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# Metaheuristic Approaches for Solving School Bus Routing Problems: A Comprehensive Review.

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***ABSTRACT***

*The school bus routing problem (SBRP) is a complex NP-Hard combinatorial constraint optimization problem that involves a fleet of buses tasked with picking up/dropping off students in an optimal sequence such that the overall distance covered is minimized. This study systematically evaluates the performance of different metaheuristic algorithms, on benchmark instances of the SBRP. Through extensive experimentation and analysis, we identify the strengths and weaknesses of each algorithm in terms of solution quality, convergence speed, robustness, and scalability. Furthermore, we discuss potential strategies for overcoming the challenges associated with applying metaheuristics to the SBRP and we highlight directions for future research. Overall, this comparative study provides valuable insights into the effectiveness of metaheuristic approaches for solving the SBRP and informs the development of efficient and reliable bus routing solutions in real-world transportation systems.*

***Keywords***: *School bus routing (SBR), Combinatorial Optimization Problem, Operation Research, Route Scheduling*

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## I. Introduction

The School Bus Routing Problem (SBRP) involves efficiently planning routes for school buses to transport students, aiming to minimize total travel distance while adhering to constraints. This problem is typically modeled using a graph $\mathbf{G = (V, E)}$, where $\mathbf{V}$ represents locations like bus stops, and schools, and E represents connections between them. Variables include the total number of buses available **(B),** the time horizon **(T)** , distance between locations $\boldsymbol{d_{ij}}$, time windows for pickups/drop-offs$T_{ij}$, student demand at each location$\boldsymbol{\lambda_i}$fixed travel costs $\boldsymbol{f_{ij}}$, and binary variables indicating bus routes $\boldsymbol{V_{ij}}$. The objective is to minimize the total cost or distance traveled, typically expressed as $\sum \boldsymbol{ij\, \epsilon V f_{ij} V_{ij}}$. Various constraints ensure that buses adhere to capacity limits, time windows, routing, and availability.

To the best of our knowledge there is no known exact solution that exists for this problem making it a NP-Hard. To justify this statement, we reduce it to a similar sister variant known as the traveling salesman problem (TSP) which is a well-known NP-Hard problem. In the TSP, denoted as T, there exists a set of cities $\boldsymbol{C}$ and a distance matrix $\mathbf{d_{ij}}$ representing the distance between city $\boldsymbol{i}$and city $\boldsymbol{j}$. To demonstrate the NP-hardness of SBRP, we construct an instance of SBRP, denoted as $\boldsymbol{S}$, that mirrors TSP. Given the correspondence between the two problems, if a polynomial-time algorithm exists for solving SBRP, it could efficiently solve TSP, contradicting the NP-hardness of TSP. This reduction establishes the NP-hardness of SBRP, affirming its computational complexity of optimization problems.

Approaches for solving the SBRP can be classified into several strategiesSuch as *Metaheuristic Methods, Hybrid Methods and Constraint Programming models*.Metaheuristic Methods offer flexible and robust optimization techniques that can efficiently explore complex solution spaces and find near-optimal solutions to the SBRP. Algorithms such as genetic algorithms, simulated annealing, tabu search, and ant colony optimization iteratively improve solutions through stochastic search processes, allowing for effective balancing between exploration and exploitation. Hybrid Methods combine multiple optimization techniques to leverage their respective strengths and mitigate their weaknesses. By integrating elements of exact, heuristic, and metaheuristic methods, hybrid algorithms can achieve enhanced performance and scalability while addressing various aspects of the SBRP. Constraint Programming models the SBRP as a set of constraints and objectives, allowing for the systematic exploration of feasible solutions.By specifying constraints related to bus capacities, time windows, and geographical placements, constraint programming techniques can generate high-quality solutions by efficiently pruning the search space. Each of these strategies offers distinct advantages and trade-offs, and the choice of approach depends on factors such as problem size, computational resources, and the desired balance between solution quality and runtime efficiency. By understanding and leveraging these different methodologies, researchers and practitioners can develop effective solutions to the challenging School Bus Routing Problem.

In this comparative study, we aim to evaluate and compare the performance of various optimization algorithms for solving the SBRP. Our objective is to assess the strengths and weaknesses of different approaches in terms of solution quality, computational efficiency, and scalability. By systematically analyzing the performance of algorithms we seek to provide insights into their effectiveness in addressing the complexities of the SBRP. Through extensive experimentation and analysis on benchmark instances of the problem, we aim to identify promising strategies and best practices for optimizing school bus routes. Additionally, we intend to highlight potential areas for improvement and future research directions in the field of school bus routing optimization.

The main contributions of this work are summarized as follows:

i. We identified and analyzed the challenges associated with applying metaheuristic algorithms to the SBRP, including issues related to convergence, computational complexity, parameter sensitivity, and scalability. Understanding these challenges is crucial for devising effective strategies to improve algorithmic performance and overcome limitations in practical applications.

ii. We systematically evaluated the performance of prominent metaheuristic algorithms. Through extensive experimentation, we assess the algorithms' ability to generate optimal or near-optimal bus routes while considering factors such as solution quality, convergence speed, and robustness.

iii. Based on our findings, we discussed potential strategies for addressing the challenges posed by the SBRP and enhancing the effectiveness of metaheuristic approaches. We highlighted areas for future research and development, including algorithmic enhancements, hybridization techniques, and real-world implementation considerations.

To this end, the next sections are organized as follows, Section 2, discusses various articles of related works and Section 3, focuses on Meta-heuristic while Section 4, analyzes and offers future recommendations and lastly section 5 concludes our study by summarizing and highlighting areas for future research and development.

## II. Related works based on Problem formulations

In this section, we reviews metaheuristic, hybrid metaheuristic and constraint Programming approaches in solving combinatorial optimization problems related to SBRP.Metaheuristic approaches are vastly used to solve wide ranges of NP hard combinatorial optimization problems[1],[2].Thispaper provides an overview of the existing research and literature in the SBRP. Early research to address the complexity and real-world constraint in SRBP deployed exact algorithms that focus to discover the most effective solutions by utilizing exhaustive search techniques. Nevertheless, because the problem is NP-hard, exact algorithm frequently encounters challenges in terms of scalability, particularly when dealing with real-world scenarios.[3]that involve a substantial number of students and bus stops.

### 2.1 Metaheuristic Approach

Metaheuristic algorithms (MAs) have become a widely accepted approach[4],[5],[6], providing efficient and flexible optimization strategies for addressing combinatorial optimizationproblems such as the SBRP. Ant colony optimization (ACO)[7],Genetic algorithms (GAs)[8]Simulated annealing (SA)[9] and Tabu search (TS)[10] (alphabetically identified) are widely researched metaheuristic algorithms[11]. These algorithms offer efficient approaches to explore the solution space and discover nearly optimum solutions within practical computing time limits. Study by [12] successfully uses metaheuristics algorithm to solve SRBP with Mix load variant , the following objective were achieved, minimized number of buses, solution quality and computational efficiency was improved. In another study [4] propose metaheuristics approach to solve SBRP with school bell adjustment and multiple schools objective variant the study significantly achieved cost saving to relax budget constraint.A study by [13] proposes a metaheuristics ( Simulated annealing algorithm and heuristic local search) to solve two dimensional loading heterogenous fleet in vehicle routing Problem (VRP).In review study by [14] reviews metaheuristics application in vehicle routing problem (VRP) and its variant. Metaheuristic approaches are alsoapplies in otherfields such telecommunication [15], engineering [16] and intelligence application [17].However , according to [18]the metaheuristic algorithms harbors challenges in estimating fitness values for new solutions, especially as problem dimensionality increases, resulting in performance declines. In their study[18] , they further recommends that fast evaluation techniques could reduce computational bottlenecks and speed up optimal solution generation. . Hybrid metaheuristics approaches obtain better solutions than classical metaheuristics algorithms. Hybrid algorithms combinesexact, heuristic, and metaheuristic approaches to enhance the quality of solutions and computing efficiency.The motivation towards metaheuristics hybridization is to complement the weakness and strength of different metaheuristics algorithmsto solving combinatorial optimization problem with large problem size and multi objectives.A study by [19] proposes integration of memetic algorithm with greedy randomized adaptive search to solve vehicle routing problem (VRP) with stochastic demands. The study achieves to validated a cross a benchmark of 40 instance with 385 customers, with fast computation speed making the exploration of problem closer to real life application. In study by [20]a hybrid metaheuristic approach successful determines optimal set of routes for a simultaneously delivery and pick up demands to satisfies 50 to 400 customers. in benchmarking instance. In study by[21] deploys hybrid metaheuristics system for smart waste collection with work load concern to Portuguese waste management company. Where the register 42 % profit margins. Additional study by [22] proposes a novel hybrid multi-objective optimization algorithm, showcasing superior performance across 24 benchmark functions and seven engineering problems, highlighting its effectiveness in real-life optimization tasks. In a review study by [23] hybrid metaheuristics approaches achieves to solve different combinatorial optimization problem. While in other study by [24] argues that hybrid metaheuristics approach although there are effective in solving real world problems they demand significant time investment and their design requires sophisticated expertise in integrating different metaheuristics algorithms.Constraint programming is novel approach in solving combinatorial problems. uses wide range techniques from artificial intelligence(AI), operation research (OP) and graph theory(GT) [25]. In study by[26] address timetable scheduling problem in high school using Constraint programming approach integration of operation research model and local search model. A study by [27] uses constraint programming model to address premarshalling problem in port terminal , to optimize crane movement for efficient loading and unloading of containers. The study outperforms the linear programming models. In study by [28] uses chance - constraint programming model to allocate emergences resources and vehicle routing schedule under stochastic demand in real case study of the Wenchuan earthquake in China. In study by [29] uses constraint programming to address TSP with parallel drones scheduling to optimize delivery time for customer severed by trucks and drones .They study demonstrates improved efficiency , optimal solution quality and effective optimization approach. In review study by[23] hybrid metaheuristics with constraint programming were integrated to solve combinatorial problem. In other study[30] uses Constraint programming with Mixed integer linear programming to solve Job scheduling problem. From on our knowledge we know there are very inadequate literature on constraint programing on solving SRBP.

## III. Comparative Analysis of Metaheuristic Algorithms in solving SRBP

In this section we discus metaheuristic approaches that provide adaptable and resilient optimization tools to tackle the challenges in the SBRP. These methods employ interactive processes to continuously enhance solutions by exploring and exploiting the solution space. The common metaheuristic algorithms for the combinatorial optimization problems includes, ant colony optimization, genetic algorithms, simulated annealing, and tabu search. Ant Colony Optimization (ACO)[7],[31] is a problem-solving technique that draws inspiration from the foraging behavior of ants. It involves the iterative construction of solutions using pheromone trails to direct the search process. ACO techniques, including the ant system and the max-min ant system, have been utilized in the SBRP to effectively achieve a balance between exploration and exploitation, resulting in the efficient discovery of high-quality bus routes. In study by [32] uses improved ACO to reduce operational costs and improve service quality of school bus routes. In another study by [33]use ACO to solve travelling salesman problems.(TSP). In another study by[29]address TSP using ACO integrated to constraint programming model to minimize total delivery time by optimizing drones scheduling with vehicle routing for parcel distribution . In review presented by [7].examines the convergence of ACO. The result shows positive. Later in separate research by [34]they proposes adaptive ACO to mitigate premature convergence by establish pheromone trails with three groups of artificial ants, ordinary, abnormal and random to identify optimal paths. The simulation results confirm effectiveness in solving the travelling salesman problem (TSP). Genetic algorithms (GA)[8] applies the concepts of natural selection and evolution to progressively improve solutions. GA is a stochastic optimization technique that avoids mutation operator trapping in local optimums. Initial random solutions are termed the population. Each population solution is a chromosome. These chromosomes evolve across generations. Every generation, chromosomal fitness is assessed. Best-fitting chromosomes are more likely to be used for crossover and mutation. After a set number of generations, the GA finds a near-optimal solution.

GA address combinatorial optimization problems by finding the optimal arrangement of finite set elements. TSP, VRP, working schedule, bin packing, and DNA sequence alignment are some of examples of combinatorial problems that literature reveilles to have been solved using GAs. Despite the wide range of use GAs in solving combinatorial optimization problems[36],[37],[38],[35], it still harbors some weakness such as premature convergence and computational complexity.In study by[35]improves the GAcomputation operations by enhancing the convergence spend and the search capabilities by redesigning the crossover operators and improving the local search techniques. In another studyby[39]enhances convergence and optimization ability GA to minimize delivery time as objective function in optimization model for Vehicle routing problem with simultaneously pickups. In review by[8] GA suffers from convergence and parameter sensitivity , the main advantage of the GA is that uses evolution to solve combinatorial problems this make GA applicable in immeasurable applications in optimization and machine learning.Simulated annealing (SA), an innovative method developed by Kirkpatrick, Gelatt Jr, and Vecchi in 1983 [9], emulates the annealing process found in metallurgy to efficiently explore solution spaces and avoid the drawbacks of prematurely converging to poor solutions. It draws inspiration from the motion of atoms in hot substances. The positions of the points are subject to random movement, which is determined by a temperature variable, in accordance with the Metropolis algorithm. Although it possesses versatility and effectiveness, it necessitates numerous settings and may exhibit sluggishness. Scientists are currently focusing on enhancing these characteristics and accelerating the process using parallelization approaches.

Simulated annealing is gaining popularity due to its quick adaption and efficiency in solving diverse challenges. Its application has wide range in TSP[40], VRP[41],[42], work scheduling[43], bin packing[44].The main disadvantage of this approach is its large array of parameters. (e.g., initial temperature, temperature decline rule, stage duration), making it empirical.

In the context of the SBRP, SA employs an iterative process to systematically explores the feasible solutions, while also probabilistically accepting worse solution to escape the local optimal. The capacity of SA to effectively manage both exploration and exploitation makes it highly suitable for addressing the SBRP.[45] introduces optimization model using SA for solving the SBRPconsidering uncertainty in travel times between bus stops. [12] combines tabu search and simulated annealing in solving mix load in SBRP. Tabu search (TS), developed by Glover in 1989 [10], is a highly adaptable metaheuristic known for its capacity to broaden search boundaries and overcome stagnation Tabu Search is a versatile optimization algorithm that extends search bounds and avoids stagnation using memory-based mechanisms. It utilizes prior solutions to improve the efficiency of local search by commencing at a specific position, examining neighboring alternatives, and selecting the most optimal one. This process continues iteratively until a predetermined point of cessation is attained. Prohibited solutions are identified and saved to prevent them from being repeated in future iterations. Tabu search efficiently explores intricate search areas by employing tabu lists and aspiration criteria.[46] introduces a tabusearch heuristic for the multi-trip vehicle routing and scheduling problem (MTVRSP), which addresses real-world restrictions such several trips per day, client time windows, vehicle capacity, restricted access, driver schedules, and unloading times. [47] introduces a tabu search algorithm for the single-depot vehicle routing problem(VRP) that uses a unique neighborhood generation procedure based on dealers' locations, traditional improvement techniques, and intensification efforts to achieve competitive performance on benchmark problems.[48] successfully uses tabu search for salesman travelling problem . [49] combines Ant colony optimization algorithm with tabusearch algorithm to solve the Salesman travelling problem.According to ourknowledge there is inadequate literature on tabu search in solving SRBP compared to other metaheuristic approaches.

### 3.1 Addressing Metaheuristic Challenges

The challenges inherent in metaheuristic strategies for combinatorial optimizations involve multiple crucial considerations. Memory consumption is a major difficulty in the implementation of efficient metaheuristics. Metaheuristicsapproaches rely on memory mechanisms to steer the search process using previous information. This feature is included in algorithms such assimulated annealing,tabu search. Furthermore, the inclusion of randomization is essential for investigating a wide range of solutions inside the search space, a characteristic inherent in algorithms such as simulated annealing, ant colony optimizations. Another problem in metaheuristic algorithms is the need for precise adjustment of dynamic parameters. This adjustment must be done during the search process to guarantee the algorithms' robustness and adaptability. In addition, the use of extensive local structures, along with filtering methods, allows for exploration of the solution space, with a focus on promising solutions and the avoidance of expensive evaluations of the entire neighborhood. The complexity of algorithm design and execution presents a major challenge, requiring skills in algorithmic approaches, coding, data structures, algorithm engineering, and statistics to create efficient metaheuristic algorithms for targeted optimizations problems. It is essential to tackle these obstacles in order to create metaheuristic algorithms that can effectively solve intricate combinatorial optimization problems. In literature review on metaheuristics techniques for solving health industry by [50] urges that metaheuristic approaches suffers from slow convergence , have no clear direction in pursuit of optimization parameters ,they converge prematurely to a local optimal. Novel approaches were proposed to solve the problem [50]. To address the challenges of metaheuristics, various strategies are employed[51]. These include maintaining a diverse set of solutions, accelerating convergence process, ensuring scalability, improving robustness, handling constraints, managing memory usage, fine-tuning parameters, adjustment to dynamic environments, ensuring interpretability, and integrating different techniques. These strategies are essential for efficiently optimizing complex problem. Computation Experimental Analysis[51]. Table 1 below in summary shows literature review on metaheuristic approaches on strength, weakness,and improvement

**Table 1. Metaheuristic challenges**

| | Research | Authors & year | Metaheuristic approach | Strength | Weakness | Improvement |
|---|---|---|---|---|---|---|
| 1 | School Bus Routing using Metaheuristics Algorithms | [52] Xue et al, 2023 | Adaptive genetic algorithms (AGA) | AGAs use adaptive methods to alter algorithm parameters during optimization based on problem characteristics or search progress. This adaptability can improve the genetic algorithm's efficiency and efficacy, promising improved solutions. | Genetic and adaptive genetic algorithms require tuning numerous parameters for optimal performance. Finding the correct balance between exploration and exploitation, crossover and mutation rates, and other factors may need lengthy experimentation. | Tune algorithmic parameters could speed up the process and increase result quality. |
| 2 | SpeedRoute, Fast, efficient solutions for school bus routing problems. | [53] | Hybrid of Simulated Annealing and Tabu search | The hybrid Simulated Annealing-Tabu Search algorithm uses both methods' strengths. Tabu Search intensifies local search, while Simulated Annealing explores the solution space globally, improving solutions more effectively. | The iterative approach and hybrid optimization methods may slow down complex problem computations. | Parallelization, adaptive parameter adjustment, and enhanced data structures can reduce calculation times and improve scalability for bigger issue cases. |
| 3 | School Bus Route Optimization Based on Improved Ant Colony Algorithm | [32] Han & Zhang ,2019 | Anti-Colony Optimization | The algorithm incorporates road traffic during operation, making optimised school bus routes more realistic and applicable. By considering traffic, the algorithm can find more efficient routes. | Parameter Sensitivity: ACO algorithms must fine-tune pheromone evaporation rate, heuristic information, and exploration-exploitation trade-off parameters. Incorrect parameter settings might impair algorithm performance and solution quality. | Dynamic Parameter Adjustment: Using problem characteristics or search progress to dynamically modify algorithm parameters during runtime might improve adaptability and performance across problem cases. |
| 4 | Integration of efficient multi-objective ant-colony and a heuristic method to solve a novel multi-objective mixed load school bus routing model | [54] | Hybrid multi-objective ant colony optimization (h-MOACO) algorithm, | Ant colony optimization and multi-objective optimization are combined in the h-MOACO algorithm. This hybrid technique effectively explores the solution space and offers different solutions that balance competing objectives. | The algorithm may not scale to larger problems. The computational complexity of the optimization process may increase exponentially with problem size, increasing execution time and memory requirements. | Developing strategies to enhance the scalability of the algorithm, such as parallelization techniques or adaptive search strategies, can improve its efficiency in solving larger problem instances |
| 5 | A Metaheuristic Algorithm for Routing School Buses with Mixed Load. | [12] Hou et al., 2020b | Hybrid Metaheuristic | A Guided Permutation Strategy in management of malt objective function | Complexity in parameter tuning. | Automating parameter tuning |
| 6 | A School Bus Routing Heuristic Algorithm Allowing Heterogeneous Fleets and Bus Stop Selection | [55] Sciortino et al., 2022 | A heuristic approach based on an iterated local search (ILS) | Iterative local search generates and improves candidate solutions to explore the solution space. Thus, the algorithm efficiently finds high-quality solutions by | As a heuristic algorithm, its solution quality may not be optimal. It can efficiently identify high-quality answers, but they may not be globally optimal, especially for complicated problems. | Combining the iterated local search strategy with genetic algorithms or simulated annealing may improve its performance by |

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|---|---|---|---|---|---|---|
| | | | | balancing intensification (exploitation of good regions) with diversification (research of new regions). | | combining their strengths. |

## IV. Conclusion and Future work

We propose various avenues for future research to enhance the current level of school bus route optimization.Potential areas of investigation encompass novel metaheuristic approaches specifically designed for the SBRP, Hybridization strategies metaheuristics with Exact or heuristic approaches(hybrid metaheuristic's),Constraint programming and practical implementation factors such as dynamic routing and fleet management. Effective collaboration among researchers, practitioners, and policymakers is crucial for tackling the practical obstacles associated with adopting optimized bus routing solutions in real-world transportation systems.

**Conclusion**

In conclusion, this comparative study offers useful insights into the efficacy of metaheuristic techniques in addressing the School Bus Routing Problem. Through a rigorous evaluation and comparison of renowned optimization algorithms, we have discovered the strengths and shortcomings of these algorithms in dealing with the intricacies of the SBRP. The analysis we conducted identifies prospective techniques to enhance the performance of algorithms and address practical issues related to the application of metaheuristics in optimizing bus routing.

In order to make progress, it is necessary to do further research and development to enhance the current level of school bus route optimization. Through the utilization of cutting-edge algorithmic techniques, hybridization approaches, and careful consideration of real-world implementation factors, we may provide solutions that are both more efficient and dependable for the complex SBRP. This study establishes a basis for future research endeavors and collaboration focused on enhancing the efficiency of school bus routes and transportation systems in educational sectors.

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