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Distribution Path Segmentation Using Route Relocation and Savings Heuristics for Multi-Depot Vehicle Routing

Farid Morsidi*[1]

[1]*Faculty of Art, Computing and Creative Industry, Universiti Pendidikan Sultan Idris, 35900 Tanjong Malim, Perak, Malaysia.*

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ABSTRACT

This paper uses routing segmentation optimization for the planning of optimal distribution networks between urban depots and their respective customers. In this experiment, three steps are proposed in concession: search for the initial solution using local search properties, improve the solution using route relocation and perturb the solution using tabu search incorporating the savings heuristic. By applying multi-depot simultaneous deployment with ideal scheduling strategies and routing heuristics ensuring cost-optimal routing, the study presents an alternative to enhanced scheduling system optimization. Based on repopulation and sequential insertion algorithms, the initial solution is created, while route relocation and tabu swap mechanisms constitute the improvement strategy and perturbation. Test results comparing the proposed solution strategy to the previous genetic algorithm solution result in a better arrangement of route segregation aspects representing customer clusters. This strategy has proven to be more successful in optimizing route segregation than the original genetic algorithm solution. This demonstrates a significant improvement in route optimization.

1. INTRODUCTION

Routing systems are often synonymized with planning and execution of strategic deployment efforts reflective of a distribution network for successful completion of task distributions, be it service or commodity dissipation. These cost optimality could be in the sense of determining the elaborate value of participating scheduling variables, for example, permitted maximum vehicle capacity, number of populated transportation across the distribution network, and the presumption of the farthest possible reach of propagation distance. Vehicle routing problems and their variants are incorporated with scheduling systems to predict and accommodate the optimal round trip for each vehicle deployment, along with formulating the ideal value of scheduling variables for the assessment and emulation of a proficient distribution system pattern. Implementation of routing instance variants on complex optimization strategies had been widely utilized on problem constraints involving freight distribution and constraint-based scheduling, where its variance with the conventional routing approaches is in its characteristics of permitting a multitude of synergized vehicle deployment from their respective sectors to all participating depots with the ending rule of imposing a mandatory return to its original departing position to emulate real-world performance scenarios.

Several scheduling constraint adaptations were used to examine the scheduling system's ability to use modeling variables of different magnitudes and sizes. One aspect of it is the interjection between strategic distribution points and their structure as dissipation nodes. Internally, routing modeling instances simulate a distribution network of scattered vehicle transmissions over their initial domain. Depending on how a problem instance is organized with its objective functions, various scheduling variables are derived and put into practice. To create a more effective synergized scheduling system that

*Corresponding author:
E-mail address: Farid Morsidi <farid.mors90@gmail.com>

can operate synchronously under a maximal cost optimization strategy to accommodate particular routing constraints, particularly in regards to ideal multi-depot deployment transpositions, this study tries to highlight the benefit of incorporating an intensive local search strategy with accommodating routing heuristics. The perturbation strategy was used as a framework for discussing the iterative exploration of generated solutions. Common perturbation steps include swapping, destroying, and repopulating solution sizes. These modeling heuristics were used to examine the extent to which the solution steps could be enhanced in line with the requirements of the routing models.

2. RELATED WORKS

Two components have been altered to enhance the existing routing heuristics: iterated local search and savings heuristics. Simple heuristics build routes by creating segments one at a time until a full route is created, in contrast to metaheuristics like population-based algorithms and local search heuristics that have improved the generation of solution steps. For the best possible solution output, the foundations of further exploration and exploitation phase call for the creation of appropriate modeling variables, integration with advanced search algorithms, assimilation with feed data, validation with current benchmarks, and implementation among compatible local search mechanisms. These features have been recently used in works on intelligent pathing segmentation to get the best route placement.

Many related routing studies had incorporated iterated local search with other routing heuristics to formulate a better strategy for emulating desirable scheduling performance, be it in terms of cost optimality or figuring out the relevant routing variables to generate a feasible scheduling strategy that caters to all common issues. The vehicle routing and scheduling problem was addressed using two new neighborhood operators and the destroy/repair heuristic [1]. Iterated local search heuristics are an additional suggested solution strategy for routing instances that are based on the deterministic neighborhood search and Tabu search algorithm [2]. Different mutation operators that had been used to implement genetic algorithms as metaheuristics were modified for use with the VRP. The outcomes showed that chromosome representation, searching operators, and selection operators all contributed to the global solution without getting stuck at a local optimum. To reduce transportation costs, the multi-depot open location routing problem with a heterogeneous fixed fleet was developed [3]. The algorithm discovered new, better solutions for the benchmark instances of the MDOVRP while still producing results quickly. It was used to determine the most economical and effective path for transporting produce on pallets from farms to the main depot. Multiple-neighborhood iterated adaptive hyper-heuristics—local search algorithms for sophisticated simulation of routing instances—are tested using low-level heuristics in a study on the HyFlex hyper-heuristic framework [4]. The problem of capacitated team orienteering with time windows was addressed using the technique of iterated local search [5]. In research, the Vehicle Routing Problem with the Time Window Model and its variants have been used to improve the results of perturbation-based local search methods [6]. To solve the VRP with stochastic demand, a heuristic and meta-heuristic approach was suggested for municipal waste collection in the City of Niš [7]. The suggested solution can cut the cost of fuel used in mechanization by 10%.

The savings algorithm is a subservient routing heuristic that is used to compare better solutions after in-depth solution exploitation. It is a calculation of the cost savings realized by providing services to two customers simultaneously along the same route. It is inherently parallel and can be used sequentially, improving the optimization capability of acquiring the best selection of route selection and maximizing cost allocation purposes. Many routing researchers have innovated niche solution strategies with beneficial traits of parallelism in savings heuristics to negate the trade-off between existing optimization strategies and negate minor drawbacks from the savings algorithm itself.

The savings heuristic is a calculation of the cost savings realized by providing services to two customers simultaneously along the same route. The operation of the heuristic savings system was tested with several improvements, such as defining new parameters, evaluating penalty multipliers, adding a probabilistic approach, and implementing a post-improvement procedure to control the impact of neighborhood structures. The issue of green vehicle routing was raised as a potential resolution in addition to a multi-objective approach that takes workload equity for both private fleets and common carriers [8]. Numerous optimization heuristics for real-time disruption problems are used to investigate the disruption of the vehicle routing problem [9]. The outcomes are comparable to performance assessments made using standard benchmarks and analysis of the selected algorithms. Using poultry distribution from Indonesia, the issue of vehicle routing with capacity has also been solved [10]. This study used Euclidean distance to calculate the distance between all coordinates, create a distance matrix between destinations and perform calculations using combinatorial calculations. The savings heuristic was used as the solution strategy in a mathematical model for LPG gas distribution that was based on VRP and had simultaneous pickup and delivery [11]. The results showed promising cost savings between deployed vehicle collections where the vehicle travels a total of 160 km, while the company travels 201 km, saving 20.3% of the total mileage. Another application of the savings heuristic is developed for the steel distribution industry in Thailand [12]. The effectiveness of the suggested algorithm is evaluated using a real-world Capacitated Vehicle Routing Problem. The proposed algorithm performs 8.08% better than the traditional method, primarily due to the creation of the saving list and the distance-saving procedure for each pair of customers. The Nearest Neighbor, Saving Matrix, and Sequential Insertion algorithms were applied in the development of CVRP for distribution routes serving the Grobogan district [13]. There are 19 villages included in the data cluster and the data on customer demand was generated at random. The three algorithms covered a combined distance of 126.6 km, 136.4 km, and 133.7 km. The cost of the route was drastically reduced in the process. This criterion demonstrated that the savings heuristic has the potential to perform better when selecting realistic distribution routes.

3. MATHEMATICAL FORMULATION

A typical route scheduling is considered when vehicle deployment begins at the initial node with materials for the first customer, completes depot D_1 delivery and pickups, travels to nearby depots to replenish the load to a predetermined quantity, loads relief commodity, delivers the commodity according to priority to the next depot D_2 delivery, and then returns to the starting depot with all leftover materials in between the subsequent deliveries.

These genetic operators and their altered role in generating solution steps are discussed as follows in the integrated framework.

Table 1. Phases involved in the mutation strategy for the solution steps

Selection	Using tournament search, the future parent chromosome is selected from the best 5 lists of candidates.
Crossover	In each inherited parent chromosome, there is an indication of the likelihood of experiencing crossover.
Mutation	Following selection and crossover, individuals will mutate with a certain probability.
Relocation	Both insertion and swapping were used to reposition objects. Variables on chromosomes, such as customer location, were switched. The average number of customers per route is equal to *n*/*r*, and *r* is the total number of routes. *Insertion moves*: Select clients who will get moved when a better candidate solution is produced. The insertion move is represented by $n\ (r - 1)\ n/r = n^2 (1 – 1/r)$. *Swapping move*: Exchange of two route-specific customers. The execution of these transactions could be randomized. The complexity for swapping is represented by $[n\ (n - 1) / 2] \times 2\ (n / r)$.
Two-opt move	During a route relocation procedure (intra-/inter-), two non-adjacent arcs from the corresponding customers are chosen and switched until no better solution can be found. This is only applicable if there are more than two customers in the routing instance.

3.1 Algorithm Implementation

In addition to identifying ongoing improvements in solution quality, the local search algorithm seeks to identify the best solution for subsequent exploration stages. To find the lineage of the solution chromosome that corresponds to each step in the neighborhood structure, improvement steps are used to create the best solution. Route relocation is a step in the improvement process.

3.1.1 Modeling Notations

The modeling parameters that emphasized routing scheduling are referenced from related works on multi-depot VRP [14], [15] and minimized according to the magnitude of problem instance complexity.

$$\text{Minimize:} \quad \sum_{k=1}^{\bar{k}} \sum_{i=0}^{n} \sum_{j=0}^{n} c_{ij}\, x_{ijk} \tag{1}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{\bar{k}} x_{ijk} = 1, j = 1, \dots, n \tag{2}$$

$$\sum_{i=0}^{n} x_{ijk} - \sum_{i=0}^{n} x_{jik} = 0, j = 0.1, \dots, n; k = 0, 1, \dots, \bar{k} \tag{3}$$

$$\sum_{j=1}^{n} x_{0jk} \leq 1, k = 1, \dots, \bar{k} \tag{4}$$

$$y_{ij} + z_{ij} \leq Q \sum_{k=1}^{\bar{k}} x_{ijk}, i, j = 0, 1, \dots, n \tag{5}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij}\, x_{ijk} \leq L, k = 0, 1, 2, \dots, \bar{k} \tag{6}$$

$$x_{ijk} \in \{0, 1\}, y_{ij} \geq 0, z_{ij} \geq 0, i, j = 0, 1, \dots, n, k = 0, 1, \dots, \bar{k} \tag{7}$$

Constraints (1, 2, 3, 4, 5, 6, and 7) ensure that objective functions are minimized, one vehicle frequents each node, each mobile vehicle would arrive and depart from each port that it serves, $\bar{k}$ vehicles are used at specific deployment times, procurement and dispatch requirements are only represented through arcs, maximum distance coverage is limited, and default of decision variable is defined.

3.2 Genetic Algorithms

This study presents a genetic algorithm that views chromosomes as paths and is based on the baseline. Chromosome exchange, competition searching, population diversity, and repopulation are all involved. Selection and crossover are carried out sequentially until a viable child chromosome is obtained. Repopulation diversity is induced when new chromosomes are thought to be the most suitable to finish the initial population generation.

3.2.1 Chromosome and fitness evaluation

A workable optimization solution is produced by routing and scheduling, which take into account the frequency of the vehicle and distance traveled between nodes to determine a chromosome's fitness value.

Selection operation: The best fitness candidates are chosen after a random sorting operation to be used in selecting high-caliber methods for producing potential offspring. Tournament search is preferred because it is not affected by the genetic algorithm's scaling.

Crossover operation: Specific parameters from a targeted vector are substituted for the corresponding parameters of a solution vector that was generated randomly to create a trial vector. The behavior is to control the mutation value related to the issue, randomly choose one route, select numbers corresponding to customers' genes, and replace the original gene with the replacement gene.

Mutation operation: Mutation stages are used to restore genetic diversity and enhance probabilistic search optimizations for evolutionary computations. Generation *n*-1 is subjected to insertion, inversion, and swapping during iteration. The swap operator selects two organisms at random from solution vectors *i* and *j*, where $i \neq j$. An approach to switching operator mains neighboring information while preserving broken link order.

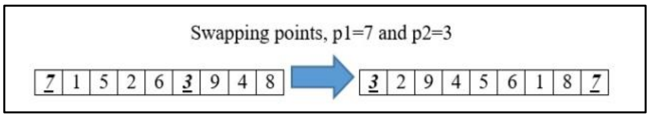


Fig. 1. Process of undergoing swapping for chromosomal contents

The optimal criterion value for the problem constitutes the fitness of solution steps, and chromosome C is a permutation of all customers (c_1, c_2, …, c_n). The length of the traversal arc (c_i, c_j), l is represented by the shortest distance of n +1 between the possible routes. The fitness value of traversal graph G is constructed by iterative visualization of the shortest path, SP_{ik} among the initial customer until the final customer c_0 to c_i with k arc at most.

3.2.2 Constructing the initial population

Based on a hierarchical arrangement of routing characteristics, including the number of vehicles, coordinates, load capacity, starting and destination points, visiting frequency, and range of traversal nodes, the candidate solution composition representing a single chromosome is shown. Phase 1 involves the generation of basic population size with constant parameter values and randomly generated chromosomes. The empty initial solution is scheduled with placeholder routes for the closest pick-up points between the depots and customers. To increase population diversity, phase two involves repopulating distinct types with random chromosomes. If there is no feasible route, the best-quality chromosomes would be randomly maintained while the least-quality chromosomes would be replaced in part by the new population.

3.2.3 Improving feasible chromosomes using local search

For genetic algorithms and other combinatorial optimization techniques, local search is recommended to naturally explore the solution space. This work proposes tabu search as a metaheuristic local search method. This method switches between solutions to iteratively explore the range of potential solutions. Search is supported by anti-cycling strategies, and the tabu status can be disregarded if certain conditions are met. Route relocation, tabu search, savings lists, post-improvement techniques, and local searches are combined.

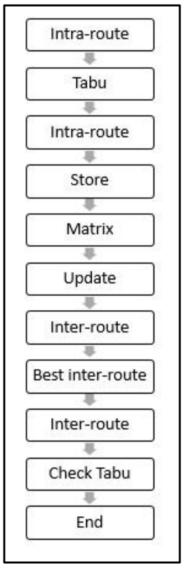


Fig. 2. The Cyclic Properties of Solution Strategy Combining Route Relocation (Intra-/Inter-) with Tabu List

Tabu search: The local search-based improvement heuristic tabu search replaces a better neighbor with the current solution. By keeping a list of neighbor node generation moves and disregarding solutions that haven't yet been generated from that list, repetitive cycles are prevented. Short-term memory is created and maintained with each tabu iteration.

Clarke-Wright savings list: The amount of savings is calculated using the Clarke-Wright savings list, which also links existing nodes. The savings list's route, which is determined by the distance between the starting and destination nodes, is where the biggest savings can be found. The proposed Clarke-Wright savings algorithm implements several modeling delimiters as follows:

$$c_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{8}$$

$$s_{i,j} = c_{1,j} - c_{i,j} \tag{9}$$

$$s_{i,j} = c_{1,i} - c_{j,1} - c_{i,j} \tag{10}$$

The physical coordinates for customers *i* and *j* are (x_i, x_j) and (y_i, y_j), respectively. The notation $c_{i,j}$ represents the distance between the depot and customer j, while $c_{i,j}$ represents the distance between customers i and j. If the total demand is within the vehicle's carrying capacity and there are no route restrictions, both customers *i* and *j* will be combined onto the same route at the top of the savings list. Steps 1 through 9 of the solution iterations describe the actions that are taken during each stage.

Step 1: Initialization

The initial route is derived from the savings algorithm & swap mechanism in Tabu search. The tabu list is initialized as 0, where the iteration count *t* is set as 1.

Step 2: City Selection

The best solution is identified from the current solution pool, with the shortest distance, lowest fixed load dispatches, and lowest chromosome identifier.

Step 3: Evaluate the candidate's moves

The swapping mechanism is used to calculate the cost of the trial solution and move the genome of the current best city back to the previous route.

Step 4: Identify the best move

The tabu search gives the attribute (i, k) a tabu status and a tabu duration using an adaptive memory diversification strategy. The tabu list has a size of 0 and is measured in [min, max] units. The parameter is changed to min (1, max) following several iterations. The precise move is noted as the trial move that provides a cheap solution that is deemed infeasible.

Step 5: Inquire about tabu status

If the selected exact move is not considered tabu and does not fulfill the aspiration criteria, remove them. Otherwise, the exact move proceeds to the next stage for execution.

Step 6: Move execution

Perform the exact move on the current generated solution step. Then revise the new total distance and solution. The current best solution contains the total cost of the new assimilated solution with the previous best solution, whether it is feasible or not.

Step 7: Tabu declaration

From the current best solution step, the latest tabu tenure is declared representing the recent move. The tabu list is revised according to the updated tabu tenure.

Step 8: Adjust the penalty values

The value of α and β is adjusted accordingly.

Capacity:

i. The solution is feasible in regards to capacity, set $\alpha = \alpha/2$
ii. The solution is infeasible in regards to capacity, set $\alpha = 2\ \alpha$

Step 9: Terminate the check

Relocation moves (i, k') are taken into account if the neighbor solution is feasible, is not on the tabu list, and has a cost that is less than the aspiration value. This updates the aspiration value for each attribute of a feasible solution. In cases where the neighbor solution and its cost are less than the smallest aspiration value, route exchange moves (i, j, k, k') are taken into consideration.

i. Stop the search after a predetermined number of iterations if the value of the objective function does not get any better.
ii. If the least cost for a feasible or infeasible solution is not decreased, stop.
iii. If max iteration, stop.

3.2.4 *Route relocation*

The attempts to construct functional chromosomes utilizing 1-0 relocation, 2-Opt exchange, and two chromosome insertions are the most crucial details in this text. When performing intra- and inter-route relocations, which simulated local neighborhood searches, cyclical iteration was added. In a 2-Opt exchange, two extra edges are substituted for two of its edges, whereas in a 1-0 relocation, one customer is moved from one position on one route to another position on the same or a different route. An inter-route technique called the 2-Opt* exchange involves switching the end pieces of two edges to produce two new routes each. Combining inter-route 1-0/2-Opt* into one route is included to investigate the possibility to decrease the necessary number of vehicles. The exchanges entail moving the segment between two edges of a given route to a new location along the same route.

Table 2. Modeling Heuristics Implemented with Route Relocation Phases

Modifications for inter-route relocation	• *Swap (1, 1)* = Swap out customer-*i*, who makes up route 1, for customer-*j*, who makes up route 2. • *Shift (2, 0)* = Transfer two nearby customers (*i* and *j*) from one route to another. • *Swap (2, 1)* = Switching between two customers from route 1 (*i* and *j*) who are nearby and customer *k* from route 2. • *Swap (2, 2)* = Change the arrangement so that two customers, *k* and *l*, connect route-2 with two customers, adjacent customers *i* and *j* from route 1. • *Cross*: Remove (*i*, *j*) from route-1 and (*k*, *l*) from route-2. After that, combine the new side into (*i*, *l*) and assign it to route-1, while assigning (*k*, *j*) to route-2.
Modifications for intra-route relocation	• *Or-opt*: For the same route, remove one or three adjacent customers and replace them. • *2-opt*: To add a second route, add the remaining two sides and subtract the two non-adjacent sides. • *Exchange*: Similar to Swap (1, 1) but occurs within the intra-route domain for the same route. • *Reinsertion*: The customer who was previously removed from the route is moved during reinsertion.

4. COMPUTATIONAL EXPERIMENTATION

4.1 *Test instances*

A small data cluster representing the supply chain for Sibu, Sarawak's largest general grocery store is used to test the proposed multi-depot heuristic. To segment routes, depot compositions are categorized according to routing instance arrangement requirements for this route. 23 customers represent participants and pick-up points in the testing dataset. In light of the lack of an equivalent collection of MDVRP instances that can be used to adapt to fixed parameter settings as required by the suggested solution strategy, a custom dataset is derived based on depot centrality, customer involvement, and the number of deployment vehicles. With the pick-up depot and customer cluster population distributions as custom values, the classic VRP dataset by Cordeau is referenced. The planned scheduling network's node array is symmetrical with customer schedules. To simulate actual deployment conditions, customer populations are distributed according to the Euclidean distance from the distribution center closest to them. Urban areas have concentrated customer groups made up of strategic store placement and high customer population density.

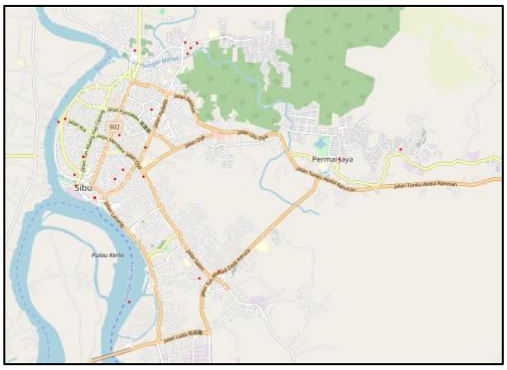


Fig. 3. Real-World Position of the 23 Participating Nodes of the Distribution Network

Routing instance selection: The Clarke-Wright savings heuristic is used to sample the locations of each customer within the distribution depot, while the load capacity is maintained constant during the entire run per the modeling restrictions. The first derivation from the baseline dataset is followed for each vehicle capacity. To explore the impact of these isolated routing factors on the effectiveness of routing optimization, problem instances are chosen based on the number of cars and consumers from a pool of 23 problem examples in the chosen emulated dataset.

Table 2. Coordinates Representing the Participating 23 Traversal Nodes to Pick-Up Points

Node	Coordinates (x, y)	The interval from the initial node (km)
1	2.29295, 111.83435	1.2
2	2.30952, 111.82063	3.2
3	2.30112, 111.91330	12.4
4	2.28764, 111.82873	0
5	2.31209, 111.84447	5.1
6	2.32842, 111.83981	5.7
7	2.29550, 111.83664	1.3
8	2.33049, 111.85705	7.5
9	2.32750, 111.85441	6.0
10	2.29098, 111.82364	0.6
11	2.29410, 111.82318	1.1
12	2.33059,111.85370	6.6
13	2.26733, 111.86326	6.7
14	2.29829, 111.89631	9.5
15	2.28767, 111.82895	0.3
16	2.30163, 111.84276	3.0
17	2.30866, 111.81881	3.1
18	2.29351, 111.84233	1.9
19	2.25895, 111.83833	4.9
20	2.30503, 111.83561	4.3
21	2.29901, 111.82561	1.5
22	2.26542, 111.85772	5.7
23	2.32903, 111.85541	7.6

4.2 Results

The small-scale sample of the custom benchmark taken from Cordeau's MDVRP works includes various features, such as non-uniform customer frequency and quantity, with scattered randomly assigned depots with varying availability. Fixed capacity restrictions (60–500 kg) and restricted vehicle use are features of the emulated problem. Pick-up points that are grouped by the savings list serve as representations of the customer locations. In all instances of the problem, there will always be a fixed number of 23 customers and a myriad of vehicle quantities ranging from 2 to 12.

Table 3. Parameter Settings Imposed for Each Algorithm Iteration

Parameter variable	Values
Population size, *NP*	40
Mutation rate	0.99*f*
Tournament size	5
Elitism %	10
Crossover factor, *F*	0.1*f*
Crossover rate	0.1*f*
Heuristic chance	1.0*f*
Number of generations	10000
Maximum run time	1000*60*5 *ms*
Intervention rate	500
Tabu iteration	200
Route relocation iteration	1000

Table 4. Total Expedited Routing Component Values for the Proposed Custom Dataset

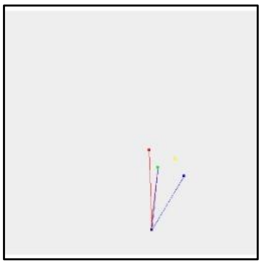
Instances	Vehicle	Customer	Depot	Load capacity (kg)
p02	2	23	4	160
p03	3	23	5	140
p05	5	23	2	200
p09	12	23	3	500
p12	5	23	2	60
p15	5	23	4	60
p18	5	23	6	60
p21	5	23	9	60

Table 5. Route Segmentation using Baseline Genetic Algorithm

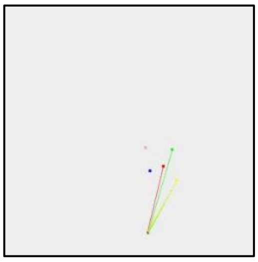
Instance	Most optimized route sequence	Target cost	Final cost
p02	14-9-8-6-3-13-11-10-7-12-17	497.21	452.15
p03	19-22-1-11-10-7-13	673.25	558.48
p05	14-6-3-9-8-13-11-7-10-17-22-21-20-1	787.53	775.06
p09	37-2-8-14	4095.23	4084.45
p12	8-9-21-1	1384.90	1201.53
p15	4-4-22	2630.69	2117.28
p18	4-4-21	3887.99	2570.44
p21	4-4-21	5748.58	2571.45

Table 6. Route Segmentation Using the Proposed Multi-Depot Routing Heuristic

Instance	Route sequence	Clarke-Wright		Route Relocation		Tabu
		Serial	***Parallel***	***Intra***	***Inter***	
p02	0-7-9-8-19-15-13-3-17-12-2-0	10496.54	8389.74	4185.0	4039.0	4017.0
p09	0-19-17-12-8-21-0	17912.08	12741.38	5982.0	5541.0	5541.0
p21	0-0-12-8-21-6-10-20-13-16-3-18-0	15143.45	10752.92	6023.0	5484.0	4904.0



p02



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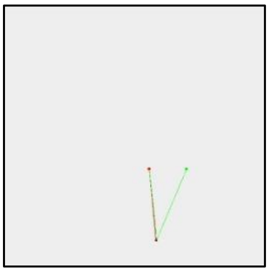

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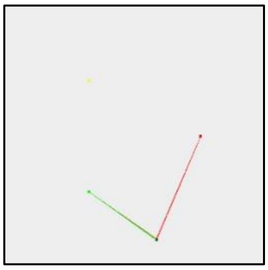

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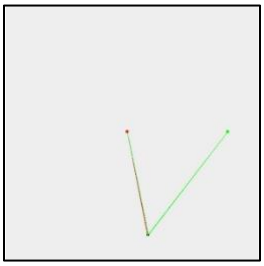

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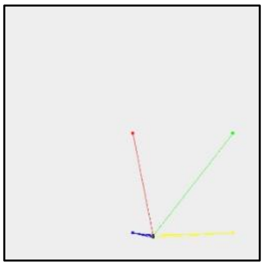

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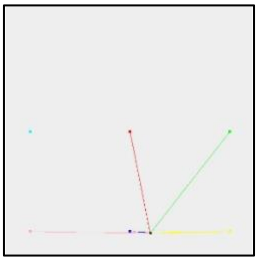

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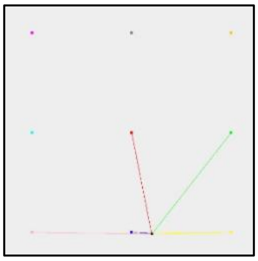

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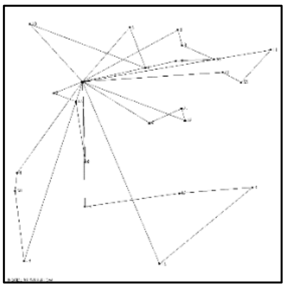
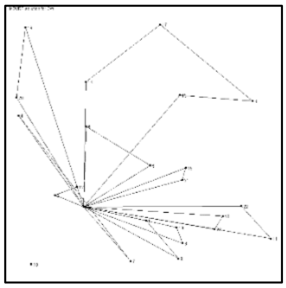
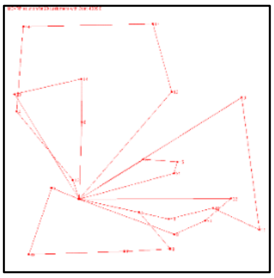
Fig. 4. Simulation Results for the Custom Dataset Run on Baseline Genetic Algorithm



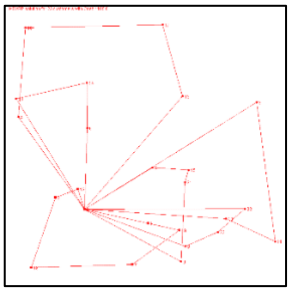
CW (Parallel)



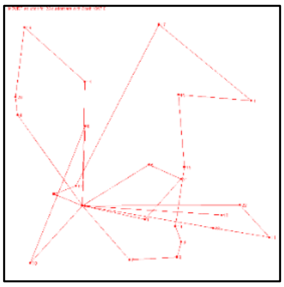
CW (Serial)



Route Relocation (Inter)

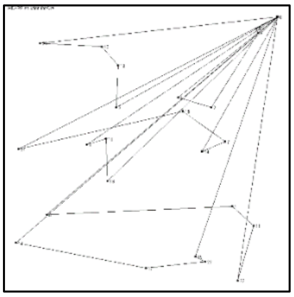


Route Relocation (Intra)



Tabu

Fig. 5. Solution Instances Run using the Proposed Routing Heuristics (Custom *p02* Instance)



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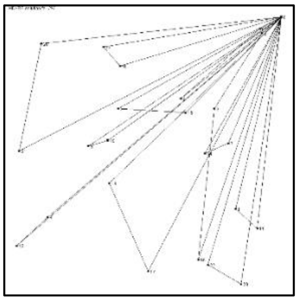

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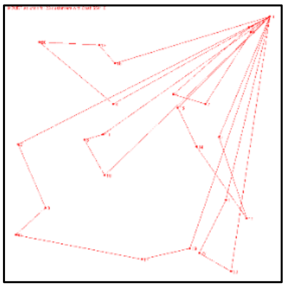

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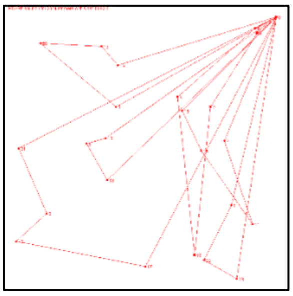

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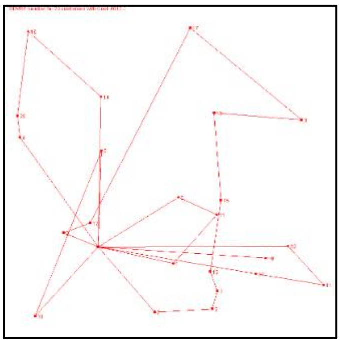
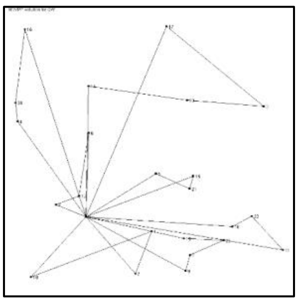
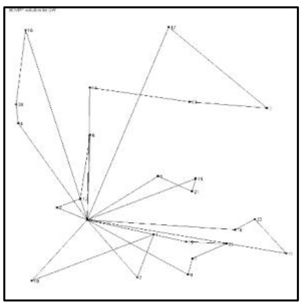


Tabu

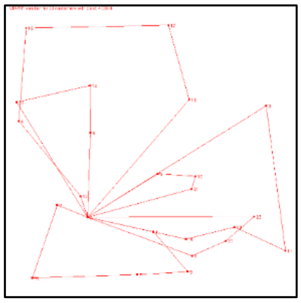
Fig. 6. Solution Instances Run using the Proposed Routing Heuristics (Custom *p09* Instance)



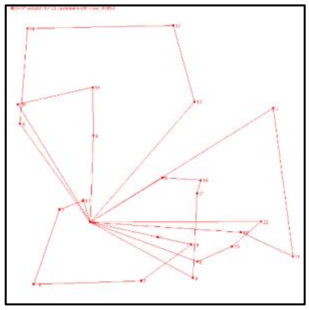
CW (Parallel)



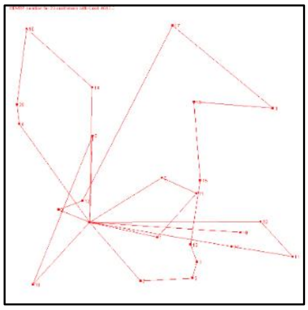
CW (Serial)



Route Relocation (Inter)



Route Relocation (Intra)



Tabu

Fig. 7. Solution Instances Run using the Proposed Routing Heuristics (Custom *p21* Instance)

The comparison of the basic genetic algorithm and the proposed approach shows the heterogeneous nature of the two solution strategies in routing optimization and cost maximization. Three of the eight tested instances produced by the genetic algorithm (p02, p09, and p21) were selected to be assessed using the suggested solution algorithm. Based on the routing order and the final expedited cost, the genetic algorithm results in a relatively lower cost and number of nodes traversed than the proposed solution heuristic. The genetic algorithm performs well under fixed constraints, but uneven variations and decreasing values are observed when the values of the imposed parameters are elevated. The proposed routing model increases the capacity for cost reduction while vacillating among the trade-off between cost optimization and maximizing vehicle deployment rate. The results of the proposed heuristic show a consistent downward trend with each parameter change even with incremental complexity spectrum.

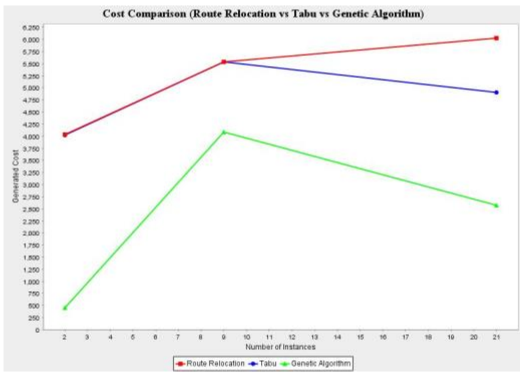


Fig. 8. The Result For The Evaluated MDVRP Benchmark Final Cost Between Genetic Algorithm and the Best Result

from Route Relocation (Intra/Inter) and Tabu Search Integration

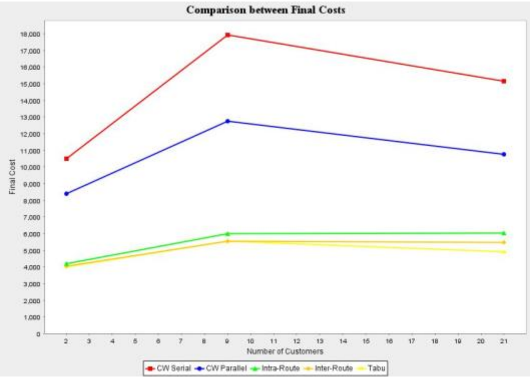


Fig. 9. The Final Cost for the Routing Instance (p02, p09, p21) Running on the Proposed MDVRP Routing Heuristic Branching from CW Savings Heuristic (Serial/Parallel), Route Relocation (Intra/Inter), and Tabu tenure

5. Conclusion

The goal of this work was to integrate the basic principles of the savings heuristic mechanism and iterated local search approach to enhance the current baseline genetic algorithm used in the solution strategy for multi-depot VRP. The baseline genetic algorithm and the suggested routing heuristic produced a range of outcomes in the experiment depending on their heterogeneous properties in performing routing optimizations according to each of the execution criteria. This work demonstrated promising results for combinatorial routing optimization methods, such as multiple simultaneous deployments, when measured against the performance of the genetic algorithm's baseline on the intended solution strategy. Future efforts could include useful metaheuristic approach incorporations to enhance routing heuristic aspiration criteria, hybridization with more compatible exact methods, and the addition of more VRP issues with problem instance typing to ascertain the prodigious traits of computational intelligence applications in viable decision-making scenarios.

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