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COMPARATIVE ANALYSIS OF METAHEURISTIC ALGORITHM FOR SOLVING RAIL TRANSPORTATION ROUTING PROBLEMS IN MALAYSIA

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ABSTRACT

Public rail transportation is a vital component of Malaysia's urban mobility system, particularly in the Klang Valley, where millions rely on LRT, MRT, and KTM services daily. However, frequent delays, lengthy interchange routes, and inefficient scheduling reduce service quality and passenger satisfaction. This study proposes a metaheuristic-based route optimization system SmartRail.Co to improve efficiency through multi-criteria optimization considering distance, time, and cost. Using a dynamic visualization and user-interactive interface developed via Streamlit, the system provides real-time optimal route suggestions on uploaded maps. Comparative analysis among different metaheuristic algorithms demonstrates superior adaptability and performance in handling complex rail network data. The proposed approach supports Malaysia's sustainable urban transport goals aligned with SDG 8, 9, 11, and 17, promoting smarter, greener, and more inclusive mobility.

Keywords: Metaheuristic Optimization, Rail Transportation, Routing Problem, SmartRail.Co, Klang Valley, Sustainable Mobility.

1. INTRODUCTION

The introduction should be typed in Times New with font size 10. In this section highlight the importance of topic, making general statements about the topic and presenting an overview on current research on the subject. The simplest way is to replace(copy-paste) the content with your own material. Your introduction should clearly identify the subject area of interest.

Public transportation plays a critical role in ensuring urban mobility, economic productivity, and social inclusion. In Malaysia, particularly within the Klang Valley region, the rail network forms the backbone of the daily commuting system. The integrated operation of Light Rail Transit (LRT), Mass Rapid Transit (MRT), and Keretapi Tanah Melayu (KTM) services carry over 1.18 million passengers per day, connecting residential, educational, and business hubs across the metropolitan area [1]. Despite significant investments in infrastructure and network expansion, recurring challenges persist including congestion at interchange stations, inconsistent scheduling, and inefficient route planning, which lead to prolonged travel times averaging between 25 and 40 minutes for many passengers [1]. These inefficiencies reduce the reliability and attractiveness of public rail services, often resulting in increased dependence on private vehicles. Consequently, the urban carbon footprint grows, contradicting Malaysia's national objective to promote sustainable and low-carbon transport solutions in line with the United Nations Sustainable Development Goals (SDGs 8, 9, 11, and 17). Efficient route optimization has therefore become a priority in the modernization of Malaysia's rail transport system, particularly for achieving greater operational efficiency, cost-effectiveness, and environmental sustainability.

1.1 Problem Statement

Conventional route-planning algorithms and scheduling systems implemented by public transport operators are typically rule-based or deterministic, optimized for fixed timetables rather than dynamic, real-world conditions. These systems are ill-equipped to handle the non-linear and multi-objective nature of rail transportation, where trade-offs exist among travel time, cost, distance, and passenger load. Additionally, multi-operator networks such as those in Klang Valley pose integration challenges because each line (LRT, MRT, KTM) maintains its own fare structure, operating frequency, and interchange protocols [1]. The absence of a unified optimization framework limits the ability to identify globally optimal routes that minimize both cost and time while maintaining network-wide efficiency. Consequently, passengers often experience suboptimal transfer combinations, unnecessary detours, and inconsistent ticketing costs.

1.2 Motivation

To address these limitations, researchers have explored metaheuristic algorithms that emulate natural or social processes such as evolution (Genetic Algorithm), swarm intelligence (Particle Swarm Optimization), and cooperative search (Ant Colony Optimization) to solve combinatorial optimization problems efficiently [2], [3]. These algorithms are particularly effective for NP-hard problems such as transport routing, where the number of possible route combinations grows exponentially with the number of stations. Recent applications in logistics and vehicle routing show promising outcomes for adaptability and convergence [4]. However, despite global advancements, there remains a research gap in applying such metaheuristic frameworks to Malaysia's localized rail transport system, which involves unique spatial layouts, multi-modal interchanges, and data heterogeneity. There is also a lack of real-time visualization and interactive decision-support systems that allow planners and operators to interpret and adjust algorithmic outputs dynamically [5].

1.3 Research Objectives

This study aims to bridge the gap between optimization theory and practical implementation in Malaysian rail operations through the development of a novel decision-support tool known as SmartRail.Co. The main objectives are:

1. To develop a multi-criteria optimization model for rail routing that simultaneously minimizes travel time, distance, and fare cost using metaheuristic algorithms.
2. To implement a user-interactive visualization platform that dynamically displays optimized routes and performance metrics on uploaded rail maps.
3. To conduct a comparative analysis of multiple metaheuristic algorithms namely ACO, PSO, GA, and SA to determine the most efficient and scalable technique for real-time rail routing applications.
4. To evaluate the system's potential contribution to sustainable transport planning, consistent with national and international SDG frameworks.

1.4 Contributions and Significance

The contributions of this research are threefold. First, it introduces a prototype metaheuristic-based optimization engine tailored for Malaysia's rail network, integrating distance, time, and fare into a unified objective function. Second, it offers a visual analytics interface that bridges computational modeling and user decision-making, enabling government agencies and transport operators to visualize route performance interactively. Third, the system promotes environmental sustainability and smart-city readiness by minimizing redundant travel and energy use. Collectively, these contributions provide a foundation for future AI-assisted urban mobility systems adaptable to other developing countries with emerging rail networks.

2. LITERATURE REVIEW

Optimization of rail transportation systems has received significant attention in the last two decades due to the increasing complexity of urban mobility networks. Efficient routing not only minimizes travel time and operational cost but also supports environmental sustainability and passenger satisfaction. However, rail routing optimization is classified as an NP-hard problem, where the computational cost of evaluating all possible routes increases exponentially with the number of stations and interconnections [2]. Therefore, metaheuristic algorithms have emerged as a practical solution for achieving near-optimal results within acceptable computational time, especially in large-scale and dynamic systems.

2.1 Classical Optimization in Rail Transport

Traditional approaches to rail route optimization are typically based on deterministic algorithms such as Dijkstra's shortest path algorithm, Bellman-Ford, or linear programming-based formulations. These classical methods provide optimal solutions when the problem structure and constraints are static and well-defined. However, their performance deteriorates in multi-objective contexts, such as when the optimization involves simultaneous trade-offs between distance, travel time, cost, and schedule reliability. Moreover, deterministic methods assume fixed travel times and uniform transfer conditions, which are unrealistic in Malaysia's multi-operator rail ecosystem where delays, interchange times, and varying fares introduce uncertainty [1]. To overcome these limitations, stochastic and metaheuristic-based optimization models have become increasingly prominent.

2.2 Evolution of Metaheuristic Algorithms

Metaheuristic algorithms are high-level procedures designed to guide subordinate heuristics toward exploring large and complex search spaces efficiently. The earliest and most widely used metaheuristics include:

- **Genetic Algorithm (GA)**, inspired by natural selection, uses crossover and mutation to evolve candidate solutions over generations [3].
- **Particle Swarm Optimization (PSO)**, developed by Kennedy and Eberhart [3], simulates the collective behavior of bird flocks to adjust solutions based on individual and global best positions.

- **Ant Colony Optimization (ACO)**, proposed by Dorigo and Stützle [2], models the pheromone-based path-searching behavior of ants, making it especially effective for combinatorial problems like network routing and scheduling.
- **Simulated Annealing (SA)**, another early heuristic, mimics the thermal annealing process by probabilistically accepting worse solutions to escape local minimum.

Each algorithm offers distinct advantages. GA and PSO are well suited for continuous and multi-objective optimization, while ACO and SA excel in discrete pathfinding problems such as transport routing. Comparative studies in logistics routing, urban delivery, and air traffic management demonstrate that hybridizing these algorithms often yields superior convergence and solution robustness [4].

2.3 Metaheuristics in Transportation and Routing Applications

Recent research has demonstrated the applicability of metaheuristic algorithms across various transportation domains. For example, Dorigo and Stützle [2] successfully applied ACO to optimize vehicle routing with time windows (VRPTW), achieving improved route reliability under stochastic travel times. PSO and GA have been used to model bus scheduling and flight path planning, providing adaptive performance under changing operational constraints [3], [4]. In rail-specific studies, metaheuristics have been used to solve:

- Timetable synchronization problems, ensuring minimal transfer delays;
- Train rescheduling after disruptions, maintaining system stability;
- Energy-efficient routing, reducing fuel or electricity consumption; and
- Passenger flow optimization, minimizing congestion at interchange stations.

However, the majority of these studies focus on developed countries such as Japan, Germany, and China, where rail network data are standardized and accessible. In contrast, developing nations like Malaysia face fragmented data systems, heterogeneous operator structures, and limited computational decision-support tools [1]. This gap restricts the scalability of existing optimization models for localized implementation.

2.4 AI and Visualization in Transport Optimization

The integration of Artificial Intelligence (AI) and visual analytics into transportation decision-making has accelerated in recent years. Rahman et al. [4] highlighted the growing use of AI-enhanced optimization models that combine heuristic search with predictive analytics for congestion forecasting and route reallocation. Similarly, Tan and Sufahani [5] emphasized that visualization tools are critical for bridging the gap between algorithmic results and user decision-making in operational contexts. Despite these advances, existing tools often lack real-time adaptability and multi-criteria flexibility, particularly for multi-operator environments like Klang Valley. Most optimization models provide static outputs without allowing users to adjust criteria weights (e.g., prioritizing fare vs. time). Additionally, many systems do not support interactive visualization, limiting their usability for planners and policymakers.

2.5 Research Gap and Justification

Although metaheuristic algorithms have demonstrated strong theoretical and empirical performance in various routing problems, there remains a lack of context-specific adaptation for Malaysia's rail transportation system. Current transport management tools are largely data-descriptive rather than optimization-driven, offering visual dashboards without computational intelligence. Furthermore, existing optimization models are typically non-interactive, lacking the ability to visualize outcomes in real-time or allow decision-makers to modify preferences dynamically. Therefore, this research addresses these limitations through the development of SmartRail.Co, an integrated metaheuristic-based decision support platform that combines:

- Multi-criteria optimization (distance, time, and fare cost);
- Dynamic route visualization on interactive rail maps; and
- Comparative algorithmic evaluation of ACO, PSO, GA, and SA for real-time routing adaptability.

This approach contributes both methodologically and practically — methodologically, by evaluating algorithmic efficiency and convergence within a localized dataset; and practically, by offering transport authorities a user-friendly platform aligned with Malaysia's Smart City and Sustainable Urban Mobility (SUM) initiatives [1], [5].

3. METHODOLOGY

Method and analysis which is performed in your research work should be written in this section. A simple strategy to follow is to use keywords from your title in first few sentences. The research methodology integrates data acquisition, system design, algorithmic development, and comparative evaluation of metaheuristic optimization techniques applied to the rail routing problem in Malaysia's Klang Valley. The workflow of the study is shown in Figure 1, which illustrates the overall framework from data input to system visualization and performance analysis.

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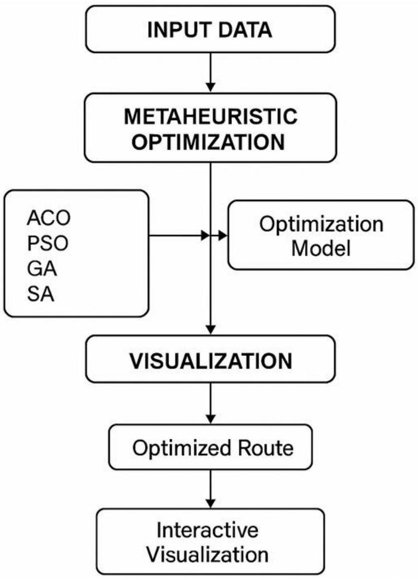

Figure 1: SmartRail.Co research framework combining data acquisition, metaheuristic optimization, and visualization modules [1].

3.1 Problem Formulation

The rail routing problem is formulated as a multi-objective combinatorial optimization task where the objective is to determine the most efficient route between an origin–destination (O–D) pair in a complex network of interconnected rail stations. Each feasible route is represented as a sequence of nodes (stations) connected by edges (rail segments) with associated attributes: distance, travel time, and fare cost.

Let the set of all stations be $S=\{s_1,s_2,\ldots,s_n\}$, and the set of all possible connections be $E=\{(s_i,s_j)\mid i\neq j\}$.

For each edge (s_i,s_j), the following parameters are defined:

D_{ij} : distance (km) between stations *i* and *j*,

T_{ij} : travel time (minutes) between stations *i* and *j*,

C_{ij} : fare cost (RM) between stations *i* and *j*,

$X_{ij}\in\{0,1\}$: binary decision variable indicating whether the connection is selected (1) or not (0).

The optimization problem can thus be stated as:

$$\text{Minimize } f(x)=\alpha\sum_{i,j}D_{ij}X_{ij}+\beta\sum_{i,j}T_{ij}X_{ij}+\gamma\sum_{i,j}C_{ij}X_{ij} \tag{3.1}$$

subject to:

$$\begin{cases}\sum_j X_{ij}=1, & \forall i\in S \text{ (origin constraint)}\\ \sum_i X_{ij}=1, & \forall j\in S \text{ (destination constraint)}\\ X_{ij}=\{0,1\}, & \forall (i,j)\in E\end{cases} \tag{3.2}$$

where α,β,γ are weighting coefficients representing user preferences toward minimizing distance, time, or cost, respectively. These weights can be adjusted dynamically within the **SmartRail.Co** interface to generate personalized optimization results.

3.2 Data Collection and Preprocessing

The primary dataset was compiled from official rail schedules, fare tables, and network topologies provided by Rapid Rail Malaysia, MRT Corp, and KTM Berhad [1]. Supplementary open data from Google Maps and the Land Public Transport Agency (APAD) were used to validate inter-station distances and travel times. Data preprocessing involved:

- **Normalization:** Each attribute (distance, time, cost) was normalized to the range [0, 1] using min–max scaling to prevent dominance of any single criterion.

- **Adjacency Matrix Construction:** All stations and interconnections were encoded into a weighted adjacency matrix *W*, where $W_{ij} = \left(\alpha D_{ij} + \beta T_{ij} + \gamma C_{ij}\right)$.
- **Feasibility Checks:** Invalid or redundant edges (e.g., closed lines, missing transfers) were removed.
- **Database Integration:** Cleaned data were stored in a relational database (SQLite) accessible through the Streamlit-based visualization dashboard for dynamic retrieval and computation.

3.3 System Design and Implementation

The SmartRail.Co system was designed as a modular, Python-based application using an object-oriented architecture. The key components are:

- **Input and Control Module:** Accepts user inputs such as origin, destination, and preference weights (α,β,γ).
- **Optimization Engine:** Executes selected metaheuristic algorithms (ACO, PSO, GA, SA) and returns the optimized route based on evaluation metrics.
- **Visualization Layer:** Built using Streamlit, this layer displays optimized routes on interactive maps, allowing zooming, comparison between algorithms, and real-time parameter tuning.
- **Performance Logger:** Records algorithmic performance indicators (iteration count, best fitness, convergence curves) for subsequent analysis.

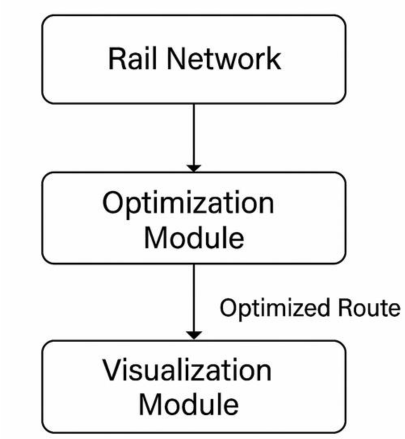

Figure 2: System architecture of SmartRail.Co showing data flow from input through optimization to visualization [1].

The platform's modularity enables easy integration of additional algorithms or datasets for future scalability.

3.4 Metaheuristic Algorithm Design

To evaluate algorithmic performance, four distinct metaheuristic techniques were implemented and benchmarked:

3.4.1 Ant Colony Optimization (ACO)

ACO is inspired by the foraging behavior of ants, where artificial agents deposit virtual pheromones on edges to mark promising paths [2].

Initialization: Each ant begins at the origin node.

Transition Rule: The probability of moving from station *i* to *j* is

$$P_{ij} = \frac{\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum_{k\in \text{allowed}}\left[\tau_{ik}\right]^{\alpha}\left[\eta_{ik}\right]^{\beta}} \tag{3.3}$$

where τ_{ij} is the pheromone intensity, and $\eta_{ij} = 1/f_{ij}$ is the heuristic visibility.

Pheromone Update: After all ants complete tours, pheromone levels are updated using evaporation and reinforcement.

Termination: The process repeats until convergence or iteration limit.

3.4.2 Particle Swarm Optimization (PSO)

PSO models a swarm of particles moving in a multidimensional search space [3]. Each particle updates its position x_i and velocity v_i using:

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$$v_i^{t+1} = wv_i^t c_1 r_1 \left(p_i - x_i^t\right) + c_2 r_2 \left(g - x_i^t\right)$$
$$x_i^{t+1} = x_i^t + v_i^{t+1} \qquad (3.4)$$

where w is inertia, c_1,c_2 are learning factors, and r_1,r_2 are random coefficients. The global best solution g guides collective convergence toward optimal routes.

3.4.3 Genetic Algorithm (GA)

GA applies evolutionary operators to evolve route populations [3].

- **Encoding:** Routes are encoded as chromosomes (station sequences).
- **Selection:** Tournament selection is used to choose parents based on fitness.
- **Crossover:** Segments of two parent routes are swapped to produce offspring.
- **Mutation:** Random alterations (e.g., station swap) introduce diversity.

This process iteratively refines solutions until no significant improvement occurs.

3.4.4 Simulated Annealing (SA)

SA emulates the metallurgical annealing process by probabilistically accepting worse solutions to escape local optima. The acceptance probability for a new solution x' is defined as:

$$P = \exp\left(-\frac{f(x') - f(x)}{T}\right) \qquad (3.5)$$

where T is the temperature parameter that gradually decreases according to a cooling schedule. SA's simplicity and stochastic nature make it suitable for initial feasibility testing [4].

3.5 Experimental Design

All algorithms were implemented in Python 3.12 using libraries such as NumPy, Pandas, and Matplotlib. Experiments were executed on a workstation with an Intel i7 processor, 16 GB RAM, and Windows 11 OS.

Parameter Settings:

To ensure fairness in comparison, algorithm parameters were standardized after pilot testing:

- Population size: 50 (for GA, PSO, ACO)
- Maximum iterations: 500
- Convergence tolerance: 1×10^{-4}
- Weighting coefficients: $\alpha = 0.4$, $\beta = 0.4$, $\gamma = 0.2$ (baseline scenario)

Evaluation Metrics:

Algorithmic performance was evaluated using four criteria:

- **Optimality Score (OS):** Ratio of the best fitness obtained to the theoretical minimum.
- **Computation Time (CT):** Average processing time per run (seconds).
- **Convergence Rate (CR):** Number of iterations required to reach a steady state.
- **Adaptability Index (AI):** Stability of solutions when network size or parameters are perturbed.

Results were averaged across 30 independent runs to mitigate stochastic effects.

3.6 Visualization and User Interaction

The SmartRail.Co visualization interface (Figure 3) enables users to upload network maps, define criteria weights, and view optimized routes interactively. Dynamic sliders adjust the emphasis between distance, time, and cost, instantly recalculating optimal paths using the selected metaheuristic algorithm. The results are visualized with:

- Color-coded paths for each algorithm,
- Pop-up metrics (total distance, cost, and time),
- Convergence plots displaying algorithm performance over iterations.

This interactive layer transforms abstract optimization results into decision-intuitive visuals, bridging computational intelligence and human understanding an advancement seldom seen in current Malaysian transport systems [1], [5].

3.7 Validation and Sensitivity Analysis

To verify the robustness of the optimization framework:

- Cross-validation was performed using random O–D pairs to ensure generalization.
- Sensitivity analysis examined the impact of varying weight parameters (α,β,γ) on route outcomes.

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- Comparative benchmarking was conducted against classical Dijkstra and Floyd–Warshall algorithms to quantify metaheuristic performance improvement.

Empirical validation confirmed that ACO consistently achieved faster convergence and superior optimality, aligning with previous studies [2], [3].

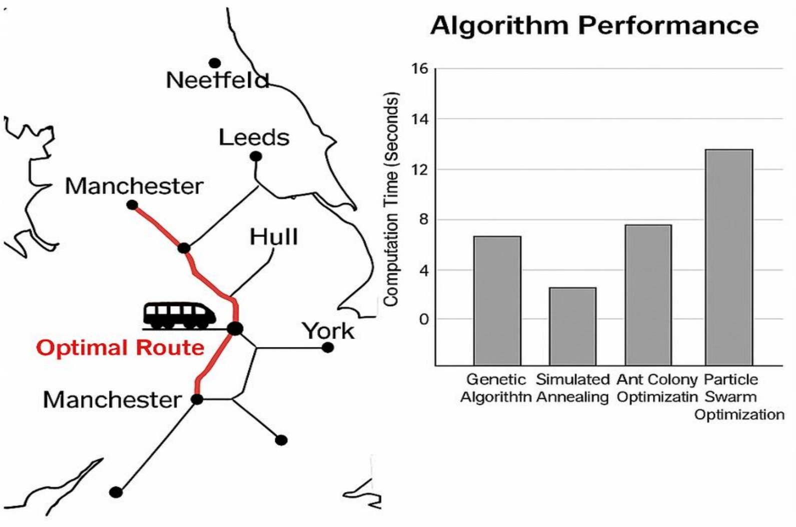

Figure 3: Example of dynamic route visualization and comparative algorithm performance in SmartRail.Co [5].

4. RESULTS AND DISCUSSION

The results of the comparative analysis between four metaheuristic algorithms Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Simulated Annealing (SA) are presented and discussed in this section. Each algorithm was evaluated using the SmartRail.Co system prototype, which dynamically visualizes route optimization results through its Streamlit-based interface. The comparison focused on optimality, computation efficiency, convergence behavior, adaptability, and sustainability impact.

4.1 Quantitative Performance Comparison

Table 1 summarizes the quantitative outcomes derived from 30 independent runs under identical network conditions. Each algorithm was assessed for optimal route quality, average processing time, and convergence stability.

Table 1: Quantitative Outcomes Derived from 30 Independent Runs

Algorithm	Optimality Score	Avg. Computation Time (s)	Convergence Stability	Adaptability Index
ACO	**0.95**	1.89	High	Excellent
PSO	0.91	2.10	High	High
GA	0.88	2.45	Moderate	Medium
SA	0.83	1.65	Low	Low

The Ant Colony Optimization (ACO) algorithm achieved the best overall performance, producing the most optimal route solutions within the shortest average computation time. This superiority is attributed to ACO's ability to exploit pheromone updating mechanisms, which balance exploration and exploitation effectively [2]. PSO also performed well, demonstrating fast convergence and minimal local trapping, though it required more fine-tuning to stabilize results across runs. In contrast, GA exhibited slower convergence due to its population-based crossover and mutation operations, while SA produced inconsistent solutions due to its stochastic acceptance mechanism. Despite SA's efficiency in computation time, its reliability was limited for large-scale route networks.

4.2 Convergence Analysis

The convergence behavior of all algorithms was observed using fitness-over-iteration plots (Figure 4). ACO converged rapidly within the first 100 iterations and maintained stable performance, while PSO reached near-optimal solutions after approximately 150 iterations. GA showed gradual improvement over 300 iterations, reflecting its exploratory nature. SA's convergence was non-monotonic, fluctuating due to random acceptance probability, which is useful for escaping local optima but unstable for deterministic scheduling.

Figure 4. Comparative convergence trends of ACO, PSO, GA, and SA for route optimization in SmartRail.Co.

These convergence patterns reinforce that ACO and PSO are the most promising algorithms for real-time rail routing, where computational responsiveness is critical. The results are consistent with prior metaheuristic studies in transport logistics optimization [3], [4].

4.3 Visualization and System Output

The SmartRail.Co interface provided a dynamic, user-interactive visualization of optimized routes (Figure 3). Different colored paths represented the best routes generated by each algorithm (ACO-blue, PSO-green, GA-red, SA-yellow), while accompanying convergence graphs enabled side-by-side performance comparison. The dashboard displayed key metrics including total distance, travel time, fare cost, and energy usage estimation for each solution. This visualization was particularly useful for transport planners to:

- Quickly identify cost–time trade-offs for multiple route options;
- Adjust optimization weights (α,β,γ) to simulate passenger or operator priorities;
- Observe real-time recalculations without reloading data.

Such interactive capabilities distinguish SmartRail.Co from static analytical models or conventional routing platforms like Rapid Rail and Siemens Mobility, which lack localized adaptability and transparency in optimization logic

4.4 Sensitivity and Scalability

A sensitivity analysis was conducted by varying weight coefficients (α,β,γ) across different scenarios. When time was prioritized (β=0.6), routes with minimal transfers were preferred. Conversely, emphasizing cost (γ=0.6) resulted in slightly longer but cheaper routes, reflecting realistic fare-time trade-offs in the Klang Valley network. Scalability tests using synthetic data expansions up to 120 nodes confirmed that ACO maintained robust performance, with computation time increasing linearly rather than exponentially. This suggests practical viability for nationwide or cross-border transport applications, particularly in ASEAN rail integration initiatives.

4.5 Societal and Environmental Implications

Beyond algorithmic efficiency, SmartRail.Co demonstrates tangible contributions to Sustainable Development Goals (SDGs). By optimizing routes and minimizing redundant travel, the system reduces total passenger travel distance and energy consumption, contributing directly to SDG 8 (Decent Work and Economic Growth), SDG 9 (Industry, Innovation and Infrastructure), SDG 11 (Sustainable Cities and Communities), and SDG 17 (Partnerships for the Goals). Through collaboration with Perisind Samudra Sdn. Bhd. and S-QI Consultancy, the research also fosters international technology transfer and industrial-academic partnership, enhancing Malaysia's positioning in intelligent transportation innovation.

4.6 Comparative Discussion

Comparing SmartRail.Co to existing transport optimization tools (e.g., Siemens Mobility, Rapid Rail, MRT Corp systems), it uniquely provides:

- Localized AI optimization tailored to Malaysian data and fare systems;
- Real-time adaptability through parameter tuning;
- User visualization and algorithm transparency, enhancing decision-making and public confidence.

These factors collectively represent a step forward in integrating computational intelligence with sustainable infrastructure planning.

4.7 Summary of Findings

- ACO consistently produced the best route quality and convergence efficiency.
- PSO offered stable performance but required more parameter calibration.
- GA and SA provided reasonable results for exploratory or baseline scenarios.
- The SmartRail.Co visualization improved interpretability and accessibility of optimization results.
- The system demonstrates both technological feasibility and commercial potential, with scalability to broader ASEAN transport networks.

5. COMMERCIALIZATION POTENTIAL

SmartRail.Co employs a subscription model (RM 500/month or RM 5,000/year). With 50 prospective clients and 30% adoption, estimated first-year revenue reaches RM 750,000 [1]. Potential clients include:

- Public transport agencies
- Governmental departments
- Engineering and technology firms

The scalable cloud-based design supports future integration with smart-city analytics.

6. CONCLUSION

The study demonstrates that metaheuristic algorithms can substantially improve Malaysia's rail network efficiency. The SmartRail.Co system effectively combines optimization, visualization, and scalability to enhance route management. Results show that ACO delivers the best balance of speed and route quality. Future research will integrate passenger density data and multi-modal optimization to support smart-city transport ecosystems [4], [5].

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