Applied Mathematics and Computational Intelligence
Volume 14, No. 2, 2025 [55-81]

Meta-Analysis on Substantive Mechanics for Maximizing Productivity and Cost Reciprocity in Routing Optimization

Farid Morsidi[1*] and Wang Shir Li[2]

[1]Computing Department, Faculty of Computing and Meta-Technology, Universiti Pendidikan Sultan Idris, Malaysia
[2]Data Intelligent and Knowledge Management, Faculty of Computing and Meta-Technology, Universiti Pendidikan Sultan Idris, Malaysia

*Corresponding author: farid.mors90@gmail.com

Received: 1 July 2024
Revised: 26 March 2025
Accepted: 16 April 2025

ABSTRACT

Routing heuristics have been created and periodically revised primarily with the idea of reduction of cost and maximizing performance in mind. The premise of cost allocation reciprocity incorporates logistics and transportation expenses into account during both the planning and implementation stages of route optimization. 80 papers from a collection of 1000 publications about routing heuristics were analyzed in this meta-analysis, with an emphasis on managing tradeoff values from expected routing optimization results and cost-aware characteristics for system optimization in scheduling models delimiter annotations. Using cost-approximating metrics derived from cost-resource allocation reciprocity, the paper examines many different facets of route optimization. To optimize efficiency and productivity, scheduling systems are used to deploy application of intelligent algorithms in a coordinated manner throughout the optimization process. Papers from relevant scientific repositories, such as ACM, Scopus, Web of Science, Hindawi, and Google Scholar, were examined in the meta-analysis. The research underlines the need of modifying cost-effective measures during tuning procedures for improving present scheduling systems and draws attention to the trend of developing aspiration criteria for routing strategies that adopt cost into consideration. The paper looks at several effective methods for different intelligent algorithm implementation disciplines, referencing the information synthesis for the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) framework as the foundation for information synthesis. The meta-analysis addresses the potential for future integration and provides a reference point for in-depth examination in distribution scheduling.

Keywords: Computational Intelligence, Cost Optimization, Location-Allocation Problems, Route optimization, Scheduling Systems.

1 INTRODUCTION

To find the most effective path for distributing goods or services across several sites, organizations must engage in the critical process of route optimization. The design for routing optimization entails examining variables such as customer demands, real-time traffic circumstances, travel distance, vehicle carrying capacity, and delivery window timing. From this practice, enterprises can save costs and improve operational efficiency by combining computational intelligence-driven advanced scheduling algorithms with cost-aware mechanisms. Time-sensitive deliveries, fuel expenses, vehicle maintenance, and other variables can be dynamically assessed using cost-aware scheduling, which is facilitated by computational intelligence techniques like machine learning and heuristic algorithms. By integrating economic factors into routing decisions, this method improves consumer satisfaction, increases resource efficiency, and promotes environmental sustainability. Route optimization and cost-aware scheduling play a critical role in helping industry sectors such as logistics, transportation, manufacturing, and healthcare adjust to changing conditions. Heuristic algorithms and computational intelligence tools are necessary for the efficient execution of route optimization in order to continuously assess and improve strategy. In terms of fuel costs, time, and total operating expenses, this strategy can result in significant savings when implemented correctly. Organizations can gain a competitive edge in their markets by adopting a cost-effective and computationally clever scheduling strategy that meets performance targets and produces the intended results. The concurrent section of this paper is structured into the following sections: *Section 1* (Research Methodology) for rationale elaboration on the critical requirements and motivations for highlighting the importance of cost-aware scheduling systems and how they reciprocate with the intended output representing the scheduling systems' purposes, *Section 2* relays the conceptualization of legacy and proprietary routing mechanisms and the implications of imposing cost-relevance correlation for location-allocation routing instances, Section 3 streamlines the influence of cost allocation reciprocity for intelligent heuristics, Section 4 is the analysis on the hybridized local search features for maximizing routing optimization, and Section 5 concludes the discussion.

1.1 Research Methodology

In the context of scheduling system optimization, this work builds on earlier published studies on cost interoperability and routing heuristics [1], [2] under the similar research scope. Based on prior researches done on the topic of routing optimization for scheduling purposes, this paper had accumulated vast information interjections on cost optimization for multi-purpose routing systems [1]. To create a scheduling system infrastructure that facilitates expansive adjustments over current advanced approaches, this meta-analysis examines how these issues relate to one another and the coherence of relevant routing characteristics. The principal objective of the paper is to discourse the fundamental characteristic for a more optimum scheduling model infrastructure that incorporates into account key scheduling variables as well as significant influencing routing variables, whilst additionally addressing the normalcy and significance of distinguishing advantageous routing features. A noticeable trend stemming from the constructive dissertations relative with the improvisations of current native routing implementations apart from the relevant mechanisms in fulfilling objective constraints was the evident lack in notion on the importance of emphasizing on the equilibrium between cost segregation in maximizing the resource allocation representing the entirety of distribution network. This balance trait could be reviewed from the perspective of minimizing coverage whilst maximizing distribution, tradeoff between increasing routing variables such as vehicle and capacity quantities for improving distribution rate, or the performance comparison among fulfilling more objective functions opposite maximization of expenditure relegation. This meta-analysis attempts to consociate mainly 2 independent traits constituting multi-purpose routing systems: (i) introducing the concept of cost reciprocity-based routing systems, and (ii) proposed intelligent heuristic constituents that have been hybridized into the annotation of a more reactive scheduling strategy. The initial phase of the analytical framework consolidates the utilization of reciprocating relationship of cost-aware scheduling strategies and their interdependence in scaffolding routing optimization, whereas the second phase attempts to identify and highlight myriads of intelligent algorithms constructed for scheduling purposes that exhibit potential for further improvisation into relevant routing mechanics for the purpose of cost optimality tuning. The proposed meta-analysis is based on total cost-aware optimality scheduling models.

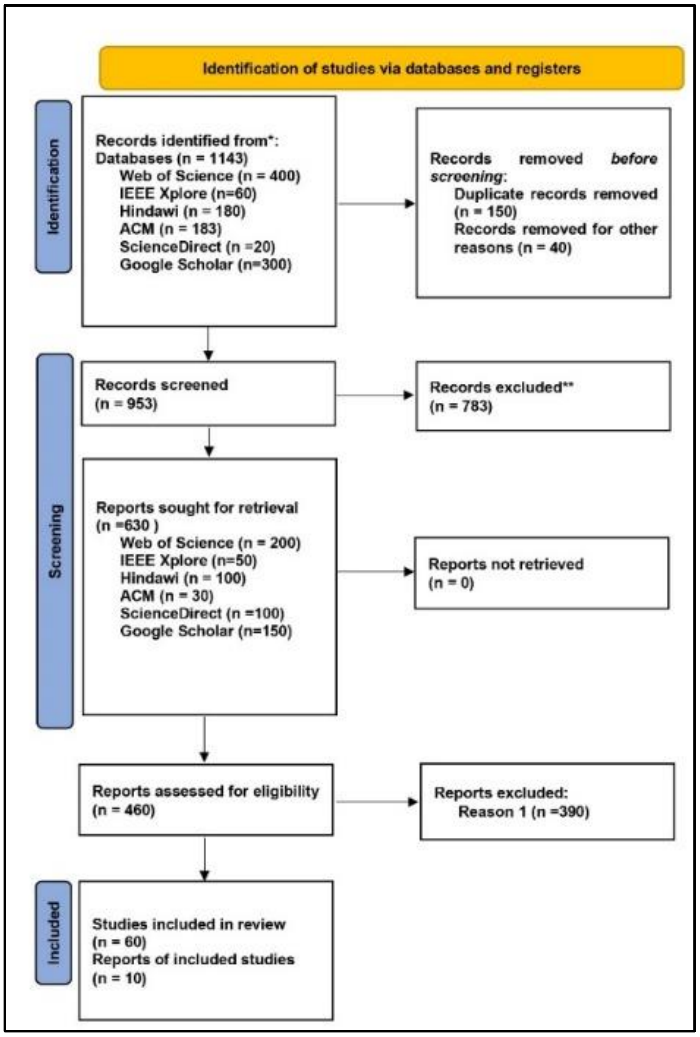

Figure 1: Process of study work identification involving the eligibility criteria involving identification, screening, and inclusion of relevant articles

1.2 Eligibility Criteria

This paper investigates a range of routing optimization techniques, such as flexible scheduling models, cost parameter adjustment, and scheduling automation versions. The discussion covers their practicality, hybridization, and refinement, as well as their coherence with present implementations. In order to solve routing complexity, the research focuses on computational intelligence approaches as a cost optimization tool. The design highlights how scheduling mechanisms that consider costs affect specialized research and stresses the necessity of a complete approach built around location-allocation measures rather than on contemporary heuristics. The discourse motivation aim is to offer a thorough, broadly applicable approach to routing optimization.

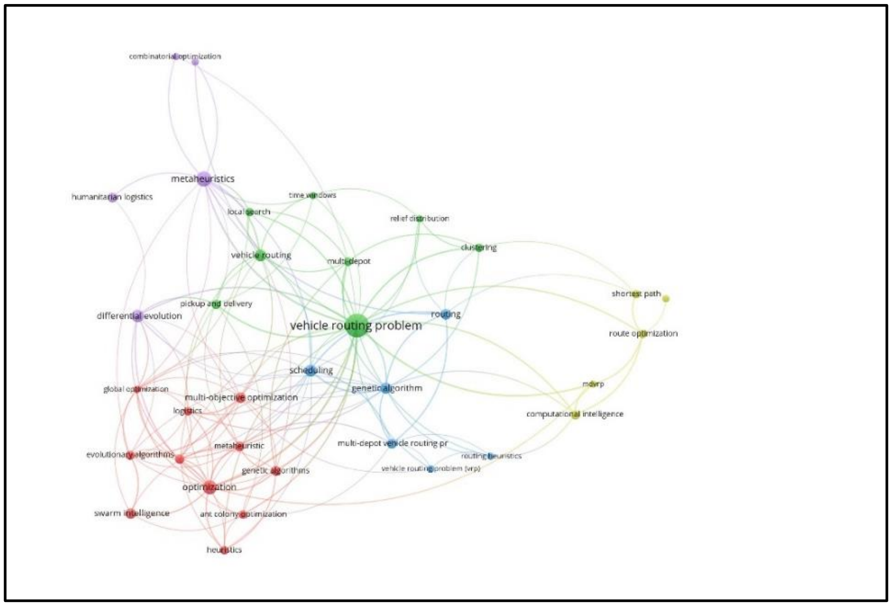

Figure 2: Visualization of the core bibliography networks for the related topics

Table 1: Cost interoperability and modeling complexity-related exclusion and inclusion criteria for correlation and topic interjections for routing systems optimization measures

	No.	Attribute	Characteristics
Inclusion Criteria	1	Vehicle routing problems (capacity, time-restricted, distance)	Research papers discussing various types of routing instances, merging multi-objective problems, modeling methodologies, and the impact of routing variables on routing improvements.
	2	Rationale & practicality with the prominent routing issues	Cost optimization features are assessed for their potential to contribute to innovative studies and for their versatility and adaptability in elevating the targeted routing system's functionality.
	3	Potentials for future endeavors	Enhancement of the cost interoperability features currently specified including the possibility of employing a heuristic to solve evident routing problems.
Exclusion Criteria	1	Relativity and relevance of cost optimization features reflected in the projected output	Routing instances studies with objective measures (single/multi) that don't focus on location-allocation issues nor optimization features
	2	Adaptability with other similar routing heuristics	Research studies on routing heuristics focus on niche purposes (limited domain), single-objective optimization, and scheduling models bearing unilateral purpose tasks that do not suit other relevant scheduling implementations.
	3	Rationale for further integrations/improvements	Research works exhibiting insufficient exposure to cost interdependence inclusiveness in combinatorial optimization routing models regarding system design architecture's adaptability to address problem-centric routing problems.

1.3 Information Repository

Using cost optimality research articles, the study investigates how resource allocation affects the cost-effectiveness of scheduling systems. In order to create effective scheduling methods, the discussion scope assesses whether cost maximization is applicable. The study's objectives are to ascertain how cost-effective routing variables and flexible scheduling procedures might improve the scheduling implementations that are now in place, as well as to consolidate present solution methodologies and comprehend cost optimality in scheduling systems.

Table 2: Academic journal repositories accessed for information dissemination

Journal Repository	Domain	Accessibility
Web of Science	https://mjl.clarivate.com/search-results	Open/Partial
IEEE Xplore	https://ieeexplore.ieee.org/	Partial
Hindawi	https://www.hindawi.com/journals	Open
ACM	https://dl.acm.org/	Partial
ScienceDirect	https://www.sciencedirect.com/	Open
Google Scholar	https://scholar.google.com/	Open

2 EFFICIENT ROUTING SYSTEMS AND COST-EFFECTIVE STRATEGIES FOR LOCATION-ALLOCATION

2.1 Significance for Route Optimizations in Scheduling Systems

i. Cost Savings: Route optimization is a technique used in scheduling systems to reduce transportation costs, labor, energy consumption, and vehicle damage [3], [4]. This strategy helps organizations attract customers by offering faster, reliable, and affordable transportation options, thereby boosting operational efficiency and achieving customer satisfaction [5], [6].

ii. Improved Efficiency: Route optimization is a technique used in scheduling systems to reduce transportation costs, labor, energy consumption, and vehicle damage. Organizations can enhance productivity, guarantee on-time service, cut down on travel time, and identify the most efficient routes for transportation by using the route optimization method [7], [8]. Dynamic data, consisting of traffic patterns and customer requests, is utilized to maintain operational efficiency, minimize disruptions, and make timely adjustments to plans [9], [10].

iii. Reduced Environmental Impact: Route optimization contributes to ecological sustainability [7], [10] by cutting down on vehicle use and emissions, upholding ecological guidelines and showcasing corporate social responsibility, and cutting down on superfluous travel time and distance[3], [11].

iv. Strategic Planning and Decision-Making: By providing significant insight into transportation operations, route optimization assists organizations in making more informed tactical decisions. Organizations can find trends, patterns, and areas for improvement by using routing data and performance indicators [12]–[14]. This information can be used to allocate resources, enhance procedures, and direct strategic planning efforts [15].

2.2 Utilization of Routing Optimization and its Impact on Cost Reciprocity

Route optimization is an essential technique in various industries, enhancing productivity and saving costs through cost-integrated frameworks and prioritized scheduling systems, based on numerous studies and real-world applications.

Table 3: Implementation fields utilizing core mechanics of cost-aware routing optimizations

Field	Corresponding Implementations	Description
Transportation and Logistics	Delivery and Distribution	Route optimization is a crucial tool for logistics organizations, e-commerce shops, and delivery services, enhancing efficiency, reducing fuel consumption, and boosting client retention by minimizing trip distance.
	Fleet Management	Fleet managers employ a strategy to optimize vehicle routes, reduce idle time, boost driver productivity, and lower operating costs across various sectors.
	E-commerce and Last-Mile Delivery	The last-mile delivery chain for online merchants ensures cost-effective and swift item delivery through shorter transit times, improved route selection, and reduced costs.
Public Transportation	Bus and Transit Routing	Public transportation companies employ a strategic approach to reduce travel time and congestion by optimizing schedules, reducing wait times, and distributing passenger loads across multiple routes.
	Paratransit and Demand-Responsive Services	The proposed solution aims to enhance the accessibility and affordability of paratransit systems and demand-responsive services, particularly for individuals with mobility issues.
Field Service Management	Maintenance and Repair Services	Route optimization is a process that enhances the efficiency of field

		service firms by improving maintenance and repair routes, reducing travel costs, and increasing daily service request completion.
	Home Healthcare and Patient Visits	Crucial for pharmaceutical shipment, home medical care, and patient transportation, improving care timeliness, reducing costs, and improving patient outcomes.
	Warehouse and Inventory Management	Route optimization in warehouse operations enhances productivity by optimizing routes for commodity and inventory selection, packing, and sending, resulting in faster order processing and increased inventory turnover.
Supply Chain and Distribution	Cross-Docking and Consolidation	Optimizing cross-docking routes improves operations, consolidates loads, reduces transportation costs, and enhances supply chain efficiency by reducing handling costs, transit times, and overall efficiency.
	Utility Services	Route optimization is a strategy employed by water, gas, and electricity providers to enhance operational efficiency, minimize disruptions, and boost customer retention.
Waste Management and Recycling	Waste Collection and Recycling	Municipalities and waste management organizations utilize route optimization to enhance waste collection efficiency by reducing fuel consumption, and emissions, and improving trash pickup routes.

2.3 Concept of Cost Allocation Reciprocity for Routing Optimality

Cost allocation reciprocity is a route optimization formulation conjecture that factors into consideration both logistics and transportation costs during the planning and execution stages. This entails total cost management, goal balancing, adapting to changing conditions, providing customization possibilities, performing total cost of ownership (TCO) analysis, and taking environmental considerations into account [5], [16]–[19]. Organizations can improve productivity, cut expenses, and increase operational efficiency by optimizing routes based on a thorough understanding of costs, ultimately accomplishing their primary objectives in logistical and transportation operations. A distribution network's TCO can be defined as all costs associated with its design, implementation, operation, and maintenance within the purpose of routing network [20]. These costs include start-up costs, ongoing expenditures, risk management, compliance, end-of-life costs, opportunity costs, and effects on the community and environment. The term cost interoperability had been classified as the incorporation of objective functions during the routing and scheduling phases with the goal of minimizing overall cost expenditure, minimizing the number of vehicles in the fleet, maintaining successful deployments, and managing reachable distance coverage on single round trips under resource constraints [2]. The equilibrium between resource allocation and deployment coverage in scheduling systems, while respecting routing constraints such as capacity limits and time windows, would directly lead to cost allocation reciprocity. Selective deployment routes and the diffusion of critical distribution node conjectures are enhanced when multi-objective combinatorial optimization techniques, clustering, and heuristic algorithms are combined, thereby reducing unnecessary expenditures [2]. This trait is expressive on the conjecture of nominal segregation of relevant routing constraints for maximizing the efficacy of the intended outcome, whether it is to cater towards fulfilling multitude of objectives or serving adjacent niche scheduling purposes only.

i. Multifaceted Cost Consideration: Cost reciprocity includes all expenses associated with logistics and transportation, while route optimization techniques only reflect costs precisely. In order to increase the distribution network's overall efficiency, routing heuristics take into account both direct and indirect costs when allocating resources [12]. These heuristics offer a more comprehensive approach to cost management by taking into account variables like fuel usage, vehicle maintenance, driver reimbursement, and even the opportunity cost of unanticipated delays [5], [21]. Organizations are able to achieve more sustainable and economical operations by balancing the short-term costs of routing decisions with the long-term financial consequences. Routing heuristics can also dynamically adapt to real-world conditions by taking into consideration variables like traffic patterns, delivery windows, and vehicle capacity, which improves supply chain flexibility and responsiveness[15], [21].

ii. Trade-offs and Optimization Objectives: To choose the most economical and practical routes for logistics and transportation, route optimization algorithms take costs and goals into account [3], [22]. In order to manage these compromises, cost reciprocity takes into account a number of cost parameters, including fuel usage, vehicle maintenance, delivery deadlines, and customer fulfillment. This procedure makes sure that operational resilience, quality of service, and environmental impact are all maintained without sacrificing cost minimization [7]. This improves the efficacy and sustainability of an organization's distribution networks by enabling it to strike the ideal balance between short-term financial savings and long-term strategic goals.

iii. Integration of Real-Time Data: For cost reciprocity systems to continuously modify cost parameters and take into account factors like energy prices, traffic, and consumer demand, real-time data streams are necessary [23], [24]. Through the use of these feed data, the system is able to optimize routing decisions by monitoring and reacting to changing conditions. Route cost-effectiveness may be impacted by real-time data on fuel costs and traffic patterns [22], [25]. The system can choose effective routes by dynamically recalibrating calculations by incorporating real-time data. Delivery priorities, scheduling adjustments, and resource allocation are all made possible by the system's real-time insights into consumer demand. Quick adaptability boosts supply chain responsiveness, boosts consumer satisfaction, and optimizes routes more precisely and efficiently.

iv. Customization and Flexibility: In a context of dynamic logistics where factors like as fuel prices, delivery windows, and traffic conditions can change quickly, route optimization systems are critical. In order to satisfy a variety of operational demands, they must be adaptable, enabling users to specify precise objectives and modify routes instantly [2]. By reliably achieving delivery expectations, this adaptability improves both operational efficiency and customer satisfaction. Optimizing strategies can be continuously improved upon over time with the use of advanced algorithms and machine learning approaches, increasing their effectiveness. These systems can customize their optimization procedures to satisfy various operational demands and guarantee that the distribution network stays flexible and responsive by letting users enter specified objectives [9], [26].

v. Evaluation of Total Cost of Ownership (TCO): Route optimization with cost interoperability takes into account the overall TCO of the transportation infrastructure, allowing for dependable resource allocation, fleet management, and planning [2], [27]. This comprehensive method ensures that decisions are based on long-term financial repercussions by evaluating expenditures such as infrastructure wear and tear, labor charges, fuel consumption, vehicle acquisition, maintenance, and labor expenses [20]. By using a comprehensive strategy, logistics strategies are enhanced, enabling firms to create more precise and long-lasting plans. Cost reciprocity makes it possible for routing heuristics to be flexible and adjust to changing circumstances, balancing direct and indirect costs without sacrificing service quality. This dual strategy makes sure that overall costs are taken into account when making strategic plans, but also keeps daily operations flexible and adaptable to changing conditions.

vi. Sustainability and Environmental Impact: Cost reciprocity is a mechanism that integrates environmental concerns into logistics and transportation systems in order to support sustainability and regulatory compliance. This leads to a notable decrease in carbon emissions as it promotes the use of fuel-efficient cars, delivery routes that are optimized, and shorter idle times [8], [28]. Companies may avert fines, improve their brand, and satisfy the increasing need for more environmentally friendly supply chains by coordinating their operating procedures with environmental rules. Cost reciprocity promotes the use of cutting-edge technology and renewable energy sources, such as electric cars and alternative fuels, which improve energy efficiency and lessen reliance on fossil fuels. Through long-term sustainability and compliance with changing regulatory norms, this strategy aids businesses in striking a balance between environmental stewardship and economic performance [11], [29].

3 IMPACT OF COST ALLOCATION RECIPROCITY ON ROUTING HEURISTICS BASED ON METAHEURISTIC APPROACHES IN COMPUTATIONAL INTELLIGENCE APPLICATIONS

Cost reciprocity is a planning metric that enhances resource allocation in routing heuristics by considering various cost factors, balancing multiple objectives, adapting to dynamic cost conditions, offering customization options, optimizing the total cost of ownership (TCO), and addressing environmental considerations. This aspect requires considering trade-offs between meeting demands and optimizing deployment allocation strategy [2], [15]. Practical optimization algorithms for intricate routing issues are observed in computational intelligence applications such as ant colony optimization, particle swarm optimization, simulated annealing, and genetic algorithms [18], [19], [30], [31]. These algorithms mimic natural processes like evolution, thermodynamics, and social behavior, identifying promising solutions and converging towards optimal solutions [22], [32]. By incorporating cost reciprocity into routing strategies, organizations can optimize resource allocation, reduce costs, and improve efficiency and sustainability in transportation and logistics operations [7], [11], [15]. Several feasible routing algorithms have become extensively used in tandem with cost reciprocity.

3.1 Benefits of Cost-Aware Reciprocity Scheduling Measures with Maximizing Route Optimality

Computational intelligence has led to the development of adaptive and self-learning routing optimization systems. These systems can continually improve and adapt to changing circumstances by analyzing historical routing data, recognizing patterns, and gaining information from previous interactions [2], [21], [33]. Advanced cost-aware routing arrangements tasks can be adapted using predictive techniques like neural networks and reinforcement learning. Genetic algorithms excel in complex problem-solving, making them excellent in cost interoperability and fluid real-time optimization [34], [35]. Ant colony optimization addresses routing problems with cost variables by using trailing pheromones and heuristic data to generate near-optimal solutions [19]. Particle swarm optimization, influenced by bird migration or fish schooling, distributes resources effectively by employing personal and global optimal solutions [36]. Probabilistic optimization, influenced by metallurgical cooling, explores the solution space while preventing local maxima [37]. Simulated annealing is an excellent example of probabilistic optimization, beneficial in routing optimization with cost reciprocity and determining optimal solutions under different conditions [38]. Tabu search efficiently redirects the search process toward high-quality routing alternatives while minimizing transportation costs [39], [40].

Real-time decision support is provided via route optimization in computational intelligence applications, which enables systems to react quickly to unforeseen circumstances like traffic congestion, crashes, or temperature fluctuations [10], [41], [42]. Cost-effective and efficient pathways can be found by utilizing computational intelligence methods such as genetic algorithms, simulated annealing, and neural networks, which can adjust to varying conditions. A vast range of route requirements and impediments can be regulated by real-time decision support systems, offering flexible solutions. These approaches are scalable and effective in resolving complex routing optimization issues with a range of limitations and factors. Real-time data transfer, continuous vehicle movement tracking, and prompt route performance evaluation are made possible by their integration with existing information systems [2], [43]. These systems facilitate quick and effective decision-making for workforces and organizations by analyzing the effects of various routing strategies, balancing costs and service quality, and applying data-driven decision-making to streamline processes and increase productivity.

The goal of multi-objective optimization (MOO), a modelling approach applied in complex route optimization, is to resolve problems with several conflicting objectives [44]. MOO algorithms are capable of simultaneously optimizing several cost elements and goals, enacting trade-offs between them. MOO algorithms that are frequently used are Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and Strong Pareto Evolutionary Algorithm II (SPEA-II). With the use of computational intelligence approaches, organizations can simultaneously optimize various goals, such as cutting down on travel time, saving fuel, and improving customer satisfaction [7], [9]. These techniques provide decision-makers a thorough grasp of routing decisions by analyzing the trade-offs between different goals and locating Pareto-optimal solutions [44], [45]. Finding routes that minimize travel time and distance, maximize vehicle utilization and minimize delays, and balance cost and quality are all possible with the use of multi-objective optimization. By examining correlations between response time and coverage targets, this can also be used for emergency response routing [24], [46]. To ensure a fair trade-off between cost-effectiveness and service excellence, MOO can offer the best scheduling options while taking vehicle utilization and customer service quality under consideration [47].

In scheduling systems, hybrid algorithms streamline cost interoperability and solution quality through the integration of numerous optimization techniques. These algorithms can be modified to adapt to various cost scenarios and improve route optimization by incorporating genetic algorithms, search-based methodologies, or machine learning techniques [31], [42]. Multidimensional scheduling systems have evolved substantially as a result of hybridization between computational intelligence and systems. Hybridization algorithms work around restrictions by fusing different optimization techniques and methods. One way to specialize in locating exceptional solutions in complicated solution spaces is to integrate metaheuristic algorithms that fuse local search heuristics and evolutionary algorithms [26]. Superior solutions are the result of this intrinsic methodical examination and exploitation of the solution space. By selecting and combining the right components based on size, complexity, and structure, hybridization algorithms can adjust to the particular characteristics of multidimensional scheduling system optimization problems. These can include repair techniques, penalty functions, and constraint fulfillment, among other constraint-handling tactics from different paradigms [35], [40], [48]. In order to provide answers that satisfy real-world requirements and preferences, hybridization algorithms can also be tailored to leverage domain-specific data or problem structures.

3.2 Promoting Cost Reciprocity in Scheduling Models and its Implementation Strategy

Encouraging cost reciprocity in scheduling models has several substantial benefits, including improved efficiency, efficacy, and adaptability of scheduling optimization methods. Cost reciprocity in scheduling models may promote efficiency through bolstering balanced resource allocation as well as minimizing wasteful schedule redundancies or omissions. This guarantees that resources are utilized adequately, leading to higher efficiency and reduced expenditures. Furthermore, cost reciprocity promotes task coordination and synchronization, paving the way for smoother workflows and elevating overall performance. The following discussion relays several key highlights for the approaches to implement the theoretical formulation of cost reciprocity.

Comprehensive Cost Consideration: When scheduling activities, cost reciprocity takes into account all relevant costs as part of a cost management approach. Energy use, maintenance, and storage fees are examples of indirect costs, while workers, equipment, and materials are examples of direct costs. In addition to improving financial performance, this strategy optimizes operating costs.

i. Optimized Resource Allocation: Cost reciprocity-aware scheduling algorithms enable businesses to allocate resources most efficiently according to fiscally prudent standards. By improving the alignment between decisions about the distribution of resources and cost-cutting objectives, these models can help operational planning and deployment strategies reduce scheduling costs and increase operational efficiency, which in turn boosts output and profitability [42].

ii. Adaptability to Changing Cost Conditions: Scheduling models that are capable of cost interoperability can respond pre-emptively to variations in cost factors including labour, material, or energy costs. Scheduling models ensure robustness and cost-effectiveness in the face of fluctuating demand, regulations, or operational constraints by integrating real-time data feeds and flexible cost adjustment algorithms for maximizing decisions [22], [28].

iii. Risk Mitigation and Scenario Analysis: Organizations can reduce risks and examine situations by using scheduling models with cost reciprocity features, which assess the implications of cost inconsistency on scheduling results. These cost reciprocity measures contribute to identifying risk variables influencing cost performance and evaluating an organization's decision-making vulnerability to changes in costs [2]. The robustness and durability of scheduling plans are improved by proactively identifying and managing cost variances utilizing analysis of scenarios and susceptibility testing.

iv. Enhanced Decision Support and Optimization: Cost-conscious scheduling models offer insights and suggestions for optimization that take costs into account for decision-makers [2]. To evaluate compromises and produce data-driven decisions, these scheduling model annotation employs cost reciprocity functions. With the use of novel simulation techniques and optimization algorithms, these models can produce approximately optimal scheduling solutions, decreasing overall operating expenses whilst meeting performance requirements and limitations [7].

v. Improved Operational Efficiency and Competitiveness: In scheduling models, cost reciprocity can improve waste reduction, promote profitability, and improve operational efficiency. These techniques allow organizations to meet customer demands, remain earning money, and supply products and services more effectively. Through financial savings, cost-aware scheduling models can support sustained expansion, revenues, and economic subjugation [49], [50].

3.3 Systematic Evaluation of Routing Optimization through Distinct Strategies: Evaluation Metric and Validation Approaches

The choice of routing method when applying cost reciprocity for routing heuristics is determined by the nature of the cost variables involved, the particulars of the problem, the processing prerequisites, and the intended degree of optimization performance. The most effective approach for a certain routing optimization problem can be found through testing and benchmarking several methods. Increasing the effectiveness, precision, and flexibility of the optimization process is the goal of many processes involved in optimizing the way cost reciprocity is currently implemented in scheduling models to minimize operational expenditure.

3.3.1 Evaluation Strategy

Cost optimization approaches' performance is validated using assessment techniques such as benchmarking against baselines, simulation and modeling, cross-validation, sensitivity analysis, performance metrics, and real-world case studies. These methodologies evaluate the effectiveness, efficiency, and resilience of optimization methods in meeting cost-cutting goals and directing decision-making processes. There have been observed and prominently mentioned strategies for establishing credible evaluation metrics for interpolation of cost reciprocity in its facilitation of devising an effective and proficient scheduling system from several relative work mention, among these include:

Table 4: Several observable evaluation criteria implemented for relevant scheduling models

Evaluation Approach	Implementation Context
Enhanced Cost Modeling	A For the scheduling model to accurately represent all relevant components, such as labour, fuel, machinery, transport, stock, and any other operating costs, a comprehensive cost study is required [10].
Dynamic Cost Adjustment	Extensive cost analysis is essential for guaranteeing that the scheduling model's cost model adequately accounts for all important cost components, such as workforce, the inventory, energy, equipment, and transportation [5].
Multi-Objective Optimization	Workload balancing, resource utilization, and shorter delivery times should all be taken into account in the scheduling model [10]. Multi-objective optimization techniques should be used to make long-term scheduling decisions, and the cost model ought to be modified to incorporate these key components.
Flexible Constraint Handling	Amendments to the scheduling model can be implemented by adding cost-reciprocity-related constraints, such as production time, resources, and regulations, and adjusting these restrictions dynamically to take operational changes and minimize costs into account [51].

Advanced Optimization Algorithms	For scheduling problems requiring cost interoperability, research studies can improvise on investigating the application of sophisticated heuristics and optimization techniques [13]. Complex scheduling models can be solved using methods such as genetic algorithms, simulated annealing, ant colony optimization, and metaheuristics [16]. Machine learning techniques can be applied to find trends, gain knowledge from past data, and generate precise predictions and recommendations.
Real-Time Decision Support	To provide operational stakeholders with prompt insights and recommendations, a real-time decision-support tool should be built in tandem with the scheduling model. This tool should include interactive scenario exploration, real-time spending analysis, and parameter modifications [52].
Continuous Monitoring and Optimization	Implement a continuous monitoring mechanism for the scheduling model to ensure its sustainability [12], [53], gather performance data, detect irregularities, and update dynamically, while also utilizing cost reciprocity data for cost reduction.

3.3.2 Assessment Methods for Determining the Degree of Routing Optimality in Various Structures

Routing heuristic cost optimization strategies are validated through the use of assessment metrics to gauge the robustness, efficiency, and efficacy of the methods in reaching cost reduction objectives. This impacts the expected routing strategy's result by pointing out regions that require more work, assisting in the refinement of algorithms, influencing decision-making processes, and encouraging the use of economical optimization techniques. Among the standard norm for measuring the competency of cost optimization approaches observed through the recent years includes devising the balance between cost reduction and system proficiencies [21], [35], adaptive scaling of the routing variables to the nearest acclimated simulation environment [15], [30], and practical implementation of the resource maximization measures in terms of formulating the ideal decision making process in determining the modelling constraint adhering the fundamental objectives [31], [54]. This following section summarizes among some of the more prominent observable postulation on the suggested solution strategies for evaluating the performance of tradeoffs between maximizing cost and minimizing resource allocation during the designation of routing optimality representing a particular routing network execution.

i. Benchmarking Against Baselines: By using benchmarking, one can assess how cost optimization techniques stack up against prevailing standards consisting of conventional routing schemes and rudimentary heuristics. Regarding cost reductions and other indicators, this serves in evaluating how well various strategies perform in comparison [14], [42].

ii. Simulation and Modeling: Through the construction of simulated datasets and the modeling of operational scenarios such as resource restrictions, demand variations, and environmental concerns, simulations analyze the robustness and scalability of optimization procedures in order to determine the efficiency of cost-optimization techniques [42], [49].

iii. Cross-Validation and Holdout Testing: Using cross-validation approaches, optimization processes' generalization performance is evaluated over a variety of datasets or issue scenarios [18], [55]. To evaluate an algorithm's performance on initially unexplored information, a dataset representing the tested simulation environment could be split into training and testing subsets utilizing the cross-validation procedure. To assess the approaches' efficacy impartially on data that has not been discovered, holdout testing comprises removing a portion of the data [56], [57]. This enables one to guarantee that the optimization strategies appropriately handle new issue cases and information distributions.

iv. Performance Metrics: Performance indicators like cost savings, route productivity, service level agreement compliance, and environmental effects are crucial for cost optimization initiatives [31], [35], reducing carbon emissions, minimizing trip distance, meeting service level agreements, and reducing operational expenditures.

v. Sensitivity Analysis: A sensitivity analysis takes into account variables such as labor expenses, energy costs, and demand trends, and it identifies critical performance and decision-making aspects [28]. This assesses how robust optimization strategies are against changes in input parameters or cost estimations.

vi. Real-World Case Studies: Assess the efficacy of cost-cutting techniques in real-world challenges by conducting operational implementations or practical case studies with industry partners or stakeholders [27], [42].

4 ENHANCING ROUTE OPTIMIZATION WITH HYBRID LOCAL SEARCH FEATURES

Through the integration of several optimization procedures, the continuous improvisation of existing method's proficiencies for generating best solution that takes into consideration constraints on resource wastage and segregating the best scheduling strategy for conventional distribution network using hybridization algorithm have seen fruitful in terms of improving performance indicators like robustness, convergence speed, and solution quality. Better scheduling systems are achieved through enhancing cost reciprocity, reducing operational expenses, and streamlining resource allocation in scheduling scenarios [15], [26], [58]. With respect to scheduling optimization problems, these recommended hybrid approaches outperform individual optimization methods by refraining from their limitations and improvise on existing mechanism conducts [59]. Putting these techniques into practice results in better scheduling performance, reduced operating costs, and more efficient resource allocation. Taking into account simulated performance or planned output, heuristic and metaheuristic algorithms have undergone myriads of modification to handle specialized applications of cost optimization in preemptive scheduling models.

4.1 Metaheuristic/Heuristic Approach

Using metaheuristic frameworks in existing scheduling systems as a focal point, this subsection addresses prominent routing heuristics and hybridization procedures utilizing computational intelligence that have been addressed in recent works. While preserving compatibility for intricate routing issues, researchers seek to consistently improve the foundational scheduling systems for legacy systems all in the sense of promoting heterogeneity, inclusiveness of routing solution probabilities in formulating the most acceptable solution strategy, together with the importance of highlighting the relevancy of inculcating better aggregation of cost reciprocity for scheduling models.

4.1.1 Genetic Algorithms (GA)

Genetic algorithms are the most widely applied population-based techniques that mimic natural selection and are frequently used in multi-objective optimization [31], [35], [58]. Convergence and solution quality are enhanced by integrating local search operators such as 2-opt and hill climbing [18], [39] [60]. Performance for scheduling optimization problems can be enhanced by merging a local search strategy with the population-based structure of genetic algorithms [19], [34]. The use of metaheuristic techniques includes Tabu search [40], Variable Neighborhood Search [3], and simulated annealing [58] have seen their applicability to be imposed with the characteristics for genetic computation in terms of mutation strategy and crossover qualities for garnering acceptable solution quality within the domain range. These algorithm characteristics provide plausible alternatives for scheduling optimization issues, particularly in addressing irregularities such as premature convergence and stagnation [30], [61], [62].

An observable instance of the hybrid strategy incorporated using the baseline genetic algorithm with other relative counterparts is the assimilation of local search features catered towards genetic strategy's mutation phase for the pretense of enhancing cost optimization in routing scheduling [31], [58]. Initial populations of conceivable solutions are generated by genetic algorithms, and variations that result in inferior solutions are regulated using iterated strategies such as simulated annealing [32]. This leads to better cost optimization by striking a balance between local exploitation and global exploration. In the supply chain sector, an ACO hybridization study have being conducted with the objective of cutting expenditures and accelerating package delivery [24]. The correlation between trip region parameters and CO2 emissions is evaluated using the metaheuristic link prediction approach [24]. To circumvent returning back to previously examined solutions, another technique that integrated genetic algorithms and Tabu search is designated as hybridization of genetic algorithms with Tabu search [40]. In order to enhance distribution networks between urban depots and consumers, a study that combined evolutionary algorithms with Tabu hybridization also included route relocation optimization, initial solution search, and tabu search perturbation [40]. When comparing the suggested method to the proprietary genetic algorithm solution, there are significant amounts of enhancements in route segregation.

Genetic algorithms and Variable Neighborhood Search (VNS) is also seen possible to be utilized as a metric to explore diverse neighborhoods in the solution space [63]. This hybridization strategy provides an initial set of potential solutions that develop over time. Several proposed improvisation mechanics proposed with this hybridization strategy includes concurrent application of various neighborhood structures, selected individuals engage in variable neighborhood search, aside from promoting cost optimization in routing scheduling [39], [64]. This versatility and robustness in achieving cost reciprocity demonstrate the versatility of genetic algorithms. The Pareto front idea and multi-objective evolutionary algorithm have also been devised to tackle complex routing problems in multimode urban transportation networks [30]. This proposed technique was evaluated with four transport modalities and three minimization objectives on a synthetic network with 150 vertices and 2600 edges. The collected results demonstrate the algorithm's ability to solve the problem quickly and outperform other advanced approaches in practice.

4.1.2 Localized Search Algorithms

The optimization of scheduling systems can be enhanced by combining local search method heuristics with exploration and exploitation features such as simulated annealing and Tabu searches. Simulated annealing is a probabilistic optimization strategy that gradually reduces parameter dimensionality to avoid local maxima [15], [55], [63], while Tabu search is a metaheuristic method that periodically traverses the search space while avoiding previously visited solutions [39], [40], [65]. These local search algorithms operate in a manner in which they scour through local dimensionality, concurrently generating best competing solution before being converged through the global neighborhood clusters' prime solutions hence in turn further promoting heterogeneity and the cream of the crop quality solutions. Combining these approaches allows for a wide range of solutions while eliminating stagnation in local optima, improving the quality of solutions and the speed of convergence for scheduling optimization [58], [66]. Among the more prominent variants of local search algorithms commonly initiated during local search exploration being explored extensively in this paper includes Tabu search, genetic search, particle swarm, and memetic algorithm. Simulated annealing, inspired by the cooling process in metallurgy, generates global optima in complex search spaces and is particularly beneficial when the objective function is non-convex and consists of multiple local maxima [32]. Tabu search iteratively advances from one solution to another while monitoring "tabu" or forbidden movements [67]. Both simulated annealing and Tabu search are part of the metaheuristic family, providing general-purpose optimization frameworks for various problems without requiring problem-specific information [58], [67]. Several works had interjected on the actuality of proposing various incorporations for certain local search heuristics for the extent of maximizing cost allocation and minimizing operating wastage [2], [31], [68]. Hybridizing local search strategies can also promote solution heterogeneity and cost interoperability, enabling strategic deployment planning.

4.1.3 Particle Swarm Optimization (PSO)

Particle Swarm Optimization has shown significant contributions to hybridization in cost optimality for managing niche routing optimization issues [19], [42], [69]. This algorithm mechanics incorporates voracity exploration traits, making it an inclusion criterion for other swarm-based optimization strategies like Ant Colony Optimization [37], [70], [71]. The fundamental underworking for PSO, inspired by communal actions of fish schools and bird flocks, visualizes a population of possible solutions as particles traveling around the search space. Each particle modifies its position based on both the global best-known position and its individual best-known position [72]. This movement is guided by exploration in new areas of the solution space and exploitation in refining known solutions [73]. PSO provides a more general framework for solving optimization problems across various domains and is considered a metaheuristic algorithm within the field of evolutionary computation as PSO can efficiently search for near-optimal solutions, making it suitable for a wide range of optimization problems [31].

In terms of its applicability for promoting heterogeneity and cost reciprocity values representing the entirety of distribution network, PSO implementation is incorporated within the dimensionality of global solution search space exploration where PSO performs similarly with Tabu search however varies in terms of deciding on the inclusion criterion for inter local search space exploitations [74]. PSO is observed to be a method used to produce a baseline population of particle solutions for potential route configurations [18], [75]. Via the intrinsic segregation of inclusion criterion in anticipating the estimated stopping criterion should the solution had been deemed to achieve its peak, particles are directed across the search space through experimentation with multiple setups to minimize costs as a whole. After each cycle, selected particles undergo a iterated strategies such as 2-opt local search operation, improving the route by swapping edges [75]. The most effective solutions are kept and used to update particle locations and velocities in subsequent iterations [76]. Simulated annealing, a stochastic local search technique [73], and hybrid PSO are systems that integrate PSO with annealing to improve routing solutions and minimize costs. PSO generates an initial population of particle solutions, while simulated annealing controls the probability of accepting moves that lead to worse solutions [69]. This is shown to assist in escaping local optima while still converging to better solutions over time. Another instance observable with recent work trend for incorporating the swarm properties of PSO with other intelligent optimization algorithms is via the inclusion of PSO with Tabu search operating as a hybrid of PSO and the local search approach, offering an initial population of particle solutions and coordinates particle movement throughout the search space [74]. This proposed adaptable local search capacity have shown promising accomplishment of to be compatible to amplify the enhancement of local search exploration by choosing suitable locations, expediting the algorithm's search for optimal routing options while at the same time reducing costs [39], [40], [65]. An instance of the successful implementation of this approach is done by a study proposing a single-vehicle routing strategy for simultaneous loading and unloading of goods between depots and quarantine facilities, incorporating dynamic programming and particle swarm optimization for resilient healthcare supply chain [5]. This concluded study provides recommendations on the best operational sequences in terms of cost and computation times, as well as improving healthcare supply chain reaction capacities in times of emergency.

4.1.4 Simulated Annealing (SA)

Simulated annealing is a stochastic metaheuristic technique for exploring and locating near-optimal solutions to complex optimization problems. Natural selection and genetics constitute the basis for genetic computation mechanisms employed by simulated annealing that included selection, crossover, and mutation [35], [77] with the expectation to improvise the evolution of potential solutions. Simulated annealing [38], [58] and genetic algorithms [34], [77] are two potent optimization methods with distinct mechanisms for exploration and exploitation that have been popularly regulated as alternatives in optimization utilization. Their relative advantage can be taken use of by combining them into a hybrid algorithm. For instance, the hybrid technique attempted to be incorporated via prior works involve the use of genetic algorithms for global solution space search and simulated annealing for fine-tuning solutions and escaping local optima [58]. By merging these two techniques, the anticipated hybrid approach is capable of improving scheduling optimization problem performance with regard to of convergence time and solution quality at an improved rate as compared with the conventional versions of the similar algorithms operating as standalone units. By eliminating local optima and providing high-quality routes, hybrid algorithms that combine the finest characteristics of both of these algorithms can be leveraged to optimize local searches on individuals [35], [58].

An example stemmed from the mechanics of simulated annealing being leveraged in other intelligent algorithm is adapted by the Clone Adaptive Ant Colony Optimization (CAACO) done in a study as a suboptimal solution finder for the last mile assignment problem (LMAP) in the Chinese delivery industry [58]. In comparison to previous optimization methods, this proposed CAACO exhibits faster convergence rates and lower economic costs thanks to its unique clone operator, adaptive operator, and enhanced cost fitness function. Moreover, this study indicated that transportation costs are reduced by using mixed-integer programming approach that incorporates simulated annealing and evolutionary methods [18]. This suggested solution model employs a neighbor search technique to prohibit local optimum solutions, hence accommodating time-varying velocity, loads, and delay. By extending the path distribution problem and widening the vehicle-routing problem, this model have provided alternative approach for time-varying networks.

4.1.5 Tabu Search (TS)

A hybrid algorithm for cost reciprocity that involves synergy between modelling constraints and routing environment executions combine metaheuristic techniques like Tabu Search [33], [40] and neighborhood-based searching heuristics like Variable Neighborhood Search [64], [78] in order to maximize the benefits and potential of generating ideal solutions. For instance, Tabu Search iteratively improves solutions, avoiding revisiting previously examined regions [65]. This approach maintains a tabu list to prevent revisiting recently observed solutions, encouraging variety in the search process [40]. Variable Neighborhood Search (VNS) is another metaheuristic algorithm specialized for local search exploration similar with Tabu search conceptualizations that iteratively adapt predefined neighborhood layouts to a solution if no improvement is found within the first one [39], and had seen several iterations with Tabu search for scheduling purposes [39], [64]. VNS dynamically modifies the intensity of neighborhood exploration, promoting a more diverse and intense search process.

The integration of TS and VNS hybridization have shown prowess to be compatible in enhancing solution space exploration and exploitation [39], resulting in higher solution quality and efficiency when searching for optimal or near-optimal routing solutions. Implementations involving the TS and VNS hybridization initiates from a random or heuristic solution followed by a Tabu search to improve the current result [39], where the algorithm then shifts to Variable Neighborhood Search to explore alternative neighborhoods and accelerate the search for better solutions. This hybridization approach encourages heterogeneity and amplification in the search process [39], [64]. An example for this incorporated implementation can be seen In the Vehicle Routing Problem with Multiple Trips and Simultaneous Delivery-Pickup (VRPMTSDP), a Bandung-based drinking water distribution firm developed a variant of the Tabu Search algorithm, that had managed to reduce delivery costs by 11.22% compared to the company's current route [16]. This study also suggested the necessity of sensitivity analyses to help users understand how different Tabu Search operators affect VRPMTSDP delivery costs.

4.1.6 Memetic Algorithms (MA)

Memetic algorithms, also known as a hybrid optimization approach, combine local search techniques and genetic algorithm elements for resolving combinatorial optimization. The functionalities operate by using local structures in the solution space while retaining global exploration capabilities of genetic algorithms. Most memetic algorithms used in recent scientific literatures adhere to PSO or GA frameworks, with the Simplified Swarm Optimization framework being less common [22]. Memetic algorithms is observed to be viable in a hybrid strategy, combining genetic algorithms and Tabu search, to build an initial pool of possible solutions and segregate quality solutions [48], [79]. Each solution expressed from this method conjecture undergoes a local search procedure to optimize iteratively, matching global exploration and local exploitation, resulting in high-quality routing solutions than the average intelligent estimations.

From the sense of hybridization implementations with other associating algorithms in promoting better values of cost interoperability representing the entire logistics network, memetic algorithms can be used to evolve a population of routes while regulating the probability of adopting shifts that might result in inferior solutions [80], [81]. An instance of the proposed incorporation using memetic algorithm for advanced routing optimization is seen plausible using iterated local search mechanisms for extended solution space exploration [82], among the methods being circulation includes using simulated annealing and variable neighborhood search. In keeping with diversity and exploration, hybridization between genetic components in memetic algorithm with its counterparts blend the algorithm's ability to identify nearly-optimal routing solutions with neighboring features from other cluster-based population algorithms. In combination with the memetic algorithm, variable neighborhood search can generate an assortment of routes by iteratively implementing multiple neighborhood structures for exploring and making adoption of different regions inside the solution space [83]. A study on transportation planning for municipalities suggested lowering distribution costs for the Heterogeneous Fleet Vehicle Routing Problem (HFPRP) Time-Varying Continuous Speed Function by employing a mathematical model and the Simplified Swarm Optimization heuristic [22], highlighting the importance of annotating iterative search exploration properties of memetic algorithm with its complementary representatives. The utilization of memetic algorithms in local search heuristics enhances the routing heuristic structure's ability to navigate intricate solution landscapes and steer clear of local optima [28], hence optimizing its potential to find a multitude of excellent routing solutions in optimization problems. Better solution quality and faster convergence times could be achieved by using this hybrid method to schedule optimization problems.

5 CONCLUSION

Cost reciprocity in scheduling models offers numerous benefits, including cost consideration, optimized resource allocation, adaptability to changing costs, risk mitigation, enhanced decision support, and improved operational efficiency. Through the integration of cost-conscious scheduling tactics into data-driven and algorithmic strategies, organizations can harmonize scheduling choices with cost reduction objectives, resulting in enhanced financial outcomes and competitiveness. By including cost reciprocity criteria into computation intelligence techniques, improved forecasting models can be developed, facilitating proactive schedule optimization as trends emerge. Real-time schedule modifications are possible through the use of techniques such as time-series forecasting, regression analysis, and reinforcement learning, which analyze historical cost data to find trends. Prospective studies could include investigating cost reciprocity components in scheduling systems using complimentary techniques in computational intelligence.

ACKNOWLEDGEMENTS

The author would like to thank Universiti Malaysia Perlis and Universiti Pendidikan Sultan Idris for supporting this research and publication. Furthermore, the author appreciates the reviewers for their constructive feedback regarding the article.

REFERENCES

[1] F. Morsidi, S. L. Wang, H. Budiman, and T. F. Ng, "Overview Discourse on Inherent Distinction of Multiobjective Optimization in Routing Heuristics for Multi-Depot Vehicle Instances," *Artif. Intell. Appl.*, vol. 2, no. 3, pp. 179–187, May 2023.

[2] F. Morsidi, "Using Routing Heuristics to Improve Cost Interoperability: Strategy, Modelling Annotations, and Dynamism," *Int. J. Glob. Optim. Its Appl.*, vol. 2, no. 2, pp. 84–100, Jun. 2023.

[3] J. F. Castaneda Londono, R. A. G. Rendon, and E. M. T. Ocampo, "Iterated local search multi-objective methodology for the green vehicle routing problem considering workload equity with a private fleet and a common carrier," *Int. J. Ind. Eng. Comput.*, vol. 12, no. 1, pp. 115–130, 2020.

[4] Y. U. Kasanah, N. N. Qisthani, and A. Munang, "Solving the Capacitated Vehicle Routing Problem with Heterogeneous Fleet Using Heuristic Algorithm in Poultry Distribution," *J. Ilm. Tek. Ind.*, vol. 21, no. 1, pp. 104–112, 2022.

[5] P. Maheshwari, S. S. Kamble, A. Belhadi, S. Gupta, and S. K. Mangla, "Resilient healthcare network for simultaneous product allocations during supply chain disruptions," *Supply Chain Forum*, vol. 00, no. 00, pp. 1–21, 2023.

[6] M. Gansterer and R. F. Hartl, "Collaborative vehicle routing: A survey," *European Journal of Operational Research*, vol. 268, no. 1. pp. 1–12, 2018.

[7] S. Luo, Y. Wang, J. Tang, X. Guan, and M. Xu, "Two-Echelon Multidepot Logistics Network Design with Resource Sharing," *J. Adv. Transp.*, vol. 2021, 2021.

[8] S. Zhan, P. Wang, S. C. Wong, and S. M. Lo, "Energy-efficient high-speed train rescheduling during a major disruption," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 157, no. December 2021, 2022.

[9] L. Zhang, Z. Liu, L. Yu, K. Fang, B. Yao, and B. Yu, "Routing optimization of shared autonomous electric vehicles under uncertain travel time and uncertain service time," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 157, no. June 2021, p. 102548, 2022.

[10] A. Szmelter-Jarosz, J. Ghahremani-Nahr, and H. Nozari, "A Neutrosophic Fuzzy Optimisation Model for Optimal Sustainable Closed-Loop Supply Chain Network during COVID-19," *J. Risk Financ. Manag.*, vol. 14, no. 11, 2021.

[11] B. Dong, M. Christiansen, K. Fagerholt, and S. Chandra, "Design of a sustainable maritime multi-modal distribution network – Case study from automotive logistics," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 143, no. September, p. 102086, 2020.

[12] S. Elatar, K. Abouelmehdi, and M. E. Riffi, "The vehicle routing problem in the last decade: variants, taxonomy and metaheuristics," *14th Int. Conf. Ambient Syst. Networks Technol.*, vol. 220, pp. 398–404, 2023.

[13] S. Y. Tan and W. C. Yeh, "The vehicle routing problem: State-of-the-art classification and

review," *Appl. Sci.*, vol. 11, no. 21, 2021.

[14] K. Corona-Gutiérrez, S. Nucamendi-Guillén, and E. Lalla-Ruiz, "Vehicle routing with cumulative objectives: A state of the art and analysis," *Comput. Ind. Eng.*, vol. 169, no. February, 2022.

[15] F. Morsidi and I. Y. Panessai, "Overview of the Integral Impact of MDVRP Routing Variables on Routing Heuristics," *Appl. Inf. Technol. Comput. Sci.*, vol. 4(1), no. 1, pp. 1723–1738, 2023.

[16] F. N. Rizkiani, I. Geraudy, and A. Imran, "Solving the Vehicle Routing Problem with Multiple Trips and Simultaneous Delivery-Pickup for Drinking Water Distribution Company," *E3S Web Conf.*, vol. 484, 2024.

[17] M. Karami and V. R. Ghezavati, "A differential evolution algorithm to solve new green VRP model by optimizing fuel consumption considering traffic limitations for collection of expired products," vol. 11, no. 2, pp. 251–269, 2018.

[18] C.-M. Chen, S. Lv, J. Ning, and J. M.-T. Wu, "A Genetic Algorithm for the Waitable Time-Varying Multi-Depot Green Vehicle Routing Problem," *Symmetry (Basel).*, vol. 15, no. 1, p. 124, 2023.

[19] J. K. Chowlur Revanna and N. Y. B.Al-Nakash, "Vehicle Routing Problem with Time Window Constrain using KMeans Clustering to Obtain the Closest Customer," *Glob. J. Comput. Sci. Technol.*, vol. 22, no. April, pp. 49–64, 2022.

[20] A. Grauers, S. Borén, and O. Enerbäck, "Total cost of ownership model and significant cost parameters for the design of electric bus systems," *Energies*, vol. 13, no. 12, 2020.

[21] F. Morsidi and H. Budiman, "Influence of Shortest Route Approximation on Relegating Urban Area's Transportation Network Priorities," *Asia-Pacific J. Inf. Technol. Multimed.*, vol. 12, no. 02, pp. 240–257, Dec. 2023.

[22] W. C. Yeh and S. Y. Tan, "Simplified swarm optimization for the heterogeneous fleet vehicle routing problem with time-varying continuous speed function," *Electron.*, vol. 10, no. 15, 2021.

[23] J. Zhao, Y. Guo, and X. Duan, "Dynamic Path Planning of Emergency Vehicles Based on Travel Time Prediction," *J. Adv. Transp.*, vol. 2017, 2017.

[24] J. K. C. Revanna and N. Y. B. Al-Nakash, "Metaheuristic link prediction (MLP) using AI based ACO-GA optimization model for solving vehicle routing problem," *Int. J. Inf. Technol.*, vol. 15, no. 7, pp. 3425–3439, 2023.

[25] J. Pinto, A. Quadros, D. Rathod, and J. Mittal, "ROUTE AND COST OPTIMIZATION FOR WAREHOUSES," *Int. Res. J. Eng. Technol.*, vol. 7, no. July, pp. 3316–3320, 2020.

[26] J. Ochelska-Mierzejewska, A. Poniszewska-Marańda, and W. Marańda, "Selected Genetic Algorithms for Vehicle Routing Problem Solving," *Electronics*, vol. 10, no. 24, p. 3147, Dec. 2021.

[27] P. Suryawanshi and P. Dutta, "Optimization models for supply chains under risk, uncertainty, and resilience: A state-of-the-art review and future research directions," *Transp. Res. Part E*

Logist. Transp. Rev., vol. 157, no. December 2021, p. 102553, 2022.

[28] H. Zhang and S. Ni, "Train Scheduling Optimization for an Urban Rail Transit Line: A Simulated-Annealing Algorithm Using a Large Neighborhood Search Metaheuristic," *J. Adv. Transp.*, vol. 2022, 2022.

[29] H. Ouhader and M. El kyal, "Combining Facility Location and Routing Decisions in Sustainable Urban Freight Distribution under Horizontal Collaboration: How Can Shippers Be Benefited?," *Math. Probl. Eng.*, vol. 2017, 2017.

[30] H. Faroqi, "Multiobjective route finding in a multimode transportation network by NSGA-II," *J. Eng. Appl. Sci.*, vol. 71, no. 1, p. 81, Dec. 2024.

[31] Y. Wang, Y. Sun, X. Guan, and Y. Guo, "Two-Echelon Location-Routing Problem with Time Windows and Transportation Resource Sharing," *J. Adv. Transp.*, vol. 2021, 2021.

[32] M. Tanha, M. Hosseini Shirvani, and A. M. Rahmani, "A hybrid meta-heuristic task scheduling algorithm based on genetic and thermodynamic simulated annealing algorithms in cloud computing environments," *Neural Comput. Appl.*, vol. 33, no. 24, pp. 16951–16984, Dec. 2021.

[33] E. Žunić, D. Đonko, and E. Buza, "An Adaptive Data-Driven Approach to Solve Real-World Vehicle Routing Problems in Logistics," *Complexity*, vol. 2020, 2020.

[34] H. Li, K. Xiong, and X. Xie, "Multiobjective Contactless Delivery on Medical Supplies under Open-Loop Distribution," *Math. Probl. Eng.*, vol. 2021, 2021.

[35] Q. Fu, J. Li, and H. Chen, "Resource Scheduling Method for Optimizing the Distribution Path of Fresh Agricultural Products under Low-Carbon Environmental Constraints," *Sci. Program.*, vol. 2022, 2022.

[36] A. Rajasekhar, N. Lynn, S. Das, and P. N. Suganthan, "Computing with the collective intelligence of honey bees – A survey," *Swarm and Evolutionary Computation*, vol. 32. Elsevier, pp. 25–48, 2017.

[37] M. Lin, J. Xi, W. Bai, and J. Wu, "Ant Colony Algorithm for Multi-Objective Optimization of Container-Based Microservice Scheduling in Cloud," *IEEE Access*, vol. 7, pp. 83088–83100, 2019.

[38] P. Chokanat, R. Pitakaso, and K. Sethanan, "Methodology to Solve a Special Case of the Vehicle Routing Problem: A Case Study in the Raw Milk Transportation System," *AgriEngineering*, vol. 1, no. 1, pp. 75–93, 2019.

[39] Y. Christopher, S. Wahyuningsih, and D. Satyananda, "Study of variable neighborhood descent and tabu search algorithm in VRPSDP," *J. Phys. Conf. Ser.*, vol. 1872, no. 1, 2021.

[40] F. Morsidi, "Distribution Path Segmentation Using Route Relocation and Savings Heuristics for Multi-Depot Vehicle Routing," *Malaysian J. Sci. Adv. Technol.*, vol. 3, no. 2, pp. 72–80, May 2023.

[41] L. De Giovanni, N. Gastaldon, M. Losego, and F. Sottovia, "Algorithms for a Vehicle Routing Tool

Supporting Express Freight Delivery in Small Trucking Companies," in *Transportation Research Procedia*, 2018, vol. 30, pp. 197–206.

[42] Y. Wang, L. Ran, X. Guan, and Y. Zou, "Multi-Depot Pickup and Delivery Problem with Resource Sharing," *J. Adv. Transp.*, vol. 2021, 2021.

[43] D. G. N. D. Jayarathna, G. H. J. Lanel, and Z. A. M. S. Juman, "Industrial vehicle routing problem: a case study," *J. Shipp. Trade*, vol. 7, no. 1, 2022.

[44] Y. Zhou and X. Jiao, "Knowledge-Driven Multi-Objective Evolutionary Scheduling Algorithm for Cloud Workflows," *IEEE Access*, vol. 10, pp. 2952–2962, 2022.

[45] A. Verma and S. Kaushal, "A hybrid multi-objective Particle Swarm Optimization for scientific workflow scheduling," *Parallel Comput.*, vol. 62, pp. 1–19, 2017.

[46] C. Cao, C. Li, Q. Yang, and F. Zhang, "Multi-objective optimization model of emergency organization allocation for sustainable disaster supply chain," *Sustain.*, vol. 9, no. 11, 2017.

[47] B. Vahdani, D. Veysmoradi, F. Noori, and F. Mansour, "Two-stage multi-objective location-routing-inventory model for humanitarian logistics network design under uncertainty," *Int. J. Disaster Risk Reduct.*, vol. 27, no. May 2017, pp. 290–306, 2018.

[48] L. Cheng Hao, W. Yan Hong, Q. J. Wei, D. W. Zhao, and S. Rui, "Product Service Scheduling Problem with Service Matching Based on Tabu Search Method," *J. Adv. Transp.*, vol. 2020, 2020.

[49] R. A. Haidri, C. P. Katti, and P. C. Saxena, "Cost-effective deadline-aware stochastic scheduling strategy for workflow applications on virtual machines in cloud computing," *Concurr. Comput. Pract. Exp.*, vol. 31, no. 7, pp. 1–24, 2019.

[50] Z. Ahmad, A. I. Jehangiri, M. A. Ala'anzy, M. Othman, and A. I. Umar, "Fault-Tolerant and Data-Intensive Resource Scheduling and Management for Scientific Applications in Cloud Computing," *Sensors (Basel).*, vol. 21, no. 21, p. 7238, Oct. 2021.

[51] A. Louati, R. Lahyani, A. Aldaej, R. Mellouli, and M. Nusir, "Mixed integer linear programming models to solve a real-life vehicle routing problem with pickup and delivery," *Appl. Sci.*, vol. 11, no. 20, 2021.

[52] S. Sularno, D. P. Mulya, R. Astri, and D. Mulya, "Determination of The Shortest Route Based on BFS Algorithm for Purpose to Disaster Evacuation Shelter," *Sci. J. Informatics*, vol. 8, no. 1, pp. 33–42, 2021.

[53] E. Boumpa *et al.*, "A Review of the Vehicle Routing Problem and the Current Routing Services in Smart Cities," *Analytics*, vol. 2, no. 1, pp. 1–16, 2022.

[54] P. Han, C. Du, J. Chen, and X. Du, "Minimizing Monetary Costs for Deadline Constrained Workflows in Cloud Environments," *IEEE Access*, vol. 8, pp. 25060–25074, 2020.

[55] M. Alweshah *et al.*, "Vehicle routing problems based on Harris Hawks optimization," *J. Big Data*, vol. 9, no. 1, 2022.

[56] G. A. Zeni, M. Menzori, P. S. Martins, and L. A. A. Meira, “VRPBench: A Vehicle Routing Benchmark Tool,” pp. 1–24, 2016.

[57] M. Ahmadlou *et al.*, “Flood susceptibility assessment using integration of adaptive network-based fuzzy inference system (ANFIS) and biogeography-based optimization (BBO) and BAT algorithms (BA),” *Geocarto International*, pp. 1–21, 2018.

[58] Y. Zhang, Y. Liu, C. Li, Y. Liu, and J. Zhou, “The Optimization of Path Planning for Express Delivery Based on Clone Adaptive Ant Colony Optimization,” *J. Adv. Transp.*, vol. 2022, 2022.

[59] H. Qin, X. Su, T. Ren, and Z. Luo, “A review on the electric vehicle routing problems: Variants and algorithms,” *Front. Eng. Manag.*, vol. 8, no. 3, pp. 370–389, 2021.

[60] B. S. Yıldız, “A comparative investigation of eight recent population-based optimisation algorithms for mechanical and structural design problems,” *Int. J. Veh. Des.*, vol. 73, no. 1/2/3, p. 208, 2017.

[61] A. P. Piotrowski, M. J. Napiorkowski, J. J. Napiorkowski, and P. M. Rowinski, “Swarm Intelligence and Evolutionary Algorithms : Performance versus speed,” vol. 384, pp. 34–85, 2017.

[62] Y. Zhou, J. Wang, Y. Zhou, Z. Qiu, Z. Bi, and Y. Cai, “Differential evolution with guiding archive for global numerical optimization,” *Appl. Soft Comput. J.*, vol. 43, pp. 424–440, 2016.

[63] A. Nura *et al.*, “Research on Hybrid Real-Time Picking Routing Optimization Based on Multiple Picking Stations,” *J. Adv. Transp.*, vol. 2022, no. 1, p. 124, 2022.

[64] Y. Tao, C. Lin, and L. Wei, “Metaheuristics for a Large-Scale Vehicle Routing Problem of Same-Day Delivery in E-Commerce Logistics System,” *J. Adv. Transp.*, vol. 2022, 2022.

[65] Y. Shi, L. Lv, F. Hu, and Q. Han, “A heuristic solution method for multi-depot vehicle routing-based waste collection problems,” *Appl. Sci.*, vol. 10, no. 7, 2020.

[66] Y. Kocaoglu, E. Cakmak, B. Kocaoglu, and A. Taskin Gumus, “A Novel Approach for Optimizing the Supply Chain: A Heuristic-Based Hybrid Algorithm,” *Math. Probl. Eng.*, vol. 2020, 2020.

[67] S. Chandana Kaja, “A New Approach for Solving the Disruption in Vehicle Routing Problem During the Delivery: A Comparative Analysis of VRP Meta-Heuristics,” Blekinge Institute of Technology, 2020.

[68] J. Schmidt and S. Irnich, “New neighborhoods and an iterated local search algorithm for the generalized traveling salesman problem,” *EURO J. Comput. Optim.*, vol. 10, 2022.

[69] A. E. Ezugwu, *Nature-inspired metaheuristic techniques for automatic clustering: a survey and performance study*, vol. 2, no. 2. Springer International Publishing, 2020.

[70] G. Calabrò, V. Torrisi, G. Inturri, and M. Ignaccolo, “Improving inbound logistic planning for large-scale real-world routing problems: a novel ant-colony simulation-based optimization,” *Eur. Transp. Res. Rev.*, vol. 12, no. 1, 2020.

[71] H. Xu, P. Pu, F. Duan, and A. S. Hendy, "A Hybrid Ant Colony Optimization for Dynamic Multidepot Vehicle Routing Problem," *Discret. Dyn. Nat. Soc.*, vol. 2018, 2018.

[72] Z. J. Wang *et al.*, "Dynamic Group Learning Distributed Particle Swarm Optimization for Large-Scale Optimization and Its Application in Cloud Workflow Scheduling," *IEEE Trans. Cybern.*, vol. 50, no. 6, pp. 2715–2729, 2020.

[73] H. Alinezhad, S. Yaghubi, S.-M. Hoseini-Motlagh, S. Allahyari, and M. Saghafi Nia, "An Improved Particle Swarm Optimization for a Class of Capacitated Vehicle Routing Problems," 2018.

[74] L. Shen, F. Tao, and S. Wang, "Multi-depot open vehicle routing problem with time windows based on carbon trading," *Int. J. Environ. Res. Public Health*, vol. 15, no. 9, 2018.

[75] S. Nucamendi-Guillén, A. Gómez Padilla, E. Olivares-Benitez, and J. M. Moreno-Vega, "The multi-depot open location routing problem with a heterogeneous fixed fleet," *Expert Syst. Appl.*, vol. 165, no. August 2020, 2021.

[76] V. F. Yu, P. Jodiawan, and A. A. N. P. Redi, "Crowd-shipping problem with time windows, transshipment nodes, and delivery options," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 157, no. December 2021, p. 102545, 2022.

[77] F. Morsidi, "Multi-Depot Dispatch Deployment Analysis on Classifying Preparedness Phase for Flood-Prone Coastal Demography in Sarawak," *J. ICT Educ.*, vol. 9, no. 2, pp. 175–190, Dec. 2022.

[78] H. Derbel, B. Jarboui, and R. Bhiri, "A skewed general variable neighborhood search algorithm with fixed threshold for the heterogeneous fleet vehicle routing problem," *Ann. Oper. Res.*, vol. 272, no. 1–2, pp. 243–272, 2019.

[79] H. Dai, L. Li, R. Mao, X. Liu, and K. Zhou, "A Solution-Based Tabu Search Algorithm for the Resource-Constrained Project Scheduling Problem with Step Deterioration," *Math. Probl. Eng.*, vol. 2023, pp. 1–11, 2023.

[80] M. Huang, F. Wang, and S. Wu, "The Implementation of Multiobjective Flexible Workshop Scheduling Based on Genetic Simulated Annealing-Inspired Clustering Algorithm," *Wirel. Commun. Mob. Comput.*, vol. 2022, 2022.

[81] Z. Liang, M. Liu, P. Zhong, C. Zhang, and X. Wang, "Hybrid Algorithm Based on Genetic Simulated Annealing Algorithm for Complex Multiproduct Scheduling Problem with Zero-Wait Constraint," *Math. Probl. Eng.*, vol. 2021, 2021.

[82] M. El Krari, B. Ahiod, and B. El Benani, "A Memetic Algorithm Based on Breakout Local Search for the Generalized Traveling Salesman Problem," *Appl. Artif. Intell.*, vol. 34, no. 7, pp. 537–549, 2020.

[83] Y. Zhang, Y. Mei, K. Tang, and K. Jiang, "Memetic algorithm with route decomposing for periodic capacitated arc routing problem," *Appl. Soft Comput. J.*, vol. 52, pp. 1130–1142, 2017.