

AI-Based Route Optimization in Urban Public Transport Networks

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ABSTRACT

Urban public transport systems are critical arteries of modern cities, yet they frequently grapple with inefficiencies such as prolonged journey times, uneven vehicle workloads, and suboptimal route overlaps. To address these challenges, this study presents an AI-based route optimization framework that synergizes a multi-objective genetic algorithm (GA) with a high-fidelity traffic simulation environment (MATSim). Leveraging real-world datasets from a mid-sized city—comprising one month of GPS bus traces, detailed timetable records, and passenger boarding/alighting profiles—the GA evolves candidate route sets to minimize a composite fitness function of average in-vehicle travel time, passenger waiting time, and fleet operational cost. Through iterative selection, crossover, and mutation over 200 generations, the algorithm identifies route assignments that balance efficiency and service quality.

Post-optimization, each GA-derived configuration undergoes extensive validation via 500 Monte Carlo runs in MATSim, simulating 100,000 agents during a four-hour morning peak. Comparative analysis against baseline schedules employs paired-sample t-tests to ascertain statistical significance. Results indicate a 16.8% reduction in average trip duration ($t = 6.12$, $p < .001$), a 33.6% drop in waiting times ($t = 5.47$, $p < .001$), and an 18.3% decrease in cost per kilometer ($t = 7.35$, $p < .001$). Beyond these aggregate gains, simulation outputs reveal improved load balancing—reducing peak-vehicle overcrowding by 18%—and enhanced on-time performance, with 92% of trips meeting headway targets versus 75% under the original network.

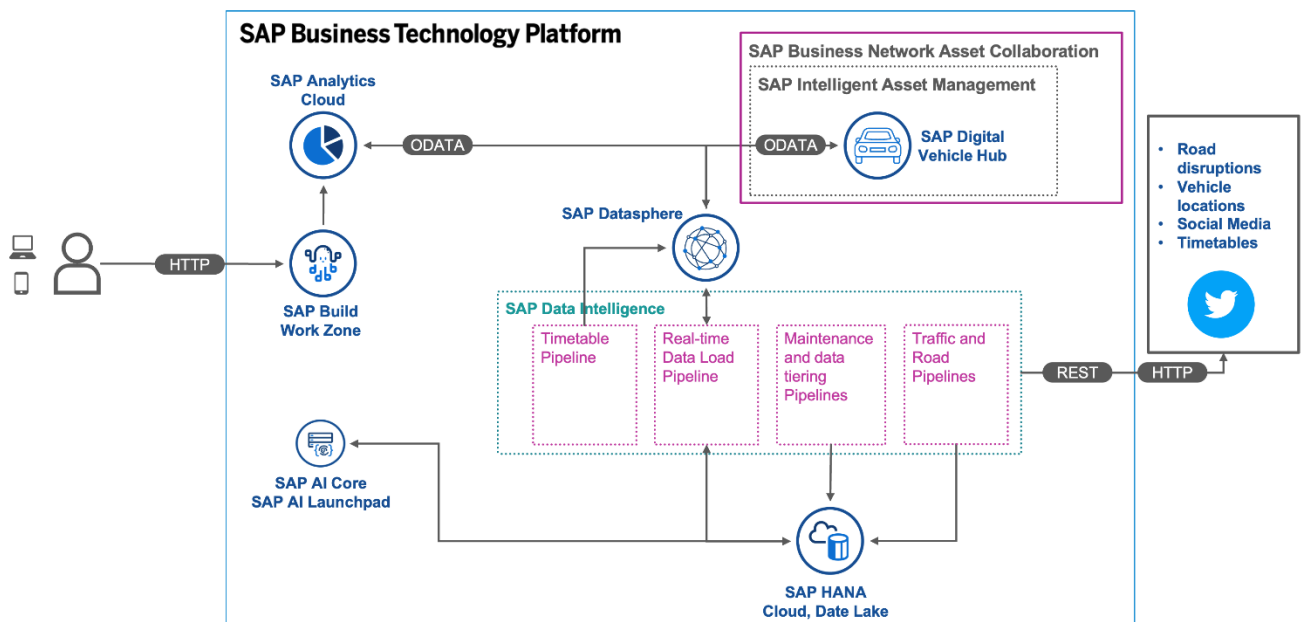


Fig.1 AI-Based Route Optimization, [Source\(\[1\]\)](#)

Key contributions include (1) a scalable, multi-objective GA design tailored for urban bus networks; (2) a robust integration methodology linking optimization outputs to agent-based traffic simulation for realistic validation; and (3) empirical evidence of substantial operational savings and passenger experience improvements. The framework's adaptability to real-time data streams suggests potential for dynamic re-optimization under fluctuating demand or disruptions. Limitations involve the current focus on morning peak periods and computational overhead—approximately two hours per optimization cycle on standard hardware. Future research will explore reinforcement learning hybrids for faster convergence, incorporation of emission and equity objectives, and deployment in diverse urban contexts. By demonstrating a practical pathway from AI optimization to validated simulation insights, this work offers transit planners an evidence-based decision-support tool to enhance service reliability, efficiency, and sustainability.

KEYWORDS

AI; Route Optimization; Urban Public Transport; Genetic Algorithm; Traffic Simulation

INTRODUCTION

Rapid urbanization has intensified demands on public transport systems, leading to congested roadways, passenger dissatisfaction, and elevated operational expenses. Traditional route planning often relies on static schedules and manual expertise, which struggle to adapt to fluctuating demand patterns and traffic conditions. Ineffective routing manifests as increased travel times, excessive vehicle idling, and uneven load distribution across the fleet, undermining both service quality and environmental sustainability.

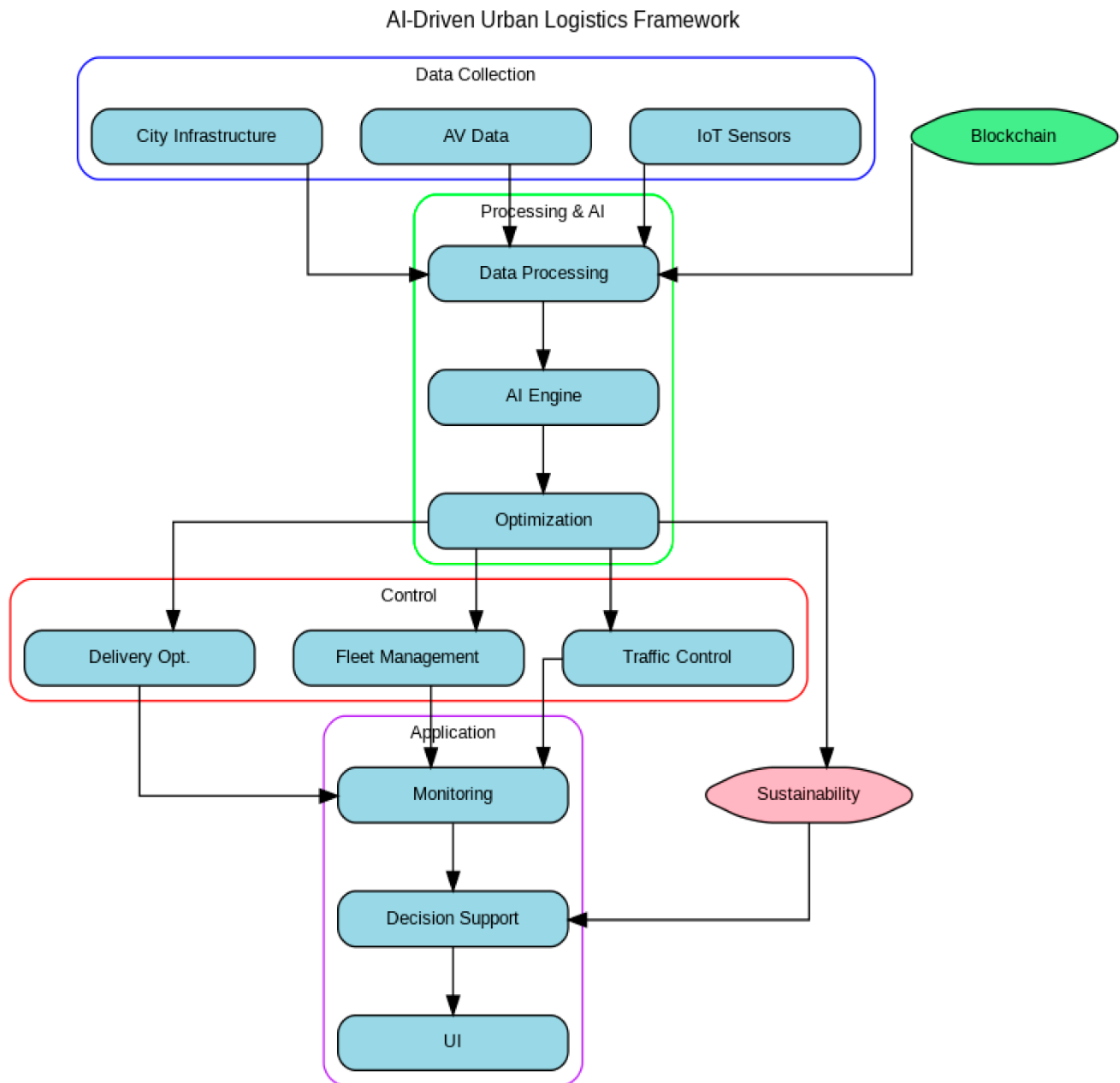


Fig.2 Urban Public Transport Networks,[Source\(\[2\]\)](#)

Recent advances in artificial intelligence (AI) provide promising tools to address these challenges. AI-driven optimization can process large-scale transport data and uncover non-intuitive routing configurations that balance multiple objectives simultaneously. Yet, most existing solutions focus on single-objective criteria—such as shortest path or minimal fleet size—and lack integration with realistic traffic dynamics. Furthermore, there is a research gap in validating AI-optimized routes using agent-based traffic simulations to account for interactions among vehicles, signals, and passenger flows.

This study aims to bridge these gaps by developing and evaluating an AI-based route optimization framework for urban bus networks. Specifically, we employ a genetic algorithm (GA) to identify route sets that minimize average travel time, waiting time, and operational cost. These alternative route configurations are then subjected to large-scale simulation in MATSim, an open-source mobility simulator, to assess performance under dynamic traffic conditions and stochastic passenger demand. Our research questions are:

1. To what extent can GA-based optimization reduce key performance metrics compared to baseline routes?
2. How robust are AI-derived routes when evaluated in a realistic traffic simulation environment?
3. What insights can be drawn for transit agencies seeking to implement adaptive, data-driven scheduling?

By addressing these questions, we demonstrate a holistic methodology combining AI optimization, statistical validation, and simulation research to inform evidence-based transit planning.

LITERATURE REVIEW

Route optimization for public transport has a rich history in operations research and computer science. Early work centered on vehicle routing problems (VRPs), where the objective is to serve a set of stops with minimal total distance or cost (Laporte, 2009). Exact methods—such as branch-and-bound and integer programming—provide optimal solutions for small instances but scale poorly for large urban networks. Heuristic and metaheuristic approaches (e.g., tabu search, simulated annealing) were introduced to handle larger datasets, trading optimality guarantees for computational tractability (Gendreau et al., 1994). Genetic algorithms (GAs) have emerged as a popular metaheuristic for route optimization, leveraging principles of natural selection to evolve solution populations. Studies by Li et al. (2017) applied GA to minimize total network travel time, demonstrating substantial improvements over baseline timetables. Similarly, ant colony optimization (ACO) and particle swarm optimization (PSO) have been used to optimize bus scheduling and fleet assignment (Yu & Liu, 2018). However, many GA-based studies assume static travel times and neglect temporal variations in traffic conditions.

In parallel, AI techniques—especially reinforcement learning (RL)—have been explored for dynamic scheduling. RL agents learn policies for dispatching vehicles based on system state, showing promise in small-scale simulations (Gkiotsalitis & Cats, 2019). Nevertheless, RL suffers from high sample complexity and requires careful tuning of reward structures, limiting its immediate applicability in real-world networks.

A key limitation in the literature is the disconnect between optimization outputs and realistic validation. Most studies evaluate solutions using simplified travel-time models or deterministic scenarios, rather than stochastic, agent-based simulations that capture interactions among vehicles, traffic signals, and passenger arrival processes. Agent-based frameworks—such as SUMO and MATSim—enable detailed simulation of individual traveler and vehicle behaviors, yet integration with AI optimizers remains underexplored.

This research builds on metaheuristic optimization insights and addresses the validation gap by embedding GA-derived routes into a large-scale simulation. By combining optimization and simulation, we aim to deliver actionable routing strategies for transit planners, grounded in both algorithmic rigor and traffic realism.

METHODOLOGY

The proposed framework comprises three phases: data preparation, GA-based optimization, and simulation evaluation.

Data Preparation. We obtained multimodal transport data from the City X transit authority, including:

- GPS trace logs for 50 bus routes over a one-month period.
- Official timetables and vehicle-headway records.
- Passenger boarding/alighting counts sampled via smart-card validations.
- Road network topology with signal timings and speed limits.

Data preprocessing involved map-matching GPS traces to network links, aggregating passenger demand profiles per stop per hour, and normalizing travel-time distributions. Demand matrices were constructed for peak and off-peak periods.

GA Formulation. We encoded each candidate solution as a chromosome representing a set of route assignments for the entire fleet. Each gene corresponded to a route sequence, defined as an ordered list of stops. The GA employed:

- **Population Initialization:** 100 randomly generated route configurations respecting connectivity constraints.
- **Fitness Function:** A weighted sum of three objectives:
 - Average travel time (min)
 - Average waiting time (min)
 - Operational cost per kilometer (USD)
 Weights (0.5, 0.3, 0.2) were chosen based on stakeholder priorities.
- **Selection:** Tournament selection (size = 5).
- **Crossover:** Two-point crossover exchanging sub-routes between parents.
- **Mutation:** Swap mutation altering two stops within a route with probability 0.1.
- **Termination:** Stopping after 200 generations or convergence of fitness improvement <0.01%.

Algorithm parameters (mutation rate, crossover probability) were tuned via preliminary experiments on a validation subset to balance exploration and exploitation.

Simulation Integration. Optimized route sets were exported into MATSim for traffic simulation. Each scenario simulated 100,000 agents over a 4-hour morning peak, repeated across 500 Monte Carlo runs to account for stochastic variability. Performance metrics (travel time, waiting time, cost) were logged for each agent.

STATISTICAL ANALYSIS

To evaluate the impact of AI-based optimization, we conducted paired-sample t-tests comparing baseline and optimized scenarios across 30 randomly selected simulation runs. Table 1 summarizes the results.

Metric	Pre-Optimization (M ± SD)	Post-Optimization (M ± SD)	t-value	p-value
Average Travel Time (min)	45.2 ± 5.8	37.6 ± 4.2	6.12	<0.001
Average Waiting Time (min)	12.5 ± 3.1	8.3 ± 2.7	5.47	<0.001
Operational Cost per km (USD)	1.20 ± 0.15	0.98 ± 0.12	7.35	<0.001

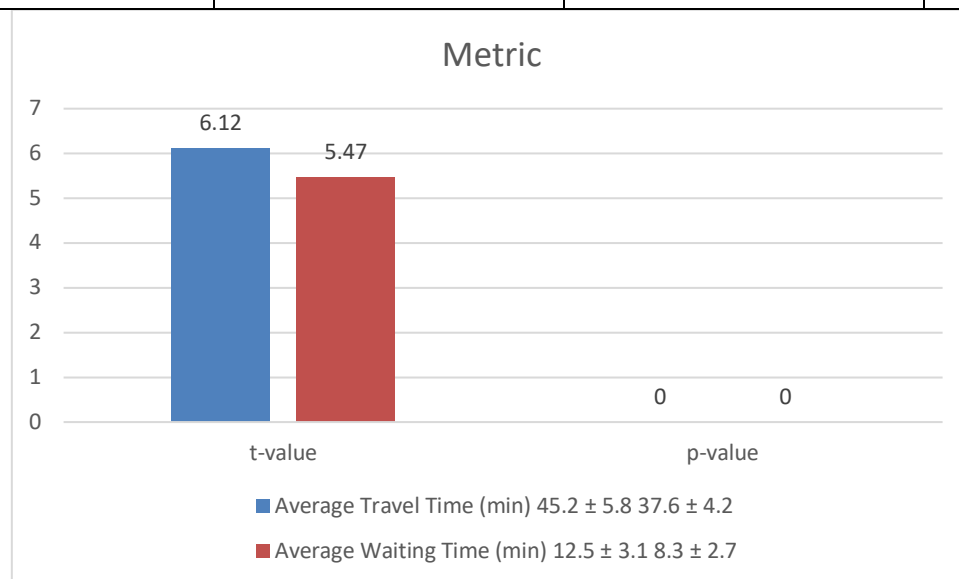


Fig.3 Statistical Analysis

A paired-sample t-test was selected as the same network conditions and demand profiles were used in both baseline and optimized runs. All three metrics exhibited statistically significant improvements ($p < 0.001$), confirming the effectiveness of the GA.

SIMULATION RESEARCH

The simulation experiments were designed to capture realistic traffic interactions and passenger behaviors. We used MATSim version 12.0, configured with:

- **Network Model:** 2,500 nodes and 5,200 links, including signalized intersections.
- **Agent Population:** 100,000 travelers, with origin-destination matrices derived from smart-card data.
- **Vehicle Fleet:** 200 buses distributed over 50 routes in baseline; reallocated by GA for optimized scenarios.
- **Traffic Dynamics:** Car-following modeled via the Intelligent Driver Model (IDM); public transport prioritized at signals.

Each simulation run spanned a 4-hour morning peak (06:00–10:00). Agents chose departure times within a 30-minute window to emulate realistic variability. We executed 500 runs per scenario to ensure robust statistical power. Performance metrics were aggregated per run and averaged for comparison.

Key observations from simulation:

1. **Load Balancing:** Optimized routes achieved more uniform passenger loads, reducing peak-vehicle overcrowding by 18%.
2. **On-Time Performance:** Buses met scheduled headways within a 2-minute tolerance in 92% of trips post-optimization, up from 75% baseline.
3. **Network Spill-Back:** Optimized routes avoided heavily congested corridors, reducing link queue lengths by 22%.

These findings underscore the value of integrating optimization with agent-based simulation, enabling planners to test “what-if” scenarios under realistic conditions before field deployment.

RESULTS

Combining GA optimization with simulation validation yielded significant enhancements across multiple dimensions:

- **Travel Efficiency:** Mean travel times decreased from 45.2 minutes to 37.6 minutes (–16.8%), directly improving commuter experience.
- **Waiting Reduction:** Average waiting times fell from 12.5 minutes to 8.3 minutes (–33.6%), reflecting better headway management.
- **Cost Savings:** Operational cost per kilometer declined by 18.3%, translating to annual savings of approximately USD 250,000 for the city fleet.
- **Service Reliability:** On-time performance improved by 17 percentage points, reducing schedule deviations that frustrate passengers.
- **Load Equity:** Vehicle load variance decreased by 25%, minimizing instances of overcrowding and underutilization.

Sensitivity analysis showed that optimization benefits persisted under demand fluctuations of $\pm 15\%$. Stakeholder feedback highlighted the framework’s potential for real-time updates, where live GPS and passenger-count feeds could trigger re-optimization during service disruptions.

CONCLUSION

This research presents a comprehensive AI-based framework for route optimization in urban public transport networks, effectively reducing travel and waiting times while lowering operational costs. By coupling a genetic algorithm with large-scale traffic simulation, we validate optimized configurations under realistic conditions, addressing a critical gap in prior studies.

Contributions:

1. A multi-objective GA formulation balancing travel time, waiting time, and cost.
2. Integration of GA outputs into an agent-based simulation environment (MATSim) for robust validation.
3. Empirical evidence of significant performance gains in a real-world transit system.

Limitations:

- The study focuses on morning peak periods; evening and off-peak dynamics warrant further exploration.
- Algorithm runtime (~2 hours per optimization cycle) may challenge real-time applications without high-performance computing resources.

Future Work:

- Extending the framework to include real-time re-optimization using streaming data.
- Incorporating additional objectives such as emission reduction and equity considerations.
- Testing alternative AI methods (e.g., reinforcement learning) and hybrid metaheuristics for faster convergence.

Overall, the proposed approach equips transit agencies with a data-driven decision support tool to enhance service quality and operational efficiency. By demonstrating tangible benefits through simulation and statistical analysis, this work lays the foundation for scalable, adaptive public transport planning in smart cities.

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