVRP by up to 74.55%.

Table 11: Percentage deviation (Δ (%); Gap) and standard deviation (Std) between the IWFA and other state-of-the-art methods

The experimental results indicate that the constructive methods have diversified the solution search process compared with the standard precipitation operation in the basic WFA. The analysis of the IWFA results shows that it has better performance than other variants as it improves the precipitation operation mechanism. However, the capability of the IWFA gradually decreased during the search process. This problem occurred because of two reasons. First, the results show that IWFA focuses more on exploration rather than exploitation, which is considered a drawback of most P-metaheuristics. Second, in the context of the IWFA, when the solution is generated by the IWFA improvisation process “splitting and moving operation,” it is usually infeasible and requires a repair mechanism. This mechanism leads to the decreased quality of the generated solution because it focuses only on the feasibility regardless of the quality of the solution. Consequently, the hybridization of the IWFA with S-metaheuristics aims to control the balance between the diversification and intensification processes. Improving solution quality through the exploitation capability can be done in future research.

This work introduces an improved WFA algorithm for CVRP. In the improved WFA, the modifications on precipitation operation are used, namely, NN, RM, and GRASP. The experimental results show that the three proposed improved WFA variants outperform basic WFA in terms of solution quality, Avg, Std, and Gap. In addition, WFA-NN obtains the best result against the other constructive method variants and ranks first among the other variants. Furthermore, IWFA obtains better results than those of state-of-the-art methods in terms of quality and average solution. This result is attributed to the nature of the NN, which considers quality and diversity of solutions in the precipitation operation to construct new solutions instead of duplicating the solutions during the search process.

7. CONCLUSION

An IWFA was introduced in this study. The precipitation operation in the algorithm has been improved using three constructive heuristics, namely, NN, RM, and GRASP, to diversify solutions during the route-building process. This finding indicates that the proposed modification within the basic WFA can enhance solution diversity to produce effective-quality CVRP solutions. The proposed algorithm was tested on 55 well-known CVRP instances. The results confirmed the effectiveness of the proposed algorithm in comparison with other state-of-the-art methods, with results showing improved solution quality of up to 74.55%.

Limitations of this work, the capability of IWFA gradually decreases during the search process. This problem occurs because of two reasons: first, IWFA focuses more on exploration rather than on exploitation, which is regarded as a drawback for most P-metaheuristics. Second, in the IWFA context, when the solution is generated by the IWFA improvisation process “splitting and moving operation,” it is usually infeasible and thus requires a repair mechanism. This mechanism decreases the quality of the generated solution because it focuses on only the feasibility while ignoring the quality of solution. For future works, we suggest to hybridize IWFA with another metaheuristic component to improve the solution quality via the exploitation capability and will focus on implementing the proposed improved IWFA algorithm to other variants of VRPs as well as to different COPs.

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Table 5: Comparison of the minimum solution (distance) and gap between the basic WFA and the proposed methods (i.e., NN, RM, and GRASP)

Dataset	Minimum distance				Differences from the basic WFA		
	Basic WFA	WFA-NN	WFA-RM	WFA-GRASP	WFA-NN	WFA-RM	WFA-GRASP
E-n22-k4	**375.28**	**375.28**	**375.28**	**375.28**	0	0	0
E-n23-k3	**568.56**	**568.56**	**568.56**	**568.56**	0	0	0
E-n33-k4	**837.67**	**837.67**	**837.67**	**837.67**	0	0	0
E-n51-k5	545.25	**527.67**	536.60	536.50	−17.58	−8.65	−8.75
E-n76-k8	774.41	**745.96**	751.35	749.41	−28.45	−23.06	−25
E-n76-k10	876.78	**854.98**	865.45	857.83	−21.8	−11.33	−18.95
E-n101-k8	878.55	**838.47**	842.97	848.17	−40.08	−35.58	−30.38
E-n101-k14	1,144.11	**1,112.15**	1,125.30	1,127.89	−31.96	−18.81	−16.22
M-n101-k10	864.95	**827.32**	841.83	840.32	−37.63	−23.12	−24.63
M-n121-k7	1,285.32	**1,063.76**	1,205.70	1,232.04	−221.56	−79.62	−53.28
M-n151-k12	1,149	**1,078.28**	1,084.37	1,080.44	−70.72	−64.63	−68.56
M-n200-k17	1,462.22	**1,390.20**	1,406.38	1,397.85	−72.02	−55.84	−64.37
G-n262-k25	6,403.05	**6,125.34**	6,330.33	6,304.22	−277.71	−72.72	−98.83

Table 12: Comparison of the Min, Avg, and Std of all of the proposed constructive heuristics (i.e., WFA-NN, WFA-RM, and WFA-GRASP)

Dataset	WFA-NN			WFA-RM			WFA-GRASP		
	Min	Avg	Std	Min	Avg	Std	Min	Avg	Std
E-n22-k4	**375.28**	**375.28**	**2.89**	**375.28**	377.97	3.79	**375.28**	377.31	3.85
E-n23-k3	**568.56**	**568.56**	**1.16**	**568.56**	578.49	20.32	**568.56**	577.13	12.69
E-n33-k4	**837.67**	**845.04**	**4.60**	**837.67**	851.38	10.56	**837.67**	850.87	12.68
E-n51-k5	**527.67**	**550.66**	**12.10**	536.60	565.25	18.71	536.50	563.43	22.65
E-n76-k8	**745.96**	775.51	**15.38**	751.35	**771.95**	13.32	749.41	772.20	17.31
E-n76-k10	**854.98**	**884.14**	**17.66**	865.45	898.83	24.69	857.83	893.51	26.54
E-n101-k8	**838.47**	**875.11**	**19.66**	842.97	881.31	28.66	848.17	890.10	25.68
E-n101-k14	**1,112.15**	1,146.30	21.08	1,125.30	**1,141.87**	**14.76**	1,127.89	1,155.38	18.35
M-n101-k10	**827.32**	**854.56**	**14.35**	841.83	895.83	42.14	840.32	940.87	47.25
M-n121-k7	**1,063.76**	**1,100.74**	**17.34**	1,205.70	1,351.98	70.49	1,232.04	1,343.64	63.31
M-n151-k12	**1,078.28**	**1,126.84**	**31.74**	1,084.37	1,164.41	44.30	1,080.44	1,152.05	34.54
M-n200-k17	**1,390.20**	**1,440.27**	**36.29**	1,406.38	1,483.21	44.75	1,397.85	1,473.44	38.40
G-n262-k25	**6,125.34**	**6,421.43**	**107.28**	6,330.33	6,544.71	133.10	6,304.22	6,565.01	137.32

Table 13: IWFA against other state-of-the-art methods

Dataset	BKR	Objective function (distance)						Computational time (s)
		CS-Ouaarab		CENTPSO		IWFA		IWFA
		Min	Avg	Min	Avg	Min	Avg	
A-n32-k5	784	799	819.13	820	821.29	**787.08**	**787.08**	0.5
A-n33-k5	661	685	708.1	687.04	687.88	**662.11**	**662.32**	0.65
A-n33-k6	742	756	771.57	762.39	763.38	**742.69**	**743.99**	0.48
A-n36-k5	799	829	854.63	826.21	827.1	**802.13**	**821.4**	0.79
A-n37-k5	669	700	724.13	693.18	693.92	**672.47**	**685.84**	1.27
A-n45-k6	944	976	1,015.6	988	988.91	**944.88**	**971.16**	4.29
A-n46-k7	914	954	1,021.5	978.23	979.33	**917.72**	**919.93**	1.82
A-n48-k7	1,073	1,145	1,177.1	1,132.15	1,133.13	**1,087.48**	**1,110.11**	1.83
A-n55-k9	1,073	1,117	1,162	1,118.4	1,118.98	**1,074.46**	**1,083.15**	4.60
A-n60-k9	1,354	1,406	1,488.2	1,436.5	1,437.33	**1,355.78**	**1,370.25**	29.9
A-n61-k9	1,034	1,097	1,129.8	–	–	**1,045.08**	**1,074.79**	13.1
A-n62-k8	1,288	1,350	1,419.4	–	–	**1,313.05**	**1,327.08**	20.58
A-n63-k9	1,616	1,720	1,783.6	–	–	**1,633.94**	**1,656.12**	5.82
A-n63-k10	1,314	1,379	1,432	–	–	**1,320.22**	**1,344.77**	6.66
A-n64-k9	1,401	1,500	1,534	–	–	**1,426.33**	**1,459.76**	15.18
A-n65-k9	1,174	1,254	1,302.6	–	–	**1,181.69**	**1,205.39**	14.24
A-n69-k9	1,159	1,239	1,297.8	–	–	**1,170.54**	**1,187.27**	20.47
A-n80-k10	1,763	1,893	1,952.4	–	–	**1,786.94**	**1,811.55**	17.31
B-n35-k5	955	976	983.83	–	–	**956.29**	**958.81**	0.92
B-n38-k6	805	820	831.43	–	–	**808.7**	**811.5**	1.9
B-n41-k6	829	847	861.47	–	–	**834.3**	**840.74**	1.27
B-n43-k6	742	**745**	757.27	–	–	746.98	**754.35**	1.5
B-n45-k5	751	774	798.17	–	–	**756.52**	**768.53**	0.63
B-n63-k10	1,496	1,585	1,628.3	–	–	**1,517.3**	**1,544.36**	13.39
B-n64-k9	861	903	932.8	–	–	**868.85**	**881.01**	18.4
B-n66-k9	1,316	1,381	1,412.6	–	–	**1,329.1**	**1,343.17**	6.37
B-n67-k10	1,032	1,095	1,110.9	–	–	**1,040.93**	**1,067.13**	3.76
B-n68-k9	1,272	1,326	1,355	–	–	**1,286.1**	**1,300.60**	39.17
B-n78-k10	1,221	1,302	1,336.1	–	–	**1,230.46**	**1,261.93**	81.82
E-n22-k4	375	–	–	378.56	379.4	**375.28**	**375.28**	0.36
E-n23-k3	569	–	–	–	–	**568.56**	**568.56**	0.3
E-n30-k3	534	–	–	–	–	535.8	537.73	0.16
E-n33-k4	835	–	–	847.38	848.19	**837.67**	**845.04**	0.73
E-n51-k5	521	–	–	544	**545.83**	**527.67**	550.66	2.2
E-n76-k7	682	–	–	–	–	694.36	718.25	45.7
E-n76-k8	735	–	–	–	–	745.96	775.51	23.82
E-n76-k10	830	–	–	–	–	854.98	884.13	52.15
E-n76-k14	1,021	–	–	–	–	1,048.73	1,069.1	53.67
E-n101-k8	815	–	–	–	–	838.46	881.31	59.1
E-n101-k14	1,067	–	–	–	–	1,112.15	1,146.29	116.01
P-n50-k8	631	658	679.53	654.87	**655.67**	**642.61**	663.65	12.9

To be continued

Continuation

Dataset	BKR	Objective function (distance)						Computational time (s)
		CS-Ouaarab		CENTPSO		IWFA		IWFA
		Min	Avg	Min	Avg	Min	Avg	
P-n50-k10	696	741	756.97	–	–	**704.51**	**711.29**	4.22
P-n51-k10	741	784	807.3	773.48	774.41	**741.5**	**756.94**	2.57
P-n60-k10	744	814	827.73	772.86	773.9	**751.29**	**768.98**	19.03
P-n60-k15	968	1,029	1,051.5	1,012.9	1,013.87	**971.58**	**986.62**	6.66
P-n65-k10	792	850	884.17	–	–	**795.66**	**818.83**	16.9
P-n70-k10	827	886	917.67	–	–	**841.40**	**861.92**	10.5
P-n76-k4	593	648	688.1	–	–	**610.67**	**628.94**	86.17
P-n76-k5	627	695	715.8	–	–	**650.13**	**687.5**	5.54
P-n101-k4	681	758	781.07	–	–	**698.9**	**732.28**	306.82
M-n101-k10	820	–	–	–	–	827.32	854.56	12.8
M-n121-k7	1,034	–	–	–	–	1,063.71	1,100.74	27.8
M-n151-k12	1,015	–	–	–	–	1,078.28	1,126.84	201.03
M-n200-k17	1,275	–	–	–	–	1,390.2	1,440.27	360.05
G-n262-k25	6,119	–	–	–	–	6,125.34	6,421.43	85.57

Table 14: Percentage deviation (Δ (%); Gap) and standard deviation (Std) between the IWFA and other state-of-the-art methods

Dataset	BKR	Percentage deviation (Gap)			Standard deviation (Std)		
		CS-Ouaarab	CENTPSO	IWFA	CS-Ouaarab	CENTPSO	IWFA
A-n32-k5	784	1.91	4.59	**0.39**	10.61	25.46	**2.18**
A-n33-k5	661	3.63	3.94	**0.17**	16.97	18.41	**0.78**
A-n33-k6	742	1.89	2.75	**0.09**	9.90	14.42	**0.49**
A-n36-k5	799	3.75	3.41	**0.39**	21.21	19.24	**2.21**
A-n37-k5	669	4.63	3.61	**0.52**	21.92	17.10	**2.45**
A-n45-k6	944	3.39	4.66	**0.09**	22.63	31.11	**0.62**
A-n46-k7	914	4.38	7.03	**0.41**	28.28	45.42	**2.63**
A-n48-k7	1,073	6.71	5.51	**1.35**	50.91	41.83	**10.24**
A-n55-k9	1,073	4.10	4.23	**0.14**	31.11	32.10	**1.03**
A-n60-k9	1,354	3.84	6.09	**0.13**	36.77	58.34	**1.26**
A-n61-k9	1,034	6.09	–	**1.07**	44.55	–	**7.83**
A-n62-k8	1,288	4.81	–	**1.94**	43.84	–	**17.71**
A-n63-k9	1,616	6.44	–	**1.11**	73.54	–	**12.69**
A-n63-k10	1,314	4.95	–	**0.47**	45.96	–	**4.40**
A-n64-k9	1,401	7.07	–	**1.81**	70.00	–	**17.91**
A-n65-k9	1,174	6.81	–	**0.66**	56.57	–	**5.44**
A-n69-k9	1,159	6.90	–	**1.00**	56.57	–	**8.16**
A-n80-k10	1,763	7.37	–	**1.36**	91.92	–	**16.93**
B-n35-k5	955	2.20	–	**0.14**	14.85	–	**0.91**
B-n38-k6	805	1.86	–	**0.46**	10.61	–	**2.62**
B-n41-k6	829	2.17	–	**0.64**	12.73	–	**3.75**
B-n43-k6	742	**0.40**	–	0.67	**2.12**	–	3.52
B-n45-k5	751	3.06	–	**0.74**	16.26	–	**3.90**
B-n63-k10	1,496	5.95	–	**1.42**	62.93	–	**15.06**

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To be continued

Continuation

Dataset	BKR	Percentage deviation (Gap)			Standard deviation (Std)		
		CS-Ouaarab	CENTPSO	IWFA	CS-Ouaarab	CENTPSO	IWFA
B-n64-k9	861	4.88	–	**0.91**	29.70	–	**5.55**
B-n66-k9	1,316	4.94	–	**1.00**	45.96	–	**9.26**
B-n67-k10	1,032	6.10	–	**0.87**	44.55	–	**6.31**
B-n68-k9	1,272	4.25	–	**1.11**	38.18	–	**9.97**
B-n78-k10	1,221	6.63	–	**0.77**	57.28	–	**6.69**
E-n22-k4	375	–	0.95	**0.07**	–	2.52	**0.20**
E-n23-k3	569	–	–	−0.08	–	–	0.31
E-n30-k3	534	–	–	0.34	–	–	1.27
E-n33-k4	835	–	1.48	**0.32**	–	8.75	**1.89**
E-n51-k5	521	–	4.41	**1.28**	–	16.26	**4.72**
E-n76-k7	682	–	–	1.81	–	–	8.74
E-n76-k8	735	–	–	1.49	–	–	7.75
E-n76-k10	830	–	–	3.01	–	–	17.66
E-n76-k14	1,021	–	–	2.72	–	–	19.61
E-n101-k8	815	–	–	2.88	–	–	16.59
E-n101-k14	1,067	–	–	4.23	–	–	31.93
P-n50-k8	631	4.28	3.78	**1.84**	19.09	16.88	**8.21**
P-n50-k10	696	6.47	–	**1.22**	31.82	–	**6.02**
P-n51-k10	741	5.80	4.38	**0.07**	30.41	22.97	**0.35**
P-n60-k10	744	9.41	3.88	**0.98**	49.50	20.41	**5.15**
P-n60-k15	968	6.30	4.64	**0.37**	43.13	31.75	**2.53**
P-n65-k10	792	7.32	–	**0.46**	41.01	–	**2.59**
P-n70-k10	827	7.13	–	**1.74**	41.72	–	**10.18**
P-n76-k4	593	9.27	–	**2.98**	38.89	–	**12.49**
P-n76-k5	627	10.85	–	**3.69**	48.08	–	**16.36**
P-n101-k4	681	11.31	–	**2.63**	54.45	–	**12.66**
M-n101-k10	820	–	–	0.89	–	–	5.18
M-n121-k7	1,034	–	–	2.87	–	–	21.01
M-n151-k12	1,015	–	–	6.23	–	–	44.75
M-n200-k17	1,275	–	–	9.04	–	–	81.46
G-n262-k25	6,119	–	–	0.10	–	–	4.48