An Edge-Assisted Genetic Algorithm for Dynamic Multi-Objective Urban Routing

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Received: 2 March 2026 | Revised: 24 March 2026, 21 April 2026, and 8 May 2026 | Accepted: 10 May 2026

 DOI: https://doi.org/10.48084/etasr.18502

ABSTRACT

Congestion in urban areas continues to pose a challenge for rapidly developing cities, resulting in longer travel times, fuel consumption, and environmental degradation. Traditional shortest-path algorithms, although computationally efficient, are not very adaptable to dynamically changing congestion patterns. This study proposes a congestion-aware multi-objective Genetic Algorithm (GA) framework grounded on NSGA-II with Rolling Horizon Optimization (RHO) to improve the adaptability of routing to congestion patterns in urban transportation networks. The model was developed in the SUMO simulation framework and tested with real-world traffic data in Bethlehem City. The experimental findings show that the proposed strategy can reduce travel time by up to 16.7% in high congestion situations and intersection waiting time by up to 19.8% under high-traffic conditions. The stability and scalability of the framework were confirmed by experimental results in the presence of stochastic disturbances such as accidents, demand surges, and poor weather conditions. In contrast to most of the current GA-based methods tested on artificial data, this study focused on real-world validation, dynamic congestion integration, and multi-objective trade-off analysis through Pareto optimization. The results indicate the potential of evolutionary optimization methods for scalable data-driven intelligent transportation systems.

Keywords-congestion; genetic algorithm; intelligent transportation systems; smart cities; SUMO

I. INTRODUCTION

Urban traffic congestion is one of the most significant challenges cities face today, leading to longer travel times, increased fuel consumption, environmental degradation, and substantial economic losses. According to [1], congestion delays continue to increase in both developed and developing areas. The increase in population, the expansion of private vehicle ownership, and the consequent increase in demand are leading to levels that are not adequately served by traditional transportation infrastructures and control practices. A key issue in this regard is the design of reliable and efficient routing schemes. Classical shortest-path algorithms like Dijkstra's [2], Bellman-Ford, Floyd-Warshall, and A* [3] have been used on transportation networks for decades. Time-dependent variants of Dijkstra and A* also exist and are widely used in prediction and real-time routing settings [4, 5], but assuming static edge weights is a common assumption in the scheduling literature. Furthermore, several variants that provide a significant enhancement over the original paradigm have been developed, namely Yen's K-shortest paths, bidirectional search, and heuristic-based improvements [6]. However, these algorithms are essentially deterministic and often ineffective when congestion changes rapidly due to accidents, weather conditions, or changes in traffic signal timing [6]. The inherent complexities of urban traffic, such as its dynamic and stochastic nature, the presence of multiple conflicting objectives (e.g., minimizing travel time, reducing emissions, ensuring safety), and the computational burden of real-time optimization in large-scale networks, pose significant challenges for traditional routing methods.

This has led to the adoption of Artificial Intelligence (AI) and metaheuristic optimization approaches that can respond to dynamic environments and incorporate many, sometimes conflicting, objectives. Among them, the Genetic Algorithm (GA), a class of evolutionary algorithms inspired by natural selection, has been widely used for network routing, traffic signal control, and congestion management [7]. GA is regarded as a powerful search heuristic [8, 9] that can approximate near-optimal solutions in complex nonlinear search spaces, such as urban traffic networks [10]. However, several gaps persist despite extensive research [11-13], including a lack of real-world validation in many GA-based works, insufficient consideration of congestion intensity in objective functions, and inadequate comparative evaluation against adaptive classical algorithms, such as Dijkstra's shortest path algorithm, in realistic simulation environments [14].

Since developing cities experience recurring congestion, routing decisions should consider congestion intensity, waiting times, and real operational constraints rather than relying solely on shortest-path algorithms. Furthermore, transportation systems and decision makers need evidence that AI-based solutions offer real advantages. These challenges motivated the development of a congestion-aware GA framework that handles real-world data from Bethlehem City and is validated on the Simulation of Urban Mobility (SUMO) platform, which is an open-source traffic simulation platform [15]. In addition, the proposed algorithm is systematically benchmarked against conventional routing methods, bridging the gaps between algorithmic innovation and practical urban traffic management.

A. Contributions of This Study

The primary contributions of this study include:

1. Development of a congestion-aware multi-objective NSGA-II framework that integrates travel time, congestion intensity, and network delay.
2. Integration of Rolling-Horizon Optimization (RHO) to enable adaptive re-optimization under time-varying traffic conditions.
3. Real-world validation using traffic data from Bethlehem City within a calibrated SUMO simulation environment.
4. Robustness evaluation under stochastic disturbances, including demand surges and temporary road disruptions.
5. Comparative benchmarking against Dijkstra's algorithm demonstrates superior adaptability under high-density traffic conditions.

B. Related Work

Research in traffic optimization spans decades, combining classical algorithms, AI approaches, and hybrid methods, with contributions from research groups across Europe, North America, Asia, and the Middle East. An overview of the major developments, organized thematically and geographically, is presented next.

1) Classical Shortest-Path and Routing Algorithms

Classical algorithms of Dijkstra (the Netherlands, 1959) [2], Bellman-Ford (USA) [16], and Floyd-Warshall (USA) [17, 18] are still the backbone of route planning worldwide. Dijkstra's algorithm, originally developed at the Mathematical Center in Amsterdam, The Netherlands, remains one of the most widely deployed shortest-path methods in navigation and transportation systems globally. The Bellman-Ford algorithm, developed independently in the United States by Richard Bellman (Princeton University) and Lester Ford Jr., handles negative-weight edges and underpins many network routing protocols. The Floyd-Warshall algorithm, formulated by Robert W. Floyd at Carnegie Mellon University, USA, computes all-pairs shortest paths and is widely used in network analysis. Heuristic extensions such as bidirectional search, Yen's K-shortest paths (USA), and A* [3] (developed at SRI International, California, USA) have been used extensively across Europe, North America, and Asia. Time-dependent Dijkstra and A* models, applied by researchers in Turkey [19] and Greece [20], adapt to time-varying travel times caused by congestion and traffic incidents [4, 5]. Although resilient, these algorithms require accurate, predictive traffic models and are not directly applicable to optimizing multi-objective criteria such as waiting times and congestion levels.

2) AI and Machine Learning-Based Traffic Optimization

With the advent of machine learning, new capabilities for traffic prediction and management have been introduced across research centers in China, the United States, and Europe. Reinforcement Learning (RL) has been widely used in dynamic route choice and adaptive signal control [19, 20], achieving significant progress in improving urban traffic flows in simulation environments in Greece [20] and Turkey [19]. Liu and Li (China) demonstrated that a multi-agent deep RL framework can meaningfully reduce intersection delays in simulated urban networks [7]. Other classical machine learning methods, including decision trees, random forests, and Support Vector Machines (SVM), applied by researchers in the United States and Asia, have shown strong performance on travel time prediction time-series data, with substantially lower computational demands than Deep Learning (DL) approaches [21]. ML and RL models that exploit real-time sensor data for adaptive congestion management have recently been proposed across several countries; however, scalability and computational complexity remain an open challenge globally.

3) Metaheuristics and Evolutionary Algorithms

GAs are among the most widely investigated meta-heuristics for traffic optimization, with active research groups across China, the United States, Iran, and the Middle East. Stevanovic et al. (USA) [22] applied multi-objective GA optimization to traffic signal control, demonstrating measurable mobility and safety improvements. Recent research has also explored GAs and their variants for dynamic urban routing. Guo et al. (China) [23] proposed an enhanced dual-population NSGA-II for emergency supply dispatch using a truck-drone collaboration model, achieving improved solution quality in multi-objective problems. Yuan et al. (China) [24] proposed an adaptive multi-objective NSGA-II tailored for emergency path planning, demonstrating superior convergence and solution diversity. Zhang et al. (China) [25] addressed multi-objective route optimization for electric vehicle hazardous material transportation under uncertain environments. Feyzli et al. (Iran) [26] applied NSGA-II to sustainable medical waste location-routing problems during pandemics and confirmed its advantage over comparable metaheuristics. Zhao et al. (China) [27] combined rolling-horizon algorithms with deep learning-embedded NSGA-II for rescheduling of high-speed trains under interruption conditions, a method that can be directly transferred to urban traffic management. These contributions collectively demonstrate the continued evolution and practical applicability of NSGA-II across diverse real-world contexts.

Michailidis et al. (Greece) [28] surveyed GA-based and RL-based traffic signal control approaches, providing a comprehensive review of recent innovations in intelligent infrastructure. More recent works by Javadi et al. (Iran) [29] and Perez-Ramos et al. (Mexico) [30] offer evidence of hybrid GA and graph-based approaches that improve both journey efficiency and network-level robustness. Despite these promising developments, most existing studies have been validated exclusively on synthetic datasets or small-scale urban scenarios, raising important questions about their transferability to complex, real-world traffic conditions in cities in the developing world. Kazi and Khan (Pakistan) [31] proposed the Dynamic Trilateral Enrolment (DyTE) protocol to improve routing in urban Vehicle Ad-hoc Networks (VANETs). By using a dynamic trilateral zone to constrain node communication based on geographic coordinates, the protocol significantly reduces the broadcast storm problem and addresses high-speed mobility challenges through path optimization. Evaluated against traditional protocols (AODV, DSR), DyTE achieved a 23% improvement in packet delivery ratio, demonstrating its potential for vehicle communication in dense urban environments. Cao et al. (Vietnam) [32] presented a coordinated start-up approach for Cooperative Adaptive Cruise Control (CACC) vehicle strings at signalized arterial intersections. Leveraging Vehicle-to-Vehicle (V2V) and Infrastructure-to-Vehicle (I2V) communication, the method enables simultaneous movement of stationary vehicles, substantially reducing start-up delay. The results highlight the advantages of connected-vehicle strategies over conventional individual vehicle behavior at signalized intersections in densely trafficked urban corridors.

4) Identified Research Gaps

Despite the breadth of international contributions reviewed above, the literature remains lacking in studies that:

1. Validate with real-world data from cities in developing regions such as Palestine.
2. Normalize multiple objectives (travel time, waiting time, congestion) into unit intervals for normalized optimization.
3. Provide thorough comparisons with classical and adaptive routing algorithms.
4. Translate findings into policy recommendations for urban stakeholders.

This study directly addresses these gaps by developing and validating a GA framework with real Bethlehem City data, including objective normalization. Then it compares the results against traditional and contemporary approaches in the field.

II. METHODOLOGY

This section presents the proposed Multi-Objective Optimization (MOO) framework for minimizing travel time, congestion, and delay. The framework generalizes the common single-objective GA to a multi-objective evolutionary optimization approach to capture complex tradeoffs in real-life traffic systems [33]. The methodology is based on three main components: data collection and preprocessing, the formulation of a multi-objective model, and the integration of simulation and optimization. Figure 1 shows the sequential steps, from identifying the research gap to collecting suitable data, performing GA optimization, performing SUMO simulations, and analyzing the results.

A. Data Collection and Preprocessing

To validate the effectiveness of the proposed model, real-world traffic data were collected from Bethlehem City over two weeks (1–14 September 2024). This initial period served as a pilot study to establish the feasibility of real-world data integration within the SUMO simulation environment, given resource and logistical constraints. While limited in temporal scope, this duration provided sufficient data for proof-of-concept and initial performance evaluation.

Traffic data were captured from the Bethlehem urban network during several observation windows, using vehicle counts, signal logs, and floating-car data. Over this two-week period, the collected data amounted to approximately 200,000 vehicle trajectories and 1,500 hours of signal log data across 15 major intersections. The data were converted to a digital road network and processed using SUMO's network conversion tools. Each link in the network has a set of properties, including length, capacity, free-flow speed, and dynamic levels of congestion. To allow time-dependent analysis, link travel times were aggregated in rolling time slices (Δt = 5 min) and dynamically updated during the simulation using SUMO's Traffic Control Interface (TraCI) [15]. This always allows for optimization of the actual traffic conditions. Figure 2 illustrates the dynamic fluctuations in traffic volume at a critical intersection over a typical 24-hour period, showcasing morning and evening peaks. This type of data was collected and used for model calibration.

Figure 3 shows a section of the Bethlehem Road network, which highlights major roads, intersections, and traffic signals used in the SUMO simulation.

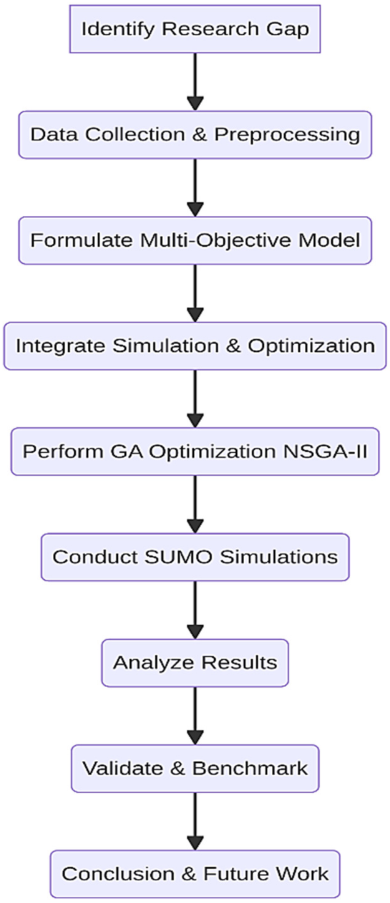

Fig. 1. Data flow schematic of the proposed methodology.

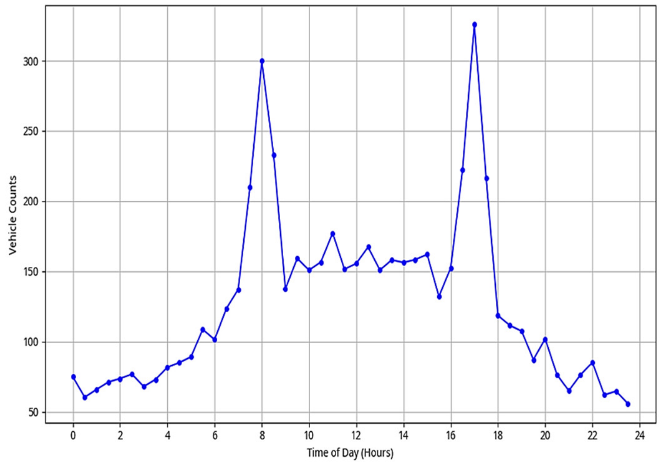

Fig. 2. Sample vehicle counts at a major intersection (typical day).

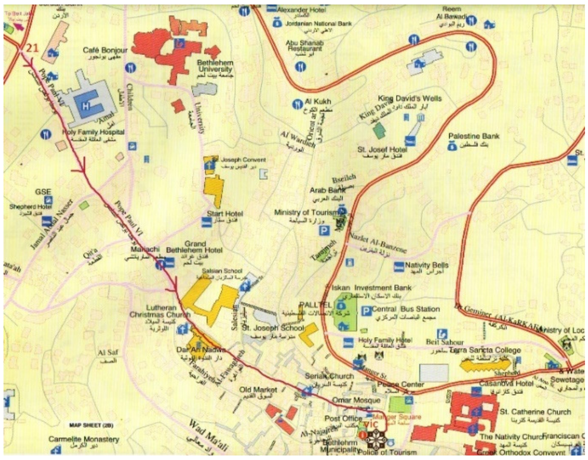

Fig. 3. Simplified map of the Bethlehem City transportation network.

B. *Multi-Objective Genetic Algorithm (NSGA II)*

MOO deals with problems that have two or more objectives that should be optimized simultaneously. MOO produces a Pareto front, which is a set of trade-off solutions across different objectives. Actually, it facilitates selecting the best compromise that fits the application context. The Pareto front represents solutions in which improving one objective cannot be done without harming another [34].

In this case, three objective functions (average travel time, congestion intensity, and total network delay) need to be optimized simultaneously [33]. So, the multi-objective function can be expressed as:

$$Minimize\ F = \{f_1(x), f_2(x), f_3(x)\} \quad (1)$$

where $f_1(x)$ is the average travel time, $f_2(x)$ is congestion intensity (vehicle density per link), and $f_3(x)$ is the total network delay.

The optimization engine here uses the Non-dominated Sorting Genetic Algorithm II (NSGA-II), a multi-objective genetic algorithm known for its balance between solution quality and computational efficiency. NSGA-II improves the original NSGA approach by integrating fast non-dominated sorting, a superior selection mechanism, and a crowding distance operator to preserve diversity across the Pareto front. During evolution, populations are ranked by non-domination level, and offspring are selected by merging the parent and child populations to preserve the elite individuals from successive generations. The crowding distance metric ensures that the distribution of solutions is uniform, reducing premature convergence and allowing a comprehensive exploration of the objective space [35, 36].

Each chromosome in NSGA-II encodes routing, signal configuration, and signal timing parameters. The population is initialized with feasible configurations, and Pareto dominance sorting, a fundamental mechanism in Multi-Objective Evolutionary Algorithms (MOEAs) that organizes and ranks solution candidates based on their relative performance across multiple objectives, is performed to identify non-dominated solutions. In this approach, a solution is considered non-dominated if no other solution in the population outperforms it in all objectives; non-dominated solutions form the first Pareto front, and successive fronts are identified by recursively removing previously ranked solutions and re-evaluating dominance relations. Non-dominated sorting enables MOEAs to maintain a diverse set of trade-off solutions that approximate the Pareto front, guiding selection, crossover, and mutation operations toward regions of the search space with superior multi-objective trade-offs. Recent work continues to refine dominance sorting procedures and integrate them into hybrid evolutionary frameworks to improve convergence and diversity across complex Pareto front shapes. Convergence and diversity are maintained by adaptive crossover and mutation. The output is a Pareto front of non-dominated solutions, providing planners with options and several optimal solutions.

C. Rolling-Horizon Optimization (RHO)

RHO is a dynamic decision-making method for large-scale, time-dependent optimization problems. It partitions a long horizon into a sequence of overlapping, shorter sub-problems, which are solved iteratively. At each iteration, a one-time window is optimized using the most recent system information. This process enables RHO to adapt to real-time changes and uncertainty in system states. By repeatedly incorporating new information at each iteration, RHO balances solution quality with practical feasibility in environments with uncertain and dynamic constraints [37]. The GA runs in an RHO context, where, after each optimization interval (e.g., 15 min), the network state is retrieved from SUMO via TraCI and used to reinitialize the population for the next optimization step. Fitness values are recalculated with new link weights corresponding to time-varying congestion. This way, it is possible to adapt almost instantly to traffic dynamics.

D. Evaluation and Comparison

Optimized configurations were tested in SUMO across different congestion levels, focusing on travel and waiting times. Then, the results were compared with the state-of-the-art methods.

III. EXPERIMENTAL SETUP AND ROBUSTNESS EVALUATION

A. Updated Dataset and Simulation Scenarios

The dataset was augmented to cover more time periods (morning and evening peaks) and an additional city, Hebron, with a different topology and traffic density. Data from both cities were standardized in the SUMO simulation and validated by calibration against observed speed and volume data.

B. Stochastic Modeling of Disturbances

To test the system's resilience, artificial disturbances were driven through the simulation:

- Accidents: random closures of lanes or links lasting 5-15 min.
- Weather: 10–30% minus on vehicle speeds.
- Demand Surges: 10–25% temporary increases in traffic.

Each scenario was generated using probabilistic methods to account for real-world variability.

C. Comparative Performance Analysis: GA vs. Dijkstra

A comparative analysis was conducted by running simulations in SUMO, comparing GA-based optimization with Dijkstra's algorithm across different congestion levels to assess their effects on travel time and evaluate GA's adaptability to congestion fluctuations. The results are shown in Figure 4. Dijkstra's shortest-path routing was implemented as a baseline using link travel-time weights obtained from the simulation at each evaluation step. The baseline was executed without evolutionary re-optimization, representing a classical deterministic routing strategy under the same network conditions.

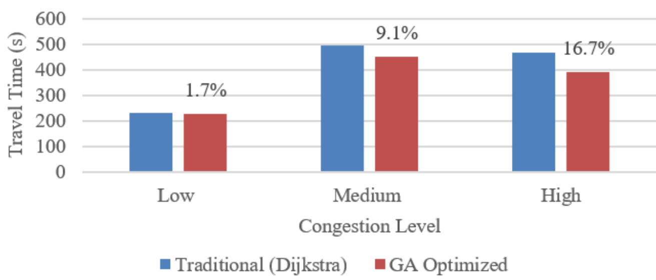

Fig. 4. Impact of congestion on GA travel time reduction.

D. Statistical Analysis

A detailed statistical analysis was performed to critically evaluate the importance of the performance improvements that were observed. To begin with, the paired t-test ($\alpha = 0.05$) was used to examine the difference in mean travel time and waiting period decrease obtained by the GA-based method and the Dijkstra algorithm at different congestion levels. This test established that the changes, which were noticed in the high-congestion conditions, were significant.

Second, a two-way Analysis of Variance (ANOVA) was conducted to further investigate the impacts of the type of algorithm (GA vs. Dijkstra) and the congestion level (low, medium, high) on the performance metrics. The ANOVA also found there are significant main effects of the type of algorithm and level of congestion, meaning that both variables have independent effects on the travel time and waiting time. What is more important is that there was a significant interaction effect, which presupposes that the difference in performance between GA and Dijkstra is not fixed, but varies greatly with the level of congestion. This statistical fact supports the assertion that the GA-based model has better flexibility, especially in dynamic and congested road conditions.

Under high congestion conditions, the proposed GA framework achieved a maximum travel time reduction of 16.7% compared to Dijkstra's algorithm. Performance gains were less pronounced under low-congestion scenarios, where classical shortest-path algorithms remain effective. These findings indicate that the primary advantage of the proposed approach emerges in highly dynamic and saturated traffic environments.

The impact of GA optimization on intersection waiting time was analyzed, with the results presented in Figure 5. The results show that GA reduces waiting time at major intersections by up to 19.8% in high-traffic scenarios. This improvement is achieved by adaptive route selection, reducing vehicle congestion at traffic lights, while no significant gain is observed under low congestion, as traffic flows naturally.

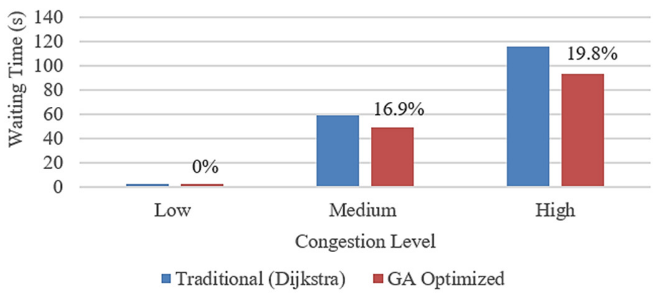

Fig. 5. Impact of congestion on GA waiting time reduction.

E. Scalability and Processing Efficiency

To evaluate GA's scalability, simulations were run at increasing vehicle densities. Table I presents the impact on processing time.

TABLE I. SCALABILITY TEST – GA PROCESSING TIME VS. TRAFFIC DENSITY

Number of vehicles	GA processing time (s)
500	3.4
1000	5.8
1500	8.1
2000	11.6

GA scales efficiently with increased vehicle density, maintaining consistent travel time reductions, and processing time remains reasonable (< 12 s for 2000 vehicles), making it suitable for real-time deployment. Similar reductions in travel and waiting times were reported in comparative studies in other cities [28-30], which were consistent with our findings. This observation confirms the usefulness and universality of GA-based traffic optimization strategies.

Each scenario was simulated using multiple independent runs with different random seeds. Each configuration was evaluated over 20 independent simulation runs, and reported values represent mean ± standard deviation. Reported metrics correspond to the mean performance across runs, and variability is summarized using standard deviation. A paired statistical test ($\alpha = 0.05$) was applied to compare GA against Dijkstra, confirming that the observed improvements in high-congestion scenarios are statistically significant.

F. Comparisons with the State-of-the-Art Methods

The results in Table II provide a qualitative comparison of the proposed algorithm with other state-of-the-art algorithms in the optimization of city traffic. This work demonstrates not only the promising results of advanced methods, but also the need for real-world data validation in developing urban settings, the incorporation of RHO to ensure dynamic adaptability, and the endurance testing in case of stochastic disturbances of traffic. The comprehensive quantitative comparison with a broader range of more complex algorithms, including those using RL or hybrid metaheuristics, is an essential field for future research.

TABLE II. QUALITATIVE COMPARISON WITH THE STATE-OF-THE-ART ALGORITHMS

Method	Study	Traffic conditions	Travel time reduction	Waiting time reduction	Additional considerations
Proposed Algorithm	Urban Traffic	Dynamic	16.7%	19.8%	Dynamic adjustment of routes, real-time data integration, real-world data validation, stochastic disturbance robustness
[33]	Urban Traffic	-	15%	-	Focus on fuel consumption reduction and environmental impact
[32]	Mixed Traffic	Adaptive	20%	18%	Adaptive signal control with real-time adjustments
[31]	High Traffic Load (HTL)	Multi-objective	22%	-	MOO for vehicle routing and signal control
A* [3]	Static Traffic	-	-	-	Traditional method, no dynamic traffic management

IV. PARETO FRONT ANALYSIS

The optimization results are displayed as a Pareto front, showing the trade-offs among the objectives of journey time, congestion, and delay. A series of non-dominant solution points were generated by NSGA-II, depicted in Figure 6.

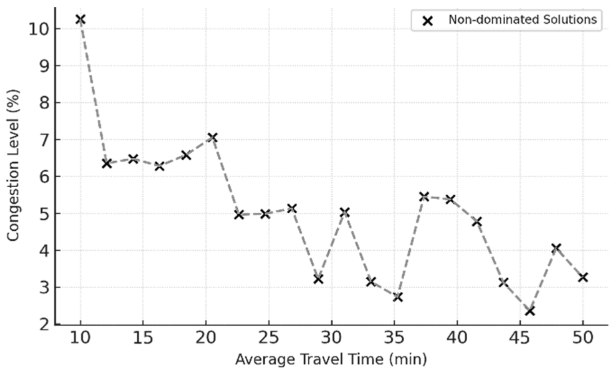

Fig. 6. Pareto front showing trade-offs between travel time, congestion, and delay from MOO.

Regarding the results, an inverse relationship is noticed between travel-time savings and congestion alleviation, thereby verifying the impact of the multi-objective methodology. To operationalize the Pareto front for decision-making, a representative solution was selected, using a compromise criterion (knee-point/weighted compromise), prioritizing travel time reduction while maintaining acceptable congestion and delay. The selected compromise solution lies near the knee region of the Pareto front, where marginal improvements in travel time would result in disproportionately higher congestion levels. This selected solution was subsequently used for the reported GA-Dijkstra comparisons in Figure 3-4. This visualization tool helps decision-makers identify operational strategies that support their policy objectives (e.g., focusing on reducing congestion while maintaining acceptable travel times).

V. DISCUSSION AND IMPACT

A. Fitness Normalization and Computational Complexity.

Objective values were normalized to [0, 1] using min-max scaling as

$$f_i^{norm} = \frac{f_i - f_i^{min}}{f_i^{max} - f_i^{min}} \quad (2)$$

Min-max scaling was also used to map the objective values from the internal platform to an objective value within [0, 1]. This avoids the domination of a single objective and allows a stable convergence trajectory. The computational complexity of NSGA-II is commonly dominated by the non-dominated sorting step and is $O(MN^2)$, where M is the number of objectives and N is the population size. In our setting, the runtime remained suitable for near-real-time re-optimization as reflected by the processing times reported in Table I.

Although the achieved travel time reduction (16.7%) is comparable to, rather than superior to, some previously reported GA-based approaches, the proposed framework differentiates itself through three key aspects:

1. Real-world data validation from a developing urban context.
2. Integration of RHO for dynamic adaptability.
3. Robustness testing under stochastic traffic disturbances.

These elements enhance practical applicability and policy relevance beyond purely simulation-based optimization studies.

B. Policy and Planning Implications

The suggested framework provides a sound basis for data-driven policy formulation. Weight tuning enables an explicit trade-off between minimizing travel time and alleviating congestion. Rolling-horizon control provides a way to make responsive signal-timing corrections. A wide range of scenarios is simulated to inform both infrastructure development and regulatory deliberation, while the results provide practitioners with specific and practical leverage points for developing sustainable mobility.

C. Reproducibility and Open Research

All SUMO scenarios, the GA/RL codebase, and representative datasets are publicly accessible in [38], increasing transparency and facilitating independent work to reproduce scenarios.

VI. CONCLUSION

This study presented a congestion-aware multi-objective GA framework for adaptive urban traffic routing. By integrating NSGA-II with RHO and validating the approach using real-world traffic data, the proposed method demonstrated measurable improvements under high congestion levels, achieving up to 16.7% reduction in travel time compared to classical shortest-path routing. The robustness of the proposed framework under stochastic disturbances and scalability across increasing traffic densities suggest its suitability for real-time intelligent transportation systems. Rather than relying solely on numerical superiority, the contribution of this work lies in bridging algorithmic innovation with practical urban traffic management through validated and adaptive optimization.

On a more general level, the findings of this research have value for consideration in urban mobility planning in a wider range of cities in the Global South that experience rapid growth and face economic and logistical challenges in expanding infrastructure. The proposed framework shows that tangible improvements in traffic management can be achieved using optimization methods that are both data-driven and computationally feasible, and without the need for high infrastructure investment.

The NSGA-II multi-objective evolutionary paradigm and RHO allow decision makers to choose from a spectrum of solutions that represent a trade-off between various objectives instead of a single hard-coded optimum. This is especially useful in policy settings where various, even competing, objectives (like speed minimization, emissions reduction, and equity in access) need to be addressed. The proposed framework is a useful tool for decision support and can be tailored to different municipal priorities and governance goals, as the Pareto-front visualization provided.

To wrap up, this study presented a validated, flexible, and efficient approach for computing an intelligent urban routing solution based on the combination of evolutionary MOO and traffic characteristics, which is suitable for practical applications. It connects theory and algorithmic research with real implementation, providing a reproducible approach for cities facing traffic congestion problems and looking for data-informed and cost-effective solutions. Future work may explore hybrid evolutionary-learning architectures, computational acceleration strategies, and broader multi-city deployments.

DECLARATION OF COMPETING INTEREST

The authors declare no competing financial interests or personal relationships that could have influenced the work reported in this manuscript.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the Deanship of Graduate Studies and Scientific Research at Bethlehem University for their continued support and encouragement. This research was conducted with the support of Research Group #RG-BU006, whose guidance and collaboration were instrumental. Their contributions are deeply appreciated.

DATA AVAILABILITY

The dataset generated during this study is available at [38], along with the code for the proposed method.

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