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AI–Powered Routing Mechanisms for IoT Networks in Smart Cities

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Abstract

As urban areas expand, the need for secure, efficient, and eco-friendly urban solutions becomes more pressing. Smart cities tackle these issues by utilizing the Internet of Things (IoT) to link physical infrastructure with advanced digital systems. This synergy improves the management of urban resources and greatly enhances the quality of life for residents. A key element in this advancement is the function of Artificial Intelligence (AI) in refining routing methods within IoT networks, allowing cities to adapt effectively to changing conditions. This paper examines the crucial elements involved in designing smart cities, stressing the significance of AI-driven routing techniques in IoT networks. We introduce a novel AI-IoT framework that prioritizes real-time monitoring and traffic management. By implementing IoT sensors throughout urban environments—on highways, bridges, and energy systems—the framework collects and analyzes real-time data to enhance vehicle routing. This optimization alleviates congestion, reduces fuel usage, and lessens emissions, supporting broader urban sustainability efforts. Our thorough simulations and case studies across various urban contexts reveal notable enhancements in traffic flow and environmental effects. Furthermore, we explore the role of Unmanned Aerial Vehicles (UAVs) within smart city infrastructure. We create a multi-objective routing strategy that produces efficient, non-dominated solutions by optimizing drone trajectories in IoT networks while addressing obstacles and restricted zones. These UAV routes are evaluated using advanced visualization tools, which assist in reconciling competing goals and ensuring smooth integration into urban environments. This study offers valuable perspectives for policymakers, urban planners, and transportation officials. It underscores the scalability and cost-effectiveness of AI-enhanced routing solutions that can improve connectivity and sustainability in smart cities.

Keywords: Smart cities, Artificial intelligence, Internet of things, Routing mechanisms, Unmanned aerial vehicles.

1 | Introduction

Cities today are complex systems characterized by vast numbers of interconnected citizens, transportation networks, communication systems, and various services and businesses aimed at improving urban lifestyles. The ongoing influx of people into urban areas places significant pressure on city governments to provide

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essential services for daily life. This excess population and rapid urbanization present numerous challenges, including socio-economic, technical, and organizational issues and risks to urban areas' environmental and economic sustainability. Many modern cities grappling with rapid urbanization have inadvertently generated pollution, traffic congestion, and socio-economic inequality, further complicating the urban landscape.

In recent years, many individuals have migrated to urban areas. Projections indicate that by 2030, 60% of the global population will reside in urban settings. This escalating urbanization has prompted the introduction of various smart applications designed to enhance urban living, thereby contributing to the development of smart cities [1–4]. The smart city concept entails the intelligent management of vital components such as transportation systems, medical services, utility services, residential areas, agriculture, and environmental sustainability. By leveraging advanced technologies, smart cities aim to create efficient, livable, and sustainable urban environments that cater to the needs of their residents.

To achieve these goals, smart cities require diverse telecommunication and wireless infrastructures to deliver services effectively and connect millions of devices. Machine-to-Machine (M2M) communication, network virtualization, wireless sensor networks, and gateways are essential for fostering this connectivity. Furthermore, integrating Artificial Intelligence (AI) and the Internet of Things (IoT) is pivotal in optimizing urban management [5–7]. These technologies facilitate real-time monitoring and data-driven decision-making, shifting the paradigm from traditional, labor-intensive infrastructure management methods to intelligent, automated solutions.

AI, in particular, has emerged as a significant force in transportation engineering, especially in predicting and managing traffic congestion. Traffic congestion not only diminishes the efficiency of urban mobility but also exacerbates pollution levels and hampers economic productivity. AI's capacity to process vast amounts of real-time data positions it as a powerful tool for enhancing transportation efficiency and optimizing vehicle routing in urban settings. By harnessing AI's potential, urban transportation systems can adapt dynamically to changing conditions, minimizing travel times and mitigating congestion-related issues.

Moreover, Unmanned Aerial Vehicles (UAVs) have gained traction as an innovative solution in urban logistics [8], [9]. While UAVs were initially associated with recreational and commercial uses, their application has expanded to include freight transport and delivery services. E-commerce growth has further fueled interest in UAVs, allowing for the efficient movement of goods, especially in congested or remote areas.

This introduction lays the groundwork for a comprehensive examination of how AI-powered routing mechanisms can enhance IoT networks in smart cities. By integrating AI, IoT, and UAV technologies, urban planners can develop smarter, more resilient urban environments that effectively address the challenges posed by rapid urbanization and enhance residents' overall quality of life.

2 | Literature Review

Integrating AI with the IoT has become pivotal in advancing smart city initiatives. Recent studies have highlighted the effectiveness of AI-driven routing algorithms in optimizing traffic management and enhancing urban mobility. For instance, Tao et al. demonstrated [10] that machine learning algorithms can analyze real-time traffic data to predict congestion and dynamically adjust routes, reducing travel times by up to 30%. Similarly, Kong et al. explored [11] the application of deep reinforcement learning in vehicle routing, showing significant improvements in energy efficiency and reduced emissions.

Furthermore, Alahi et al. [12] work emphasizes the role of AI in integrating various IoT devices within smart city infrastructure. Their research suggests that AI-powered systems can seamlessly manage data from multiple sources—such as sensors and cameras—to create a holistic view of urban transportation networks. This capability not only aids in optimizing traffic flow but also contributes to the overall sustainability of urban environments.

Despite these advancements, challenges remain, particularly in data privacy and security concerns associated with IoT networks. Future research must address these issues to fully realize AI's potential to enhance smart city functionalities. Overall, the intersection of AI and IoT presents promising opportunities for developing efficient routing mechanisms that can significantly improve the quality of urban life.

2.1|Route Optimization Algorithms

2.1.1|A* algorithm

The A* algorithm is a popular heuristic pathfinding and graph traversal search method. Combining elements of Dijkstra's algorithm (for finding the shortest path) with a heuristic estimate (like straight-line distance to the target), A* efficiently navigates complex networks [13]. The algorithm keeps track of the nodes it has visited, estimating the total cost to reach the goal from each node. Because it evaluates actual movement cost and an optimistic "guess" at future cost, A* is effective in applications where quick, efficient paths are needed—such as in IoT networks that adapt to dynamic urban traffic.

Algorithm 1. A*

```
function reconstruct_path(cameFrom, current)
total_path := {current}
    while current in cameFrom.Keys:
        current := cameFrom[current]
        total_path.prepend(current)
    return total_path
function A_Star(start, goal, h)
    openSet := {start}
    cameFrom := an empty map
    gScore := map with default value of Infinity
    gScore[start] := 0
    fScore := map with default value of Infinity
    fScore[start] := h(start)
    while openSet is not empty
        current := the node in openSet having the lowest fScore[] value
        if current = goal
            return reconstruct_path(cameFrom, current)
        openSet.Remove(current)
        for each neighbor of current
            tentative_gScore := gScore[current] + d(current, neighbor)
            if tentative_gScore < gScore[neighbor]
                cameFrom[neighbor] := current
                gScore[neighbor] := tentative_gScore
                fScore[neighbor] := tentative_gScore + h(neighbor)
                if neighbor not in openSet
                    openSet.add(neighbor)
```

return failure

2.1.2 | Dijkstra's algorithm

Dijkstra's algorithm finds the shortest path between nodes in a graph by systematically exploring nodes starting from an initial source [14] By incrementally calculating the minimum distance to each node and updating routes to reflect this, Dijkstra's algorithm is particularly suited for finding reliable paths in networks with fixed routes and predictable traffic. While computationally intensive in larger networks, it's a robust choice for scenarios where real-time data is unnecessary. However, accurate, efficient routing is essential—like in municipal utility management or preplanned delivery routes.

Algorithm 2. Dijkstra's algorithm

1. Initialize the distance to the starting node as 0 and all other nodes as infinity.

2. Create a set to track visited nodes.

3. Set the current node to the starting node.

4. While there are unvisited nodes:

   a) For each unvisited neighbor of the current node:

      i) Calculate the tentative distance.

      ii) If the tentative distance is less than the known distance, update the distance.

   b) Mark the current node as visited.

   c) Select the unvisited node with the smallest distance and make it the current node.

5. Repeat until all nodes are visited or the smallest distance is infinity.

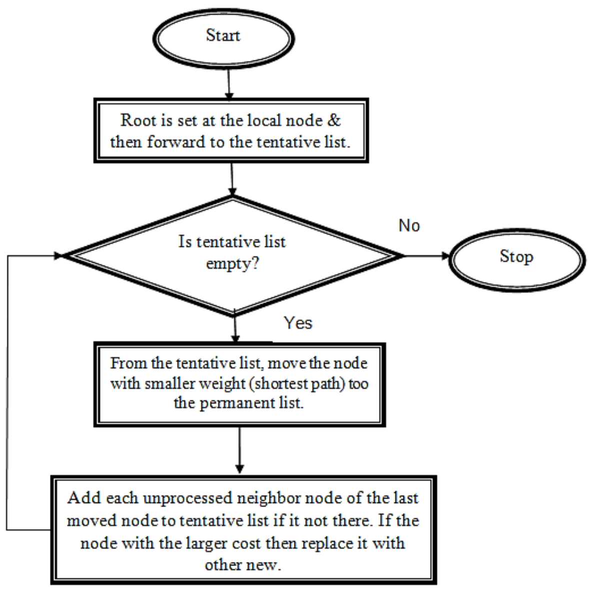

Fig. 1. Dijkstra's algorithm flowchart.

2.1.3 | Genetic algorithms

Genetic algorithms draw inspiration from biological evolution to find optimized solutions by "evolving" a population of possible solutions. The process involves selection, crossover, and mutation of "genomes" (candidate solutions) based on their "fitness" (quality of the solution). Over successive generations, the algorithm converges on high-quality solutions for route optimization problems. GAs are particularly useful for large, complex networks with numerous variables, such as IoT-based delivery networks, where traditional deterministic approaches are less practical.

Algorithm 3. Genetic algorithms

1. Initialize a random population of routes (chromosomes).

2. Evaluate the fitness of each route.

3. While the termination condition is not met:

   a) Select individuals for mating based on fitness.

   b) Perform crossover to create new offspring.

   c) Mutate the offspring.

   d) Evaluate the fitness of the new generation.

   e) Replace the old population with the new generation.

4. Return the best solution found.

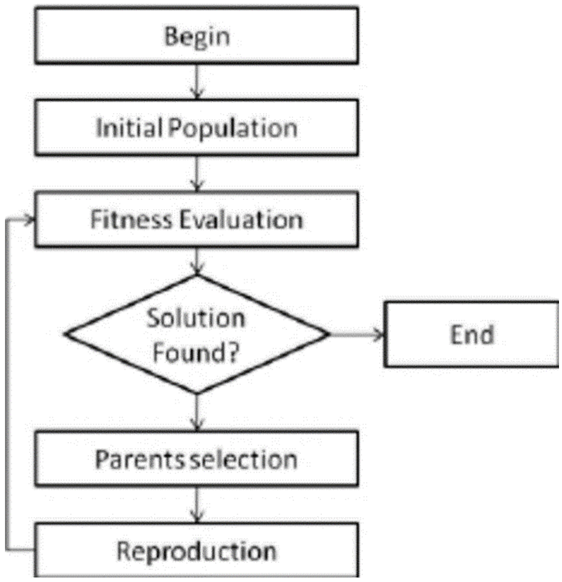

Fig. 2. Flowchart of genetic algorithms.

Genetic Algorithms are particularly effective in solving optimization problems that involve a large search space, where traditional methods might struggle. In the context of smart cities, GAs can help optimize routes for delivery vehicles, public transport, and emergency services by balancing various factors such as distance, traffic congestion, and time constraints. By iteratively refining routes based on the principles of natural selection, cities can improve transportation efficiency and reduce operational costs.

2.1.4 | Particle swarm optimization

Particle Swarm Optimization (PSO) is a metaheuristic approach inspired by the collective movement of flocks of birds or fish [15]. In PSO, individual "particles" move around the search space, influenced by their own best positions and the best-known positions of other particles. This "swarming" behavior enables PSO to converge on optimal routes, especially when parameters fluctuate quickly. PSO is well-suited for IoT networks where data points like traffic volume and congestion constantly shift, such as in smart city transportation systems.

Algorithm 4. Particle swarm optimization

1. Initialize a swarm of particles with random positions and velocities.

2. Evaluate the fitness of each particle.

3. While the termination condition is not met:

   a) Update personal best and global best for each particle.

   b) Update the velocity and position of each particle using the equations.

   c) Evaluate the fitness of the new positions.

4. Return the best solution found.

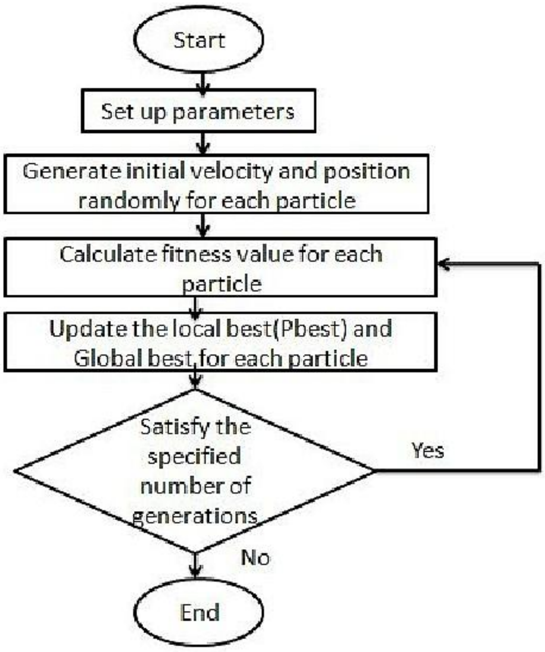

Fig. 3. Flow chart of particle swarm algorithm.

2.1.5 | Reinforcement learning

Reinforcement Learning involves training an agent to make decisions by rewarding desirable actions and penalizing undesirable ones [15]. Over time, the agent learns to maximize its cumulative reward by choosing routes that minimize travel time, fuel consumption, or other costs. RL is highly adaptive, making it ideal for environments where conditions vary continuously, as seen in IoT-enabled traffic systems. By constantly updating its routing strategy based on real-time data, RL can respond dynamically to unexpected roadblocks, congestion, or accidents, offering a practical solution for complex urban mobility.

Algorithm 5. Reinforcement learning

1. Initialize the Q-table for states and actions.

2. For each episode:

   a) Reset the environment to a random state.

   b) While the episode is not done:

      i) Choose an action based on the current policy (e.g., ε-greedy).

      ii) Take action and observe the new state and reward.

      iii) Update the Q-value using the learning rule:

      $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma * \max Q(s', a') - Q(s, a)]$.

iv) Update the current state to the new state.

3. Return the learned policy.

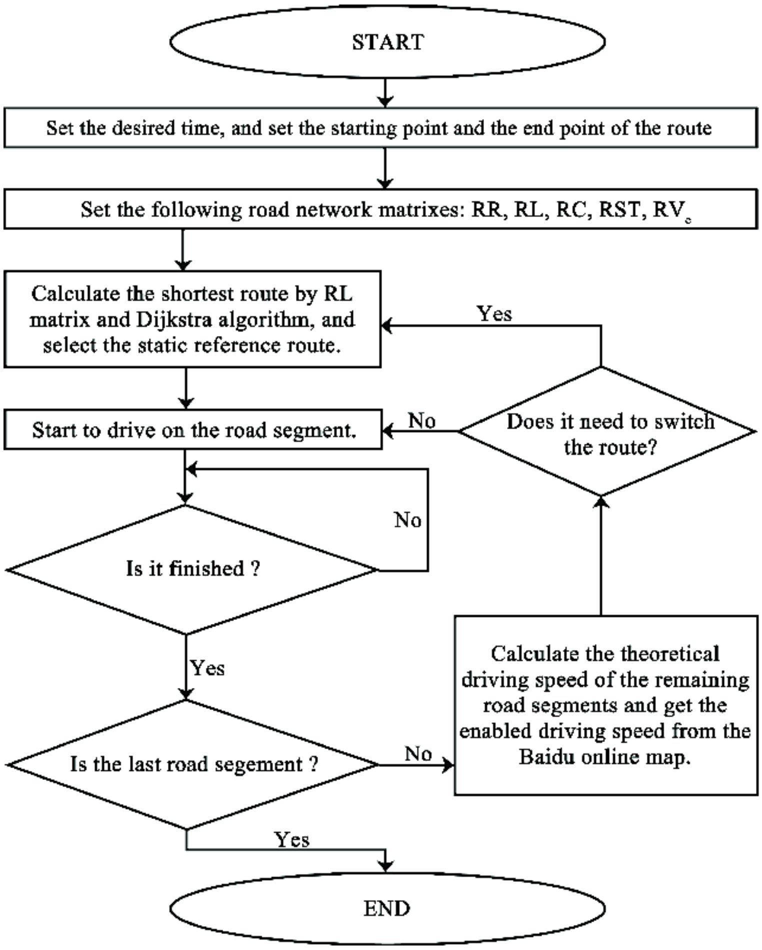

Fig. 4. Reinforcement learning flowchart.

3 | Challenges Associated with Route Mechanisms

Addressing the challenges requires innovations in data processing, energy-efficient algorithm design, and cybersecurity measures, making route optimization in smart cities an evolving area of research and application. The various challenges are mentioned below

3.1 | Dynamic Traffic Conditions

Traffic congestion, accidents, and sudden road closures can significantly impact route optimization. Real-time updates are essential, but accounting for constant fluctuations in traffic flow remains challenging.

Smart city IoT networks aim to provide real-time traffic data; however, integrating and processing this massive amount of information in real-time for optimal decision-making remains complex.

3.2 | Scalability with High Traffic Volumes

As urban populations grow, the number of vehicles and users in a city's transportation network increases, resulting in scalability challenges for route optimization algorithms. Traditional algorithms may become inefficient, leading to delays in routing decisions. AI-based algorithms often require significant computational resources, which may limit scalability, especially in IoT networks with multiple connected devices and sensors.

3.3|Data Accuracy and Completeness

Route optimization relies heavily on data accuracy from GPS systems, traffic sensors, and other data sources. Inaccuracies or data gaps (e.g., due to sensor malfunctions or network issues) can lead to suboptimal routing decisions. Ensuring real-time and reliable data availability in IoT networks is challenging, as intermittent connectivity issues can affect the continuous flow of information needed for optimization.

3.4|Energy and Resource Constraints

IoT devices used in route optimization often operate under power constraints, especially if they are battery-powered (e.g., sensors on vehicles or infrastructure). Constantly relaying data and performing complex computations can quickly drain these resources. Route optimization techniques need to balance the energy demands with the quality of service, which is especially critical in IoT-based smart city implementations where resource efficiency is prioritized.

4|Conclusion

As cities become more populated and urban demands intensify, the need for intelligent, adaptable solutions has grown substantially. This paper examined how AI-powered route optimization techniques enhance urban mobility, reduce congestion, and promote sustainable infrastructure in smart cities. With the integration of IoT networks, smart cities can now rely on real-time data from millions of interconnected devices to make precise and efficient routing decisions. Techniques such as A*, Dijkstra's algorithm, genetic algorithms, PSO, and reinforcement learning are pioneering methods in computational efficiency and vital tools in building responsive and resilient urban transport systems.

Each algorithm explored in this study offers unique advantages, from heuristic simplicity to the adaptive strength of machine learning approaches, meeting urban infrastructure's diverse and dynamic requirements. Challenges remain, particularly around scalability, computational load, and adaptability to changing environments. However, as AI and IoT technologies advance, these obstacles will likely be addressed through enhanced algorithms and new data-handling capabilities.

In conclusion, leveraging AI-driven routing mechanisms in IoT-enabled smart cities optimizes transportation and contributes to overall urban sustainability. These technologies mark a significant step forward in modern urban planning by alleviating congestion, reducing energy consumption, and enabling faster, more reliable movement within cities. Future research should focus on refining these techniques, addressing current limitations, and exploring innovative applications to align with the vision of sustainable, intelligent, and citizen-centered smart cities.

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Data Availability

The data used and analyzed during the current study are available from the corresponding author upon reasonable request.

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