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Intelligent GA-Based Vehicle Routing within Smart Urban Infrastructure

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ABSTRACT The perpetual growth in vehicle numbers, coupled with traffic congestion, environmental challenges, and the suboptimal utilization of transport networks, underscores the necessity for intelligent traffic management strategies. A pivotal component of such management involves the efficient identification of optimal routes, which contribute to shortened travel times, reduced fuel consumption, and diminished environmental pollution. This paper introduces a route planning method for smart city transport infrastructure utilizing a genetic algorithm. The proposed approach comprises two principal stages: identifying the primary route and generating a set of alternative routes amidst dynamic urban road congestion. The essential genetic algorithm operators, which are integral to the solution's evolutionary process, are delineated. To assess the effectiveness of the proposed method, comparisons are drawn with a greedy algorithm and an ant colony optimization algorithm. Analysis of the results illustrates that the genetic algorithm–based method proposed herein reduces vehicle travel time by 18% compared to the ant colony algorithm, owing to its ability to ascertain the optimal route. The greedy algorithm, characterized by its locally focused decision-making processes, was unable to establish a complete route, terminating at intermediate nodes without reaching the intended destination.

KEYWORDS Genetic algorithm; intelligent transport systems; ant colony optimization; greedy algorithm.

I. INTRODUCTION

INCREASING pressure on urban road infrastructure, coupled with a continuous increase in vehicle numbers, has resulted in severe congestion during peak hours, with adverse effects on both the economy and the environment. Navigation systems are an integral part of modern transport infrastructure, contributing to optimizing traffic flow and reducing congestion [1], [2]. They help redistribute traffic, ease the load on arterial roads, and help avoid heavily congested areas.

Modern navigation systems and mobile applications such as Google Maps, Waze, and Garmin employ route search algorithms to ensure efficient vehicle movement in urban environments. These algorithms enable not only the identification of the shortest path between two points but also the adaptation of routes according to real-time traffic conditions, incidents, and weather changes.

Heuristic search–based algorithms play an important role in navigation services. Genetic algorithms are considered a promising approach to optimizing vehicle routes [3]–[7], especially given the complexity of traffic patterns in large cities, where traditional algorithms (e.g., Dijkstra or A*) often prove inefficient due to the dynamic nature of traffic and the large number of possible routes [8]. Genetic algorithms, inspired by natural selection, crossover, and mutation mechanisms, enable effective optimization in complex and dynamically changing environments.

Thus, route-search algorithms are a core component of modern navigation systems. Navigation technologies have significantly simplified both urban and intercity travel. However, they often do not meet the operational needs of emergency services, such as ambulances, police, or fire departments. Furthermore, traffic congestion frequently shifts from one route to another because navigation systems provide identical directions to all users simultaneously [9].

II. RELATED WORK

In [10], the authors introduced a congestion detection and mitigation framework for road intersections leveraging the Internet of Vehicles (IoV) paradigm. In this approach, the Road Side Unit (RSU) evaluates traffic conditions by analyzing road-segment occupancy as a function of the vehicle arrival rate. The effectiveness of the proposed method was quantified using two performance indicators: path cost and travel time. For route optimization, a modified EG-Dijkstra algorithm was employed. Simulation results indicated that the IoV-based scheme supports real-time traffic state estimation and facilitates the provision of alternative route recommendations.

In [11], the authors proposed an Improved Enhanced Cooperative Algorithm (IECA) for optimal route planning of electric vehicles with constrained battery capacity. The method utilizes two concurrently evolving populations and exploits the best solutions from each, which are then integrated with an enhanced ant colony optimization scheme to update pheromone information efficiently while simultaneously promoting the generation of diverse route configurations. Simulation results demonstrated a 4% reduction in the average route length, thereby substantiating the effectiveness of the proposed approach.

Although swarm intelligence techniques such as Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) exhibit strong performance in graph-based pathfinding problems owing to their pheromone-mediated feedback mechanisms, they encounter distinct difficulties when applied to parameter optimization. As highlighted in comparative analyses [12], Genetic Algorithms (GA) frequently display greater robustness than Tabu Search in discrete parameter optimization tasks, such as tuning of traffic signal timings. This advantage is largely attributable to the GA's capacity to preserve population diversity, thereby mitigating the risk of premature convergence to local optima, a phenomenon commonly observed in Tabu Search when the tabu list is not adapted dynamically.

The study in [13] addresses the electric vehicle routing problem through a three-stage methodological framework. The first stage focuses on vehicle dispatching, the second stage employs a genetic algorithm to determine the optimal route, and the third stage identifies and selects the most appropriate charging stops required to complete the route. The algorithm was implemented in Google Colab Pro Plus, and numerical simulations demonstrated its effectiveness on data sets comprising between 5 and 15 clients.

In [14], the authors propose a deep reinforcement learning-based, multi-objective path planning (DMOP) method that simultaneously considers travel distance and energy consumption. The proposed framework incorporates a convolutional neural network architecture, a reward function with penalty mechanisms, a hybrid learning strategy that integrates conventional and heuristic techniques, and cubic spline interpolation for generating the final planned path. Simulation results demonstrated that the proposed method outperforms classical A* and Dijkstra algorithms, particularly with respect to planning speed.

Furthermore, contemporary studies reveal an increasing adoption of hybrid metaheuristic frameworks aimed at improving decision-making accuracy. In particular, the integration of Artificial Neural Networks with Fuzzy Logic, commonly referred to as Neuro-Fuzzy systems, has attracted considerable attention [15], [16]. Such hybrid architectures exploit the adaptive learning and pattern-recognition capabilities of neural networks in conjunction with the transparency and rule-based reasoning of fuzzy logic, thereby providing an effective means of modeling and managing the uncertainty and imprecision inherent in traffic-related data. Although these methods substantially decrease the computational time associated with decision-making, Genetic Algorithms continue to be widely employed for global optimization, especially in contexts characterized by complex, high-dimensional, and non-convex search spaces.

In [17], a multicriteria shortest path search method was proposed that incorporates temporal parameters to generate sets of optimal routes in real time. The recommended routes are adaptive and user-specific, as they account for individual requirements such as trip departure time and current traffic conditions (e.g., congestion, accidents). The solution integrates geospatial information from heterogeneous data sources within the smart city infrastructure to enable personalized routing. To efficiently process large volumes of geospatial data and ensure scalability, an Attributes Time Aggregated Graph structure was employed. System performance was evaluated in terms of processor time and memory consumption, and the obtained results demonstrated the effectiveness and scalability of the proposed approach.

The study in [18] introduces an Internet of Things (IoT) network model for electric vehicle routing that employs a fuzzy logic-based data fusion technique to assess congestion levels based on sensor measurements. The Open Source Routing Machine (OSRM) was utilized to compute shortest paths while accounting for real-time traffic conditions. Georeferenced sensors deployed along road segments collected data on vehicle speed, CO_2 concentration, noise levels, and temperature. Experimental validation confirmed the effectiveness and practical applicability of the proposed solution.

In [19], the authors proposed a hierarchical, two-level path planning framework for autonomous vehicles. At the road level, a classical A* algorithm is applied for global route planning, with the objective of reducing the number of lane nodes and the associated computational complexity. At the lane level, an additional optimization stage is introduced to mitigate frequent lane changes, dead ends, and other local inefficiencies. This is achieved via a hierarchical lane planning method based on a Proportional–Integral–Derivative (PID) Q-network, constructed upon an enhanced deep Q-network. Simulation results demonstrated that the proposed model outperforms the conventional A* algorithm in terms of both efficiency and route quality.

The work in [20] presented an enhanced path planning algorithm designed to improve the detection and correction of irregular routes based on the A* algorithm. The method integrates A* with interpolation techniques and further refines the resulting paths using geometric optimization rules. A filtering function was implemented to remove excessive turning angles and other irregularities, while cubic B-spline interpolation was employed to generate smooth trajectories. The proposed algorithm effectively reduced both the number of turns and the total route length.

III. MATERIALS AND METHODS

In the context of smart cities, several fundamental categories of vehicular communication can be distinguished, namely Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and communication involving Roadside Units (RSUs) [21], [22].

V2V denotes a communication paradigm that enables direct wireless data exchange between vehicles without the need for intermediate infrastructure. An RSU is a stationary communication device deployed along roadways or embedded within traffic management infrastructure. These units are usually connected by optical transport infrastructure over end-to-end virtual channels. It constitutes a critical component of the vehicular communication architecture in smart cities, as it supports both inter-vehicular communication (V2V) and communication between vehicles and infrastructure (V2I).

Consequently, RSUs, V2V, and V2I form core elements of the intelligent transportation system infrastructure, enabling continuous, real-time interaction between vehicles and the surrounding environment. The data collected from these communication channels are exploited to model and predict traffic congestion, optimize traffic signal control, and support route planning and guidance.

Figure 1 depicts a road intersection in a smart city scenario, designed for route planning applications, where multiple communication modes may coexist, including Infrastructure-to-Infrastructure (I2I), V2V, V2I, and Vehicle-to-Everything (V2X). The latter encompasses, for example, communication with pedestrians, personal mobile devices, and other connected entities in the urban environment.

Direct inter-device and vehicle-to-vehicle/vehicle-to-infrastructure communication relies on wireless access technologies, such as 5G [23]–[25]. Traffic signs and traffic lights are equipped with intelligent sensor systems that monitor vehicular flow and implement adaptive signal control as a function of traffic density. Vehicles continuously broadcast data regarding their position, speed, and direction both to neighboring vehicles and to the roadside infrastructure. Sensor data from vehicles and roadside units (RSUs) are integrated with cloud-based services to enable real-time road-condition assessment, traffic-congestion prediction, and route optimization.

In conventional vehicle routing optimization, route selection criteria typically prioritize either minimal distance or minimal travel time. However, actual traffic conditions

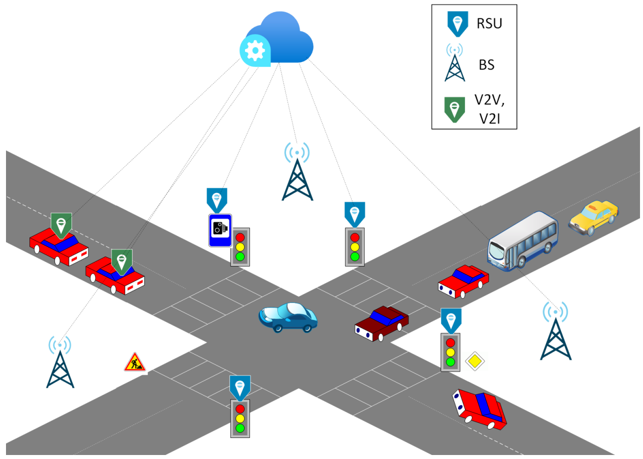

Figure 1. A segment of a transportation infrastructure scheme for a smart city.

are inherently complex, highly dynamic, and influenced by multiple factors.

Consequently, effective routing must account for a broader set of variables, such as congestion, roadworks, and other transient disruptions that can substantially affect actual travel time and may render nominally shorter routes less efficient than longer but less congested alternatives.

The proposed approach consists of two primary stages (Figure 2): (i) determining the optimal route under the current traffic and infrastructure conditions and (ii) generating a set of alternative (backup) routes by employing a genetic algorithm.

Depending on the specific characteristics of the transport network, either the full approach (including both stages) or only the first stage (focused on identifying a single optimal route) may be applied.

The network is modelled as a graph $G(V, E)$, where V denotes the set of vertices (locations), and E represents the set of edges (distances between nodes/vertices). During the initial population generation phase, individual solutions (routes) are formed $V_i = (v_1, v_2, \ldots, v_n)$, each of which has identical starting and ending points. The fitness function $F(X_i)$ evaluates the quality (i.e., optimality) of each potential route by summing the weighted distances of the path segments:

$$F(X_i) = \min \sum_{j=1}^{n-1} \left(w_k \cdot d(v_j, v_{j+1})\right), \quad (1)$$

where n is the number of nodes in the route, $d(v_j, v_{j+1})$ is the Euclidean distance between nodes, and $w_k \in \{w_1, w_2, w_3, w_4\}$ is the weight coefficient selected based on the current congestion level of the edge (v_j, v_{j+1}).

The weight coefficients are defined as follows: $w_1 = 1$ (free flow), $w_2 = 1.5$ (low congestion), $w_3 = 2$ (moderate congestion), and $w_4 = 3$ (severe congestion/blockage). These values were justified empirically: w_1 serves as the

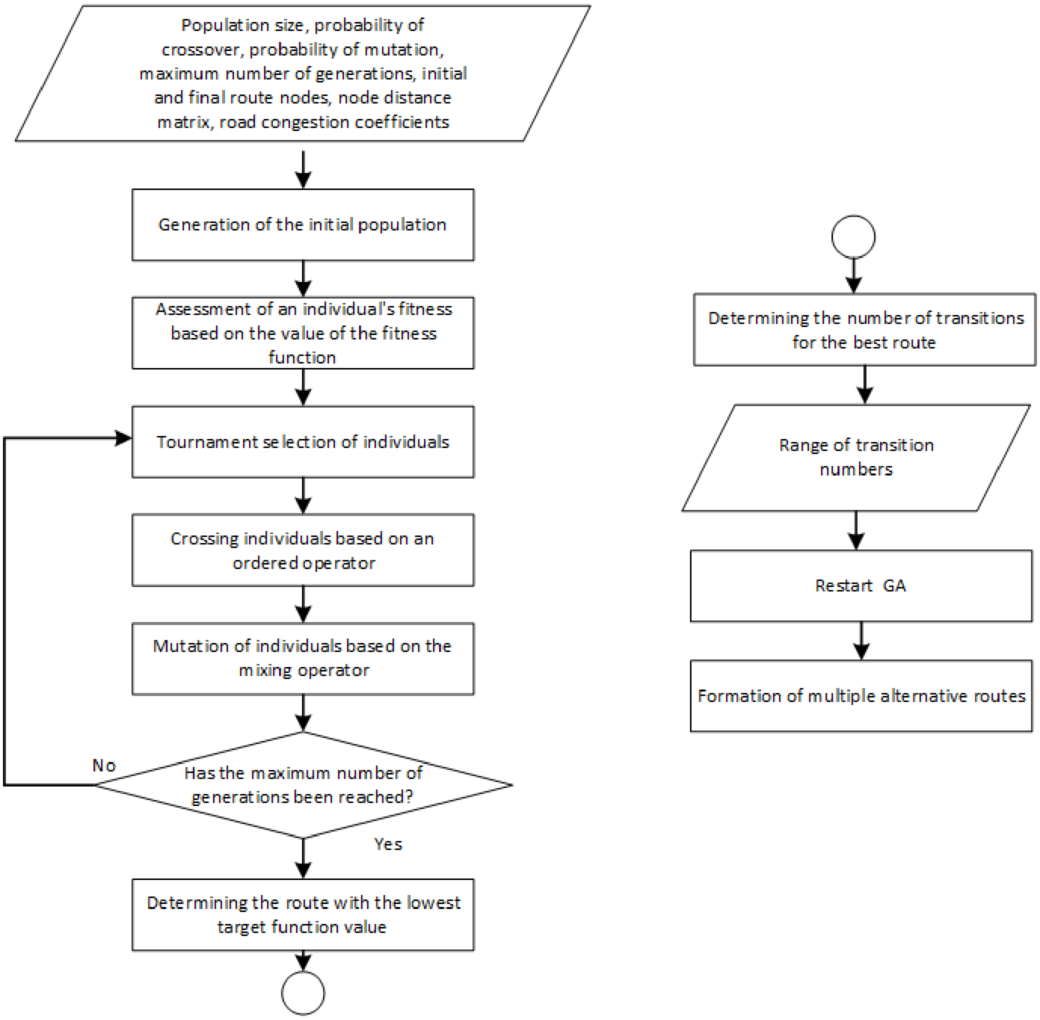

Figure 2. Block diagram of the proposed method.(a) - optimal route identification; (b) - generation of a set of backup routes based on the number of transitions criterion.

baseline for ideal conditions, while w_4 reflects a scenario where travel time is tripled, effectively penalizing routes that pass through blocked or heavily congested sectors despite shorter physical distances.

A multi-criteria matrix is employed to evaluate the fitness of each route. This matrix contains data on the nodes, the distances between them, and penalty values of 10,000 applied in cases where a direct connection between two vertices is absent or inaccessible due to roadworks or other force majeure conditions.

The generation of a set of alternative routes is grounded in the determination of an admissible range for the number of transitions, which is, in turn, derived from the corresponding parameter value associated with the best-performing route. The availability of these alternative routing options enables the system to adapt dynamically to perturbations in the road infrastructure—such as accidents, traffic congestion, and other disruptions—without requiring a complete recomputation of the globally optimal route.

Moreover, the use of alternative routes helps to achieve a more balanced distribution of traffic flows, as reliance on a single route by all vehicles increases the likelihood of congestion. The core operators of the GA are selection, crossover, and mutation, each playing a critical role in the evolutionary process of solution improvement. To ensure reproducibility of the experimental results, the specific parameter settings used in the genetic algorithm are detailed in Table 1.

Table 1. Genetic Algorithm Parameter Settings

Parameter	**Value**
Population Size	50
Max Generations	100
Crossover Rate	0.8
Mutation Rate	0.05
Selection Method	Tournament ($k = 3$)

Tournament selection is among the most commonly used selection mechanisms, offering a balance between global exploration of the solution space and the prevention of premature convergence:

$$S = \{x_1, x_2, \ldots, x_k\}, \quad x_{\text{best}} = \arg\max_{x \in S} f(x), \qquad (2)$$

where S is a subset of randomly selected individuals, $f(x)$ is the fitness function, x_{best} is the best individual that passes to the next generation, k is the size of the tournament. In this work $k = 3$ [26].

Ordered crossover is used for permutation problems, in particular route optimization. According to the principles of this operator, two positions in the route are randomly selected, and the fragment between them is passed on to the offspring unchanged. The rest of the genes are copied in the corresponding order from the other parent individual. Mutation is necessary to maintain genetic diversity. The shuffling operator randomly selects a part of the sequence in the route and shuffles its elements, after which the updated route is added to the population.

IV. RESULTS

For simulation modelling, smart city nodes (sensors, RSU, etc.) are assumed to be randomly distributed across the study area, subject to a maximum communication range of 200 meters.

Additionally, nodes are placed at every intersection and turn in the transport network to improve connectivity and maintain communication where traffic changes direction.

The study focuses on the Sykhiv district of Lviv, a large, dynamic area with developed transport infrastructure, dense buildings, and heavy traffic, making it suitable for evaluating the effectiveness of vehicle routes.

The route between two control points is analyzed. Figure 3 shows the location of smart city nodes in the study area.

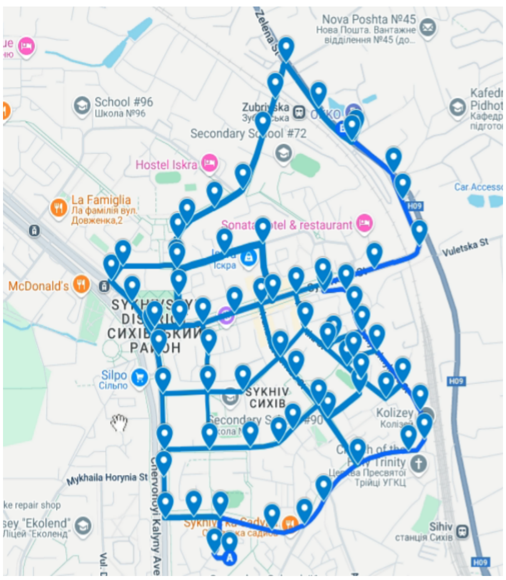

Figure 3. Placement of nodes in the study area to determine the route between points A and B.

The geographical coordinates of each network node are determined, and Euclidean distances between all 73 nodes are calculated and stored in a distance matrix. Using these distances, a network graph is constructed (Fig. 4), where node 0 is the departure point and node 22 is the arrival point.

A. UNDER VARYING ROAD CONDITIONS

Taking into account the coefficients according to (1), the transport network of the studied territory is presented in Fig. 5a, where green corresponds to w_1, yellow to w_2, orange to w_3, and red to w_4.

At the second stage of the method, a set of alternative routes was formed by selecting routes whose number of transitions lay within $k_{trans\_best\_r} \pm 4$, where $k_{trans\_best\_r}$ is the number of transitions on the best route. Since this value was 23, the range was 19–27.

For comparison, the simulation results are shown in Table 2, assuming a vehicle speed of 30 km/h to determine travel time. The data demonstrate that the proposed solution identifies multiple routes with similar characteristics, highlighting its ability to adapt to different scenarios and offer flexible path selection under traffic congestion.

To evaluate the efficiency of the developed algorithm, a comparative analysis was performed against routes generated using the Greedy algorithm [27] and the ACO algorithm [28] (Fig. 8 a,b).

The following parameters were used for the ACO algorithm: $n_{\text{antx}} = 10$, $n_{\text{iterations}} = 100$, $\alpha = 1$, $\beta = 2$, $rate_{\text{evaporation}} = 50\%$, $q = 100$, where n_{antx} is the number of ants, $n_{\text{iterations}}$ is the number of algorithm iterations, α is coefficient determining the influence of pheromone level on the selection of the next node, β is coefficient determining the influence of edge weight on the selection of the next node, $rate_{\text{evaporation}}$ is parameter controlling pheromone evaporation rate after each iteration, q is parameter for pheromone update.

As shown in Fig. 8 a, the Greedy algorithm failed to reach the destination node, stopping at node 39. In contrast, the ACO (Fig. 8 b) successfully constructed a complete route to the target node.

Table 3 presents the simulation results obtained from Figs. 5-8.

The analysis of the data in Table 3 reveals that the GA developed produced the optimal route under the examined conditions.

B. UNDER CONDITIONS OF VARYING CONGESTION AND ROAD INACCESSIBILITY

An additional experiment examined route generation under restricted network accessibility, accounting for blocked road segments. Figure 9 shows the study area's transport network, with two inaccessible segments in purple. Figure 10 shows the solution produced by the proposed algorithm.

Figures 11 shows the set of routes generated by the genetic algorithm, with their simulation results summarized in Table 4. As shown in Figure 12, the greedy algorithm failed to reach the terminal node, stopping at node 24.

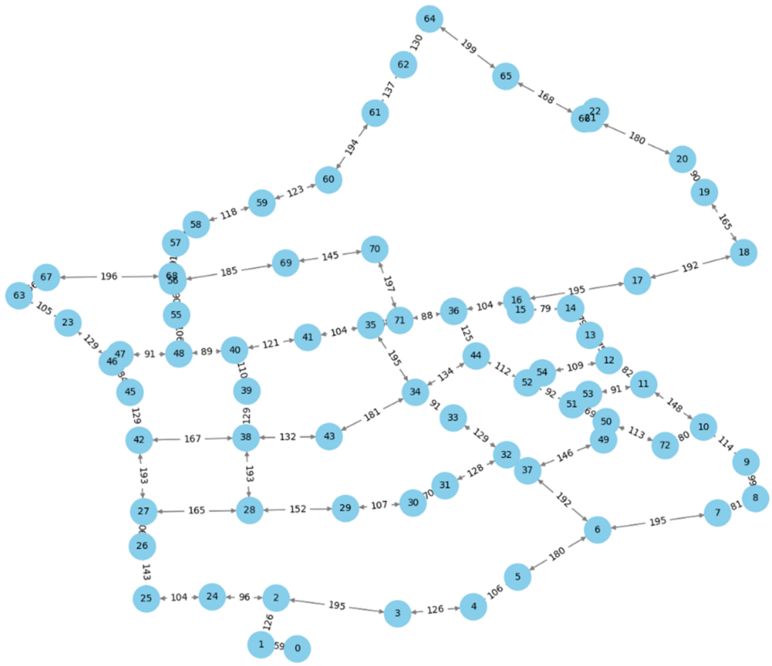

Figure 4. Graph of the investigated network.

Table 2. Routes Obtained Using the Developed GA, Taking into Account Road Congestion

Route number	Nodes of the formed route	Number of transitions	The value of route assessment	Time of vehicle movement, s
1	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 53, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]	23	2655	318.6
2	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 52, 44, 36, 16, 17, 18, 19, 20, 21, 22]	20	2680	321.6
3	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 52, 54, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]	23	2682	321.84
4	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]	22	2710	325.2
5	[0, 1, 2, 3, 4, 5, 6, 37, 32, 33, 34, 44, 36, 16, 17, 18, 19, 20, 21, 22]	19	2735	328.2
6	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 72, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]	23	2799	335.88
7	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 53, 11, 12, 54, 52, 44, 36, 16, 17, 18, 19, 20, 21, 22]	24	2943	353.16
8	[0, 1, 2, 24, 25, 26, 27, 28, 38, 43, 34, 44, 36, 16, 17, 18, 19, 20, 21, 22]	19	2944	353.28

Table 3. Comparison of Routes Obtained Using Genetic, Greedy and ACO Algorithms, Taking into Account Road Congestion

Type of algorithm	Nodes of the generated route	Route value	Vehicle travel time, s
Genetic	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 53, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]	2655	318.6
Greedy	[0, 1, 2, 24, 25, 26, 27, 28, 29, 30, 31, 32, 37, 49, 50, 51, 53, 11, 12, 13, 14, 15, 16, 36, 71, 35, 41, 40, 48, 47, 46, 45, 42, 38, 39]	-	-
ACO	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 72, 50, 51, 53, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22]	2952	354.24

Table 5 compares route construction results in the transport network (Figures 10 and 12), considering traffic dynamics and inaccessible road sections, for three approaches: a genetic algorithm, a greedy algorithm, and an ant colony optimization (ACO) algorithm.

The genetic algorithm achieved the best balance between route length and travel time. Its strong global search capability enabled it to find an efficient route despite restricted links, resulting in a relatively low total route cost and the shortest travel time, indicating its suitability for complex, dynamic transport logistics.

The ACO algorithm produced a feasible alternative route but with worse execution time. The greedy algorithm could not construct a complete route, confirming its limitations in obstacle-rich, constrained networks.

To allow comparison under the same conditions, route

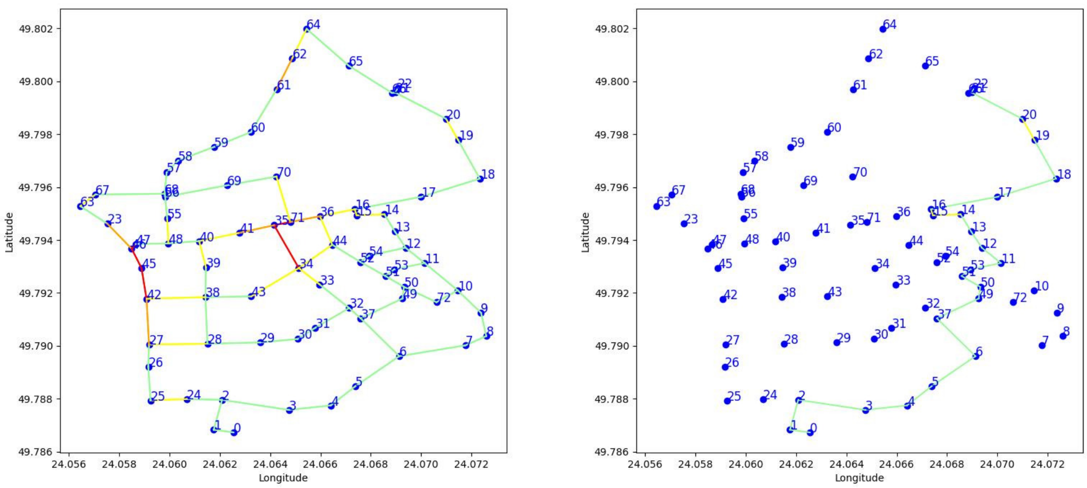

Figure 5. (a) - Transport network of the studied areas with road congestion; (b) - The optimal route for the considered transport network obtained using the developed GA.

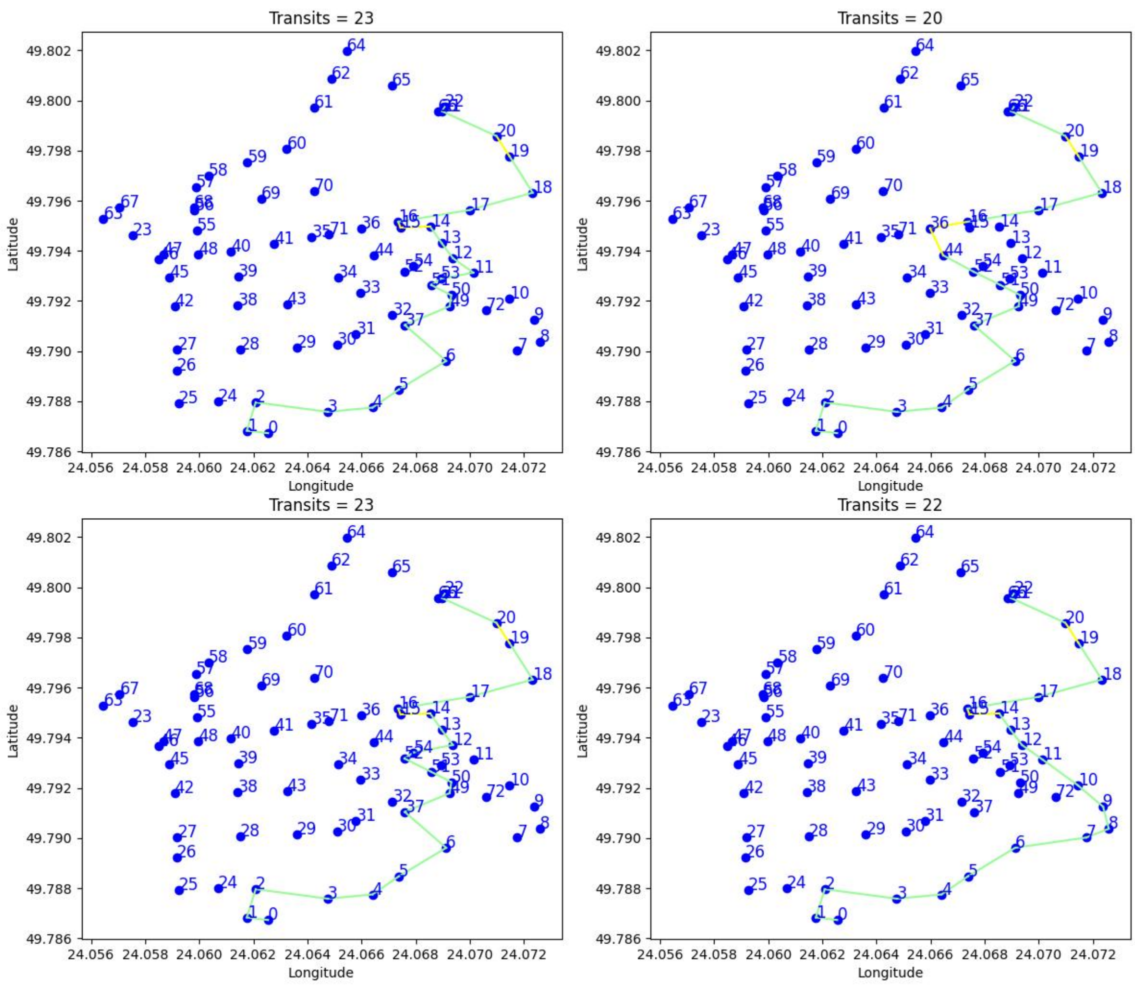

Figure 6. Set of backup routes numbered 1–4.

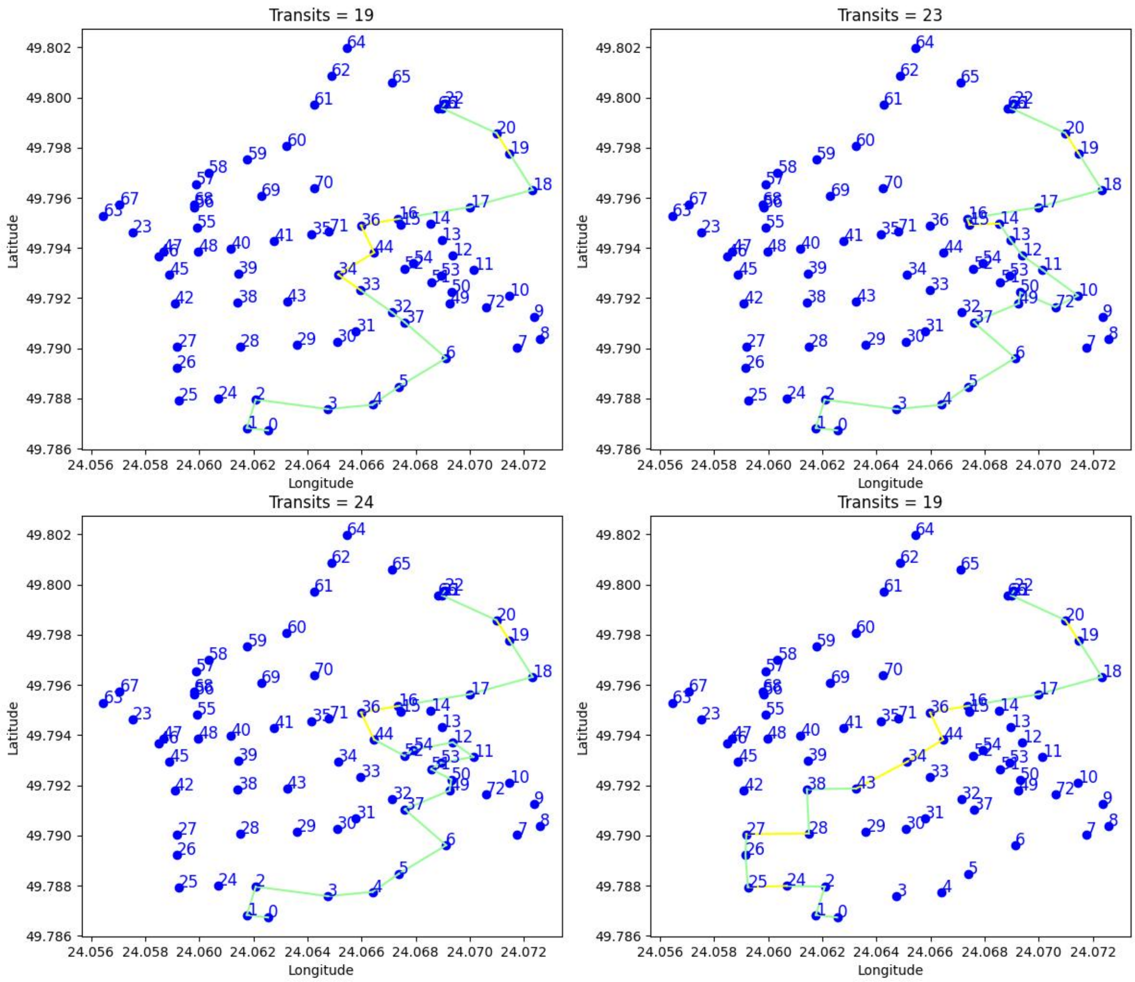

Figure 7. Set of backup routes numbered 5–8.

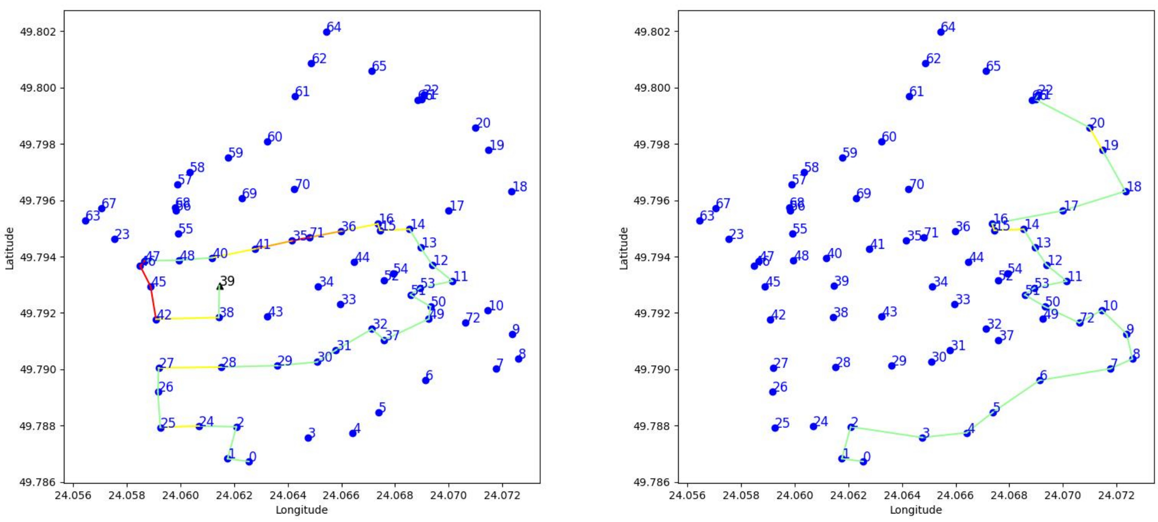

Figure 8. Route generated using (a) - the greedy algorithm; (b) - the ACO.

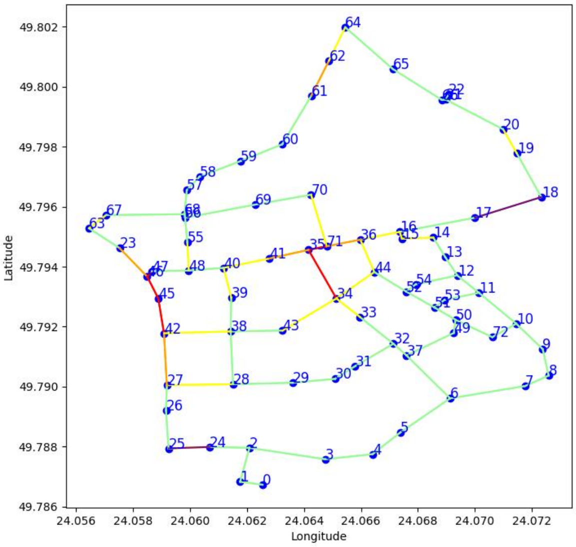

Figure 9. Transport network of the study area considering road congestion and inaccessible segments.

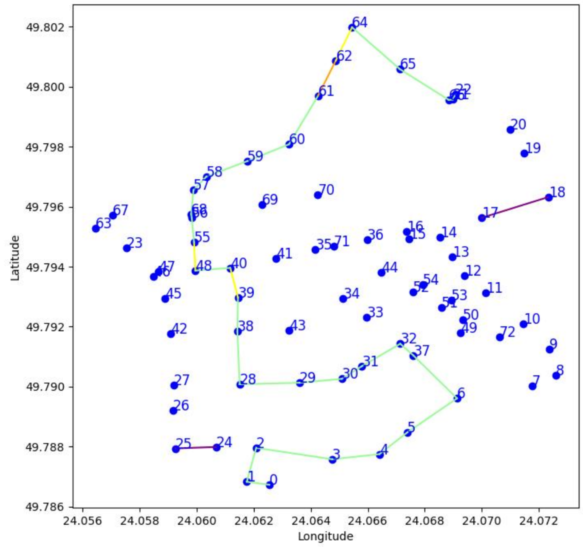

Figure 10. Optimal route generated using the developed GA.

Table 4. Routes Obtained Using the Developed GA under Conditions of Varying Load and Road Inaccessibility

Route number	Nodes of the formed route	Number of transitions	The value of route assessment	Time of vehicle movement, s
1	[0, 1, 2, 3, 4, 5, 6, 37, 32, 31, 30, 29, 28, 38, 39, 40, 48, 55, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	30	3787	454.44
2	[0, 1, 2, 3, 4, 5, 6, 37, 32, 33, 34, 43, 38, 39, 40, 48, 55, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	29	3805	456.6
3	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 52, 44, 36, 71, 70, 69, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	29	3904	468.48
4	[0, 1, 2, 3, 4, 5, 6, 37, 32, 33, 34, 44, 36, 71, 70, 69, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	28	3959	475.08
5	[0, 1, 2, 3, 4, 5, 6, 37, 32, 33, 34, 35, 41, 40, 48, 55, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	28	4082	489.84
6	[0, 1, 2, 3, 4, 5, 6, 37, 32, 33, 34, 35, 71, 70, 69, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	27	4124	494.88
7	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 52, 44, 36, 71, 35, 41, 40, 48, 55, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	32	4150	498.0
8	[0, 1, 2, 3, 4, 5, 6, 37, 49, 50, 51, 52, 44, 34, 43, 38, 39, 40, 48, 55, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	32	4152	498.24

searches were also performed using greedy [27] and ACO [28] algorithms (Fig. 12).

V. CONCLUSION

This study presents a two-stage genetic-algorithm-based method for vehicle route planning in smart urban infrastructures, explicitly modelling traffic congestion and road inaccessibility via weighting coefficients and penalty functions. To improve search efficiency, the genetic algorithm uses standard evolutionary operators: tournament selection, ordered crossover, and shuffle mutation. The transportation network is modelled as a graph of nodes (intersections) and edges (road segments). The method's performance was compared with a greedy algorithm and an Ant Colony Optimization (ACO) algorithm. Simulations show that the proposed approach reduces travel time by 18% compared with ACO through more efficient route selection, while the greedy algorithm was unable to reach the destination node under the tested conditions.

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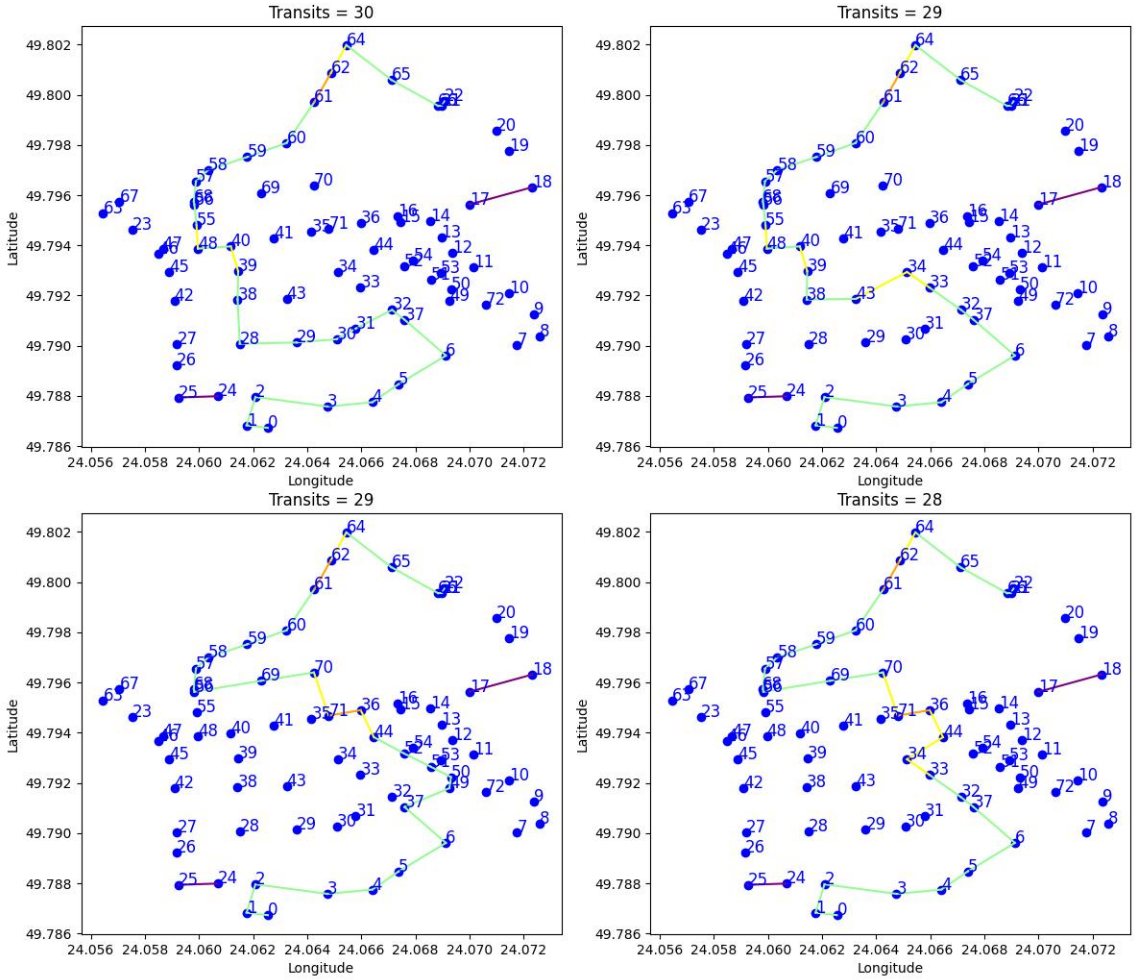

Figure 11. Set of backup routes numbered 1–4.

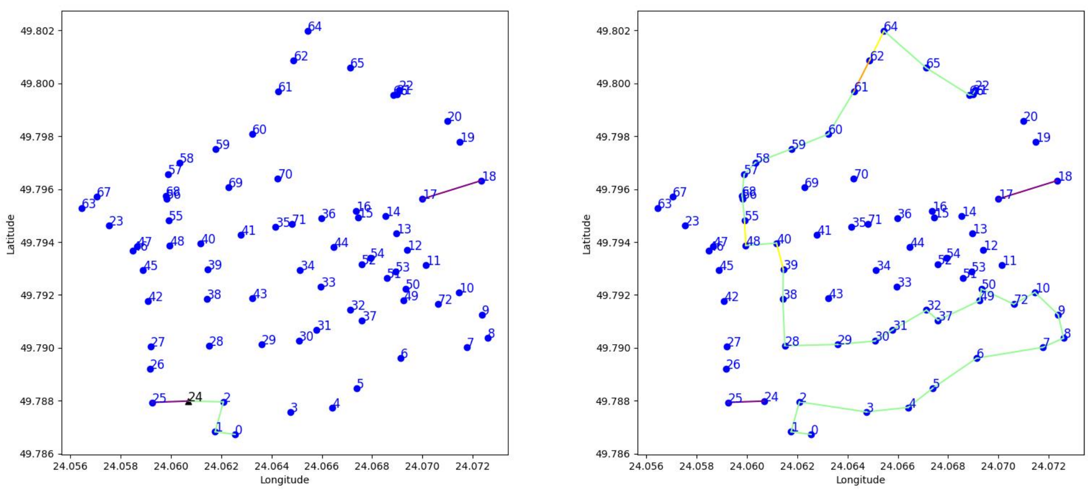

Figure 12. Route generated using (a) - the greedy algorithm; (b) - the developed GA.

Table 5. Comparison of Routes Obtained Using the Genetic, Greedy, and ACO Algorithms under Varying Traffic Conditions and Road Inaccessibility

Type of algorithm	Nodes of the route	Route value	Vehicle travel time, s
Genetic	[0, 1, 2, 3, 4, 5, 6, 37, 32, 31, 30, 29, 28, 38, 39, 40, 48, 55, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21,	3787	454.44
Greedy	[0, 1, 2, 24]	-	-
ACO	[0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 72, 50, 49, 37, 32, 31, 30, 29, 28, 38, 39, 40, 48, 55, 56, 68, 57, 58, 59, 60, 61, 62, 64, 65, 66, 21, 22]	4470	536.4

References

[1] H. Wassaf, J. H. Rife, and K. Van Dyke, "Resiliency characterization of navigation systems for intelligent transportation applications," in 2023 IEEE/ION Position, Location and Navigation Symposium (PLANS), 2023, pp. 609–620.

[2] O. Shpur, Y. Pyrih, T. Havryliv, N. Peleh, O. Urikova, and A. Branytskyi, "Development of a road traffic monitoring system," in 2021 IEEE 16th International Conference on the Experience of Designing and Application of CAD Systems (CADSM), 2021, pp. 10–14.

[3] Z. Wang, M. Zhang, S. Liang, S. Yu, C. Zhang, and S. Du, "A multi-objective path-planning approach for multi-scenario urban mobility needs," Algorithms, vol. 18, no. 1, 2025. [Online]. Available: https://www.mdpi.com/1999-4893/18/1/41

[4] P. Bykovyy, Y. Pigovsky, V. Kochan, A. Sachenko, G. Markowsky, and S. Aksoy, "Genetic algorithm implementation for distributed security systems optimization," in 2008 IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, 2008, pp. 120–124.

[5] M. A. Rahman, K. M. Nazib, M. R. Islam, and L. E. Ali, "Solving traveling salesman problem through genetic algorithm with clustering," International Journal of Intelligent Systems and Applications, 2025. [Online]. Available: https://api.semanticscholar.org/CorpusID:279005861

[6] A. W. Wambua and G. M. Wambugu, "A comparative analysis of bat and genetic algorithms for test case prioritization in regression testing," International Journal of Intelligent Systems and Applications (IJISA), vol. 15, no. 1, pp. 13–21, 2023.

[7] M. A. Rahman, K. M. Nazib, M. R. Islam, and L. E. Ali, "Solving traveling salesman problem through genetic algorithm with clustering," International Journal of Intelligent Systems and Applications (IJISA), vol. 17, no. 3, pp. 15–33, 2025.

[8] S. Chiodini, G. Polato, A. Valmorbida, M. Pertile, G. Giorgi, C. Narduzzi, and E. C. Lorenzini, "Impact of data augmentation on labelling confidence in deep learning terrain traversability analysis for unmanned ground vehicles," Acta IMEKO, vol. 14, no. 3, pp. 1–8, 2025.

[9] E. Boumpa, V. Tsoukas, V. Chioktour, M. Kalafati, G. Spathoulas, A. Kakarountas, P. Trivellas, P. Reklitis, and G. Malindretos, "A review of the vehicle routing problem and the current routing services in smart cities," Analytics, vol. 2, no. 1, pp. 1–16, 2023. [Online]. Available: https://www.mdpi.com/2813-2203/2/1/1

[10] Z. Khan, A. Koubaa, and H. Farman, "Smart route: Internet-of-vehicles (iov)-based congestion detection and avoidance (iov-based cda) using rerouting planning," Applied Sciences, vol. 10, no. 13, 2020. [Online]. Available: https://www.mdpi.com/2076-3417/10/13/4541

[11] S. Zhu and C. Wang, "An interaction-enhanced co-evolutionary algorithm for electric vehicle routing optimization," Applied Soft Computing, vol. 165, p. 112113, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1568494624008871

[12] M. Osman and B. Ram, "A comparative study of metaheuristic algorithms for solving the traffic signal timing optimization problem," International Journal of Swarm Intelligence Research, vol. 12, no. 2, pp. 1–20, 2021.

[13] M. Abid, M. Tabaa, and H. Hachimi, "Electric vehicle routing problem with an enhanced vehicle dispatching approach considering real-life data," Energies, vol. 17, no. 7, 2024. [Online]. Available: https://www.mdpi.com/1996-1073/17/7/1596

[14] X. Wu, S. Huang, and G. Huang, "Deep reinforcement learning-based 2.5d multi-objective path planning for ground vehicles: Considering distance and energy consumption," Electronics, vol. 12, no. 18, 2023. [Online]. Available: https://www.mdpi.com/2079-9292/12/18/3840

[15] G. Kaur and D. K. Singh, "Neuro-fuzzy systems for traffic control: A comprehensive review," Artificial Intelligence Review, vol. 50, pp. 1–34, 2018.

[16] M. Collotta, L. L. Bello, and G. Pau, "Adaptive traffic signal control system using neuro-fuzzy logic," IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 5, pp. 2583–2596, 2015.

[17] A. M. Hendawi, A. Rustum, A. A. Ahmadain, D. Hazel, A. Teredesai, D. Oliver, M. Ali, and J. A. Stankovic, "Smart personalized routing for smart cities," in 2017 IEEE 33rd International Conference on Data Engineering (ICDE), 2017, pp. 1295–1306.

[18] R. R. Rout, S. Vemireddy, S. K. Raul, and D. Somayajulu, "Fuzzy logic-based emergency vehicle routing: An iot system development for smart city applications," Computers Electrical Engineering, vol. 88, p. 106839, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0045790620306935

[19] G. Xu, L. Chen, X. Zhao, W. Liu, Y. Yu, F. Huang, Y. Wang, and Y. Chen, "Dual-layer path planning model for autonomous vehicles in urban road networks using an improved deep q-network algorithm with proportional–integral–derivative control," Electronics, vol. 14, no. 1, 2025. [Online]. Available: https://www.mdpi.com/2079-9292/14/1/116

[20] G. Tang, C. Tang, C. Claramunt, X. Hu, and P. Zhou, "Geometric a-star algorithm: An improved a-star algorithm for agv path planning in a port environment," IEEE Access, vol. 9, pp. 59 196–59 210, 2021.

[21] M. Peyman, T. Fluechter, J. Panadero, C. Serrat, F. Xhafa, and A. A. Juan, "Optimization of vehicular networks in smart cities: From agile optimization to learnheuristics and simheuristics," Sensors, vol. 23, no. 1, 2023. [Online]. Available: https://www.mdpi.com/1424-8220/23/1/499

[22] B. M. Mohsen, "Ai-driven optimization of urban logistics in smart cities: Integrating autonomous vehicles and iot for efficient delivery systems," Sustainability, vol. 16, no. 24, 2024. [Online]. Available: https://www.mdpi.com/2071-1050/16/24/11265

[23] W. Jiang, B. Han, M. A. Habibi, and H. D. Schotten, "The road towards 6g: A comprehensive survey," IEEE Open Journal of the Communications Society, vol. 2, pp. 334–366, 2021.

[24] J. Su, M. Beshley, K. Przystupa, O. Kochan, B. Rusyn, R. Stanisławski, O. Yaremko, M. Majka, H. Beshley, I. Demydov, J. Pyrih, and I. Kahalo, "5g multi-tier radio access network planning based on voronoi diagram," Measurement, vol. 192, p. 110814, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0263224122001117

[25] T. Maksymyuk, M. Klymash, and M. Jo, "Deployment strategies and standardization perspectives for 5g mobile networks," in 2016 13th International Conference on Modern Problems of Radio Engineering, Telecommunications and Computer Science (TCSET), 2016, pp. 953–956.

[26] Y. Pyrih, M. Klymash, M. Kaidan, and B. Strykhalvuk, "Investigating the efficiency of tournament selection operator in genetic algorithm for solving tsp," in 2023 IEEE 5th International Conference on Advanced Information and Communication Technologies (AICT), 2023, pp. 170–173.

[27] Y. Klymash, B. Strykhalyuk, and I. Strykhalyuk, "Algorithm for greedy routing based on the thurston algorithm in sensor networks," in 2016 13th International Conference on Modern Problems of Radio Engineering, Telecommunications and Computer Science (TCSET), 2016, pp. 652–654.

[28] W. Peng, L. Wang, H. Yang, and G. Lu, "Research on path planning based on improved ant colony algorithm," in 2024 IEEE 3rd International Conference on Electrical Engineering, Big Data and Algorithms (EEBDA), 2024, pp. 715–718.

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