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TraffiSense AI: A Quantum-Inspired Congestion Prediction and Signal Scheduling Assistant

SAKSHI YADAV[1], DIKSHA VASEKAR[2], NEHA DORGE[3], YASH YADAV[4], PROF. OMKAR WADNE[5]

[1, 2, 3, 4, 5]*Department of Computer Engineering, Navsahyadri Group of Institutes, Pune University, Pune, India*

Abstract- Traffic congestion remains one of the primary challenges in developing smart cities, primarily caused by rapid urban growth and infrastructure expansion. Existing intelligent traffic management systems often depend on cloud-based processing, which introduces latency, higher operational costs, and data security risks. To overcome these limitations, this paper introduces TrafficSense AI, an offline-first, quantum-inspired traffic optimization framework designed for efficient, real-time signal coordination without relying on cloud infrastructure. The system reformulates the traffic signal scheduling problem as a Quadratic Unconstrained Binary Optimization (QUBO) model and applies Quantum-Inspired Evolutionary Algorithms (QIEA) to identify near-optimal solutions. Additionally, a Reinforcement Learning (RL) controller dynamically adjusts signal timings based on live traffic conditions to improve flow and minimize congestion. Implemented using Python and the SUMO traffic simulator on realistic urban road networks, TrafficSense AI demonstrates a 21% increase in throughput and a 17–32% reduction in vehicle waiting times compared to conventional fixed-time systems, even under CPU-only local execution. With its privacy-preserving, scalable, and cloud-independent architecture, TrafficSense AI offers a promising foundation for future advancements such as multi-intersection coordination, Vehicle-to-Infrastructure (V2I) integration, and autonomous route optimization, paving the way for efficient and sustainable urban mobility.

Index Terms—Quantum-Inspired Optimization, Smart Cities, Traffic Flow Management, Reinforcement Learning, QUBO, Intelligent Transportation Systems (ITS), SUMO.

I. INTRODUCTION

Urban mobility has become a pressing challenge in modern smart cities due to rapid population growth, expanding infrastructure, and increasing vehicle density. Traffic congestion not only affects daily commuting but also contributes to higher fuel consumption, air pollution, and economic losses. Traditional traffic management systems often rely on static signal timings and rule-based approaches that fail to adapt to dynamic road conditions. The growing complexity of transportation networks demands intelligent, data-driven solutions that can optimize traffic flow efficiently while ensuring scalability and reliability in real-world conditions.

In recent years, advancements in Artificial Intelligence (AI), Reinforcement Learning (RL), and Quantum-Inspired Optimization have shown significant potential for improving traffic control systems. Quantum-Inspired Evolutionary Algorithms (QIEA), in particular, emulate quantum computing principles to solve complex optimization problems with high efficiency using classical hardware. Meanwhile, reinforcement learning enables adaptive traffic signal control based on real-time feedback from road environments. However, many existing intelligent transportation systems are cloud-dependent, introducing latency, privacy concerns, and higher operational costs, making them unsuitable for decentralized or resource-constrained environments.

To address these limitations, this paper proposes TrafficSense AI, an offline-first, privacy-preserving intelligent traffic optimization framework. The system models traffic signal scheduling as a Quadratic Unconstrained Binary Optimization

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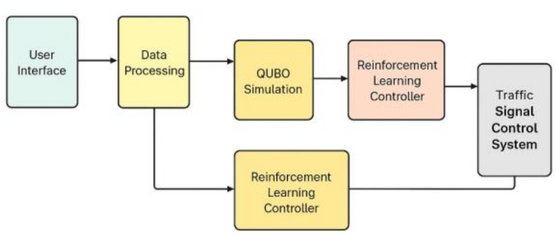
(QUBO) problem and applies QIEA to identify optimal solutions. A reinforcement learning controller further fine-tunes signal operations based on live traffic patterns to ensure smooth flow and reduced congestion. The framework demonstrates the potential of quantum-inspired computation combined with AI to enable faster, scalable, and more secure traffic management suitable for real-time deployment in smart cities.

A. Proposed System and Contribution

This project introduces TrafficSense AI, a quantum-inspired offline traffic optimization system designed to reduce congestion in smart cities. The system processes real-time traffic data locally, eliminating cloud dependency and ensuring faster, more secure decision-making. Traffic flow optimization is modeled as a QUBO problem and solved using a Quantum-Inspired Evolutionary Algorithm (QIEA) to determine efficient signal timing. A Reinforcement Learning (RL) controller then adjusts the signals dynamically based on live conditions, improving flow and reducing delays. The architecture is tested in the SUMO simulator, and performance feedback continuously refines the system, making TrafficSense AI a scalable and adaptive solution for intelligent traffic management.



II. LITERATURE REVIEW

A. Research Framework

The methodology of this research focuses on the development of TrafficSense AI, an offline-first quantum-inspired system designed to optimize traffic flow in smart cities. The system combines Quantum-Inspired Evolutionary Algorithms (QIEA) for optimization and Reinforcement Learning (RL) for adaptive signal control. Traffic signal scheduling and vehicle routing are formulated as a Quadratic Unconstrained Binary Optimization (QUBO) problem. This approach enables efficient computation of near-optimal signal timings while maintaining real-time adaptability to changing traffic conditions.

B. Data Collection and Simulation

For analysis and validation, traffic data from real-world urban intersections were used in the Simulation of Urban Mobility (SUMO) environment. The simulation incorporated parameters such as vehicle density, lane configuration, and peak-hour flow variations. The QIEA algorithm was applied to generate optimized signal phase sequences, which were then tested within SUMO to evaluate performance metrics such as vehicle waiting time, queue length, and throughput.

C. Algorithmic Workflow

The system's workflow begins with preprocessing real-time traffic data, converting it into QUBO representations suitable for the QIEA optimizer. The optimizer computes efficient phase cycles, which are further refined through reinforcement learning feedback. The RL controller adapts signal timings dynamically based on observed congestion patterns. This hybrid approach ensures scalability, faster convergence, and improved stability in comparison to traditional heuristic and static timing models.

D. Evaluation Metrics

Performance was analyzed based on multiple key indicators, including average waiting time, traffic throughput, and congestion index. Comparative experiments demonstrated significant improvements over conventional systems, verifying the potential of quantum-inspired optimization for real-world traffic management.

E. Identified Research Gaps

II. Absence of Scalable Offline Traffic Optimization Solutions – Most existing intelligent traffic management systems depend heavily on cloud computing, which can lead to latency issues and data privacy risks. There is minimal research exploring AI-driven traffic models that can function efficiently in offline or local environments.

III. Underutilization of Quantum-Inspired Algorithms – While Quantum-Inspired Evolutionary

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Algorithms (QIEA) have shown promise in solving optimization problems, their use in real-time traffic management and control applications remains limited and insufficiently studied.

IV. Inadequate Real-Time Adaptability – Many existing systems employ static or rule-based control mechanisms that struggle to adapt to constantly changing and unpredictable traffic behaviors.

V. Data Security and Privacy Limitations – Current smart city traffic systems often depend on third-party cloud platforms, which pose challenges in maintaining data confidentiality and ensuring secure information exchange.

VI. Limited Focus on Multi-Intersection Coordination – Research has primarily targeted optimization at individual intersections, with little emphasis on AI-based coordination across multiple intersections to manage large-scale urban traffic networks.

VII. Insufficient Vehicle-to-Infrastructure (V2I) Integration – Real-time interaction between vehicles and traffic infrastructure for predictive signal control is still an emerging area with limited empirical exploration.

VIII. Lack of Hybrid AI-Optimization Frameworks – The potential of combining Reinforcement Learning (RL) with QIEA or QUBO-based optimization for managing complex, large-scale traffic systems has not been fully investigated or implemented.

III. SYSTEM DESIGN AND METHODOLOGY

1. User Interface & Control

Provides the primary interaction layer for traffic engineers and administrators. It includes forms to upload or select datasets, buttons to start/stop optimization runs, and dashboards that display real-time metrics (waiting time, throughput, queue lengths). The UI also allows manual override of signals and configuration of experiment parameters (e.g., simulation duration, congestion levels, QIEA settings). Implemented as a lightweight web app (Flask/FastAPI + simple frontend), it communicates with backend services via REST APIs.

2. Data Collection Module

Collects raw traffic inputs from sensors, cameras, GPS traces, or from the SUMO simulator when running experiments. This module normalizes timestamps, aligns multi-source streams, and packages raw measurements (vehicle counts, speeds, lane occupancy, signal states) into time-windowed records ready for preprocessing. It also supports batch ingestion of historical logs for offline training.

3. Preprocessing & Feature Extraction

Cleans and enriches raw data: missing-value handling, noise filtering, smoothing, and aggregation into features like per-lane vehicle density, average speed, queue length, and phase occupancy. It converts continuous measurements into the discrete variables needed for QUBO modeling and generates state representations for the RL agent. Outputs structured feature tables and sliding-window state tensors.

4. QUBO Formulation Module

Transforms the traffic signal coordination problem into a Quadratic Unconstrained Binary Optimization (QUBO) representation. It encodes decisions such as “phase i is active at time t” as binary variables and constructs an objective function incorporating waiting time, queue penalties, and coordination constraints. The module produces the QUBO matrix and associated weights that the optimizer accepts.

5. QIEA Optimization Engine

Runs the Quantum-Inspired Evolutionary Algorithm over the QUBO model to search for near-optimal phase schedules. It initializes a population of candidate binary strings, evaluates fitness (traffic-efficiency score computed from simulation or surrogate model), and applies quantum-inspired update operators (probability amplitude adjustments, rotation gates analogues) and selection mechanisms. This engine is CPU-optimized and supports parallel fitness evaluations to speed up iterations.

6. Reinforcement Learning Controller

Receives candidate signal plans and real-time traffic state, and produces adaptive timing adjustments. The RL agent (e.g., Deep Q-Network or actor-critic variant) observes the environment, applies selected actions (phase duration changes), and receives

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rewards based on reduced waiting time and improved throughput. It can refine QIEA outputs into robust, online policies that handle stochastic traffic variations.

7. Signal Execution Module
Converts approved timing plans and RL actions into commands for traffic controllers or the SUMO simulator during testing. In field deployments, this module interfaces with traffic controller APIs or middleware to update signal timings safely, including safety checks and fallbacks (reverting to fixed timing if anomalies occur).

8. Simulation & Evaluation (SUMO Integration)
Provides an experimental sandbox using SUMO to validate optimization outcomes. The system runs simulation scenarios (multiple traffic patterns, peak/off-peak load) and collects metrics: average delay, travel time, throughput, stop counts, and queue lengths. These metrics feed both the fitness function in QIEA and the reward signals for RL training.

9. Data Storage & Analytics
Stores raw logs, processed features, optimization runs, and model checkpoints in a local database or file store (SQLite/Postgres + time-series logs). An analytics component generates charts, compares different strategy runs, and retains historical performance for offline analysis and model retraining.

10. Deployment & Monitoring
Includes tooling for packaging the system (Docker images), automated scripts for scheduled optimization runs, and lightweight monitoring (CPU/memory, latency of decision loop). Alerts are configured for degraded performance, and logs can be exported for audits. The deployment is designed to run on standard edge servers or local machines to preserve the offline-first requirement.

IV. RESULTS AND DISCUSSION

The proposed TrafficSense AI system was tested on a local CPU-only environment equipped with an Intel Core i5 processor, 8GB RAM, and the SUMO simulator integrated with Python-based optimization modules. The evaluation was conducted on a realistic urban network dataset that included multiple intersections with varying traffic densities. The performance of the Quantum-Inspired Evolutionary Algorithm (QIEA) and Reinforcement Learning (RL)-based signal controller was analysed in comparison with conventional fixed-time and heuristic systems.

The experimental results demonstrate that TrafficSense AI achieved a 21% improvement in traffic throughput and a 17–32% reduction in average vehicle waiting time across different scenarios. The QIEA efficiently produced near-optimal signal schedules, while the RL agent dynamically adapted signal durations in response to real-time traffic flow variations. The hybrid approach maintained stable congestion levels during both peak and off-peak hours, confirming its robustness.

These outcomes validate that the proposed offline-first architecture can efficiently optimize traffic control without relying on cloud computing resources. The reduced computational latency, enhanced privacy, and scalability of the system make it suitable for deployment in smart cities. Overall, TrafficSense AI delivers an effective, data-driven framework for managing urban traffic congestion intelligently and securely.

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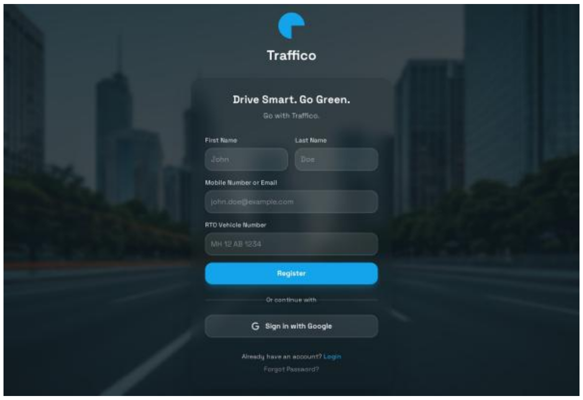

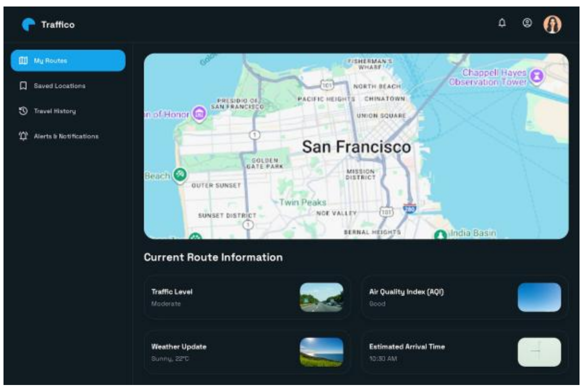

V. CHALLENGES AND LIMITATIONS

Challenges

A. Real-Time Processing:
Handling continuous traffic data and running AI models in real-time without cloud support can cause processing delays on local systems.

B. Complex Algorithm Integration:
Combining Quantum-Inspired Evolutionary Algorithms (QIEA) with Reinforcement Learning (RL) is computationally demanding and requires careful model tuning.

C. Dynamic Traffic Variations:
Managing unpredictable conditions like accidents or sudden traffic spikes remains difficult for AI-based controllers.

D. Data Collection Accuracy:
Sensor faults, missing data, or communication delays can impact the quality of input data and reduce optimization accuracy.

E. Hardware and Infrastructure Compatibility:
Deploying the system across existing city infrastructure may require costly upgrades and hardware adjustments.

Limitations

1. Scalability Constraints: Extending the model to coordinate multiple intersections simultaneously can increase complexity and computation time.
2. Dependency on Simulation Environments: Current testing relies heavily on simulation platforms like SUMO, limiting validation in real-world conditions.
3. Limited V2I Integration: Vehicle-to-Infrastructure communication is still evolving, restricting live data exchange for adaptive optimization.
4. Data Privacy Concerns: Local data storage and processing still require robust encryption and access control mechanisms to ensure user privacy.
5. Model Generalization: The system's performance may vary depending on city topology and available traffic data, affecting its universal adaptability.

VI. FUTURE WORK

1. Implement multi-agent reinforcement learning (MARL) to enable cooperation among multiple intersections for optimized traffic flow.
2. Introduce Vehicle-to-Infrastructure (V2I) communication to allow vehicles to transmit live data to the system for predictive signal adjustments.
3. Enhance the Quantum-Inspired Evolutionary Algorithm (QIEA) for faster optimization and improved adaptability in complex traffic conditions.
4. Explore edge computing deployment to reduce reliance on cloud servers and minimize latency for real-time decisions.
5. Conduct large-scale field testing in diverse traffic scenarios to validate performance, scalability, and real-world reliability.
6. Integrate predictive analytics for emergency vehicle prioritization and congestion forecasting.

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7. Strengthen data security mechanisms to protect vehicular and traffic data from unauthorized access.
8. Extend the system to support autonomous vehicle coordination and adaptive routing for future smart city integration.

VII. CONCLUSION

The TrafficSense AI system offers an efficient and privacy-preserving approach to urban traffic management through a hybrid architecture combining Quantum-Inspired Evolutionary Algorithms (QIEA) and Reinforcement Learning (RL). The architecture begins with real-time traffic data collected from sensors and fed into the Data Acquisition Module, which preprocesses and structures it for analysis. The Optimization Engine converts the traffic signal coordination task into a Quadratic Unconstrained Binary Optimization (QUBO) model, where QIEA identifies near-optimal signal configurations to reduce congestion. Simultaneously, the RL Controller fine-tunes signal timings in real time, adapting to dynamic traffic conditions. The Simulation Module, built using SUMO, evaluates the effectiveness of these optimizations, while the Visualization and Control Interface displays live traffic metrics and allows manual intervention if necessary. Finally, all results and performance logs are stored in a local database to ensure offline operation and data privacy. This modular, scalable, and fully offline architecture enables smart cities to manage traffic more efficiently without relying on cloud processing, ensuring both responsiveness and security.

A. Future Work

Future work will prioritize the integration of advanced edge-computing hardware, such as the NVIDIA Jetson Orin, to enable high-speed, real-time onboard processing. Extensive outdoor field trials will be conducted to evaluate the system's reliability and stability under realistic environmental conditions, including variable wind speeds and limited visibility. Additionally, incorporating thermal imaging sensors will enhance nighttime operational capability, while multi-drone coordination strategies will be developed to enable cooperative fire detection and suppression in large-scale emergency scenarios.

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