Hybrid an Improvement Water Flow-like Algorithm with Single Based Metaheuristic for CVRP

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Abstract
Water-flow-like algorithm (WFA) has shown a reasonable solution for the Capacitated Vehicle Routing Problem (CVRP). However, applying the basic WFA has problems in terms of slow convergence and being faster trapped in the local optimum and later it has been improved it quality solution at precipitation mechanism especially on diversification strategic at precipitation operation known as IWFA. However, the diversification strategy only solved exploration problem rather than exploitation. Therefore, this paper aims to propose a hybrid IWFA with single-solution-based metaheuristics to overcome the problem. Four algorithms which are Best Improvement (BI), First Improvement (FI), Great Deluge (GD) and Simulated Annealing (SA) have been tested. Experiments were conducted using the Standard CVRP dataset benchmark. The experiment results show that Hybrid IWFA with Great Deluge has obtained the best solution. The proposed algorithm not only be able to obtain the benchmark solution for small datasets similar state of art algorithm but it's also able to obtain better solution for large datasets compare with the state of art algorithm faster.

Key words:
Water- flow like algorithm, CVRP, Great Deluge, Hybrid metaheuristic

1. Introduction

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]. Various metaheuristic algorithms such as genetic algorithm (GA) [2], [3], particle swarm optimization (PSO) [4], cuckoo search (CS) [5], [6] and ant colony optimization (ACO) [7], [8] are used for CVRP. Those algorithms are focusing on exploration rather than exploitation, which premature convergence and low convergence speed. Boussaïd, et al. (201) has discussed the comparison on the performance of the algorithms in terms of the speed and accuracy but for solving the Traveling Sales Problem. WFA is characterized as being simple and flexible, thus motivating scholars to perform several modifications to improve its performance [39][40].

The basic WFA has been applied for the CVRP solution (WFA-CVRP) [15]. WFA-CVRP has shown its ability for the quality solution. However, applying WFA-CVRP has problem trapping at the local optima. This causes a 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 [16], [17], [18]. This is important because diversification is crucial to the performance of the population-based algorithm [19].

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 [20], [13], [21]. This precipitation operation often does not elicit adequate attention toward the WFA design. Enhancing such strategy can increase the diversity of the solution to support the efficiency of finding the global minimum [20], 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 generating constructive heuristics, which create the solutions instead of duplicating them. In this paper, to enhance the operation, three constructive heuristics have been used to improved WFA which is nearest neighbour (NN), random generation method (RGM), and greedy random adaptive search procedure (GRASP). The result shows NN has shown the best solution. However, the IWFA focus on exploitation but lack of exploration. Therefore, this paper aims to improve the IWFA, after the splitting process in WFA using a single based metaheuristic.

The remainder of this paper is organized into sections. Section 2 provides related work on WFA and CVRP. Section 3 proposed the hybrid IWFA algorithm for CVRP. Section 4 discusses the experimental setup while section 5 presents the computational and performance result of the Hybrid IWFA compare with IWFA and other state-of-the-art methods, followed by the last section is concludes the finding.

2. Related Work

The CVRP is described as a graph-theoretic problem. We let G = (N, E) be a complete and undirected graph, where N = (0, …, n) is the node-set and E = ((i, j): i, j N) is the edge set. Node set N = (0, 1, 2, …, n) corresponds to n customers,

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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 Qk. 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 [15].

2.1 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 [8], [6]. 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 [8].

Jie-Sheng [3] has proposed an 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. The research of combining the sweep algorithm with GA to enhance the exploration of the GA, thereby avoiding convergence in a limited region had to enhance the search capability of the GA in approaching a close-to-optimal solution [2]. Other researches proposed by [22] and [23] have improved GA by using a mutation to preserve the solution diversity. Enhanced ACO using NN to overcome the shortcomings of the ACO, such as its slow computing speed and local convergence increased the performance of the algorithm and the quality of the solutions [24]. Another method of improvement applied, a combination of LNS and ACO, aimed to provide a satisfactory level of diversification [8]. Meanwhile, Xiaoxia [25] had proposed the ACO with a scatter search to obtain the capability to explore different parts of the solution space and to find better solutions. The combinatorial expanding neighborhood topology particle swarm optimization (CENTPSO) method has been introduced, which aimed to take advantage of the exploration capabilities of a global neighborhood structure [4]. Besides, Wedyan and Narayanan [37] had proposed IWD to solve problem-related to capacitated vehicle routing. They applied IWD and the results of this show that the IWD algorithm gives optimal and near-optimal solutions for some CVRP instances. Another research using a cuckoo search algorithm to gain significant improvements in solution quality where it able to discover a near-optimal solution in practical time [5]. Mazidi [38] proposed an improved genetic algorithm and use the ant colony algorithm to solve the CVRP problem.

2.2 Water Flow-like Algorithm for CVRP

Zainuddin et al. (2015) has applied the WFA to solve the CVRP (i.e., WFA-CVRP). Although the analysis of the experimental results shows that the WFA-CVRP has exhibited good performance especially time, 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. The diversity of the WFA in the TSP by improving the initial solution using simulated annealing had increased [26]. Meanwhile, Ching [21] and Che [20] 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 [27], [28], RM [29], [30], GRASP [31], [32], saving heuristic of Clarke and Wright [33], [34] and insertion heuristics [35], [36].

The Improvement WFA (IWFA) uses an 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 prevent flows from stopping the search process. The precipitation operation handles two possible conditions, namely, enforced precipitation and regular precipitation.

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. The result found that NN algorithm has obtained the best result for IWFA.

3. A Hybrid IWFA with Local Search

An IWFA is improved using a single local search after flow splitting and moving to further improve the quality solution. The four local searches have been observed, which using Best Improvement (BI), First Improvement (FI), Great

Deluge (GD) and Simulated Annealing (SA). The algorithm for each local search can be found in [41][41][42][39] respectively. The IWFA shows the improvement of the ability on exploration, which the hybrid IWFA aims to improve the algorithm exploitation. Each local search is triggered. Figure 1 illustrates the flow on how the IWFA been hybrid with local search as a highlighted process after flow splitting and moving, and before the water merging. Applying local search in this step has obtained a better list of candidates for water merging.

The proposed hybrid IWFA algorithm shows more detail in the form of pseudocode in Figure 2 as shown in line 1-23. The hybrid with the three local searches is add in line 9 as mark as bold. Each local search pseudocodes are shown in section 3.1 respectively. Figure 3 below shows the Nearest Neighbour (NN) algorithm as part of the IWFA algorithm. The NN algorithms can be found in [15].

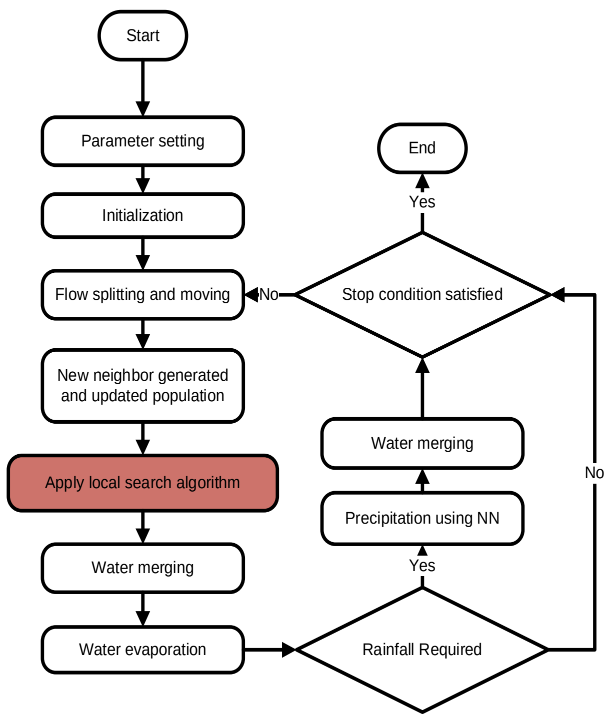


Fig 1 The Hybrid Water Flow

Hybrid IWFA for CVRP

1. WFA parameters setting (Set base momentum T, initial mass W0, initial velocity V0, gravitational acceleration g, upper limit on the number of sub-flows split from a flow $\overline{n}$, iteration limit G).
2. Generate an initial solution Sol "randomly".
3. bestSol ← Sol
4. Do {
5. For each flow i ∈ {1,2,…..N} if velocity > 0. {
6. Calculate the number of sub-flows ni.
7. For each sub-flow k ∈ {1,2,…. ni}. {
8. Distribute velocity (V) and mass (W).
9. Applying local search to generate Sol*.
(using either FI/BI/GD/SA)
10. Calculate solution cost.
11. If (f(Sol*) < f(bestSol))
12. { bestSol ← Sol* } } }
13. Update total number of flows (solutions).
14. Run merging operations.
15. Water evaporation.
16. If (Regular_precipitation conditions meet){
17. Run a regular precipitation operation
18. Run merging operation.}
19. If (Enforced_precipitation conditions meet){ (using NN)
20. Run enforced precipitation operation.
21 Run merging operation.}
22. Update the iteration counter.
23. } while (iteration counter < max_iteration_value)

Fig 2 Hybrid IWFA algorithm with a single based meta-heuristic

4. Experiments Setup

Several parameters have been assigned before the IWFA initiates the search process. Several algorithms dynamically adjust these parameters during the optimization process. However, the parameter in Table 1 (Number 1-4) shows the best result compared to the results of different parameter values to set the appropriate values of the parameters of the IWFA to solve the CVRP. This parameter is a similar setting by Srour, et al. [14].

Three sets of experiments are conducted using three different local searches to identify the best hybrid IWFA. Each experiment runs 30 times. Table 1 (Number 5-12) also shows the number iterations set for each local search and other parameters follow by Srour, et al [14]. The BI and FI were set as 100 iterations while SA and GD were set 1000 iteration.

Table 1: Parameter setting of Hybrid IWFA

Number	Parameter	Value
1	Base momentum T	20
2	Initial mass W0	8
3	Initial velocity V0	5
4	Limit number of sub-flows $\overline{n}$	3
5	BI Number of iteration (NI)	100 iterations
6	FI Number of iteration (NI)	100 iterations
7	SA Number of iteration (NI)	1000 iterations
8	GD Number of iteration (NI)	1000 iterations
9	Initial temperature (Temp)	50 set preliminary experiment
10	Final temperature (Tin)	0.5
11	Cooling rate (Tcool)	0.99
12	level	objective function value of initial solution x

The proposed algorithm WFA-CVRP 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).

5.Experiments Results

The performance of the proposed Hybrid IWFA is evaluated with three experiments. The first experiment investigates the performance of each hybrid IWFA with either one of the four local searches using FI, BI, GD and SA against the IWFA.
The experiment aims to investigate the performance of the four types of hybrid IWFA. The best result is defined as the best solution for proposed hybrid IWFA which known as HIWFA. Then, the proposed evaluation is comparing the propose HIWFA with the performance of the state of the art algorithm.

5.1 Hybrid IWFA with Local Search

Table 2 shows the experiment results of variant hybrid IWFAs; IWFA-BI, IWFA-FI, IWFA-GD, and IWFA-SA according the minimum distance, maximum distance and standard deviation. The bold value indicates the best results. The table shows that all variant hybrid IWFA obtained the shortest result for data set E-n22-k4 and E-n23-k3. However, the IWFA-GD shown has obtained the best result in most data sets term in the minimum route, the average and the standard deviation, follow by hybrid IWFA-BI and hybrid IWFA-FI, whilst the hybrid IWFA-SA has shown the less performance.
Later the performance of variant hybrid IWFAs is compared with IWFA algorithm based p-value using t-test. Table 3 shows the experiment results of variant hybrid IWFAs; IWFA-BI, IWFA-FI, IWFA-GD, and IWFA-SA compare with IWFA. The symbol "+" denotes that IWFA is significantly better than the contending proposed algorithm (p-value < 0.05), the "–" denotes that IWFA is less performed by the contending proposed algorithm (p-value > 0.05), whilst the "=" denotes that IWFA has the same performance with the contending proposed algorithm (p-value = 0.05). The hybrid IWFA-GD has shown "-" values for all data set accepted the first two instances (E-n22-k4 and E-n23-k3) which are the same. GD has ability to help exploitation of IWFA by improving the quality of the obtained results. The second was the hybrid IWFA-BI, where it has loose on data set M-n200-k17, follow by hybrid IWFA-FI where it obtained better result compare to IWFA in 5 data sets, 7 data sets were same, and one data set was loose, similar to hybrid IWFA-BI. On the other hand, the hybrid IWFA-SA shows a very little improvement, where it only be able to improve 2 data set only (E-n22-k4 and G-n262-k25).
Furthermore, a box-whisker analysis is conducted to investigate the distribution of solutions obtained by the algorithms adopted in this experiment. Figure 3 shows the plot of box-whisker for three dataset result which is E-n51-k5, E-n101-k8 and E-n76-k10. The box-whisker for E-n51-k5 and E-n101-k8 data set has shown that the hybrid IWFA-GD has shown the smallest box-whisker, which indicates the better distribution of solution compare to the other hybrid IWFA variants. However, the Box-whisker for data set E-n76-k10 shows that the performance of hybrid IWFA-GD almost same with IWFA-BI.
Moreover, Table 4 presents the average ranking for each algorithms using Friedman test. The algorithms ared ranked in ascending order. The lower rank indicated the better performance. Notably, IWFA-GD ranked first. Thus, IWFA-GD was selected as a controlling method based on the Holm and Hochberg statistical test, which used later in next evaluation method. The results of the statistical tests from Table 4 revealed that IWFA-GD outperforms the other proposed algorithms on most tested instances.
The last evaluation of performance proposed hyrid IWFAs is using the Holm and Hochberg statistical test.

Table 3: p-value of each IWFA variant against the HIWFAs variant

IWFA vs. Ins. Name	*p-value*			
	IWFA-GD	IWFA-BI	IWFA-FI	IWFA-SA
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	-	-	-	-

Table 4: Average ranks obtained by the Friedman test for each HIWFAs variant with IWFA

#	**Algorithms**	**Unadjusted p**	**p Holm**	**p-Hochberg**
1	IWFA-GD	0.000001	0.000005	0.000005
2	IWFA-BI	0.000103	0.000308	0.000308
3	IWFA-FI	0.001013	0.002026	0.002026
4	IWFA-SA	0.151494	0.151494	0.151494

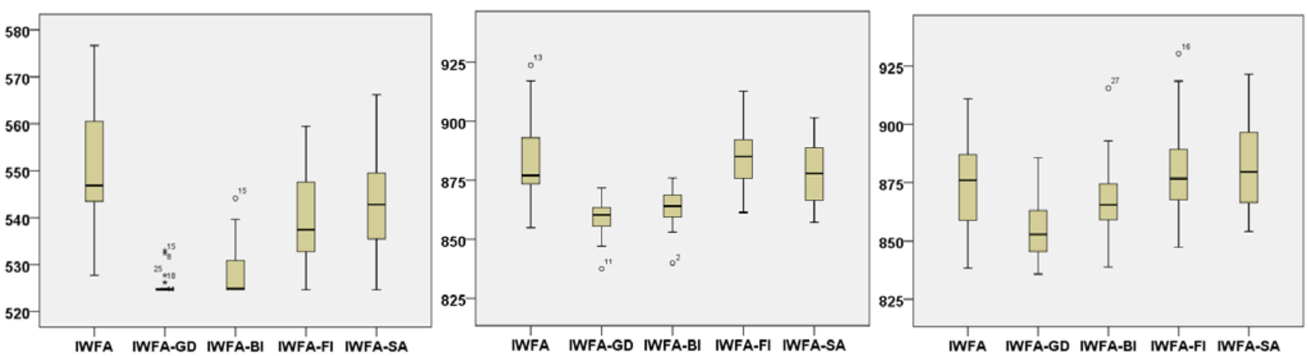
Table 5 shows the Holm and Hochberg statistical test for evaluate the performance of proposed algorithm. The table shows the IWFA-GD has the most less unadjusted p compared to others. However, the other two variants of hybrid IWFA-BI and IWFA-FI also have less p value (0,05) as well. The result shows the IWFA-SA has undjusted p for 100%.

Table 2: Adjusted p-value obtained by Holm and Hochberg statistical test for the IWFA-GD versus other algorithms

#	Algorithms	Ranking
1	IWFA-GD	1.3929
2	IWFA-BI	2.25
3	IWFA-FI	3.3571
4	IWFA	3.7143
5	IWFA-SA	4.2857

Table 2 Comparison result between variation of hybrid IWFAs Dataset

	IWFA-BI			**IWFA-FI**			**IWFA-GD**			**IWFA-SA**		
	Min	**Avg**	**Std**	**Min**	**Avg**	**Std**	**Min**	**Avg**	**Std**	**Min**	**Avg**	**Std**
E-n22-k4	**375.28**	**375.28**	**1.7**	**375.28**	**375.28**	**1.7**	**375.28**	**375.28**	**1.7**	**375.28**	**375.28**	**1.7**
E-n23-k3	**568.56**	**568.56**	**1.16**	**568.56**	**568.56**	**1.16**	**568.56**	**568.56**	**1.16**	**568.56**	**568.56**	**1.16**
E-n33-k4	**837.67**	**837.67**	1.16	**837.67**	838.28	1.15	**837.67**	**837.67**	**1.16**	**837.67**	843.24	5.87
E-n51-k5	**524.61**	528.13	5	**524.61**	539.98	9.42	**524.61**	**525.39**	**2.06**	**524.61**	550.77	11.11
E-n76-k8	745.93	764.68	12.26	749.43	773.32	13.32	**741.91**	**757.82**	**9.45**	778.42	807.17	19.62
E-n76-k10	839.98	864.03	7.43	861.42	884.98	13.55	**837.52**	**859.10**	**7.07**	875.09	895.42	15.15
E-n101-k8	838.97	866.59	15.86	847.32	878.06	18.85	**835.85**	**855.95**	**14.05**	900.14	941.04	26.17
E-n101-k14	1106.01	1129.38	13.60	1107.93	1143.46	18.53	**1096.24**	**1121.24**	**14.46**	1140.6	1182.15	19.30
M-n101-k10	820.92	837.94	14.62	819.56	844.96	13.17	**819.56**	**828.10**	**9.34**	839.81	864.67	10.71
M-n121-k7	1047.27	1065.70	15.03	1048.53	1073.94	18.07	**1042.97**	**1054.11**	**10.51**	1068.56	1102.86	15.89
M-n151-k12	1074.58	1113.97	23.49	1073.73	1134.41	29.58	**1045.59**	**1081.90**	**16.13**	1170.88	1224.62	27.08
M-n200-k17	1391.05	1454.75	39.91	1400.61	1456.60	29.57	**1336.98**	**1399.94**	**31.52**	1489.65	1558.19	36.08
G-n262-k25	5762.14	5969.79	128.64	5814.86	6049.21	104.03	**5683.80**	**5856.91**	**89.82**	6054.54	625044	101.09



E-n51-k5 E-n101-k8 E-n76-k10

Fig 3 The distribution of solutions obtained by the IWFA and hybrid IWFA Based on these results, IWFA-GD is chosen as the best improvement method which named is as HIWFA compare with IWFA and become the state of the art methods.

The significant improvement achieved by the IWFA-GD compared with that of the IWFA and other proposed hybridized algorithms is due to the use of GD as an improvement method to drive the diverse solutions to different local optima. GD can improve the quality of the obtained results further by exploiting the promising area and improve solution diversity.

5.2 Comparison of Proposed HIWFA with the State of Art Algorithm

In order to know how far the performance of the HIWFA in solving CVRP, the results of HIWFA are compared with the other algorithms in the literature. Numerous studies have been proposed in the literature for CVRP, these studies achieved good results as well, so they were selected for comparison with the proposed method.

Appendix 1 presents the best quality solutions obtained from nine algorithms of CS, CS-Ouaarab, CENTPSO, IGA, ALNS, PSO-VNS, RABC, WFA and IWFA, uses 57 standard benchmark datasets with the best-known results (BKS). The bold value indicates the best solution amongst the algorithms. HIWFA obtain better results for most algorithms such as ACO, IWD, CS, IGA, PSO-VNS and RABC, accept in CS-Quaarab in E-n43-k6. HIWFA obtained a better result than RABC for all reported instances except one instance (A-n33-k5), which is same.The results also show ALNS has obtained the best result for 8 data set especially for small instants datasets (A-n32-k5 to A-n55-k9 and A-n46-k7 to A-n55-k9). However, it clearly shown that the propose HIWFA has shown obtained the best solution for 25 data sets out of 57 data sets, especially for larger datasets compare with other methods. However, 11 of data sets are same performance with WFA and/or IWFA, i.e A-n45-k6, A-n4,5-k6, A-n65-k9, B-n35-k5, B-n43-k6, E-n22-k4, E-n23-k3, E-n30-k3, E-n33-k4, P-n51-k10 and P-n65-k10.

Furthermore, the ΔBKS has calculates how far the proposed HIWFA is better than the shortest solution benchmark (BKS), whislt the Δthe best calculates how far the proposed HIWFA is better than the best state of art algorithms. The sign "-" indicates the proposed HIWFA is performed better, whilst the value without "-" indicates how far HIWFA less performed compare with others.

The ΔBKS value has shown 4 negative values. This means HIWFA has performed better that the BKS, however the values is very little which is 0.3-0.5 as assumed it almost same. However, HIWFA performed better that the BKS in data set G-n262-k25 with differences 435.2 and become new BKS solution for the data set.

Furthermore, the proposed HIWFA is evaluated the complexity of the algorithm based on computational time. As stated earlier that the strength of WFA is computational time. Appendix 2 shows the comparison result computation time of HIWFA with 5 other state of art algorithm in second (sec) which is CS, Cs-Quarrab, CENTPSO, WFA and IWFA. The result clearly shows HIWFA shown less computational time for all algorithms and data sets, except IWFA. HIWFA has shown same performance with IWFA in 3 data sets (A-n32-k5, E-n22-k4 and E-n23-k3), and IWFA has perform less time in 4 data sets (A-n33-k5, A-n45-k6, B-n35-k5 and E-n23-k3). The 'Not WFA' column shows the how far HIWFA performs better compare with not WFA algorithm, while column 'include WFA' show the differences performance HIWFA compare with the best WFA. The result shows the differences up to 158.11 sec in data setA-n80-k10, while within the WFA up to 564.52 sec in data set G-n262-k25.

6. Conclusion

The propose hybridization of the IWFA algorithm with four S-metaheuristics such as BI FI, SA, and GD have improved the IWFA solution for CVRP solution. However, the hybrid IWFA with GD has shown the best solution (IWFA-GD), while IWFA-SA does not show any significant improvement. The experiment IWFA-GD has shown it has improved the quality of the obtained results further by exploiting the promising area. In addition, the hybrid IWFA-GD also has shown good performance for large data sets as well. Furthermore, the IWFA-GD has also shown the lowest computation time amongst other states of the art algorithm, even within the group of WFA family as well.

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Appendix 1 Best results of WFA, IWFA, and HIWFA compared with state of the art algorithms

Instances	BKS	ACO	IWD	CS	CS-Ouaarab	CENTPSO	IGA	ALNS	PSO-VNS	RABC	WFA	IWFA	HIWFA	Δ BKS	Δ the best
A-n32-k5	784	-	806	-	799	820	787	**784**	807.3	-	787.1	787.1	787.1	3.1	3.1
A-n33-k5	661	-	673	-	685	687.04		**661**	685.3	660.8	662.1	662.1	662.1	1.1	1.3
A-n33-k6	742	-	753	-	756	762.39		**742**	762.8	-	742.7	742.7	742.7	0.7	0.7
A-n36-k5	799	-	815	-	829	826.21		**799**	811.5	802.1	802.1	802.1	802.1	3.1	3.1
A-n37-k5	669	-	705	-	700	693.18		**669**	691.0	691.4	672.5	672.8	672.5	3.5	3.5
A-n45-k6	944	-	-	-	976	988		955	977.4	-	977.5	944.9	944.9	0.9	0.0
A-n46-k7	914	-	-	973	954	978.23		**915**	950.3	918.8	918.1	917.7	917.7	3.7	2.7
A-n48-k7	1073	-	-	-	1145	1132.15		**1073**	1088.9	1130.2	1074.3	1087.5	1074.3	1.3	1.3
A-n55-k9	1073	-	-	-	1117	1118.4	1075	**1074**		1131.5	1074.5	1074.5	1074.5	1.5	0.5
A-n60-k9	1354	-	-	1414	1406	1436.5		1366		1465.6	**1355.8**	**1355.8**	**1355.8**	1.8	-10.2
A-n61-k9	1034	-	1103	-	1097	-	1050	1045		1096.3	1051.7	1045.1	**1040.3**	6.3	-4.7
A-n62-k8	1288	-	-	-	1350	-		1302		1418.4	1316.2	1313.1	**1295.7**	7.7	-6.3
A-n63-k9	1616	-	-	-	1720	-	1650	1644		-	1648.5	1633.9	**1622.1**	6.1	-11.8
A-n63-k10	1314	-	-	-	1379	-		1325		1403.4	1322.9	1320.2	**1313.5**	-0.5	-6.8
A-n64-k9	1401	-	-	-	1500	-		1442		1530.9	1438.5	1426.3	**1403.3**	2.3	-23.1
A-n65-k9	1174	-	-	-	1254	-		1189		1274.5	1183.3	1181.7	**1181.7**	7.7	0.0
A-n69-k9	1159	-	-	-	1239	-		1169		1259.3	1175.8	1170.5	**1166.0**	7.0	-3.0
A-n80-k10	1763	-	1889	-	1893	-	1814	1790		2070.2	1801.4	1786.9	**1766.5**	3.5	-20.4
B-n35-k5	955	-	987	962	976	-	-	-	-	-	**956.3**	**956.3**	**956.3**	1.3	0.0
B-n38-k6	805	-	824	-	820	-	-	-	-	-	808.7	808.7	**807.9**	2.9	-0.8
B-n41-k6	829	-	840	-	847	-	-	-	-	-	836.4	834.3	**833.7**	4.7	-0.6
B-n43-k6	742	-	748	-	745	-	-	-	-	-	**747.0**	**747.0**	**747.0**	5.0	2.0
B-n45-k5	751	-	-	770	774	-	-	-	-	-	760.6	756.5	**754.0**	3.0	-2.6
B-n63-k10	1496	-	-	-	1585	-	-	-	-	-	1540.7	1517.3	**1503.1**	7.1	-14.2
B-n64-k9	861	-	-	-	903	-	-	-	-	-	871.3	868.9	**868.2**	7.2	-0.7
B-n66-k9	1316	-	1381	-	1381	-	-	-	-	-	1331.1	1329.1	**1326.2**	10.2	-2.9
B-n67-k10	1032	-	-	-	1095	-	-	-	-	-	1046.7	1040.4	**1039.5**	7.5	-1.5
B-n68-k9	1272	-	-	1320	1326	-	-	-	-	-	1300.2	**1286.1**	1286.7	14.7	0.6
B-n78-k10	1221	-	1311	1284	1302	-	-	-	-	-	1264.4	1230.5	**1227.9**	6.9	-2.6
E-n22-k4	375	376.5	379	-	-	378.56	-	-	-	-	**375.3**	**375.3**	**375.3**	0.3	0.0
E-n23-k3	569	579.3	570	-	-	-	-	-	-	-	**568.6**	**568.6**	**568.6**	-0.4	0.0
E-n30-k3	534	-	551	565	-	-	-	-	-	-	**535.8**	**535.8**	**535.8**	1.8	0.0
E-n33-k4	835	865.2	851		-	847.38	-	-	-	-	**837.7**	**837.7**	**837.7**	2.7	0.0
E-n51-k5	521	606.6	538	590	-	544	-	-	-	-	545.2	527.7	**524.6**	3.6	-3.1
E-n76-k7	682	-	-	746	-	-	-	-	-	-	696.1	694.4	**687.6**	5.6	-6.8
E-n76-k8	735	911.5	-	-	-	-	-	-	-	-	774.4	746.0	**741.9**	6.9	-4.1
E-n76-k10	830	1065	904	-	-	-	-	-	-	-	876.8	854.9	**837.5**	7.5	-17.5
E-n76-k14	1021	-	-	-	-	-	-	-	-	-	1059.4	1048.7	**1024.9**	3.9	-23.8
E-n101-k8	815	1103	-	-	-	-	-	-	-	-	878.6	838.5	**835.9**	20.9	-2.6
E-n101-k14	1067	1431	-	-	-	-	-	-	-	-	1144.1	1112.5	**1096.2**	29.2	-15.9
P-n50-k8	631	-	655	-	658	654.87	-	-	-	-	654.2	642.6	**637.6**	6.6	-5.0
P-n50-k10	696	-	-	-	741	-	-	-	-	-	700.7	704.5	**699.6**	3.6	-1.1
P-n51-k10	741	-	780	-	784	773.48	-	-	-	-	750.0	**741.5**	**741.5**	0.5	0.0
P-n60-k10	744	-	-	-	814	772.86	-	-	-	-	**748.1**	751.3	**748.1**	4.1	0.0
P-n60-k15	968	-	-	-	1029	1012.9	-	-	-	-	976.0	971.9	**971.6**	3.6	0.0
P-n65-k10	792	-	-	-	850	-	-	-	-	-	**795.7**	**795.7**	**795.7**	3.7	0.0
P-n70-k10	827	-	-	-	886	-	-	-	-	-	838.4	841.4	**834.6**	7.6	-3.8
P-n76-k4	593	-	-	679	648	-	-	-	-	-	622.8	610.7	**605.1**	12.1	-5.6
P-n76-k5	627	-	-	-	695	-		-	-	-	639.6	650.1	**634.3**	7.3	-5.3
P-n101-k4	681	-	-	758	758	-	725	-	-	-	722.9	698.9	**691.3**	10.3	-7.6
M-n101-k10	820	-	-	844	-	-	-	-	-	-	865.0	827.3	**819.6**	-0.4	-7.8
M-n121-k7	1034	-	-	1088	-	-	-	-	-	-	1285.3	1063.7	**1043.0**	9.0	-20.7
M-n151-k12	1015	-	-	-	-	-	-	1048	-	-	1149.4	1078.3	**1045.6**	30.6	-2.4
M-n200-k17	1275	-	-	-	-	-	-	1331	-	-	1462.2	1390.2	**1329.7**	54.7	-1.3
G-n262-k25	6119	-	-	-	-	-	-	5875	-	-	6403.1	6125.3	**5683.8**	-435.2	-191.2

Note: the (-) indicates that researcher did not use these instances in their works

Appendix 2 The time between HIWFA state of art algoritms

Instances	CS	CS-Ouaarab	CENTPSO	WFA	IWFA	HIWFA	Not WFA	Include WFA
A-n32-k5	-	819.13	821.29	809.81	**787.08**	**787.08**	-32.05	0
A-n33-k5	692	708.1	687.88	662.73	**662.32**	662.93	-24.95	0.61
A-n33-k6	-	771.57	763.38	751.09	743.99	**743.86**	-19.52	-0.13
A-n36-k5	-	854.63	827.1	815.67	821.4	**816.78**	-10.32	1.11
A-n37-k5	-	724.13	693.92	686.34	685.84	**683.16**	-10.76	-2.68
A-n45-k6	-	1015.6	988.91	1054.83	**971.16**	976.03	-12.88	4.87
A-n46-k7	994.76	1021.5	979.33	954.79	919.93	**919.13**	-35.66	-0.8
A-n48-k7	-	1177.1	1133.13	1110	1110.11	**1085.46**	-47.67	-24.54
A-n55-k9	-	1162	1118.98	1102.44	1083.15	**1082.79**	-36.19	-19.65
A-n60-k9	1413.49	1488.2	1437.33	1401.18	1370.25	**1361.91**	-51.58	-8.34
A-n61-k9	-	1129.8	-	1137.88	1074.79	**1060.47**	-69.33	-14.32
A-n62-k8	-	1419.4	-	1340.14	1327.08	**1315.16**	-104.24	-11.92
A-n63-k9	-	1783.6	-	1675.55	1656.12	**1640.9**	-142.7	-15.22
A-n63-k10	-	1432	-	1358.66	1344.77	**1325.01**	-106.99	-19.76
A-n64-k9	-	1534	-	1480.04	1459.76	**1433.36**	-100.64	-26.4
A-n65-k9	-	1302.6	-	1254.8	1205.39	**1187.42**	-115.18	-17.97
A-n69-k9	-	1297.8	-	1201.88	1187.27	**1172.15**	-125.65	-15.12
A-n80-k10	-	1952.4	-	1852.24	1811.55	**1794.29**	-158.11	-17.26
B-n35-k5	966.37	983.83	-	969.91	**958.81**	959.13	-7.24	0.32
B-n38-k6	-	831.43	-	814.65	811.5	**808.57**	-22.86	-2.93
B-n41-k6	-	861.47	-	868.07	840.74	**833.82**	-27.65	-6.92
B-n43-k6	-	757.27	-	760.91	754.35	**746.98**	-10.29	-7.37
B-n45-k5	794.88	798.17	-	802.21	768.53	**761.82**	-33.06	-6.71
B-n63-k10	-	1628.3	-	1575.35	1544.36	**1535.96**	-92.34	-8.4
B-n64-k9	-	932.8	-	934.68	881.01	**872.03**	-60.77	-8.98
B-n66-k9	-	1412.6	-	1374.25	1343.17	**1330.22**	-82.38	-12.95
B-n67-k10	-	1110.9	-	1084.77	1067.13	**1050.81**	-60.09	-16.32
B-n68-k9	1326.73		-	1330.48	1300.6	**1294.77**	-31.96	-5.83
B-n78-k10	1307.94	1336.1	-	1297.44	1261.93	**1242.26**	-65.68	-19.67
E-n22-k4	-	-	379.4	383.31	**375.28**	**375.28**	-4.12	0
E-n23-k3	-	-	-	583.88	**568.56**	**568.56**		0
E-n30-k3	559.07	-	-	541.21	**537.73**	539.73	-19.37	1.97
E-n33-k4	-	-	848.19	874.27	845.04	**837.67**	-10.52	-7.37
E-n51-k5	618.28	-	545.83	614.83	550.66	**525.39**	-20.44	-25.27
E-n76-k7	763.69	-	-	717.4	718.25	**705.83**	-57.86	-11.57
E-n76-k8	-	-	-	832.75	775.51	**757.82**		-17.69
E-n76-k10	-	-	-	952.8	884.13	**859.1**		-25.03
E-n76-k14	-	-	-	1084.04	1069.1	**1046.05**		-23.05
E-n101-k8	-	-	-	952.18	881.31	**855.95**		-25.36
E-n101-k14	-	-	-	1197.1	1146.29	**1121.24**		-25.05
P-n50-k8	-	679.53	655.67	705.92	663.65	**653.48**	-2.19	-2.19
P-n50-k10	-	756.97	-	715.52	711.29	**703.11**	-53.86	-8.18
P-n51-k10	-	807.3	774.41	781.73	756.94	**748.25**	-26.16	-8.69
P-n60-k10	-	827.73	773.9	765.39	768.98	**752.39**	-21.51	-13
P-n60-k15	-	1051.5	1013.87	995.15	986.62	**977.03**	-36.84	-9.59
P-n65-k10	-	884.17	-	815.66	818.83	**803.92**	-80.25	-11.74
P-n70-k10	-	917.67	-	872.82	861.92	**848.83**	-68.84	-13.09
P-n76-k4	688.27	688.1	-	648.47	628.94	**619.31**	-68.79	-9.63
P-n76-k5	-	715.8	-	680.32	687.5	**651.91**	-63.89	-28.41
P-n101-k4	760.75	781.07	-	764.59	732.28	**717.56**	-43.19	-14.72
M-n101-k10	843.69	-	-	985.42	854.56	**828.1**	-15.59	-15.59
M-n121-k7	1110.22	-	-	1458.94	1100.74	**1054.11**	-56.11	-46.63
M-n151-k12	-	-	-	1241.4	1126.84	**1081.9**		-44.94
M-n200-k17	-	-	-	1573.38	1440.27	**1384.74**		-55.53
G-n262-k25	-	-	-	6782.96	6421.43	**5856.91**		-564.52