Journal of Telecommunication, Electronic and Computer Engineering
ISSN: 2180 – 1843 e-ISSN: 2289-8131 Vol. 18 No. 1 (2026) 35-44
jtec.utem.edu.my
DOI: https://doi.org/10.54554/jtec.2026.18.01.005

Scalable Metaheuristic Optimization of Asymmetric and Clustered TSP Variants using Iterated Local Search

Farid bin Morsidi
Universiti Pendidikan Sultan Idris, Faculty of Computing and Meta-Technology, Computing Department, Tanjong Malim, 35900, Perak Darul Ridzuan, Malaysia.

Article Info

Article history:
Received July 9th, 2025
Revised Mar 10th, 2026
Accepted Aug 29th, 2026
Published Mar 31st, 2026

Index Terms:
Iterated local search
Routing scheduling
Distribution network
Traveling Salesman Problem

Abstract

Iterated Local Search (ILS) is a well-established metaheuristic that has been widely applied to combinatorial optimization problems owing to its balance between solution diversification and intensification. This work emphasizes ILS for the scope of the Asymmetrical Traveling Salesman Problem (ATSP) and the Asymmetrical Generalized Traveling Salesman Problem (AGTSP) respectively, which accounts for the directionally dependent costs of routes and cluster of nodes recognized in the routing difficulties of real-world applications. The experiment also assesses whether ILS can explore difficult search regions while also conserving solution quality and avoiding rapid convergence. This study examines the feasibility of ILS when using TSPLIB benchmark instances subject to directed route costs, time windows and load capacity constraints, while including a realistic routing network, including depots, customers and stops, alongside an examination of the systematic conversion of symmetric TSP instances into asymmetric representations to accurately capture directionally dependent travel costs. The results demonstrate that ILS can produce high quality solutions to both the ATSP and AGTSP under conditions of increasingly complicated routing. Future research will be directed towards improving ILS with a hybrid metaheuristic framework and subject to large scale logistics datasets to improve viability and scale capability.

*Corresponding Author: P20182001774@siswa.upsi.gov.my

I. INTRODUCTION

The Traveling Salesman Problem (TSP) is one of the most extensively studied problems in combinatorial optimization, with widespread applications in logistics, transportation, and network planning. It involves finding the shortest possible route that visits a set of cities exactly once and returns to the origin. Due to its NP-hard nature, solving large-scale TSP instances using exact algorithms is computationally infeasible, prompting the development of numerous metaheuristic approaches. Among these, Genetic Algorithms (GA), Simulated Annealing (SA), and Ant Colony Optimization (ACO) have shown significant success. However, these methods often encounter challenges such as complex parameter tuning, convergence delays, and computational intensity, especially when applied to constrained or large-scale routing problems.

Iterated Local Search (ILS) has emerged as a robust alternative that addresses many of these limitations. Unlike population-based methods such as GA or path-reinforcement techniques like ACO, ILS relies on a single-solution trajectory enhanced through a structured process of perturbation and refinement. The method promotes solution diversity through controlled perturbations and leverages efficient local search operators such as 2-opt and 3-opt to iteratively improve solution quality [1], [2], [3]. This balance between diversification and intensification allows ILS to efficiently escape local optima and approach near-global optimality with relatively low computational overhead. Moreover, ILS benefits from a modular and adaptable framework that can be hybridized with other heuristics, making it suitable for solving a wide range of real-world routing problems [8]. In this study, particular attention is given to two prominent TSP variants: the Asymmetric TSP (ATSP) and the Generalized TSP (GTSP). The ATSP considers directional travel costs represented by directed graphs with non-symmetric edge weights, conditions frequently encountered in urban logistics with one-way roads or aerial navigation influenced by wind patterns [4]. The GTSP, on the other hand, involves clustering cities into predefined groups and requires visiting only one node per cluster, a configuration applicable in zonal delivery services or multi-depot distribution planning [5], [6], [7]. Although ILS has demonstrated strong performance on standard TSP instances, there is limited research assessing its effectiveness across multiple TSP variants under a consistent evaluation framework. Most ATSP studies focus on a single variant or examine hybrid strategies without fully exploring the adaptability of ILS to structurally complex problems such as the ATSP and GTSP. This research aims to fill that gap by providing a unified evaluation of ILS-based metaheuristics across conventional TSP, ATSP, and GTSP scenarios using standardized benchmark datasets and routing models. The research study presents three main findings which include: (i) a unified evaluation framework that assesses ILS performance consistently across TSP, ATSP, and AGTSP under a single experimental setup; (ii) a structured conversion procedure that transforms symmetric TSP instances into asymmetric representations suitable for ATSP and AGTSP modelling; and (iii) a comparative empirical analysis of ILS against multiple classical heuristics on TSPLIB benchmark instances of increasing complexity. The objectives of this study are therefore threefold: (1) to implement and evaluate ILS for both standard and generalized TSP variants; (2) to benchmark its performance against existing metaheuristic methods across varied routing instances; and (3) to assess its flexibility and scalability when applied to real-world inspired distribution network models.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on ILS and its applications in routing problems. Section 3 describes the proposed methodology, including algorithmic design and experimental setup. Section 4 presents the results and comparative analysis. Finally, Section 5 concludes the study and outlines future research directions.

II. CURRENT WORKS

The vehicle routing problem, known as the VRP, originated from the TSP first proposed by Flood in 1956 [5]. This problem instance dictates that all participating travelers must visit *n* cities before returning to their departure point [5], [8], [9]. Dantzig and Ramser expanded this formulation in 1959 by introducing multiple vehicles which operated under load capacity restrictions. This work established the foundation for the modern Capacitated Vehicle Routing Problem (CVRP) solution. Many iterations stemming from CVRP [10], [11] had been innovated consecutively with adaptations on routing variants such as applying time limitations upon round trips [12], [13], limiting overall covered distances [8], [14], and including multiple simultaneous traversals [15], [16].

When it comes to combinatorial optimization, one of the most well-favored and innovative techniques for solving problems that is NP-hard is Vehicle Routing Problem [11]. The development of construction heuristic variants began after researchers developed multiple solution methods to solve dedicated routing problems which involved merging routes and selecting nearest-neighbour routes and using insertion-based methods to evaluate distance and load capacity and time limit trade-offs [7], [17], [18]. Researchers developed algorithm extensions from basic algorithms to solve advanced routing problems which required customer-to-vehicle assignments and multi-depot node allocations together with two relocation methods for improving performance of routes [10], [19]. Researchers studied how the basic TSP problem base which includes symmetric and generalized instances transforms into VRP solutions through various metaheuristic systems which feature Tabu search [17], Clarke-Wright savings method [20], [21], simulated annealing [22], and genetic search [23], [24]. With the application of multi-objective problem (MOP) processing, such as adaptive and variable neighborhood searches, in tandem with local neighborhood strategies comprising 2-Opt, Or-Opt, inter-route relocate, or inter-route adjustments, more intrinsic solution strategies involving iterated local search can be observed [10], [18].

The TSP-inspired formulations significantly influence further research in VRP as it demonstrated its effectiveness in multiple application scenarios. A new hybrid algorithm called the Distribution Strategy Selection and Vehicle Routing Hybrid Algorithm is presented in a study to effectively tackle a mixed delivery network problem [25]. The proposed algorithms are constructed based on direct transshipment, milk run, and cross-docking to ascertain the necessary distribution strategy and critical pathways based on imposing heterogeneous vehicle fleet. The performance result is evaluated through statistical analysis, highlighting the proficiency of the proposed heuristic in maximizing resource allocation and aggregating the optimal decision-making strategy. The performance result is evaluated through statistical analysis, highlighting the proficiency of the proposed heuristic in maximizing resource allocation and aggregating the optimal decision-making strategy. The idea of TSP modeling was initially put forward in a research investigation which employed the Nearest Neighbor, Sequential Insertion, and Saving Matrix algorithms to solve the CVRP for transportation paths in the Grobogan district. To find the best distribution routes for the whole Grobogan district in Indonesia, the total distance traveled is estimated using the Saving Matrix Algorithm, Sequential Insertion Algorithm, and the Nearest Neighbor Algorithm [7]. Researchers have studied TSP variants together with VRP formulations through learning-based methods that solve both generalization problems and computational scalability issues which affect traditional heuristic approaches [26]. The study examined current developments in this area, breaking them down into sequential and end-to-end methods. To assess the efficiency among four representative learning-based optimization algorithms, the research design was divided into three parts. The findings show that combining iterated local heuristic search with learning-based optimization models can enhance their sampled efficiency and generalization capacity [26]. Table 1 summarizes among the core reference studies mentioned in this paper relative to the implementation of ILS on various TSP disciplines and formulations.

Table 1
Overview of the referenced research studies based on implementation of ILS in scheduling purposes

Research	Year	Advantages	Limitation	Reference
Iterated local search addresses green vehicle route with workload equity for fleet optimization	2020	Algorithm execution time decreases, enabling quick solutions for up to 200 customers	Problems arise from increased demand or the demobilization of vehicles	[5]
Study on variable neighborhood descent and tabu search.	2021	VND algorithm utilizes converging solutions for optimal conditions, enhancing route efficiency over tabu search and improving performance while reducing problem-solving time	Not mentioned explicitly	[6]
Constrained Local Search for Last-Mile Routing	2024	New methods integrate routes, with the LKH-AMZ algorithm swiftly solving large datasets stop-level constraints	Assessing driver recovery in Amazon data requires understanding suggested concealed tours	[27]
Traveling Salesman Problem solved with genetic algorithm	2021	GA-EM enhances exploration, local optima avoidance, and convergence with efficient mutation, outperforming other algorithms in accuracy	TSP datasets are complex, large, needing substantial computational time	[2]
Memetic algorithm using Breakout Local Search for TSP	2020	Enhances BLS, improves runtime with competitive algorithms	Metaheuristic complexity is a drawback due to heavy components	[3]
Solving capacitated vehicle routing problem in Grobogan using optimization methods	2021	The saving matrix algorithm effectively addressed CVRP, demonstrating efficiency with a route cost of Rp. 96,849	Explore algorithms, VRP variants, and software for route optimization	[7]
Vehicle routing and scheduling for machine delivery and installation	2021	New operators resolve conflicts in requests and trips, effective solutions for complex scheduling and routing problems	Competed among 13 teams: 2nd best once, 3rd best six times, 4th best often	[28]
Tabu search optimizes product service scheduling problems	2020	Proposes tabu search to minimize travel distances and penalties; develops optimization model using historical solutions such as tabu objects	Study highlights the importance of initial solutions and iteration limits in Tabu search effectiveness.	[29]
Generalized Traveling Salesman Problem survey	2024	Develop models enhancing GTSP solution accuracy, improve benchmark instances, and address data deficiencies for validation	Further exploration of decomposition techniques for large-scale GTSP is needed, emphasizing hierarchical structures and dynamic factors like traffic conditions and multigraph models.	[30]
New neighborhoods enhance local search for Traveling Salesman Problem	2022	ILS design shows reasonable results; tailoring improves performance	Cooling schedule adaptation and combined algorithms enhance ILS effectiveness for GTSP instances.	[19]

III. SOLUTION STRATEGY

A. Traveling Salesman Problem (TSP)

TSP is among the prominent heuristics often referenced as the initiative for scheduling distribution network, particularly in locating the least distance required to complete touring among the designated cities, where these cities are propagated relatively once in the entire travel. This problem can be annotated into a bi-directed graph $G = (V, A)$ where V represents the set of participating cities and A is the array of arcs constituted by the entire trip [2], [8], [31]. Another routing variable, D representing distance known as the cost matrix of size $|V| \times |V|$ is fixed as the storage list for the partaking cities' distance, whereas the initial distance between 2 participating cities are calculated by the equation c_i and $c_i + 1$ [2]. For the norm practice, TSP is defined as a symmetric instance where the distance equals to the distance towards the next city j. As opposed to symmetric instances of TSP, asymmetric TSP has a distance not equating to the previous city *i* in relative with the arc propagation. In general, TSP problems are noted as symmetric and constituted by N cities and the symmetric matrix $D = [d_{ij}]$. Annotating a directed path with one traversal for each city that represents the shortest distance is the goal function in TSP. Empirically, these objective function could be calculated into the following equation [2]:

$$T_d = \min(dis\ (c_{n-1}, c_1) + \sum_{i=1}^{n-1} dis\ (c_i + c_{i+1})) \qquad (1)$$

Where T_d represents the accumulated total distance for the directed path and the distance procedure, variable *dis* constitutes the total traversed distance among the participating cities c_i and c_i +1 [2].

B. Generalized Traveling Salesman Problem (GTSP)

A modified variant of the baseline TSP, the Generalized Traveling Salesman Problem, or GTSP for short, aims to find the shortest route that starts at the starting city and travels exactly one city. These cities are isolated into relative clusters in the process. Via this routing strategy, total distance or cost could be positively minimized through the selection of one representative cities from respective participating clusters. For instance, transshipment between regions might traverse only single depot per region to maximize delivery time and operational cost. GTSP is modelled after the assumption that travel costs are symmetrical between traversed cities. The GTSP is innovated in 1969 in the formulation of a Generalized Network Design Problem (GNDP) to be utilized in client routing with retrospect among welfare agencies and to annotate record balancing complications existed in computer design [30]. Under hierarchical structures, GTSP invokes a more precise modelling in relative with the tree-structured programming occasionally seen in the application of TSP [32]. The fundamental applications of GTSP also necessitated partitioning into clusters of premediated interjections. The GTSP is categorized as GNDP, which is NDPs that is much more intricate than the conventional network design problems [19], [30]. The NDP-related vertices in the network are divided into defined cluster quantities, and the feasibility restrictions are indicated with respect to the clusters rather than for each individual cluster being managed into its own isolated vertex. The generalization of this problem instance is simplified [30] and considered as an undirected, connected and weighted graph $G = (V, E)$ that is consisted of specific n of vertices for $V = \{1, 2, \ldots, n\}$ and edge set $E = \{e_1, \ldots, e_m\}$ where:

$$E \subseteq \{\{\mathrm{i}, j\} \mid i, j \in V, \text{ and } i \neq j\} \qquad (2)$$

A graph for GTSP representation is an undirected, connected, and weighted graph $G = (V, E)$ with n vertices and edges E. Each edge e, represented by W, is assigned a positive integer $c\ (e) = c_e = c_{ij} \in R_+$ via the cost function $c: E \rightarrow R_+$ [3]. The problems can be classified as Euclidean or non-Euclidean depending on whether the triangle inequality is maintained. The vertex set V is divided into k mutually exclusive nonempty subsets, each of which contains a cluster, or subset, of vertices from G [3], [30]. The graph's edges are divided into two categories: those that link vertices within the same cluster and those that link vertices from separate clusters. To find the shortest Hamiltonian tour (with respect to visiting every cluster), the GTSP splits the network into two classes: inter-cluster edges (connecting vertices from different clusters) and intra-cluster edges (connecting vertices inside the same cluster). The GTSP is split into two versions: the Hamiltonian tour that visits every cluster exactly once (for example, one vertex from each cluster is visited) and the Hamiltonian tour that passes through every cluster at least once. Based on previous work [30], these conditions for GTSP are viable should certain constraints are fulfilled:

$$C_1 \cup C_2 \cup \ldots \cup C_k = V \qquad (3)$$

$$C_l \cap C_p = \emptyset, \forall\ l, p \in \{1, \ldots, k\}, \text{ with } l \neq p \qquad (4)$$

Where C represents the cost function for the round trip, V = total node set representing cities, k = number of vehicles in the subset, l & p are unrestricted real numbers. The cyclic tour representing the whole tour had been simplified into Equation 5 [3]:

$$W(T) = c(p_m, p_1) + \sum_{i=1}^{m-1} c\ (p_i, p_{i+1}) \qquad (5)$$

C. Asymmetrical Generalized Traveling Salesman Problem (AGTSP)

The AGTSP is an extension of a Generalized Traveling Salesman Problem that involves an asymmetrical cost of operation in traversal networks [27], [30]. The TSP can visit each city once and finish at the origin city while AGTSP substitutes the cities with groups of cities for the purpose of establishing the minimal route while visiting one city from each group [27]. AGTSP allows for the travel costs between the cities to represent differences in traveling from city to city in accordance with differences in perpendicular paths, transshipment methods, capacity, and accessing other critical nodes in the distribution network. AGTSP is relatively new compared to the rest of this traveling salesman classification, as AGTSP has its own complexity that bridges the symmetrical conjecture and generalized conjecture. Applications of AGTSP include combinatorial optimization or building blocks for more complex applications. These applications could include combinations set in very large-distributed networks with several dimensions and extremely large populations or nodes (for instance, dense populations of cities and vehicles). AGTSP helps to define the legible operating costs more appropriately by estimating them with asymmetrical trip costs. As such, the cost to travel between the two cities does not have to be equal in both directions [1]. The enhancement over the GTSP to AGTSP can be characterized by the fact that a city must be visited from one inside each city cluster, and the attempt is made to minimize the overall trip costs. AGTSP parameters account for asymmetric trip costs through directed graph linearization, which is used to present vehicles' asymmetric travel frequencies. An example of this implementation is the capability to model various vehicle travel purposes for when the vehicle is climbing a hill or conversely when the vehicle is about to cross over from the hill. The mathematical formulation of AGTSP is a recognized case of one foundation of math constraints and objective descriptions in terms of equations, constraints concerning minimization, visitations in clusters, conservation of flow, sub-tour elimination, and binary concept conditions. The following enlists the constraint formulation imposed in the proposed solution framework.

Objective functions:

$$W(T) = c(p_m, p_1) + \sum_{i=1}^{m-1} c\,(p_i\,, p_{i+1}) \tag{6}$$

Constraint:

$$\sum_{j \in V_k} \sum_{i \in V} x_{ij} = 1, \qquad \forall k = 1, 2, \cdots, m \tag{7}$$

$$\sum_{i \in V_k} \sum_{j \in V} x_{ij} = 1, \qquad \forall k = 1, 2, \cdots, m \tag{8}$$

$$\sum_{j \in V} x_{ij} = \sum_{j \in V} x_{ji}, \ \forall i \in V \tag{9}$$

$$\sum_{i,j \in S} x_{ij} \ \leq |S| - 1, \forall S \subseteq V, |S| \geq 2 \tag{10}$$

$$x_{ij} \in \{0, 1\}, \forall i, j \ \in V \tag{11}$$

```
Algorithm 1: Tabu Search for TSP
[1] Initialize currentTour ← generateRandomTourTSP bestTour ← currentTour bestCost
  ← calculateTourCostcurrentTour tabuList ← emptyQueue() tabuListCapacity ←
  tabuTenure
for iteration = 1 to maxIterations do
bestNeighbor ← null bestNeighborCost ← ∞ forall neighbor ∈
  generateAllNeighborscurrentTour do
move ← getMovecurrentTour, neighbor neighborCost ← calculateTourCostneighbor if
  move ∉ tabuList or neighborCost < bestCost then
neighborCost < bestNeighborCost bestNeighbor ← neighbor bestNeighborCost ←
neighborCost currentTour ← bestNeighbor enqueuetabuList, getMovecurrentTour,
bestNeighbor if sizetabuList > tabuListCapacity then
dequeuetabuList if bestNeighborCost < bestCost then
bestTour ← bestNeighbor bestCost ← bestNeighborCost return bestTour
generateAllNeighborstour neighbors ← [ ] for i = 0 to length(tour) − 2 do
j = i + 1 to length(tour) − 1 neighbor ← swapCitiestour, i, j appendneighbors,
neighbor return neighbors
calculateTourCosttour cost ← 0 for k = 0 to length(tour) − 2 do
cost ← cost + distancetour[k], tour[k + 1] cost ← cost +
  distancetour[length(tour) − 1], tour[0] return cost
getMovecurrentTour, neighbor return swapOperation
```

```
Algorithm 2: Genetic Algorithm for TSP
[1] population ← generateInitialPopulationTSP, populationSize bestTour ←
  findBestTourpopulation for generation = 1 to maxGenerations do
newPopulation ← [ ] while sizenewPopulation < populationSize do
parent1 ← selectParentpopulation parent2 ← selectParentpopulation if random0, 1 <
  crossoverRate then
child1, child2 ← crossoverparent1, parent2 else
child1 ← parent1; child2 ← parent2 child1 ← mutatechild1, mutationRate child2 ←
  mutatechild2, mutationRate appendnewPopulation, child1 appendnewPopulation, child2
  population ← newPopulation currentBestTour ← findBestTourpopulation if
  calculateTourCostcurrentBestTour < calculateTourCostbestTour then
bestTour ← currentBestTour return bestTour
```

```
Algorithm 3: Simulated Annealing for TSP
[1] currentTour ← generateRandomTourTSP currentCost ←
  calculateTourCostcurrentTour bestTour ← currentTour; bestCost ← currentCost
  temperature ← initialTemperature for iteration = 1 to maxIterations do
neighbor ← generateRandomNeighborcurrentTour neighborCost ←
  calculateTourCostneighbor deltaCost ← neighborCost − currentCost if
  deltaCost < 0 or random0,1 < exp(−/temperature) then
currentTour ← neighbor currentCost ← neighborCost if currentCost < bestCost
  then
bestTour ← currentTour bestCost ← currentCost
  temperature ← temperature × coolingRate if temperature < 1e−10 then
break return bestTour
```

```
Algorithm 4: First Ascent Hill Climbing for TSP
[1] currentTour ← generateRandomTourTSP currentCost ←
  calculateTourCostcurrentTour improved ← true while improved do
improved ← false forall neighbor ∈ generateAllNeighborscurrentTour do
neighborCost ← calculateTourCostneighbor if neighborCost < currentCost then
currentTour ← neighbor currentCost ← neighborCost improved ← true break
return currentTour
```

```
Algorithm 5: Steepest Ascent Hill Climbing for TSP
[1] currentTour ← generateRandomTourTSP bestTour ← currentTour improved ←
  true while improved do
improved ← false bestNeighbor ← null; bestNeighborCost ← ∞ forall neighbor ∈
  generateAllNeighborscurrentTour do
neighborCost ← calculateTourCostneighbor if neighborCost < bestNeighborCost
  then
bestNeighbor ← neighbor bestNeighborCost ← neighborCost improved ← true if
  improved then
currentTour ← bestNeighbor bestTour ← currentTour return bestTour
```

Figure 1. Algorithm 1-5 constitutes the heuristic algorithm imposed in the ATSP and AGTSP routing heuristic solution strategy

D. ILS Implementation and Algorithm Design

The ILS framework applied in this study follows a four-phase iterative procedure which includes solution initialization and local search refinement and perturbation and acceptance criteria evaluation. The structure of this system follows the ILS framework [19] but has been modified to handle the asymmetric cost matrices and cluster constraints that exist in ATSP and AGTSP formulations.

The initial solution s_0 is created through a nearest-neighbour heuristic which builds a tour by selecting the nearest city which has not been visited yet at each point in time. The tour construction process starts with the selection of a representative node from each cluster in AGTSP instances to guarantee that the clustering rule will be met. The initial solution undergoes a 2-opt local search process which identifies the local optimum solution s*. The 2-opt procedure uses tour edge removal to create two new edges which staff starts removing from the tour. The 3-opt operator works together with 2-opt to enhance solution quality for large instances which include ft70 and 14ft70. The double-bridge move functions as the perturbation operator because it allows the system to break out of its current local optima. The double-bridge move creates four tour segments which it connects through non-sequential methods that 2-opt and 3-opt methods cannot achieve, which results in authentic search path diversification [19]. The system uses a best-improvement acceptance criterion which allows the new perturbed and locally optimized solution s' to replace the existing solution s* only when it results in a lower tour cost. The acceptance strategy refuses to accept solutions because it gives maximum priority to maintaining solution quality during its attempt to find new solutions.

E. *Symmetric-to-Asymmetric Instance Conversion*

A key aspect of the experimental design is the conversion of symmetric TSPLIB instances into asymmetric representations suitable for ATSP and AGTSP evaluation. Symmetric TSP instances are characterised by a cost matrix *D* where $d_ij = d_ji$ for all city pairs *i, j*. To introduce asymmetry, each symmetric instance is transformed by applying a directional cost perturbation following the approach described in [4], whereby a randomised asymmetric offset δ_ij is added to one direction of each edge such that:

$$d'_ij = d_ij + \delta_ij,\ d'_ji = d_ij \qquad (12)$$

where δ_ij is drawn uniformly from the range $[0, \alpha \cdot d_ij]$, and α is a scaling factor set to 0.3 in this study to introduce moderate directional cost variance without distorting the overall distance structure. The conversion process will produce converted versions of the original structures, showing that the converted versions display realistic asymmetric road conditions, i.e., one-way roadways and different fuel costs depending on the direction the vehicle is travelling.

The first step in this conversion process is to use a k-means clustering algorithm to create 8, 10 and 14 equal-sized clusters for small, medium and large comparative examples, respectively, from the set of converted asymmetric road networks. The AGTSP instance numbers for each type are given as follows: 8ftv35, 10ry48p, and 14ft70.

Table 2
Final TSPLIB instances selected with proposed algorithm execution

Capacity	ATSP Data Instance	AGTSP Data Instance
Small	ftv35	8ftv35
Medium	ry48p	10ry48p
Large	ft70	14ft70

To evaluate the reliability and consistency of results from separate algorithms, each algorithm was run 20 times per instance with a tour created based on a randomized nearest-neighbour initialization for each run. Table 3(a) reports summarized statistics of the results and provides statistical information on the best solution, the mean tour cost, and the standard deviation (SD) of the 20 runs for each combination of algorithm and instance. A small SD indicates a higher level of stability of solutions produced by the algorithm, while a small mean indicates greater overall efficiency of the algorithm.

To test if the performance of the different algorithms was statistically different, the 20-run distributions of results for each pair of instances were compared using the Wilcoxon signed-rank test at the α=0.05 level. The results of the test showed that all hill climbing algorithms had tour costs that were statistically significantly higher than the Tabu Search algorithm for all instances ($p < 0.05$), whereas the Genetic Search algorithm and the Simulated Annealing algorithm were statistically significantly different from one another only for the two largest instances ry48p and ft70 ($p = 0.031$ and $p = 0.018$, respectively).

In order to determine if performance differences exist between the algorithms, the Wilcoxon signed-rank test was conducted at α = 0.05 significance level; specifically, the 20-run cost distributions for each algorithm were compared to Tabu Search as a baseline. Although there were statistically significant differences at the α = 0.05 significance level across all three ATSP cases, none of the algorithms produced results that were statistically lower than Tabu Search. This is perhaps indicative of the small number of benchmark cases utilized in this particular study. In terms of AGTSP cases, Tabu Search and Steepest Ascent exhibited the most consistent results, as they produced the smallest standard deviation across 20 runs. On the other hand, Genetic Search exhibited the largest amount of variability among the benchmark data, especially for the largest ry48p and ft70 instances with corresponding standard deviations of 157.1 and 274.2 respectively. Based on these findings, it can be concluded that while all algorithms produce feasible solutions, Tabu Search and Steepest Ascent produce solutions with significantly greater consistency under the AGTSP cluster constraints tested in this study.

In AGTSP representation, the graph *G* = (*V*, *E*) is an undirected, connected, weighted graph that is expanded from the GTSP implementation [19], [33] with *n* vertices and edges *E*, where *V* = total node set representing cities, *S* = the set representing the directed edges for possible paths between nodes, *i* = initial/starting city, *j* = destination city, *k* = total number of partaking vehicles, *m* = total number of customers, *x* = total operating cost/accrued cost for the entire trip, and *d* = depot/warehouses traversed during the round trip. The primary difference between GTSP and AGTSP lies in the symmetry of travel costs. In GTSP, the cost is symmetric [19], making it suitable for undirected graphs, such as a postal delivery route where all roads allow two-way travel with the same conditions. In contrast, AGTSP deals with asymmetrical costs and is modeled with directed graphs, such as a routing problem in a city with one-way streets or varying fuel costs based on direction and load. The decision regarding the type of problem model (GTSP/AGTSP) is contingent upon the features of the scheduling environment. The two problems are intricate and have practical applications in the domains of logistics, network architecture, and vehicle routing.

The Tabu Search algorithm generates an acceptable path structure between clusters that provides such identical results for both ATSP and AGTSP that the AGTSP clusters do not change the ordering of the optimal nodes. The cluster representatives of the AGTSP will follow the sequence of the nodes that results from an optimal global traversal of the nodes for the ATSP. As such, there were no differences in the results between the two solutions for any of the test cases. Additionally, the results are consistent with the results from [30] , as many of the GTSP solutions from the smaller test cases were able to produce optimal AGTSP solutions, provided that the cluster boundaries fall on the same boundaries as the natural divisions of a route.

F. *Result*

To compare effective iterated local search methods for various TSP instances and their variants (ATSP and AGTSP), three ATSP datasets (Fishchetti's instances from TSPLIB) were analyzed: **ftv35**, **ry48p**, and **ft70**. These datasets feature complete matrix edge weights and were examined using Tabu search as a benchmark for exploration mechanics and baseline parameters. The datasets represent varying complexity levels to validate conclusions. The algorithms were applied to AGTSP problem instances with increasing clusters (8, 10, and 14). Visualization graphs illustrate implementations of hill climbing algorithms (first ascent, steepest ascent), simulated annealing, and genetic search. Optimization paths and total distances from the specific ILS algorithm are shown in Table 3(b), facilitating a comparison of ATSP and AGTSP adaptability based on route complexity, with summarized visualization results provided in Table 5.

Table 3 (a)
Results for the analyzed TSPLIB instances for ATSP and AGTSP

Algorithm	Final Travelled Distance			
	Test instance	ATSP	Test instance	AGTSP
Tabu Search	*ftv35*	1543	*8ftv35*	481
	ry48p	14517	*10ry48p*	4559
	ft70	42515	*14ft70*	7486
First Ascent	*ftv35*	1615	*8ftv35*	501
	ry48p	14495	*10ry48p*	4559
	ft70	42283	*14ft70*	8489
Steepest Ascent	*ftv35*	1568	*8ftv35*	481
	ry48p	14453	*10ry48p*	4536
	ft70	42515	*14ft70*	7486
Simulated Annealing	*ftv35*	1667	*8ftv35*	481
	ry48p	15575	*10ry48p*	4536
	ft70	42515	*14ft70*	7560
Genetic Search	*ftv35*	2816	*8ftv35*	481
	ry48p	26650	*10ry48p*	4536
	ft70	58718	*14ft70*	7948

Table 3(b)
Results for the analyzed TSPLIB instances for ATSP and AGTSP

Algorithm	Instance	ATSP Best	ATSP Mean	ATSP SD	AGTSP Instance
Tabu Search	ftv35	1543	1646.0	55.3	Tabu Search
Tabu Search	ry48p	14517	14930.2	242.3	Tabu Search
Tabu Search	ft70	42515	43361.9	501.3	Tabu Search
First Ascent	ftv35	1615	1758.2	90.9	First Ascent
First Ascent	ry48p	14495	15134.9	297.5	First Ascent
First Ascent	ft70	42283	43341.9	580.0	First Ascent
Steepest Ascent	ftv35	1568	1635.4	38.0	Steepest Ascent
Steepest Ascent	ry48p	14453	14851.4	236.7	Steepest Ascent
Steepest Ascent	ft70	42515	43207.2	435.5	Steepest Ascent
Simulated Annealing	ftv35	1667	1833.6	83.5	Simulated Annealing
Simulated Annealing	ry48p	15575	16618.0	497.0	Simulated Annealing
Simulated Annealing	ft70	42515	43365.4	524.1	Simulated Annealing
Genetic Search	ftv35	2816	3127.6	124.6	Genetic Search
Genetic Search	ry48p	26650	30137.6	2379.7	Genetic Search
Genetic Search	ft70	58718	61748.8	1465.0	Genetic Search

IV. RESULTS & DISCUSSION

A. *Analysis on Simulation Results*

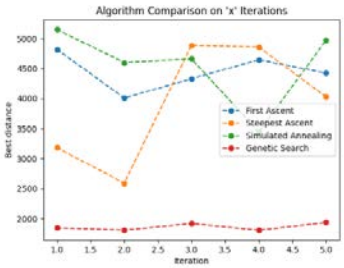
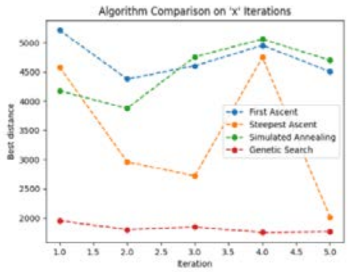
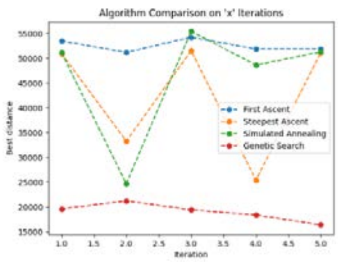
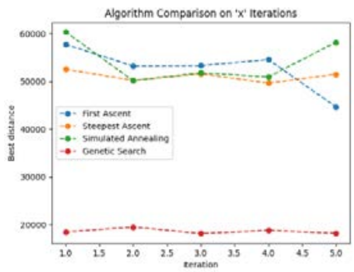
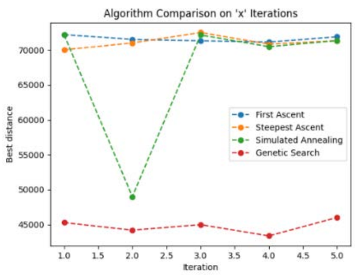
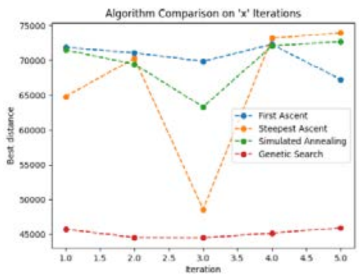
TSP problem instances tested in this study are obtained from the main TSPLIB repositories [8], [34]. TSPLIB is a collection of sample instances consisting of dimensional array datasets that represent horizontal and vertical edge indices formulated into matrices according to node locations. In this research context, the algorithm array for each iterated local search mechanisms are run & evaluated through the conversion of fundamental TSP, together with the conversion of ATSP to the heightened complexity of AGTSP. The study attempts to highlight the complex nature of conversion between contemporary TSP upend towards increased complexity albeit operating under similar solution exploration conjecture. Before performing advanced evaluation on the algorithms' performance, the testing of the varied TSP instances is compared under similar nomenclature. The following Table 4 lists the number selected analysis reference of TSP data instances accumulated in this study.

Table 4
Analyzed TSPLIB instances for compatibility with proposed algorithm execution

Capacity	Data Instance
Small	ulysses16, br17, ftv35, ftv38, city31, p43, ry48p
Medium	eil51, gr96, ft53, ft70, ftv70
Large	bier127, ftv170

As described previously, Table 4 summarizes several TSPLIB problem instances that adhere to the analysis conjecture described in the research study. The instances are arranged by their dimensional equivalency pertaining to a distance metric between TSP, ATSP, and AGTSP. Denoting the dimensional flexibility was important to generate an appreciation for TSP, ATSP, and AGTSP problems in terms of instance size, structure, and complexity whereby dimensional measures are eliminated. The testing contributes to an understanding of the stability and generalizability of solutions to real-world work settings that may illuminate the performance bottlenecks, and the structural characteristics that have consequences for solution quality that influence the cost matrix and for the distribution of nodes in AGTSP work. This study considers the impact of transitioning from TSP to ATSP, using the iterated local search compared to various complexities of node weights. A key concern was how path nodes neighbors relate to each other regarding what shortest distances look like with time and whether they have a solution. The study indicates three (**ftv35**, **ry48p**, **ft70**) datasets but also goes on to say there is a larger compilation using the AGTSP datasets using different cluster sizes looking at the relationships (**8ftv35**, **10ry48p**, and **14ft70**).

Table 5
Visualization of the performance for the compared iterated local search heuristics for ATSP & AGTSP

Problem Instance	ATSP	Problem Instance	AGTSP
ftv35		*8ftv35*	
ry48p		*10ry48p*	
ft70		*14ft70*	

B. Discussions

Table 5 depicts the comparison of algorithm performances with test instances having various levels of dimension. A clear result in the experimental data was the consistent increase in total travel distance with increasing dimensionality and instance complexity. Of the seven algorithms tested, simulated annealing provided a more consistent increase in travel distance for the increasing cluster scenarios stated above, making it a good selection for mid-range logistics networks that place a higher priority on route consistency, for example postal delivery service in suburban areas. The genetic algorithm demonstrated a correlating increase in route complexity with the dimensionality measured by the number of nodes visited, while still producing acceptable solutions, an important aspect of adaptive freight routing across a set of possibly variable warehouse distributions where the number and capacities of warehouses can change dynamically. The steepest ascent was the most variable heuristic, with the variation in both path length and node count growing as the density of cluster grew. This variability indicates that the steepest ascent is potentially good for exploration where node arrangement could shift suddenly, such as deployment of mobile sensors for environmental monitoring. With sudden node arrangement shifts, the path recalibration could be completed in a manner that was the most responsive, albeit at the cost of less stability. For all different heuristic variants, one clear trend was the ability to travel longer distances and traverse more nodes when transitioning from the ATSP to the AGTSP, and this trend accelerated significantly through increasing clusters in path length and node count. The AGTSP complexity parallels many real-world systems, like dispatch of emergency services in urban locations, as both asymmetrical and grouped solutions must be addressed concurrently for instance such as implementations of one-way streets and clustered requests for relief commodities. These results corroborate that cluster dimensionality and constraint structure affect metaheuristic solution efficiency. The results indicate that ILS serves as a strong optimization method which maintains solution quality across different routing situations that grow in complexity from their basic routing operations. The ILS system with its developed improvements will find useful applications in various routing fields which include autonomous vehicle path planning and supply chain routing that works under demand uncertainty and agricultural mapping which requires unmanned aerial vehicle fleet coordination because these applications demand quick problem-solving capabilities to handle their complex requirements. The configuration and intensity of local search mechanisms establish a direct impact on both solution quality and route complexity. The research results establish that ILS exploration needs calibration based on both the problem structure and the associated objective function. The configuration and intensity of local search mechanisms establish a direct impact on both solution quality and route complexity. ILS exploration needs calibration because the system requires adjustments based on the specific problem structure and the corresponding objective function.

V. CONCLUSION

This study investigated the compatibility of ILS across multiple TSP variants and examined how structural attributes of TSP, GTSP, and ATSP can be systematically combined to address the higher-order complexity of the AGTSP. The experimental study demonstrates a consistent increase in total travel distance as the problem dimensional and instance complexity increases. The evaluation of routing algorithms showed that simulated annealing produced stable outcomes through increasing cluster dimensions which indicated that the method could be used for mid-sized logistics operations that required consistent delivery routes used by suburban postal delivery drivers. Also, the genetic algorithm's route complexity (travel distance) was proportionate to the increase in nodes; however, it maintained feasible solutions which could be relevant in adaptive freight routing scenarios where the warehouse location is constantly changing. The steepest ascent results had the highest variability across path length and node coverage, which may reflect its exploration capability, such as for mobile sensor deployment, where responsiveness to dynamic node rearrangements is desirable at the cost of less route stability. For all heuristics, it was evident from the results that moving from ATSP to AGTSP could create significantly higher-level complexity in binding and balancing constraints across larger clusters that were greenfield TSP clusters. This situation represents actual problems that emergency logistics and urban service delivery operations encounter because their travel expenses show different patterns and their delivery networks require simultaneous solutions to their operational restrictions. The ILS method described here exhibits solid optimization capabilities across variants of TSP. ILS could be expanded to a highly complex environment with clearer parameters, autonomous vehicle routing, uncertain supply chain logistics, and UAV planning for large agricultural and mapping applications. These findings reaffirm that cluster dimensionality and constraint structure are significant determinants of metaheuristic performance and underscore the importance of developing adaptive search schemes tailored to the specific objectives and complexity of the routing problem at hand.

ACKNOWLEDGMENT

The authors would like to thank the editors for their constructive reviews of proposed improvements regarding the paper. Moreover, the authors would like to express appreciation for Universiti Pendidikan Sultan Idris in terms of publication acknowledgements.

CONFLICT OF INTEREST

Authors declare that there is no conflict of interest regarding the publication of the paper.

AUTHOR CONTRIBUTION

Farid Morsidi (Conceptualisation; Methodology; Validation; Formal analysis; Data curation; Formal analysis; Investigation; Resources; Software; Visualisation; Writing - original draft; Writing - review & editing).

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