The Vehicle Routing Problem with Time Windows Based on Agent Travel Time: An Exploration of Genetic Algorithm Reproduction Schemes

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ABSTRACT

The Vehicle Routing Problem with Time Windows (VRPTW) is a critical combinatorial optimization problem in modern logistics, where finding optimal routes is essential for minimizing operational costs and enhancing service reliability. While Genetic Algorithms (GAs) are a powerful tool for solving VRPTW, their effectiveness is often undermined by premature convergence, a phenomenon in which the algorithm stagnates at suboptimal solutions, thus failing to achieve maximum efficiency. This study directly addresses this challenge by systematically evaluating how different reproduction schemes impact GA performance. The primary objective is to identify operator combinations that mitigate premature convergence to achieve superior solution quality, measured by total travel time, while also analyzing the trade-off with computational cost. We investigate combinations of conventional operators, such as Tournament Selection (TS) and Order Crossover (OX), against more advanced schemes, including Split Rank Selection (SRS) and Multi-Parent Order Crossover (MPOX), as well as different mutation methods, namely Scramble Mutation (SM) and Inversion Mutation (IM). Results demonstrate that advanced schemes, particularly the combination of SRS, MPOX, and IM, yield the most robust convergence and the lowest average total travel time of 48,422.8 minutes. However, this superior performance requires the longest computation time at 30.9 h. In contrast, conventional operator combinations are significantly faster, with execution times as low as 8.7 h, but they produce lower-quality solutions and exhibit unstable convergence. This study highlights the crucial role of the reproduction scheme in balancing the trade-off between solution quality and computational efficiency, confirming that a synergistic combination of advanced operators is essential for solving complex VRPTW instances effectively.

Keywords-artificial intelligence; optimization; routing problem; metaheuristics; premature convergence

I. INTRODUCTION

The Vehicle Routing Problem (VRP) is a well-known operations research challenge focused on designing optimal routes for vehicles to serve geographically dispersed customers, either for deliveries or collections [1, 2]. A significant extension of this is the Vehicle Routing Problem with Time Windows (VRPTW), which introduces the additional constraint that customers must be visited within specified time intervals [3]. Both VRP and VRPTW are classified as NP-hard problems. As the scale of these problems grows, finding exact solutions becomes computationally impractical, which is why metaheuristic approaches have become essential tools for discovering high-quality, near-optimal solutions [4, 5]. The VRPTW, in particular, is vital for optimizing resource use, reducing transportation costs, and boosting delivery reliability [6, 7] and it is dominant in various logistics applications [8, 9]. These optimization problems, falling under the umbrella of intelligent systems, drive efficiency and represent a key domain for current artificial intelligence research, which is continually rethinking the nature and future direction of intelligence itself [10].

Among these methods, the Genetic Algorithm (GA) is a powerful and widely used metaheuristic for tackling the VRPTW [3, 11]. As a core technique within artificial intelligence, GAs are particularly adept at solving complex routing problems due to their ability to mimic evolutionary processes, allowing them to effectively explore vast solution spaces to find optimal or near-optimal routes [12]. GAs, inspired by natural selection and genetics, employ mechanisms such as selection, crossover, and mutation [13, 14]. Their strength lies in their global search capabilities [15], allowing them to navigate vast solution spaces and converge toward high-quality solutions [16]. The selection operator is the process of intensifying the search in promising regions of the solution space by favoring fitter individuals. Conversely, exploration, fueled by crossover and mutation operators, involves diversifying the search to discover new, potentially superior regions.

Despite their strengths, GAs are susceptible to a significant drawback known as premature convergence. This phenomenon occurs when the algorithm settles on a suboptimal solution because the diversity within the population diminishes too quickly across generations [17]. The diversity of the GA population is heavily influenced by its reproduction operators. Consequently, the overall performance of the GA is critically dependent on the specific schemes used for these operators [18, 19].

Therefore, exploring different reproduction operator schemes is crucial for enhancing GA performance and mitigating premature convergence. The specific problem characteristics should guide the choice of an appropriate scheme and require thorough testing [20], as different schemes exhibit varying strengths and weaknesses across different problem domains [21]. Numerous studies have focused on developing new reproduction schemes, such as the Improved Partially Mapped Crossover (IPMX) [22], combinations of crossover methods [23], triggering mechanisms for mutation schemes [24], and specialized crossovers, including the Balanced Crossover [25]. However, a gap remains in research concerning the combined performance of novel reproduction schemes. For instance, while Multi-Parent Order Crossover (MPOX) [26] and Split Rank Selection (SRS) have demonstrated individual improvements, their combined efficacy has not been thoroughly investigated. This study fills that gap by investigating the performance of various reproduction scheme combinations, from conventional methods like Tournament Selection (TS) and Order Crossover (OX) to advanced ones like SRS and MPOX. We analyze how these combinations affect GA convergence, solution quality, and computational cost to provide a clear understanding of their trade-offs.

II. PROBLEM FORMULATION

The problem addressed in this study is the VRPTW. It is based on the operational scenario of a company, Anekapay, which employs a fleet of collectors to visit numerous agents within a city. The core task is to design a set of optimal routes for the collectors, originating and terminating at a central branch office (depot), to serve all agents while adhering to several operational constraints. The complexity arises from the large number of agents (2,220) and the need to schedule visits efficiently within specified time frames. Effective route optimization is crucial for minimizing operational costs and ensuring timely service. The selection of an appropriate GA, particularly the exploration of its reproduction operators, is posited to significantly influence the quality of solutions for the VRPTW [27].

A. *Problem Characteristics and Constraints*

The problem involves a single depot, a set of agents (customers) to be visited, and a fleet of vehicles (collectors).

The key characteristics and constraints are:

1. Agent visits: Each of the 2,220 agents must be visited exactly once and only by one of the six collectors.
2. Working hours: Collectors operate from 07:30 to 17:00 (a total of 9.5 h).
3. Lunch break: A mandatory one-hour lunch break is scheduled for all collectors from 12:00 to 13:00. During this period, no travel or service is permitted. The effective daily working time per collector is 8.5 h (510 min).
4. Service time: Each visit to an agent requires a fixed service time of 5 min.
5. Depot: All routes must start and end at the central branch office.
6. Time windows: Each agent must be visited within the overall operational window (07:30-17:00), and service cannot overlap with the lunch break. While specific individual time windows for each agent are not detailed beyond this, the scheduling must respect these global time constraints.

For a route to be feasible, several hard constraints must be met: each agent must be visited exactly once, including that (1) all routes must start and end at the branch office, (2) no service or travel can occur during the 12:00-13:00 lunch break, and (3) each collector's total route duration (travel and service) must fit within 8.5 working hours, scheduled between 07:30 and 17:00. Beyond these, soft constraints aim for optimal solutions, primarily by minimizing the total travel time for all collectors. While balancing the collector workload is a secondary consideration, this study focuses on minimizing travel time, a common objective in the VRPTW.

B. Mathematical Model

To formally define the VRPTW, we use the following sets, indices, and parameters:

- Let $N = \{0,1,\dots,n\}$ be the set of nodes, where node 0 represents the depot (branch office) and nodes $1,\dots,n$ represent the agents.
- Let $V = \{1,\dots,K\}$ be the set of vehicles (collectors), where $K = 6$.
- c_{ij}: Travel time (or distance) from node $i \in N$ to node $j \in N$.
- s_i: Service time required at agent $i \in N \setminus \{0\}$ ($s_i = 5$ min for all agents; $s_0 = 0$).
- E_0: Earliest departure time from the depot (07:30).
- L_0: Latest arrival time at the depot (17:00).

The objective function defines the primary goal of the optimization model, which is to minimize the total travel time:

$$\text{Minimize } Z = \sum_{i\in N} \sum_{j\in N, i\neq j} \sum_{k\in V} c_{ij} x_{ijk} \quad (1)$$

The model is subject to a set of constraints:

1. Each agent visited exactly once: Each agent must be visited by exactly one vehicle. As noted in the problem description, this ensures that for each agent node j, exactly one incoming arc is active across all vehicles and all possible predecessor nodes i:

$$\sum_{k\in V} \sum_{i\in N, i\neq j} x_{ijk} = 1 \quad \forall j \in N \setminus \{0\} \quad (2)$$

2. Vehicle departure from depot: Each vehicle utilized must start its route from the depot:

$$\sum_{j\in N\setminus\{0\}} x_{0jk} \leq 1 \quad \forall k \in V \quad (3)$$

3. Vehicle return to depot: Each vehicle that leaves the depot must return to the depot:

$$\sum_{i\in N\setminus\{0\}} x_{i0k} = \sum_{j\in N\setminus\{0\}} x_{0jk} \quad \forall k \in V \quad (4)$$

III. GENETIC ALGORITHM

This section outlines the GA framework developed to address the VRPTW. The modeling focuses on chromosome structure, the reproduction operators explored, and the parameters guiding the experimental setup.

A. Chromosome Representation

To solve the VRPTW, where each agent must be visited uniquely, a permutation-based chromosome representation is employed [28]. Each chromosome encodes a complete solution, representing the sequence of agents assigned to each of the six collectors. These sequences dictate the routes each collector follows, starting and ending at the central depot. This structure inherently prevents an agent from being assigned to more than one collector or route.

B. Reproduction Operators

The core of this study's exploration lies in the reproduction operators. Specific schemes were chosen for selection, crossover, and mutation to investigate their impact on GA convergence. The selection schemes examined were TS and SRS. For crossover, OX and MPOX were utilized. Finally, the mutation schemes included Scramble Mutation (SM) and Inversion Mutation (IM). Different combinations of these schemes were systematically tested to evaluate their performance, forming various experimental setups.

The selection process, a critical step that guides the GA's search toward optimal solutions, was performed using two distinct schemes: the conventional TS and the more novel SRS. The operational flow of both methods is illustrated in Figure 1. TS operates by randomly selecting a subset of individuals from the population, with the fittest individual among them chosen as a parent [13]. SRS is a novel selection method that partitions the population based on fitness rank to maintain diversity and prevent premature convergence [18]. For crossover, OX is employed for permutation-based representations, preserving the relative order of elements from parents in the offspring [29]. MPOX extends traditional crossover by incorporating genetic material from more than two parents, aiming to enhance diversity and solution quality [26]. In terms of mutation, SM involves randomly scrambling elements within a selected subset of a chromosome to promote local exploration [30]. Lastly, IM inverts the order of genes within a randomly chosen sub-section of the chromosome, effectively generating new permutations while maintaining overall route structure [31].

C. Genetic Algorithm Parameters

The GA was configured with parameters established in prior research to ensure a robust comparison of reproduction schemes. A population size of 100 was used, considered optimal by authors in [32]. When MPOX was utilized, four parents were involved, as reported by authors in [26]. A high crossover rate of 0.9 was applied, as suggested by authors in [33], to enhance solution accuracy in similar routing problems. The mutation rate was set to 0.05, a threshold indicated by authors in [34, 35] to avoid detrimental impacts on performance. Each experimental combination was executed for 5,000 iterations and repeated over five runs to ensure consistency, a practice highlighted by authors in [26, 36]. For TS, a tournament size of 4 was used.

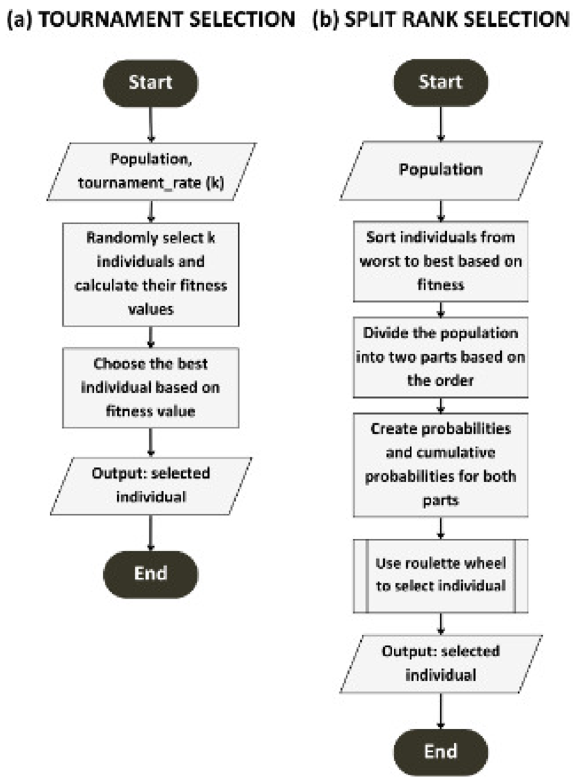

Fig. 1. Selection process diagram.

IV. RESULTS AND DISCUSSION

A. Experiment Description

This research follows the methodology outlined in Figure 2, which includes data collection, GA model development, experimentation, and analysis, and concludes with suggestions.

B. Split Rank Selection–Multi-Parent Order Crossover-Inversion Mutation

This initial experiment, combining SRS, MPOX, and IM, yielded the lowest average total travel time of 48,422.8 min. Figure 3 shows the convergence behavior was notably consistent across multiple runs, indicated by a standard deviation of 560.53 min. This stability suggests robust convergence, likely facilitated by the diversity enhancement from MPOX and the strong selective pressure of SRS. Despite achieving the best solution quality, this scheme required the longest computation time (30.9 h), highlighting a trade-off between convergence depth and computational cost. The convergence plots for this experiment showed that all runs consistently reached solutions of similar high quality. However, authors in [37] caution that even efficient GA routes may face challenges with strict real-time operational constraints.

C. Tournament Selection–Order Crossover-Scramble Mutation

The second experiment, utilizing TS, OX, and SM, demonstrated poor convergence, resulting in the highest average total travel time (61,799.2 min). The convergence process was highly inconsistent across runs, with a large standard deviation of 828.98 min, as shown in Figure 4. For example, one trial stagnated significantly until generation 2,000, indicating inefficient exploration of the solution space. This behavior aligns with the findings by authors in [38], who noted that weak operator combinations can lead to premature convergence when diversity is not effectively maintained. The suboptimal performance of traditional OX and SM here also reflects observations made by authors in [39] in VRPTW contexts. Although this combination had the second-fastest computation time (8.7 h), its unreliable convergence and the resultant low-quality solutions emphasize that speed alone is insufficient for complex problems, supporting authors in [13] regarding the importance of population diversity.

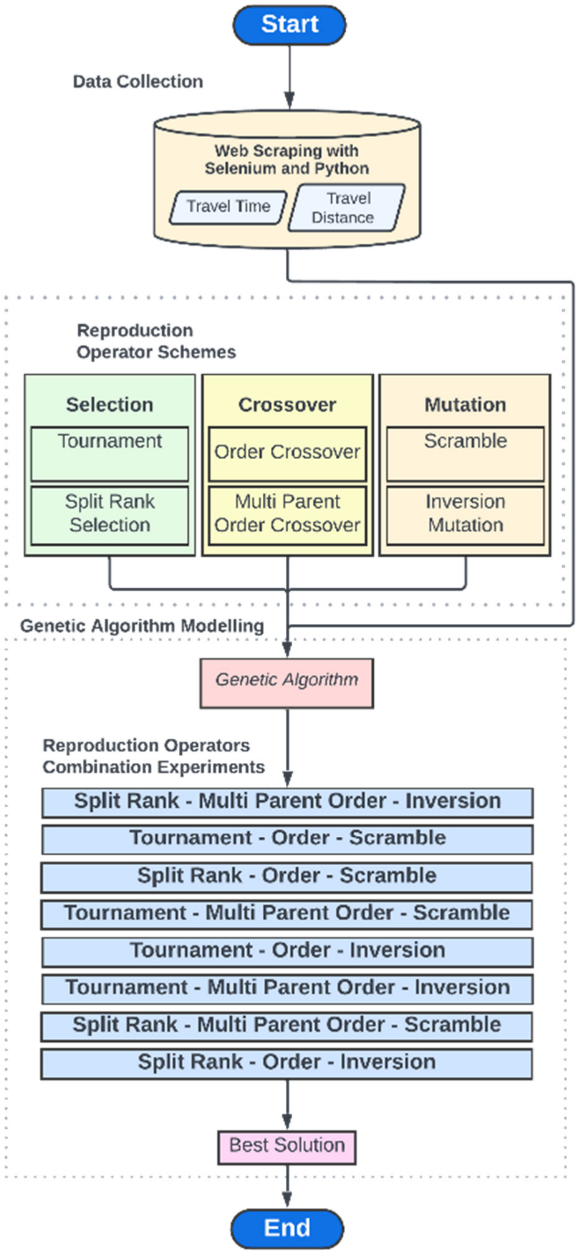

Fig. 2. Research flow.

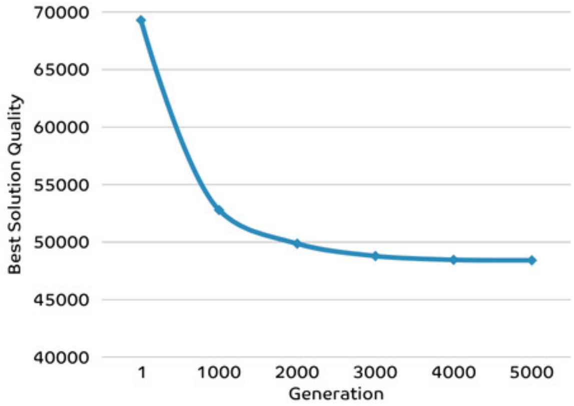

Fig. 3. SRS – MPOX – IM performance.

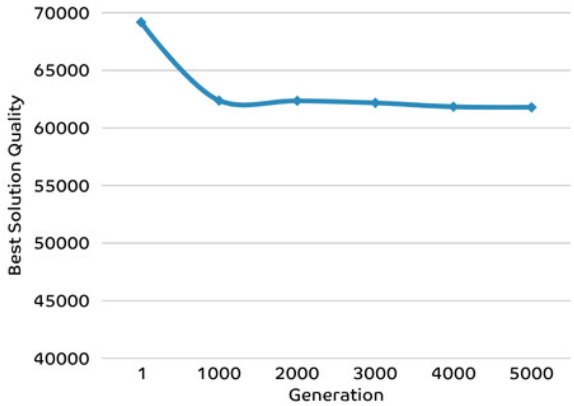

Fig. 4. TS – OX – SM performance.

D. Split Rank Selection-Order Crossover-Scramble Mutation

Figure 5 shows that combining SRS with OX and SM achieved an average total travel time of 48,422.8 min. The convergence pattern showed rapid improvement up to generation 1,500, after which the rate of improvement slowed considerably, with signs of premature convergence appearing around generation 2,500 (resulting in less than 70 min of improvement thereafter). This observation is consistent with the findings of authors in [40], who noted that non-adaptive operators, such as OX and SM, may struggle to maintain diversity in later generations despite initial progress. The computation time was 22.414 h. With a standard deviation of 758.66 min, the results were moderately consistent. This result suggests that SRS aided early convergence toward stronger solutions, whereas the standard operators (OX and SM) were less effective at sustaining exploration to avoid local optima. This finding aligns with authors in [41], who noted that simpler mutation methods lose effectiveness without adaptive mechanisms.

E. Tournament Selection- Multi-Parent Order Crossover-Scramble Mutation

Figure 6 illustrates that the fourth experiment, which combined TS, MPOX, and SM, yielded an average total travel time of 52,034.6 min. Convergence was characterized by rapid initial improvements up to generation 1,500, followed by diminishing returns. This initial enhancement aligns with authors in [31], who demonstrated that MPOX enhances early solution diversity. The average computation time was relatively efficient at 10.794 h. A key observation was the high consistency in convergence across trials, marked by a low standard deviation of 388.99 min, indicating stable convergence patterns. These results support authors in [42], who noted that multi-parent crossovers can improve solution quality early on but might require adaptive mutation strategies for sustained long-term diversity.

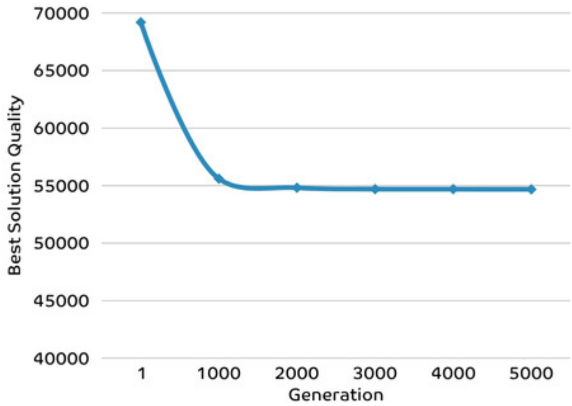

Fig. 5. SRS – OX – SM performance.

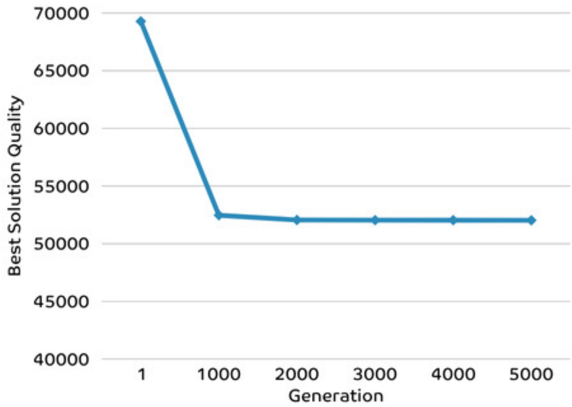

Fig. 6. TS – MPOX – SM performance.

F. Tournament Selection-Order Crossover-Inversion Mutation

Figure 7 shows that pairing IM with TS and OX resulted in the second-highest average travel time of 59,185.4 min. While this combination was the fastest in terms of computation (8.694 h) due to the low complexity of its operators, its convergence behavior was the least stable. It exhibited the highest standard deviation (1,625.80 min), indicating significant performance variability between runs and unreliable improvement patterns, including early plateaus. This failure to consistently improve aligns with authors in [31], who suggested that IM alone might not compensate for the exploration limitations of TS and OX in VRPTW, often necessitating hybrid strategies to balance speed and solution quality.

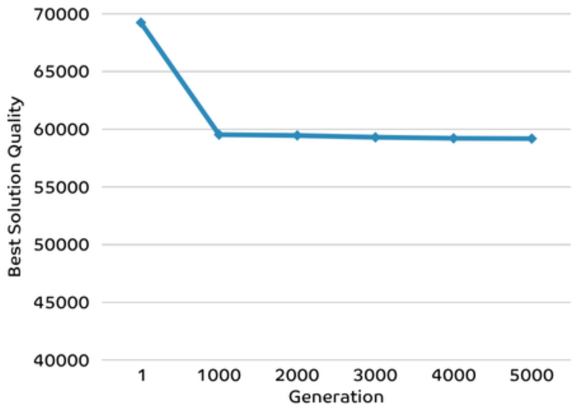

Fig. 7. TS – OX – IM performance.

G. *Tournament Selection-Multi-Parent Order Crossover-Inversion Mutation*

Figure 8 illustrates that combining TS, MPOX, and IM achieved the third-best average travel time (51,633.2 min). Convergence showed strong early improvements but tended to plateau around the 3,500th generation, with minimal gains thereafter. This convergence occurred earlier than in the top-performing experiment (SRS – MPOX – IM), highlighting a potential advantage of SRS for sustained solution refinement. The computation time averaged 10.901 h. The results showed moderate stability with a standard deviation of 900.72 min, aligning with authors in [43], who found that MPOX improved solution diversity but sometimes faced consistency challenges in complex routing scenarios. These findings suggest that MPOX can enhance diversity, but without a stronger selection mechanism, the risk of early convergence remains.

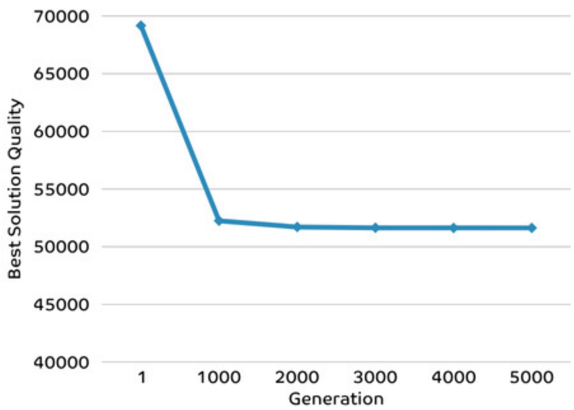

Fig. 8. TS – MPOX – IM performance.

H. *Split Rank Selection-Multi-Parent Order Crossover-Scramble Mutation*

Figure 9 shows that the combination of SRS, MPOX, and SM resulted in an average travel time of 49,315.2 min. The convergence pattern was similar to the best-performing experiment, with consistent improvements until approximately the 4,000th generation, after which gains significantly diminished. However, by generation 2,500, this setup produced slightly worse solutions (average 49,802 min) compared to the SRS – MPOX – IM experiment. This subtle decline in later-stage convergence quality may be attributed to SM, which can disrupt well-formed route structures, an observation also made by authors in [30] regarding scramble-based mutations in VRPTW. The computation time was the second slowest at 24.985 h, reflecting the demands of SRS and MPOX. The results were relatively stable across trials (standard deviation 801.86 min).

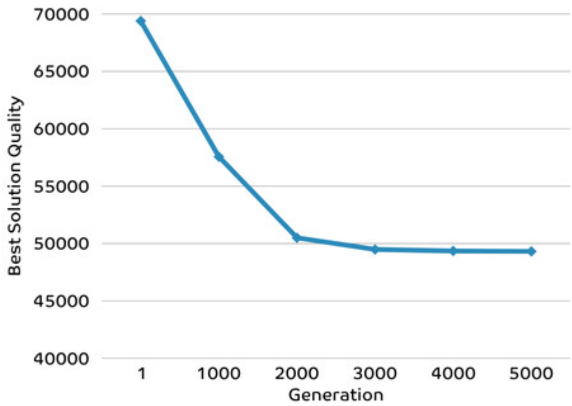

Fig. 9. SRS – MPOX – SM performance.

I. *Split Rank Selection-Order Crossover-Inversion Mutation*

Figure 10 illustrates the final experiment, using SRS, OX, and IM, yielding an average travel time of 53,335.2 min. Convergence showed noticeable early progress up to the 1,500th generation, but stagnation began relatively soon after. This early onset of stagnation is primarily linked to OX's limitations in exploration compared to MPOX. While OX is effective for sequence preservation [29], its narrower exploration capability, even when paired with SRS and IM, led to earlier convergence on solutions of comparatively lower quality. The computation time was 20.835 h. The convergence was moderately stable across trials, with a standard deviation of 578.56 min.

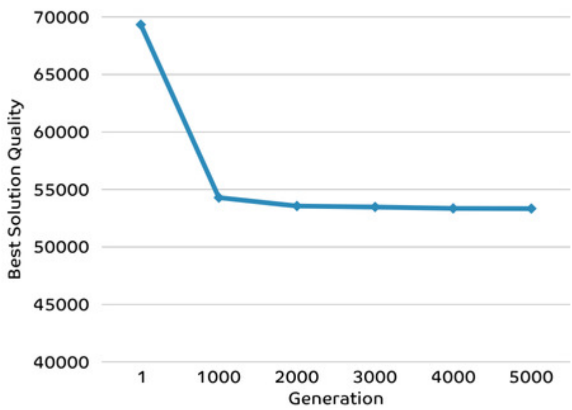

Fig. 10. SRS – OX – IM performance.

J. *Analysis of Best Parameter Combination*

The combination of SRS, MPOX, and IM proved most effective, achieving the lowest average travel time (48,422.8

min) with high consistency. However, this top-tier performance came at the cost of the longest computation time (30.9 h), highlighting a critical trade-off between solution quality and computational cost that practitioners must consider.

To mitigate these limitations, future implementations could focus on two key strategies. For the best-performing but slowest scheme, a hybrid approach integrating a fast local search method could significantly reduce runtime while maintaining high solution quality. For the faster, traditional schemes using TS and OX, incorporating diversity-enhancement mechanisms, such as an adaptive mutation rate, could improve their performance and prevent the unstable convergence observed in this study. These proposed strategies are consistent with research trends advocating adaptive and hybrid metaheuristics to balance the exploration–exploitation dilemma in complex routing problems [44].

V. CONCLUSION

This paper investigated how different combinations of reproduction operator selection, crossover, and mutation shape the convergence process of a Genetic Algorithm (GA) applied to the Vehicle Routing Problem with Time Windows (VRPTW). The primary objective was to identify operator schemes that successfully mitigate premature convergence, thereby achieving the goal of finding high-quality, stable solutions for a large-scale logistics problem. The findings conclusively demonstrate that the performance of the GA is profoundly dictated by the synergy between its operators.

The combination of Split Rank Selection (SRS), Multi-Parent Order Crossover (MPOX), and Inversion Mutation (IM) demonstrated the most desirable convergence pattern, characterized by consistent improvement that led to the lowest average total travel time of 48,422.8 min. In stark contrast, schemes reliant on conventional operators, such as Tournament Selection (TS) and Order Crossover (OX), exhibited unstable convergence, often stagnating in prolonged plateaus, and yielding inferior solutions. This highlights a critical trade-off: although the advanced scheme achieved superior performance, it required the highest computational cost (30.9 h), whereas faster combinations (as low as 8.7 h) produced unreliable results.

This research offers several key contributions. For practitioners, it provides a data-driven framework for selecting a GA configuration that balances the trade-off between solution quality and available computation time. The primary research contribution is the novel, systematic investigation into the synergistic effect of combining SRS and MPOX, providing strong empirical evidence that a holistic approach to operator selection is crucial. This insight suggests that future metaheuristic development should focus on the interaction between algorithmic components rather than on their individual improvements.

Compared to prior studies that predominantly employed standard GA operators, often treating selection, crossover, and mutation as isolated components, this work introduces a more integrated perspective. Earlier approaches, while effective in small-scale instances, frequently suffered from premature convergence and lacked robustness when scaled. By contrast, the proposed operator combination not only improves solution quality but also demonstrates resilience across multiple runs, showcasing a meaningful advancement in GA design for the VRPTW. This comparative insight reinforces the novelty of the framework and its relevance for real-world logistics optimization.

Ultimately, this study confirms that preventing premature convergence is critical to solving the VRPTW effectively, a task that requires operators that actively promote exploration and preserve diversity. Future work could build on these findings by exploring adaptive mechanisms that dynamically alter operators to manage the convergence rate. Furthermore, hybridizing the GA with local search methods could be an effective strategy to help the algorithm escape the convergence plateaus identified in this research, potentially bridging the gap between solution quality and computational efficiency.

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