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RESEARCH ARTICLE

Logistics Optimization Using Hybrid Genetic Algorithm (HGA): A Solution to the Vehicle Routing Problem With Time Windows (VRPTW)

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ABSTRACT The Vehicle Routing Problem with Time Windows (VRPTW) is paramount in elevating operational efficiency, driving cost reductions, and enhancing customer satisfaction. It is a renowned challenge with diverse real-world applications, where the core objective is determining the most efficient routes for a fleet of vehicles. This research introduces a cutting-edge Hybrid Genetic Algorithm-Solomon Insertion Heuristic (HGA-SIH) solution, reinforced by the powerful Solomon Insertion constructive heuristic to solve the VRPTW as an NP-hard problem. The performance of the proposed HGA-SIH is validated against Solomon's VRPTW benchmark instances. The results showcase the outstanding performance of HGA, achieving Best-Known Solutions (BKS) for 11 instances and enhancing BKS solutions in one instance. Experimental findings validate that HGA-SIH consistently delivers results on par with or surpasses those obtained by several cutting-edge algorithms when evaluated based on various solution quality metrics. HGA-SIH consistently excels in efficiently managing the number of vehicles while minimizing travel distances, resulting in slight deviations from BKS that remain within practical limits. The research highlights the adaptability and efficacy of HGA-SIH in addressing a wide range of VRPTW scenarios, thereby making substantial contributions to logistics and supply chain optimization.

INDEX TERMS Hybrid Genetic Algorithm (HGA), logistics and transportation, Solomon Insertion Heuristic, supply chain optimization, vehicle routing problem with time windows (VRPTW).

I. INTRODUCTION

The logistics industry plays a crucial role in supporting the functioning of society, encompassing the transportation, storage, communication, and related sectors and the overall well-being of individuals. Consequently, the progress of the contemporary economy and the enhancement of people's living standards are closely intertwined with the growth of the logistics industry. Today, transportation is a vital element of a nation's economy, significantly influencing its economic development due to its essential role in infrastructure. It encompasses activities present in all sectors, continuously impacting the production, distribution, and consumption of goods and services. The existence and feasibility of a country's overall progress and advancement depend on the availability of transportation networks, supporting facilities, equipment, and a suitable fleet. In the current global economy and the expansion of trade, transportation systems play a pivotal role in cost optimization, travel time reduction, increased speed, safety enhancement, and service levels, making their significance undeniable.

The Vehicle Routing Problem (VRP) is a pivotal transportation challenge with extensive real-life applications, particularly in logistics and transportation. It was initially

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formulated as "The Truck Dispatch Problem" [1]. It can be seen as a broader and more generalized version of the Traveling Salesman Problem [1], encompassing many potential solutions. For instance, when dealing with 15 locations to be visited, there are a staggering 15! Possible routes, which equates to 653,837,184,000 valid and viable route permutations. The complexity arises from the daunting task of determining the most optimal solution, as the search space is vast and highly combinatorial. Initially, the Traveling Salesman Problem focused on minimizing mileage, but in contemporary applications, other factors such as time and fuel consumption have become crucial optimization criteria since they are often interconnected with distance. VRP is a combinatorial integer programming problem and is classified as NP-hard [2], adding to its computational challenge. Optimizing vehicle routing can yield substantial cost reductions in specific business domains where efficient transportation adds value to the product, potentially up to 25% in total [3]. VRP plays a pivotal role in realizing economic benefits in more open markets. Additionally, technological advancements have facilitated VRP solutions in dynamic, real-time environments, where calculations can be performed based on live data [4]. This adaptability to real-time data makes VRP a valuable tool for enhancing transportation efficiency and cost-effectiveness.

The Vehicle Routing Problem with Time Windows (VRPTW) is a computationally challenging problem classified as NP-hard. Its primary objective is to determine an optimal set of routes for servicing a group of customers using a fixed fleet of vehicles within a geographical area that includes a central warehouse. Each customer in this problem has a specific demand for goods that must be delivered to them.

The key objectives of the VRPTW are as follows:

1) Each customer should be visited exactly once by a vehicle.
2) The total demand of customers on each tour must not exceed the predetermined capacity of the vehicle, denoted as Q.
3) The overarching goal is to minimize the total cost/distance/time associated with all the vehicle tours.

In practical scenarios, the VRP often introduces various additional constraints across different classes. These constraints could encompass restrictions on vehicle capacity [5], [6], designated time windows for customer service [7], [8], limitations on route lengths, or constraints related to the working hours of drivers or distribution personnel. A comprehensive overview of the diverse VRP variants and their classification can be found in recent literature [9], [10]. Similar to the fundamental VRP, most of its variants are recognized as NP-hard.In the context of the VRPTW, the problem entails routing a set of vehicles, each with a limited capacity, starting and ending their routes at a central depot. The customers are distributed across the geographical area, and their demands and predefined time windows for service are known. The primary optimization objectives are to minimize the fleet size of vehicles required and the total travel time while ensuring that capacity and time window constraints are not violated.

Due to its inherent intricacies and practical relevance, the Vehicle Routing Problem with Time Windows (VRPTW) has consistently garnered attention among researchers and established itself as a prominent issue within the domain of network optimization. Time window constraints introduce extra algorithmic complexities. For instance, when applied to customers, time windows set specific deadlines for the earliest and latest allowable departures and arrivals of vehicles at each demand point [11]. The incorporation of time windows in VRP models, which inherently pose an NP-hard problem, serves as the foundation for building the Supply Chain Network (SCN), thereby adding complexity to the issue. As a result, researchers in this field are compelled to tackle the presented challenge on a broader scale by utilizing heuristic, meta-heuristic, or optimization enhancement algorithms. As a result, numerous authors have dedicated their efforts to devising various solution methodologies, for solving VRP models involving both exact and heuristic methods [12]. Within the domain of exact algorithms [13], contemporary contributions have emerged, which harness state-of-the-art branch and cut techniques explicitly designed to address routing problems. It is noteworthy that exact methods demonstrate their efficacy in scenarios where the solution space is confined by stringent time windows. This constraint results in reduced combinatorial complexity, given the limited permutations of customer sequences to establish feasible routes [14]. Consequently, a multitude of researchers have undertaken investigations into the VRPTW, employing heuristic and meta-heuristic strategies to seek practical and computationally efficient solutions for this intricate problem.

Research in combinatorial optimization, particularly focusing on metaheuristic techniques, has experienced a surge in interest, notably since the 1990s. These approaches are designed to obtain approximate solutions within a polynomial time frame, in contrast to exact solutions, which would entail prohibitively high computational costs. There are many variants of VRP models, and VRPWTW is one of them. Various meta-heuristic methods, including but not limited to genetic algorithms (GA) [15], [16], [17], [18], [19], evolution strategies [20], simulated annealing [21], tabu search [22], [23], [24], [25], [26], and ant colony optimization [14], [27], have been introduced and applied to address the Vehicle Routing Problem with Time Windows (VRPTW). Evolutionary algorithms have undergone substantial advancements in recent years [28]. For instance, Srinivas and Deb introduced the Elitist Non-dominated Sorting Genetic Algorithm (NSGA) [29]. Building upon NSGA, Deb et al. further refined the approach with NSGA-II [30] and NSGA-III [31]. Similarly, Jiang et al. proposed the Strength Pareto-Optimal Evolutionary Algorithm (SPEA) [32] followed by enhancements such as SPEA-II [33] and

PESA-III [34]. Zhang et al. contributed to the field with the introduction of the multi-objective evolutionary algorithm based on decomposition (MOEA/D) [35] which gained significant attention, among others. Additionally, game theory principles have seen extensive application [36], [37].

In the context of addressing the Vehicle Routing Problem with Time Windows (VRPTW), researchers have not only explored metaheuristic approaches but have also considered alternative heuristics like constraint programming and local search [38], [39], [40] to name a few. Furthermore, in a distinct application domain, Agrawal et al. [15] introduced a genetic algorithm (GA) model designed for optimizing the Vehicle Routing Problem (VRP) when dealing with perishable products, taking into consideration various factors, including time windows and quality requirements. The genetic algorithm (GA) model in question is designed to optimize the Vehicle Routing Problem (VRP) with a multi-objective fitness function. This fitness function simultaneously seeks to minimize transportation costs, reduce the number of vehicles employed, and maximize customer satisfaction by adhering to quality requirements. The authors evaluate the performance of this GA model by subjecting it to various benchmark instances and comparing its outcomes with those generated by other state-of-the-art algorithms. The results reveal that the proposed GA model excels in terms of solution quality and computational efficiency when compared to alternative algorithms

In a related study, Khoo and Mohammad [41] introduced a genetic algorithm (GA) tailored for addressing the multi-objective vehicle routing problem with time windows (MOVRPTW). This particular GA leverages a two-phase distributed hybrid ruin-and-recreate strategy that amalgamates aspects of both sequential and parallel processing to enhance the algorithm's overall performance.

Furthermore, Pierre and Zakaria [42] proposed a stochastic partially optimized cyclic shift crossover (SPOCS) operator for application in multi-objective genetic algorithms (MOGAs) designed to solve the vehicle routing problem with time windows (VRPTW). The SPOCS operator amalgamates elements of cyclic shift crossover and partially mapped crossover techniques to generate novel solutions. The authors assessed the SPOCS operator's performance by applying it to diverse benchmark instances and subsequently comparing the outcomes with those obtained using other state-of-the-art Multi-Objective Genetic Algorithms (MOGAs). The outcomes highlight that the proposed SPOCS operator excels over alternative MOGAs in terms of solution efficacy and computational expeditiousness.

In their study, Ursani el al. [43] introduces a localized genetic algorithm (LGA) specifically designed to address the complex problem of the Vehicle Routing Problem with Time Windows (VRPTW). The LGA incorporates a local search procedure that integrates tabu search techniques aimed at augmenting the algorithm's overall performance. The authors conducted a comprehensive performance evaluation of the LGA, applying it to diverse benchmark instances and subsequently comparing the obtained results with those generated by other state-of-the-art algorithms. The results of this analysis clearly indicate that the proposed LGA consistently outperforms alternative algorithms in terms of both solution quality and computational efficiency.

In their research, Ghoseiri and Ghannadpour [44] put forward a multi-objective optimization model tailored for addressing the Vehicle Routing Problem with Time Windows (VRPTW). This model combines goal programming and a genetic algorithm (GA) to optimize the VRPTW, employing a goal programming framework that accounts for multiple objectives. These objectives encompass the minimization of transportation costs and the maximization of customer satisfaction. The authors conducted an extensive performance evaluation of their proposed model, subjecting it to a range of benchmark instances, and subsequently conducted a comparative analysis against other state-of-the-art algorithms. In relation to solution effectiveness and computational proficiency, the findings consistently affirm that the proposed model surpasses alternative algorithms.

Vidal et al. proposed a hybrid genetic algorithm (HGA) with adaptive diversity management (ADM) to solve a large class of vehicle routing problems with time windows (VRPTWs) [45]. The HGA-ADM approach combines elements of GA and ADM to improve the algorithm's performance. The authors evaluate the performance of the proposed approach using various benchmark instances and compare the results with other state-of-the-art algorithms. The results show that the proposed approach outperforms the other algorithms.

Meta-heuristics possess the ability to handle supplementary constraints and produce near-optimal path solutions within acceptable computational timeframe, applicable to networks of varying scales, from small to large [46]. Meta-heuristic approaches like Genetic Algorithms (GAs), Particle Swarm Optimization (PSO) algorithms, and Ant Colony Optimization (ACO) algorithms have found extensive application in addressing shortest path problems across various research domains; for example, Kumar and Kumar [47] utilized genetic algorithms (GA) to identify the shortest path in data networks. Rares tackled the shortest path routing issue in rapidly evolving networks with heavy traffic loads, employing an enhanced GA incorporating an adaptive mutation operator [48]. Mohiuddin et al. devised a fuzzy evolutionary Particle Swarm Optimization (FEPSO) algorithm to optimize routing paths and improve network operational efficiency [49]. Dudeja introduced a fuzzy-based modified PSO algorithm to address the shortest path problem in scenarios with uncertain edges, aiming to reduce both cost and time consumption [50]. Gupta and Srivastava addressed the distance optimization problem using both PSO and ACO algorithms, conducting a comparative analysis to determine their performance, with simulated results demonstrating the superior efficacy of the latter optimization approach

[51]. Wang et al. introduced an enhanced ACO algorithm tailored for managing time-triggered flows within time-sensitive networks [52]. Zangina et al. applied an improved non-dominated sorting genetic algorithm (INSGA-III) to devise a resilient vehicle routing scheme for autonomous robot navigation, optimizing both crop yield and quality while minimizing costs. Given the prevalence of uncertain or imprecise data in network designs, recent literature increasingly explores hybrid algorithms aiming to enhance system performance on both local and global scales [53]. Among these, Dib et al. proposed a solution method coupling GA with variable neighborhood search (VNS) [54]. Additionally, Dib et al. developed an advanced GA-VNS heuristic approach to address multicriteria shortest path problems in multimodal networks [55]. Garg introduced a hybrid algorithm merging GA with the gravitational search algorithm (GSA) to improve system performance, particularly for analyses based on uncertain data, focusing on critical components for cost, labor, and time savings [56]. Garg introduces a hybrid PSO-GA technique for addressing constrained optimization problems [57]. Patwal et al. devise an integrated heuristic method by combining a time-varying acceleration coefficient PSO algorithm with mutation strategies (TVAC-PSO-MS) to investigate optimal power generation scheduling for renewable energy sources [58]. Garg employs a hybrid GSA-GA algorithm to tackle constrained nonlinear optimization problems with mixed variables [59]. De Santis et al. address the challenge of minimizing travel distances for pickers in manual warehouses, proposing a metaheuristic routing algorithm that merges the ACO metaheuristic with the Floyd-Warshall algorithm [60]. Lastly, Sedighizadeh and Mazaheripour present a hybrid algorithm combining PSO with an artificial bee colony (ABC) algorithm to resolve the multi-objective vehicle routing problem under precedence constraints among customers [61].

Metaheuristics are widely recognized as effective strategies for tackling numerous challenging optimization problems [62]. A taxonomic review of VRP literature, analyzing developments from 2009 to 2017 is analyzed by [63]. They classified 299 articles, focusing on metaheuristic algorithms solving VRP and evaluated their contributions. Metaheuristic algorithms can be primarily grouped into two categories: single solution-based and population-based. Single-based heuristics are categorized into eight types (SA, TS, GRASP, VNS, GLS and ILS) [64]; [62]. In addition, the other two algorithms are the large neighborhood search (LNS) and the adaptive large neighborhood search (ALNS) heuristic [65]. Conversely, there are 16 population-based methods: ten Evolutionary Computation (EC) (GA, ES, EP, GP, EDAs, DE, CoEA, CA, SS and PR), and six Swarm Intelligence (SI) (ACO, PSO, BFOA, BCO, AIS and BBO). Six more metaheuristics are: two EC algorithms: Memetic algorithm (MA) [66] and Electromagnetism-Like Algorithm (EMA) ([67]; [68] and four SI algorithms: Firefly algorithm (FA), Cuckoo search (CS), Intelligent Water Drops Algorithm (IWD) and Shuffled Frog Leaping Algorithm (SFLA) [69]; [70]. The conclusion of the paper provides valuable insights into the use of metaheuristic algorithms for solving Vehicle Routing Problems (VRP), examining 386 different scenarios. The taxonomic review explicitly confirms that among evolutionary computation (EC) algorithms, the genetic algorithm (GA) is the most utilized method for addressing VRP models. Consequently, in our specific case, we have chosen to implement the Genetic Algorithm approach from the range of available Evolutionary Computation methods for solving our model.

The extensive review studies conducted above in the field consistently highlight the effectiveness of integrating Genetic Algorithms (GA) with either local search techniques or hybrid approaches when addressing various vehicle routing problems. These methods have shown notable success in optimizing intricate routing scenarios, which has motivated our choice to incorporate GA into our proposed algorithm.

Genetic Algorithms are a well-established category of metaheuristic techniques inspired by the principles of biological Darwinian evolution. The core process involves randomly selecting solutions from a pool of all potential solutions and applying genetic operators to introduce variations that generate the next generation of solutions. Critically, evaluation occurs at each iteration of the algorithm, meaning that assessment takes place every time a new generation is created. The algorithm then concludes once a predefined termination event is reached, such as a specific number of generations or the achievement of an adequately optimal solution, as highlighted in various studies [16], [19], [71], and [72]. Furthermore, [40] introduced an evolutionary search approach grounded in mutation. In this method, each offspring undergoes optimization to enhance the overall distance by employing a combination of local search and route elimination strategies. This demonstrates the versatility of genetic algorithms in addressing routing problems, further reinforcing our rationale for incorporating GA into our proposed approach. A many-objective gradient evolution algorithm for solving a green vehicle routing problem with time windows and time dependency for perishable products is addressed by [73]. Their proposed algorithm showed improved results; however, they suggested that better population generation models are still in need of better solutions. The aim of the hybridization and communication strategies is to maintain the diversity of populations to prevent the proposed algorithm from falling into local optima and overcome the drawbacks of a single swarm Firefly Algorithm (FA) [74]. In conclusion, metaheuristic algorithms that have been proposed to solve VRP still have drawbacks, which lead to low-quality solutions. However, the appropriate hybridization techniques and cooperative models improve their performance dramatically. The performance of a metaheuristic algorithm can be improved by integrating a component of a particular metaheuristic algorithm instead of the entire algorithm. Another direction of improvement is the use of multiple populations (cooperative model) of a metaheuristic algorithm. It has been proven from the literature and practical point of view that the hybridization and the cooperative model improve the performance of the algorithm significantly [75], [76], [77], [78]. The conventional VRP is classified among NP-hard problems [79]. Thus, achieving optimal or near-optimal solutions for medium and large-sized instances of the problem using commercial optimization packages in reasonable computational time is not possible. Therefore, in this paper, a metaheuristic approach (i.e., model-based metaheuristics) is developed to tackle this complexity. Matheuristic methods, developed based on the combination of meta-heuristic and exact methods, benefit the advantages of both methods to reach a high-quality solution with acceptable computational efforts ([80]; [81]; [82]. In this section, a metaheuristic algorithm is developed based on the combination of the MOKA with a MILP model, namely Mb-MOKA. The mathematical model is responsible for improving generated solutions in each iteration of the MOKA. Moreover, due to the high complexity of CoCEVRP, a customer clustering approach based on a MILP model is developed [83]. Note that the Solomon insertion I1 heuristic only generates feasible solutions to this model without considering the quality or the objective value. The process of finding better solutions will be conducted by the GA operator [84]. The review above explicitly demonstrates that within the domain of meta-heuristic methodologies employed for addressing VRP models, GA has exhibited noteworthy superiority over alternative techniques. Additionally, the literature presented underscores the potential for enhancing the efficacy of a particular meta-heuristic approach through the refinement of its constituent components and not all components, thereby yielding improved solutions. Furthermore, it is explained that the incorporation of elementary meta-heuristic algorithms with exact and constructive heuristics serves to mitigate the inherent limitations associated with convergence to local optima, thus enhancing the overall performance of meta-heuristic methodologies.

Hence, keeping all the above factors, in this research paper, we have introduced an innovative hybridized genetic algorithm named the Hybrid Genetic Algorithm-Solomon Insertion Heuristic (HGA-SIH) that incorporates the Solomon heuristic, which is a constructive heuristic developed to address the Vehicle Routing Problem with Time Windows (VRPWT). Solomon develops the algorithm based on five initial solution heuristics that have been evaluated [85]. The effectiveness of Solomon's Initial Heuristics (SIH) lies in both the quality of the solution it produces and the computational efficiency it demonstrates [86]. Moreover, we have added the SIH within the population generation section of GA. This combination of methodologies exhibits considerable promise for efficiently addressing complex routing challenges, particularly those with time-sensitive constraints. To validate the effectiveness of our approach, we conducted a comprehensive evaluation using widely recognized Solomon instances. In the results section, we provide an in-depth comparative analysis between the solutions generated by our model and the best-known solutions documented in the existing literature. Detailed insights into the components and workings of our developed algorithm are presented in the subsequent subsections.

II. HYBRID GENETIC ALGORITHM (HGA-SIH)

The VRP is a complex challenge within Operations Research, aiming to optimize vehicle routes for efficient customer service while adhering to capacity constraints and cost minimization. It extends the Traveling Salesman Problem (TSP), with each vehicle forming a tour from a central depot. Unlike TSP, VRP has wider practical applications and receives substantial research attention. Both are NP-Hard problems, making exact solutions challenging for larger instances. For VRP with over 50 customers, heuristic methods are often necessary due to the computational infeasibility of exact algorithms [3].

The problem becomes even harder when a time window constraint is added. Hence, solving a model of VRP with time windows becomes harder to solve than a simple VRP model. This issue is addressed by constructing a hybrid genetic algorithm where population generation is divided into two parts. The first part involved random generation, as explained earlier; however, diversification is crucial to the performance of the population-based algorithm, but the initial population in the GA algorithm is generated using a random generation, which has insufficient diversification [87]. Hence, the second part involved the use of the Solomon Insertion heuristic algorithm [85]. The solutions obtained through the Solomon insertion method were added to the previously generated population. By incorporating the Solomon heuristic in the initial solution generation, feasible solutions with good starting fitness were obtained, which aided the developed genetic algorithm in converging towards better solutions more efficiently. Furthermore, the inclusion of random solution generation expanded the search space, leading to the discovery of even better solutions. Additionally, the Solomon heuristic serves as a local search operator within the genetic algorithm, enhancing the quality of the solutions generated by the algorithm.

Constructed hybrid GA is shown as a flowchart in Fig.1 and is detailed below:

A. CHROMOSOME REPRESENTATION

To initialize the GA, we first devised a chromosome representation strategy rooted in integer encoding. A chromosome is conceptualized as an ordered sequence of demand points, signifying a prospective route. Notably, the sequencing doesn't delineate the specific routes for the vehicles. Instead, it offers an organized set of demand points, which are subsequently segmented into distinct sub-routes. Each chromosome represents a feasible vehicle route, encoded as an ordered list of K integers, where each integer refers to a

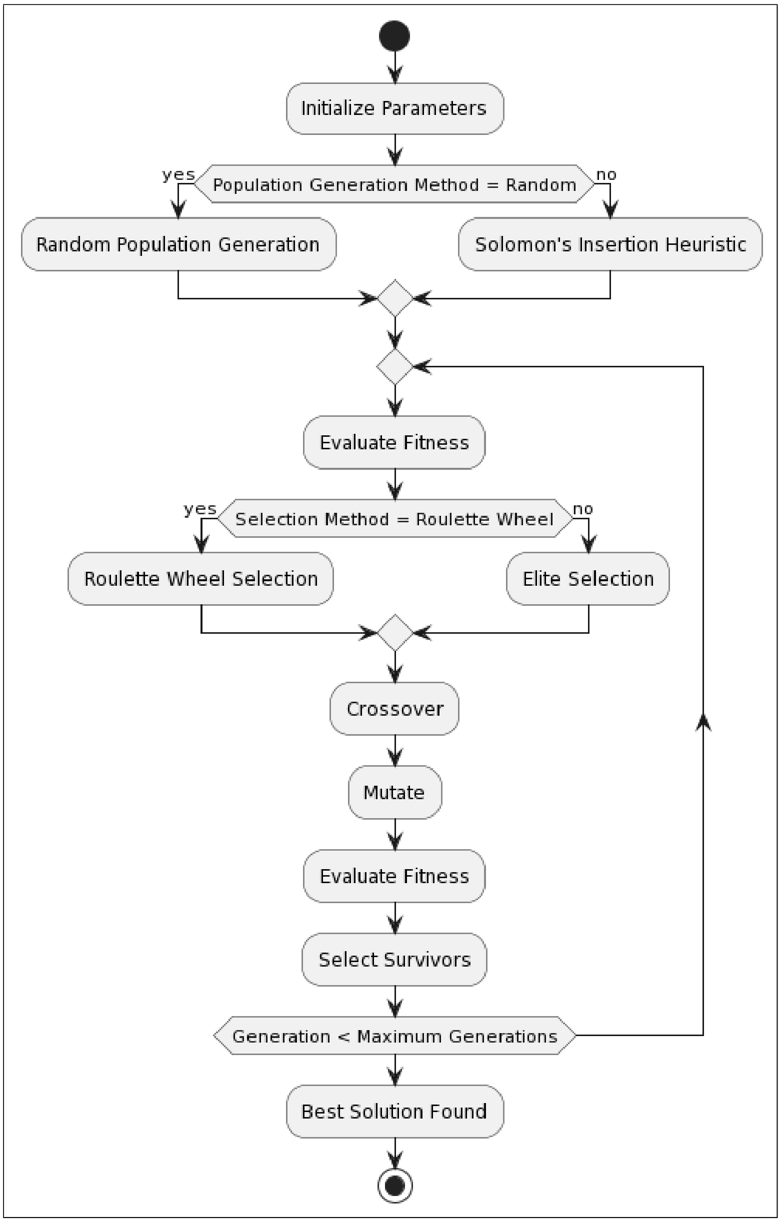

FIGURE 1. Flow chart of hybrid genetic algorithm.

specific demand point. The complete population consists of multiple such chromosomes.

B. INITIAL POPULATION FORMULATION

The commencement of the algorithm requires populating the initial solution pool. The magnitude of this population is contingent upon the pre-specified parameters for the genetic algorithm. Each entity within this pool is represented as a chromosome.

C. TECHNIQUES FOR CHROMOSOME GENERATION

1) STOCHASTIC INITIALIZATION

The algorithm employs a stochastic method to generate chromosomes by arranging the demand points in a random sequence. Given 10 demand points as an instance, a potential chromosomal configuration might be [3, 5, 7, 4, 2, 8, 1, 10, 9, 6].

2) INITIALIZATION VIA SOLOMON'S INSERTION HEURISTIC

In a divergence from entirely random configurations, the algorithm can harness the capabilities of Solomon's heuristic.The pseudo-code of Solomon Insertion is shown in Algorithm 1. This heuristic is instrumental in discerning viable routes, keeping in perspective the constraints of time windows and other pertinent conditions. By initiating chromosomes via this method, there's a conceivable elevation in the likelihood of pinpointing an optimal solution within a condensed number of generations. As a demonstration, a chromosome derived through the heuristic could appear as [2, 1, 4, 5, 9, 7, 6, 8, 10].

Algorithm 1 Solomon's I1 Insertion Heuristic

Data: A path of JSON file having Solomon instances dataset (e.g. C101)
Result: A sequence of n customers that minimizes the distance and time required to visit all customers
Initialize the route with the first customer as the seed and set the current capacity and time to 0;
while *there are still unrouted customers* **do**
    for *each unrouted customer i* **do**
        Calculate its best insertion position in the current route using criterion $c1$;
    end
    Select the unrouted customer u with the best insertion position according to $c1$;
    Calculate the best feasible insertion position for u using criterion $c2$;
    if *the insertion of u violates any capacity or time constraint* **then**
        Discard u and repeat the loop;
    end
    Insert u at the best feasible position found, update the current capacity and time, and mark u as routed;
end

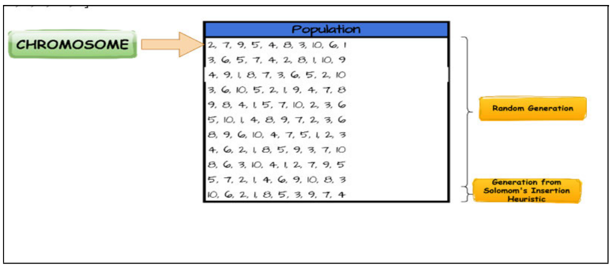

FIGURE 2. Population generation.

This population was generated using the DEAP (Distributed Evolutionary Algorithms in Python) module. Our methodology incorporates solutions derived from the Solomon heuristic algorithm into the initial random population that is visualized in Fig.2. This amalgamation yielded significant improvements in the quality of generated solutions, as highlighted in Table.3.

D. CONVERSION MECHANISM FROM CHROMOSOMES TO VEHICLE ROUTES

In the course of our HGA-based approach to solving the VRP with demand requirements, a pivotal step post-generation of a comprehensive set of chromosomes is the transformation of these chromosomes into vehicle sub-routes. This transformation depends on several primary factors: the total number of accessible vehicles, the time window constraints tied to every demand point, and the limitations related to the resources or demand requirements. The primary aim of this algorithmic step is the minimization of the cumulative time expended in the delivery operation.

The structured algorithmic procedure underscoring this transformation is depicted in Fig.3

To provide a quantitative illustration, consider a representative chromosome:

$$[5, 3, 2, 7, 1, 6, 9, 8, 4]$$

Implementing the above-outlined algorithm results in the subsequent vehicle sub-routes:

- Route for Vehicle 1: Initiated from the depot (denoted as 0), traversing through demand points [5, 3, 2], and culminating at the depot. This is denoted as $[0-5-3-2-0]$.
- Route for Vehicle 2: [7, 1, 6]
- Route for Vehicle 3: [9]
- Route for Vehicle 4: [8, 4]

Here, the nomenclature '0' is indicative of the primary depot.

E. MATHEMATICAL MODEL AND FITNESS EVALUATION

Following the delineation of chromosomes into sub-routes and the consequential update of processing times, the evolution of the algorithm gravitates towards the computation of the fitness function. Central to the theme of this investigation is the identification of an optimal chromosome that substantially curtails the total completion duration of the relief operation.

Given the heightened emphasis on temporal constraints, this study incorporates time windows into its purview. To reinforce the pursuit of solutions that abide by these constraints while concurrently reducing the overall completion time, a penalty factor is instituted. This factor is thoroughly designed to penalize those solutions that violate the specified time windows.

Objective Function: Fitness

$$C = \sum_{i=1}^{n} T_i + \lambda \sum_{j=1}^{m} P_j \tag{1}$$

where:

- C represents the fitness of chromosome C.
- T_i denotes the completion time of the ith vehicle route.
- n is the total number of vehicle routes.
- P_j signifies the penalty associated with the jth time-window violation.
- m stands for the total number of time-window violations observed.
- λ is a pre-determined weight emphasizing the gravity of time-window violations in the context of the study.

Constraints:

1. Each customer must be visited exactly once:

$$\sum_{j=1,j\neq i}^{n} x_{ij} = 1 \quad \forall i \in V, i \neq 0 \tag{2}$$

2. Vehicles must leave and return to the depot:

$$\sum_{i=1}^{n} x_{0i} = m \tag{3}$$

$$\sum_{i=1}^{n} x_{i0} = m \tag{4}$$

3. Flow conservation constraint:

$$\sum_{i=1,i\neq j}^{n} x_{ij} - \sum_{k=1,k\neq j}^{n} x_{jk} = 0 \quad \forall j \in V, j \neq 0 \tag{5}$$

4. Time window constraints:

$$a_i \leq u_i \leq b_i \quad \forall i \in V \tag{6}$$

5. Capacity constraint:

$$\sum_{i=1}^{n} q_i \cdot x_{ij} \leq Q \quad \forall j \in V \tag{7}$$

6. Arrival time computation:

$$u_i \geq u_j + q_j + c_{ji} - M \cdot (1 - x_{ij}) \quad \forall i, j \in V, i \neq 0, j \neq 0 \tag{8}$$

7. Route duration constraint:

$$u_i \leq T \quad \forall i \in V \tag{9}$$

where $G = (V, E)$ is the complete graph representing the set of all nodes and edges, $V = \{0, 1, 2, \ldots, n\}$ is the set of vertices with 0 representing the depot, E is the set of edges connecting vertices, c_{ij} is the cost (distance or time) of traveling from node i to node j, q_i is the demand of customer i, a_i and b_i are the earliest and latest time windows for servicing customer i, Q is the capacity of each vehicle, and T is the maximum allowable route duration. Also, M is a large positive constant, and m is the number of vehicles. This objective function thus serves to encapsulate the essence of the research, guiding the algorithm towards solutions that both minimize completion time and honor the designated time windows.

F. SELECTION, CROSSOVER, AND MUTATION

1) SELECTION

The selection process utilizes a two-pronged approach: the roulette-wheel method and elitism.

ROULETTE-WHEEL SELECTION

This method involves choosing individuals from a population, denoted as $P = \{G_1, \ldots, G_s\}$. Selection probabilities are computed based on the individual's fitness scores. Specifically, individuals with higher fitness values are endowed with a greater likelihood of being chosen. The probability $P(G_g)$ of selecting an individual G_g is defined as:

$$P(G_g) = \frac{f(G_g)}{\sum f(G_i)} \tag{10}$$

where $f(G_g)$ is the fitness of individual G_g, and the summation encompasses all individuals G_i in the population.

ELITISM

This method ensures that a portion of the best-performing individuals from the current population are directly transferred to the next generation without undergoing crossover or mutation. The rationale behind incorporating elitism is to prevent the loss of high-quality solutions that have been discovered. By preserving these top-performing individuals, the algorithm is guided toward faster convergence and often yields better results.

2) CROSSOVER

The recombination process brings two parental solutions, represented as $Pr1$ and $Pr2$, into the fold. They undergo a crossover using the Partially Mapped Crossover (PMX) mechanism, which operates with a probability cr. The PMX operator, credited to Goldberg and Lingle [88], crafts an offspring solution, denoted as O.

The PMX operation unfolds as follows:

1) Two random crossover points are uniformly chosen along chromosome $Pr1$. Indices nestled between these points are labeled as the "mapping segments."
2) Given parent solutions $Pr1$ and $Pr2$ with a length $l = 10$ customers and with bolded Xs indicating the crossover points, the mapping segment might consist of pairs such as 4-2, 5-8, and 6-7 (as illustrated in Fig. 4).
3) $Pr1$'s mapping segment is mirrored onto the first offspring, $O1$, whereas $Pr2$'s segment finds a home in the second offspring, $O2$. Following this, $O1$ is populated with elements from $Pr1$ and $O2$ is populated with elements from $Pr2$. If any redundancy in indices crops up within an offspring, it's realigned according to the preset mapping.

The offspring, $O1$ and $O2$, are then procured. Their fitness values are then compared against a benchmark, z^*. The fittest offspring is labeled as O.

G. INVERSE MUTATION IN GENETIC ALGORITHMS FOR VRPTW

Mutation is an essential mechanism in genetic algorithms, pivotal in enabling the algorithm to deviate from local optima within the solution landscape. In the context of the Vehicle Routing Problem with Time Windows (VRPTW), mutation aids in diversifying the search process, enhancing the algorithm's chances of finding a globally optimal solution. Nevertheless, an unrestrained application of mutation might compromise evolved beneficial patterns. Thus, it's imperative to apply mutation judiciously. For this study, the mutation probability is strategically set at 0.10 for each

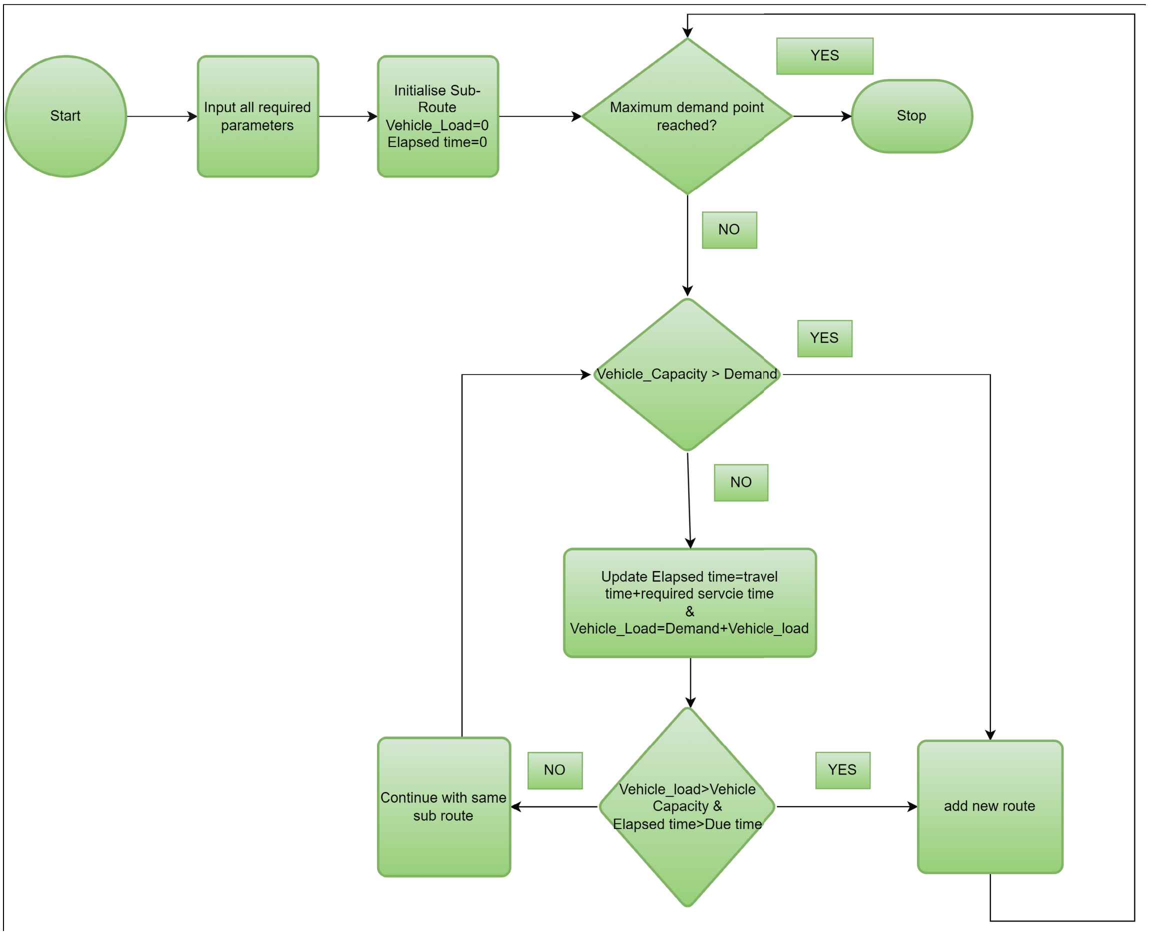

FIGURE 3. Chromosome to vehicle route generation.

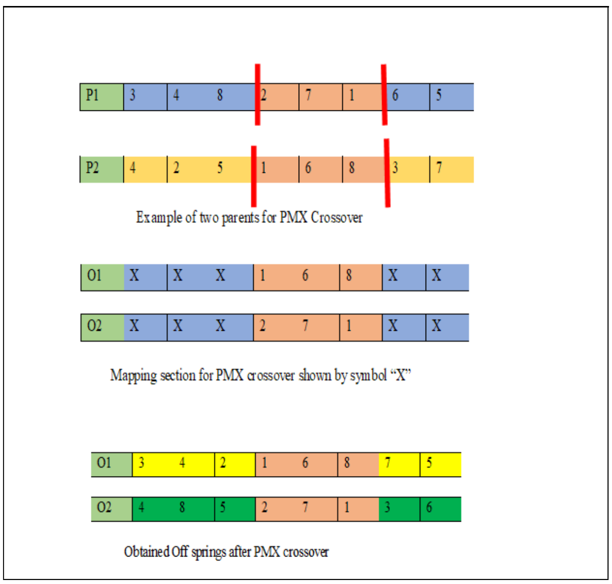

FIGURE 4. Example of crossover recombination.

chromosome. This value ensures a harmonious blend of exploration (searching for new solutions) and exploitation (refining existing solutions). Considering the significance of maintaining time window constraints in VRPTW, any mutation technique employed should introduce subtle changes to the chromosome to preserve its fundamental structure. In line with this objective, our research adopts an adapted form of the "inversion" mutation technique, as delineated by [89]. This method, predominantly used in the context of the Traveling Salesman Problem (TSP), capitalizes on permutations to represent the sequence of locations to be visited. The procedure entails the selection of two distinct cut points within the chromosome. Subsequently, the genetic sequence between these cut points is inverted. For illustrative purposes, let's consider a typical TSP chromosome: 7 5 8 4 1 3 6 2 9. Given two cut points, the section of the chromosome encompassed by them undergoes inversion: 7 5 8 4 1 3 6 2 9 → 7 5 8 2 6 3 1 4 9. This nuanced alteration ensures the chromosome's inherent characteristics remain intact yet infuses a requisite degree of diversity to the solution.

H. GA PARAMETER TUNING AND SETTINGS

Optimizing the parameters of a GA is a crucial and time-consuming task. Researchers have explored both parametric and non-parametric techniques to expedite the process of identifying optimal GA parameters. These techniques aim to mitigate the computational burden associated with the

TABLE 1. Taguchi orthogonal matrix.

Exp	Pop_size	Crossover	Mutation	Generations
1	1	1	1	1
2	1	1	1	2
3	1	1	2	1
4	1	1	2	2
5	1	2	1	1
6	1	2	1	2
7	1	2	2	1
8	1	2	2	2
9	2	1	1	1
10	2	1	1	2
11	2	1	2	1
12	2	1	2	2
13	2	2	1	1
14	2	2	1	2
15	2	2	2	1
16	2	2	2	2

iterative nature of traditional tuning methods Parametric techniques involve the systematic exploration of predefined parameter spaces, while non-parametric approaches, such as machine learning-based methods, seek to model the complex relationships between parameters and performance. Both avenues offer the potential to streamline the parameter-tuning process and enhance the efficiency of GA optimization. One notable technique employed to refine parameter values is the Taguchi Method. The Taguchi techniques [90], have seen extensive application in engineering analysis for optimizing performance characteristics across various combinations of design parameters in recent years. This methodological approach, rooted in robust design principles, systematically explores the parameter space using a fractional factorial experimental design. By conducting a series of controlled experiments, the Taguchi Method facilitates the identification of influential parameters and their optimal settings, minimizing the need for exhaustive iterations. The adoption of the Taguchi Method introduces a structured and systematic dimension to parameter tuning, offering a more strategic and resource-efficient pathway compared to traditional trial-and-error methods. This formalized approach not only reduces the computational overhead but also enhances the reliability of the parameter optimization process. Hence, for our parameter settings, we opted for this technique.

In this study, a Taguchi orthogonal matrix of 16 experimental settings was generated by considering all higher and lower values of GA parameters. Taguchi Orthogonal matrix is shown in Table 1. Here, 1 represents the smallest value, and 2 represents the highest value of GA parameters. The range of values for Population size,number of generations,crossover and mutation rate were (200-1200,200-1000, 0.1-0.8, 0.01-0.1 200-1000) respectively. Based on experimental setups of Taguchi orthogonal matrix, the algorithm was run, and parameters were set for those values where best-known solution was obtained, as shown in Table 2.The best-known solution obtained from the best experimental setup is presented in Table 3.

TABLE 2. HGA parameters settings.

Parameter	Setting
Population Size	1000
Generation Span	200
Crossover rate	0.8
Mutation rate	0.01
Selection rate	roulette wheel 90% of population size elite selection 10% of population size

III. COMPUTATIONAL RESULTS

In this computational section, we investigate the application of our developed HGA-SIH to evaluate its effectiveness using Solomon's VRPTW benchmark available at [91]. This benchmark comprises 56 samples, each containing 100 customers, and is categorized into six groups based on customer geographical locations, encompassing both random (R1 and R2), clustered (C1 and C2), and mixed random and clustered locations (RC1 and RC2). The HGA-SIH implementation was coded in Python and executed on a computer equipped with an Intel Pentium IV 1.6 MHz processor and 512 MB of memory. Significantly, the performance of meta-heuristic methods hinges on the judicious selection and fine-tuning of key parameters. These parameters include population size (N), crossover and mutation rates, the number of generations, and the selection criteria. The quest for appropriate parameter values is pivotal for optimizing the algorithm's performance.

Within our proposed HGA-SIH approach, parameters related to the genetic algorithm, namely population size, crossover and mutation rates, and the number of generations, have undergone extensive fine-tuning through multiple runs of the algorithm and using the Taguchi method. These runs involved experimenting with different parameter settings across all Solomon problem instances, leading to the determination of optimal parameter values. Table. 2, as presented herein, showcases the parameter values where HGA-SIH yielded the most favorable results after a series of rigorous experiments. Furthermore, to ensure the robustness and reliability of our approach, the HGA-SIH algorithm is executed 30 times on each tested instance. This rigorous methodology allows us to obtain the best results, thereby ensuring the credibility of our findings and the efficacy of the HGA-SIH in tackling the VRPTW problem.

The results depicted in Table 3 and Figure 6 underscore the outstanding performance of our proposed HGA-SIH in addressing standard instances. Notably, the algorithm achieves the Best-Known Solutions (BKS) for 11 instances, clearly highlighted in boldface. Moreover, it surpasses BKS solutions in 1 instance, denoted by boldface and a star.

In the domain of logistics and supply chain optimization, effective vehicle management holds paramount importance, leading to reduced operational costs, optimized fleet utilization, and alleviated road congestion. Remarkably, our HGA-SIH demonstrates its prowess in this domain by efficiently managing the number of vehicles (NV) while

TABLE 3. Best known vs HGA.

Problem	Best known NV	Best Known Solution	Ref	NV	HGA	GAP FOR TD	GAP FOR NV
C101	10	828.94	[92]	10	**828.94**	0	0
C102	10	828.94	[92]	10	**828.94**	0	0
C103	10	828.06	[92]	10	830.77	0.32727097	0
C104	10	824.78	[92]	10	864.22	4.78188123	0
C105	10	828.94	[92]	10	**828.94**	0	0
C106	10	828.94	[92]	10	**828.94**	0	0
C107	10	828.94	[92]	10	**828.94**	0	0
C108	10	828.94	[92]	10	854.31	3.06053514	0
C109	10	828.94	[92]	10	854.78	3.11723406	0
C201	3	591.56	[92]	3	**591.56**	0	0
C202	3	591.56	[92]	3	**591.56**	0	0
C203	3	591.17	[92]	3	**591.17**	0	0
C204	3	590.6	[92]	3	594.51	0.6620386	0
C205	3	588.85	[92]	3	588.88	0.00509468	0
C206	3	588.49	[92]	3	**588.49**	0	0
C207	3	588.29	[92]	3	**588.29**	0	0
C208	3	588.32	[92]	3	**588.32**	0	0
R101	20	1637.7	[92]	19	1656.55	1.15100446	-5.2631579
R102	18	1466.6	[92]	18	1476.85	0.6988954	0
R103	14	1208.7	[92]	14	1230.07	1.76801522	0
R104	11	976.61	[92]	10	1010.55	3.47528696	-10
R105	15	1355.3	[92]	14	1395.68	2.97941415	-7.1428571
R106	13	1234.6	[92]	13	1261.61	2.18775312	0
R107	11	1064.6	[92]	11	1103.77	3.67931618	0
R108	10	938.2	[92]	10	966.99	3.06864208	0
R109	13	1146.9	[92]	12	1200.2	4.64731014	-8.3333333
R110	12	1068	[92]	11	1127.28	5.5505618	-9.0909091
R111	12	1048.7	[92]	11	1096.38	4.54658148	-9.0909091
R112	10	953.63	[92]	9	982.14	2.9896291	-11.111111
R201	8	1143.2	[92]	4	1442.28	26.1616515	-100
R202	8	1034.4	[92]	4	1212.49	17.216744	-100
R203	6	874.87	[92]	3	1197.67	36.8969104	-100
R204	5	735.8	[92]	10	854.31	16.1062789	50
R205	5	954.16	[92]	4	1337.65	40.1913725	-25
R206	4	879.86	[92]	4	1114.76	26.6974291	0
R207	4	797.99	[92]	4	1055.71	32.2961441	0
R208	4	705.33	[92]	3	860.53	22.0038847	-33.333333
R209	5	859.39	[92]	2	895.4675	4.19803582	-150
R210	6	905.21	[92]	2	942.9485	4.16902769	-200
R211	4	753.15	[92]	3	1049.62	39.3640045	-33.333333
RC101	14	1619.8	[92]	16	1656.59	2.27126806	12.5
RC102	14	1457.4	[92]	13	1532.25	5.13585838	-7.6923077
RC103	11	1258	[92]	12	1344.03	6.83863275	8.33333333
RC104	10	1135.5	[92]	11	1184.9	4.35050638	9.09090909
RC105	15	1513.7	[92]	14	1662.01	9.79784634	-7.1428571
RC106	13	1378	[92]	**12***	**1344.03***	-2.46516691	-8.3333333
RC107	12	1212.8	[92]	12	1263.07	4.14495383	0
RC108	11	1117.5	[92]	11	1144.94	2.45548098	0
RC201	9	1261.8	[92]	4	1442.28	14.3033761	-125
RC202	8	1095.6	[92]	4	1212.49	10.6690398	-100
RC203	5	926.82	[92]	3	1197.67	29.2235817	-66.666667
RC204	4	786.38	[92]	10	854.31	8.63831735	60
RC205	7	1157.6	[92]	4	1337.65	15.5537319	-75
RC206	7	1054.6	[92]	4	1114.76	5.70453252	-75
RC207	6	966.08	[92]	4	1055.71	9.27769957	-50
RC208	4	778.93	[92]	3	860.53	10.4759093	-33.333333

simultaneously minimizing total travel time.This underscores the algorithm's balanced approach, not favoring one objective over the other but rather achieving the dual goals of minimizing travel times and vehicle count.Despite its commendable performance, the HGA-SIH does exhibit minor drawbacks. Specifically, there are instances where the total distance deviates slightly from the best-known solutions, ranging from 1.15% to 4.65%. While these deviations are within acceptable bounds for practical applications, they underscore the need for ongoing refinement and fine-tuning of the algorithm to achieve even greater precision.

Specifically, in problems R101, R105, R109, R110, R11, and R112, our HGA-SIH excels in minimizing the total number of vehicles while maintaining only modest

TABLE 4. Efficacy evaluation of HGA-SIH versus various heuristic approaches.

Algorithms		Group of instances (R1)	R2	C1	C2	RC1	RC2
BKS	TD	1181.45	878.79	828.38	589.86	1339.24	1004.48
	NV	13.08	4.73	10	3	12.75	6.38
	%TD	2.23	11.19	1.22	2.64	+3.19	9.42
HSFLA	TD	1210.34	951.51	828.38	589.86	1384.16	1119.24
	NV	11.92	2.7	10	3	11.50	3.25
	%TD	2.45	8.28	0	0	+3.35	11.42
CPLA	TD	1232.1	922.48	828.38	589.86	1355.40	1106
	NV	11.92	3.09	10	3	12.00	3.38
	%TD	4.29	4.97	0	0	+1.21	10.11
PITHS	TD	1209.19	951.17	828.38	589.86	1385.9	1120.53
	NV	12	2.73	10	3	12.00	3.25
	%TD	2.35	8.24	0	0	+3.48	11.55
S-PSO	TD	1232.3	1016.7	835.92	593.42	1385.5	1169.1
	NV	12.58	3	10	3	12.13	3.38
	%TD	4.3	15.6	0.91	0.6	+3.45	16.39
ACO-TS	TD	1197	951.36	829.01	590.78	1380.60	1095.8
	NV	13	4.18	10	3	12.25	4.75
	%TD	1.32	8.26	0.08	0.16	+3.09	9.09
HGA	TD	1209.1	1087.6	838.75	590.35	1391.4	1134.43
	NV	12.83	4.72	10	3	12.26	5
	%TD	2.27	19.199	0	0	4.09	3.5

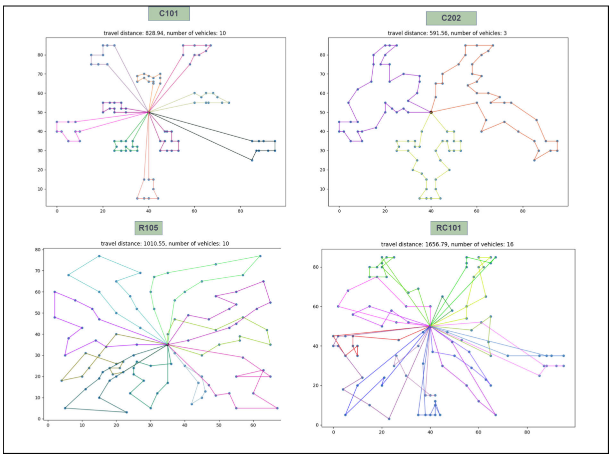

FIGURE 5. Schematic representation of optimal solutions for four distinct vehicle routing problems.

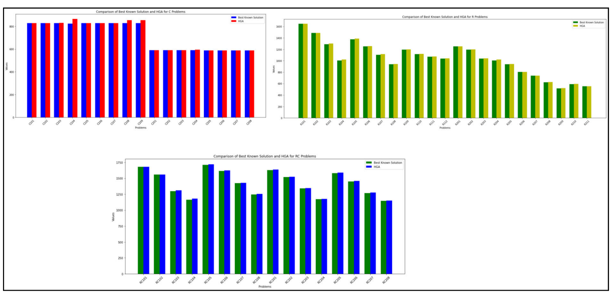

FIGURE 6. Best known VS Our HGA-SIH results for R, C and RC category problems.

deviations in total distance. This strategic trade-off is invaluable, particularly when optimizing for efficient vehicle utilization to meet specific logistics requirements. Overall on 56 Solomon instances,the HGA-SIH algorithm offers a compelling solution for logistics and supply chain optimization, combining the advantages of minimizing both travel time and vehicle count. However, continuous efforts in refining its performance will be necessary to address minor deviations and further enhance its efficacy in real-world scenarios.

The effectiveness of HGA-SIH was assessed by comparing its results to those obtained from state-of-the-art methods designed for the VRPTW problem, including CPLA: Cooperative population learning algorithm of Barbucha([93], PITSH: Parallel iterated tabu search heuristic of Cordeau and Maischberger [94], HSFLA: Novel hybrid shuffled frog leaping algorithm of Luo et.al. [95], S-PSO: Discrete particle swarm optimization approach of Gong et al. [96], and ACO-TS: A hybrid approach, which consists of ant colony optimization (ACO) and tabu search of Yu et al. [97]. The detailed experimental results can be found in Table 4 and are visualized in Fig.7., where each instance was tested. The first column in these tables contains the instance name, followed by columns indicating the distance traveled (TD) and the number of vehicles (NV) for each of the methods: CPLA, PITSH, HSFLA, S-PSO, ACO-TS, and MFGA. The results are presented for various problem groups (R1, R2, C1, C2, RC1, and RC2), and the best-performing results are highlighted in bold. Table 4 presents the average number of vehicles (NV) and the best quality solutions in terms of total distances (TD) achieved by our proposed HGA in comparison to five other algorithms: HSFLA, CPLA, PITHS, S-PSO, and ACO-TS, across Solomon's benchmark datasets (R1, R2, C1, C2, RC1, and RC2). Each row in the table comprises three parts: NV, TD, and %TD, where %TD represents the percentage deviation between the algorithms and the best-known solutions (BKS).

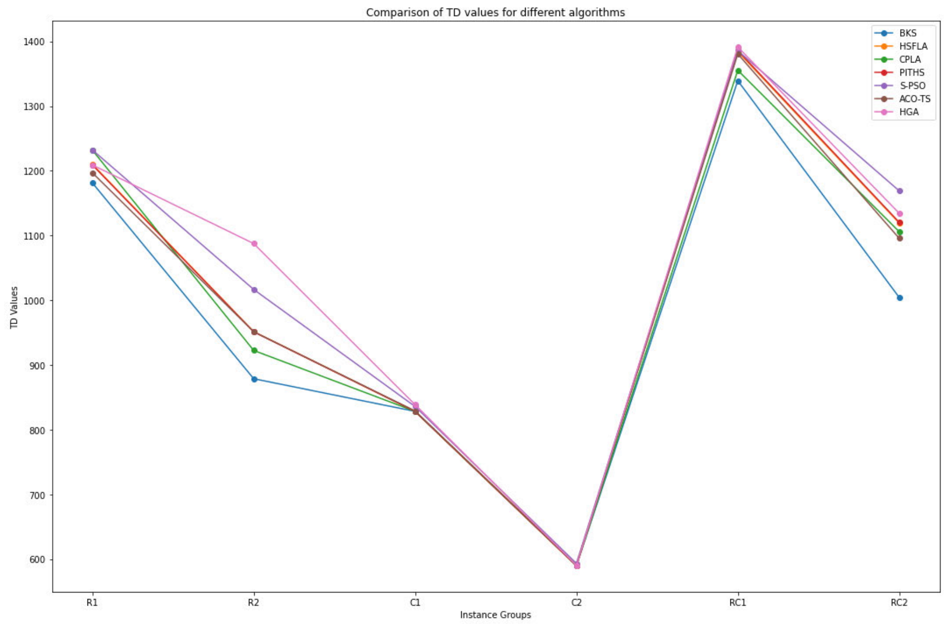

FIGURE 7. Comparison of HGA with other heuristics.

The analysis of percentage deviation underscores the consistency of HGA's performance across the various datasets under examination. As shown in Table 4, for the R1 group, HGA stands out by surpassing HSFA, CPLA, PITHS, and S-PSO, exhibiting a deviation of only 2.27% from the best-known solutions (BKS). For the instances in groups C1 and C2, HGA manages to achieve results on par with the BKS. Within the RC1 instances, HGA excels by outperforming ACO-TS with a deviation of 4.09% from the BKS. In the RC2 instances, HGA emerges as the leading algorithm, showcasing a deviation of 3.5% from the BKS. However, it's worth noting that HGA faces more significant challenges when dealing with R2 instances, where the deviation increases to 19.19% from the BKS. Overall, our proposed HGA demonstrates highly promising results, consistently outperforming state-of-the-art algorithms presented in the existing literature across a range of problem instances.

IV. CONCLUSION

This research study presents a (HGA-SIH) novel algorithm tailored to optimize the Vehicle Routing Problem with Time Windows (VRPTW), addressing a crucial logistics and supply chain management challenge. The algorithm underwent thorough computational testing, utilizing Solomon's VRPTW benchmark instances, to substantiate its efficacy and reliability in optimizing dual objectives: minimizing total travel distance and reducing the required number of vehicles. Our methodological approach was designed to be robust and adaptable. A thorough parameter tuning was performed to calibrate factors such as population size, mutation and crossover rates, and the number of generations. This allowed the HGA-SIH to consistently perform well across diverse problem instances, each presenting unique logistical challenges. The computational results showed that the HGA-SIH not only matched but also improved upon best-known solutions (BKS) for most instances.The reason for this is the implementation of an initialization strategy (SIH), which improved the diversification of the initial population. It showcased an adept ability to effectively balance both the number of vehicles utilized and the total travel distance, a critical attribute for practical applications in real-world logistics scenarios. The deviations from BKS ranged from 1.15% to 4.65%, affirming the algorithm's practical relevance in an industrial context. This study contributes significantly to the existing body of knowledge in logistics optimization by presenting a reliable and robust tool readily applicable across various logistical settings. The broad adaptability of HGA-SIH, as indicated by its performance across diverse customer geographical distributions, further underscores its utility in practical scenarios.

V. LIMITATION AND FUTURE DIRECTION

While the current study presents promising results, several avenues for future research exist. Exploring more complex variations of VRPTW or combining the HGA with other optimization algorithms may yield improved outcomes. Assessing the algorithm's efficacy across diverse VRP versions, incorporating ad-hoc techniques, and emphasizing route planning optimization by considering factors like traffic conditions, road capacities, and environmental impact would enhance the model. Furthermore, validating the HGA through implementation in real-world logistics scenarios would provide a comprehensive assessment of its effectiveness.

In conclusion, the HGA-SIH presented in this paper provides a resilient and efficient solution to the VRTPW. The proven computational success robustly advocates for its practical implementation in tackling logistics and supply chain optimization challenges. Future research can expand on these findings by applying the HGA-SIH to more complex problem variants and real-world applications, thus reinforcing its significance in the field.

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