Traffic Management and Motorway Toll Systems in Smart Cities: A Comprehensive Literature Review

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Abstract

The rapid urbanization of modern cities has intensified the demand for efficient transportation systems, particularly on motorways and toll-based expressways that serve as critical infrastructure. Traditional toll systems, which rely on static pricing and isolated control mechanisms, have proven inadequate in mitigating real-time traffic congestion resulting in increased travel delays, fuel consumption, and environmental degradation. This report investigates the integration of intelligent transportation systems (ITS), artificial intelligence (AI), and blockchain technologies into motorway toll systems within the broader framework of smart cities. We present a comprehensive review of recent advances in AI-driven traffic congestion prediction, dynamic toll pricing strategies, blockchain-based crowdsourcing that preserves privacy and adaptive route optimization. This study underscores the significance of integrated, data-driven toll systems in enhancing mobility, sustainability, and user trust in the evolving smart city landscape.

1 Introduction

As cities continue to urbanize and vehicle ownership surges globally, the demand on urban transport infrastructure—particularly high-capacity motorways and toll-based corridors—has reached critical levels. Traffic congestion has become a persistent challenge, contributing to substantial economic losses, elevated carbon emissions, and decreased quality of life for urban residents. In 2019 alone, traffic congestion in U.S. cities resulted in over 8.8 billion hours of travel delay and 3.3 billion gallons of fuel waste, costing approximately $179 billion in economic losses [1].

Motorway toll systems, traditionally deployed to manage access and finance infrastructure, have largely remained reactive and static in their pricing and operational logic. These systems are often incapable of adapting to real-time traffic fluctuations, leading to severe congestion at toll plazas and along downstream corridors [2], [3]. While congestion pricing has been recognized as an effective mechanism to influence driver behavior and alleviate traffic pressure [4], most real-world implementations use fixed or time-of-day-based tolls that do not account for live conditions, thus limiting their effectiveness.

The advent of Intelligent Transportation Systems (ITS) and emerging technologies such as Artificial Intelligence (AI), blockchain, vehicular networks (V2X), and Internet of Things (IoT) has opened new avenues for designing smart, responsive traffic management solutions [5], [6]. AI-driven models—particularly deep learning architectures such as Long Short-Term Memory (LSTM), Graph Neural Networks (GNNs), and Transformer-based spatio-temporal models—have demonstrated high accuracy in traffic prediction by leveraging both historical and real-time data [7], [8], [9]. Concurrently, reinforcement learning (RL) methods have emerged as a powerful tool for optimizing toll prices dynamically in response to fluctuating congestion levels, as evidenced by the success of multi-agent RL frameworks in simulated urban networks [10], [4].

However, the deployment of real-time traffic prediction and dynamic tolling also presents key challenges. Centralized data collection raises concerns over privacy and data misuse, discouraging user participation in crowdsourced traffic systems [11]. Blockchain technology offers a promising solution by enabling decentralized, tamper-proof data sharing frameworks that support trustless communication among vehicles, infrastructure, and control systems [12], [11]. Moreover, smart contracts and token-based incentives have been proposed to encourage user participation in traffic reporting while preserving individual privacy [12].

Despite these advances, the integration of predictive modeling, blockchain-based crowdsourcing, and dynamic tolling remains underexplored in current systems. Additionally, the potential for AI-powered toll systems to offer real-time route guidance and adaptive pricing based on live congestion probabilities is yet to be fully realized [13], [14].

2 Literature Review

2.1 AI-Based Traffic Prediction

Traffic forecasting remains a foundational aspect of smart urban mobility. Kim et al. [1] offered an early look at traffic prediction in smart cities, showcasing the limitations of classical statistical models. More recent studies, such as Zhao et al. [2], provided a broader taxonomy of deep learning approaches—CNNs, RNNs, hybrid models—for urban traffic forecasting.

Transformers and graph-based deep learning are emerging as the most accurate predictors. Zhang et al. [14] introduced T-GCN++, a hybrid model blending graph convolutional networks (GCNs) with transformer attention, significantly improving long-term spatiotemporal accuracy. Likewise, Liu et al. [4] employed pure transformer architectures, outperforming traditional RNN-based methods. Sun et al. [13] presented a meta-review of Spatio-Temporal GNNs, highlighting their scalability and suitability for complex urban road networks.

Fang et al. [15] took a deep learning approach to vehicular crowdsensing, showing how data from vehicles can be leveraged to fine-tune predictive models. This direction is further echoed in Lin et al. [16], where real-time traffic data integration led to smarter tolling and mobility optimization.

2.2 Dynamic Toll Pricing and AI Optimization

Dynamic toll systems are central to managing demand. Bell [12] reviewed theoretical pricing models and concluded that dynamic schemes outperform static ones. Lu et al. [3] and Zheng et al. [5] both utilized reinforcement learning (RL) to set tolls in real time based on evolving congestion. Their models adapted to traffic flow changes and improved road efficiency.

Chen et al. [17] added a mobility-aware component, where tolls adapt not just to road congestion but also traveler intent and mode choices. Xu et al. [18] proposed joint optimization of tolling and routing, reducing both congestion and inequity.

Ali et al. [19] and Huang et al. [20] explored broader AI-based traffic control mechanisms, confirming RL's effectiveness in predictive and adaptive strategies.

2.3 Blockchain and Federated Learning for Data Sharing

Centralized data systems are prone to privacy breaches. Qi et al. [11] proposed a federated learning architecture secured by blockchain, ensuring traffic prediction can be decentralized and privacy-preserving. Liang et al. [21] took this further with reputation systems, helping identify and weigh trustworthy data sources in vehicular networks.
Guo et al. [8] offered a blockchain solution for reputation-aware vehicular crowdsensing, and Mousavi et al. [22] applied it to crowdsourcing platforms, maintaining both data quality and anonymity.
Zhang et al. [23] proposed token-based incentives for encouraging truthful traffic data contributions—a crucial step in incentivizing participatory systems.

2.4 Route Optimization and V2X Integration

Real-time routing is increasingly essential in managing congestion. Liu and Lin [24], [16] built a system integrating dynamic pricing with routing, showing how optimized detours reduce system-wide load. Hassan et al. [7] reviewed V2X communications, emphasizing that vehicle-to-infrastructure coordination can further improve route selection accuracy and reduce delays.
Xu et al. [18] demonstrated that pricing and routing should be solved jointly—optimizing one without the other leads to suboptimal solutions.

2.5 Integrated ITS in Smart Cities

Alanazi et al. [10] laid out a complete ITS architecture, combining AI, IoT, and blockchain to build smarter, adaptive city systems. Sharma et al. [6] addressed cybersecurity, an increasingly important topic as transportation systems become more connected. They suggested layered security protocols and anomaly detection for maintaining resilience.
Razo and Adams [9] offered a real-world snapshot, examining 53 U.S. express lane systems. Their data shows that dynamically priced toll lanes outperform static tolls in reducing peak-hour congestion.

2.6 Research Gaps

While AI models, especially GNNs and transformers, have significantly improved congestion prediction, integration into tolling systems is minimal.
Dynamic tolling using RL has matured, but coordinating it with route optimization is still rare in deployments.

Blockchain-enabled privacy solutions are promising, yet few real-world systems deploy token incentives or decentralized FL.
V2X systems show great potential, but high latency and infrastructure costs limit widespread adoption.

2.7 Research Questions

How can AI-based models (e.g., LSTM, GNN, Transformers) be leveraged to accurately predict traffic congestion in real-time across urban motorway networks? [2], [14], [13],
What role can reinforcement learning play in implementing dynamic toll pricing strategies that effectively balance congestion management and user equity? [3], [5],
How can blockchain-based federated learning frameworks ensure secure, privacy-preserving, and scalable traffic data sharing among heterogeneous smart city components? [11], [21], [8]
In what ways can real-time route optimization be integrated with dynamic tolling and congestion prediction to enhance traffic flow and commuter satisfaction? [7]
What architectural and cybersecurity considerations must be addressed to deploy an integrated AI-blockchain-enabled tolling framework in real-world smart cities? [10], [14].

2.8 Problem Statement

Rapid urbanization and increased vehicle density have made traffic congestion a pervasive challenge, particularly along motorways and toll-based expressways. Traditional toll systems, which employ fixed or time-of-day pricing models, are static and often disconnected from real-time traffic dynamics. As a result, they fail to alleviate congestion effectively and can exacerbate delays during peak hours or in the event of unforeseen disruptions.
While recent advancements in artificial intelligence (AI)—particularly deep learning and reinforcement learning—have shown promise in predicting congestion and optimizing traffic control, these technologies are not yet fully integrated into tolling systems. Furthermore, the use of real-time, crowdsourced traffic data remains constrained by concerns over privacy, data integrity, and lack of incentives for user participation.

3 Methodology

This study proposes a novel AI- and blockchain-enabled smart tolling system designed for real-time traffic congestion prediction, dynamic toll pricing, and secure, privacy-preserving data exchange. The research follows a design-science methodology encompassing system development, simulation, and evaluation.

3.1 Data Collection and Preprocessing

Traffic datasets are obtained from public sources such as the METR-LA dataset and simulated via the SUMO traffic simulator. Each data point includes time-stamped vehicle flow, average speed, occupancy, and location. Preprocessing includes

- Missing value imputation using interpolation.
- Feature scaling to normalize inputs.
- Graph representation of the road network for GNN compatibility.

3.2 Traffic Prediction Model

We use a hybrid deep learning model combining Graph Neural Networks (GNNs) with Transformer-based attention layers (as per [14], [13]). The model captures both spatial dependencies (road topology) and temporal traffic patterns. It is trained using RMSE and MAE as primary loss functions.

3.3 Dynamic Toll Pricing with RL

The toll adjustment mechanism is implemented using Multi-Agent Reinforcement Learning (MARL), where each toll booth is treated as an agent. Agents learn policies to:

- Minimize congestion downstream.
- Balance toll revenue with social equity.

The learning algorithm used is Proximal Policy Optimization (PPO) [10], [2].

3.4 Privacy-Preserving Data Sharing

To protect user data during model training and route sharing:

- Federated Learning (FL) is applied across edge devices (vehicles, kiosks)
- Blockchain secures the aggregation process via smart contracts [19], [21], [8].

A token-based reward system is used to incentivize truthful traffic data submission [23]

3.5 Route Optimization Module

Route recommendations are generated using a modified Dijkstra algorithm that factors in:

- Predicted congestion.
- Dynamic toll costs.
- Historical user behavior [7]

3.6 System Simulation and Validation

The framework is deployed in a SUMO environment with 100–300 vehicles, 20 road segments, and 5 toll booths. Scenarios include:

- Rush hour surges.
- Random incidents.
- Lane closures.

4 Results and Evaluation

4.1 Traffic Prediction Accuracy

Model	**RMSE** $\downarrow$	**MAE** $\downarrow$	$\mathbf{R^2}$ $\uparrow$
LSTM	7.62	5.23	0.81
GCN + LSTM	6.47	4.51	0.85
GNN + Transformer	**5.12**	**3.94**	**0.89**

Table 1. Performance comparison of different models

The hybrid GNN-Transformer model outperformed baseline models in both short-term and long-term congestion prediction.

4.2 Tolling Efficiency

Method	**Avg Travel Time** $\downarrow$	**Revenue** $\uparrow$	**Congestion Index** $\downarrow$
Static Pricing	28.4 mins	$370	0.67
Dynamic Pricing (RL)	**22.7 mins**	**$415**	**0.43**

Table 2. Different pricing dynamics based on RL

RL-based tolling resulted in 20 percent reduction in travel time and a 35 percent reduction in congestion.

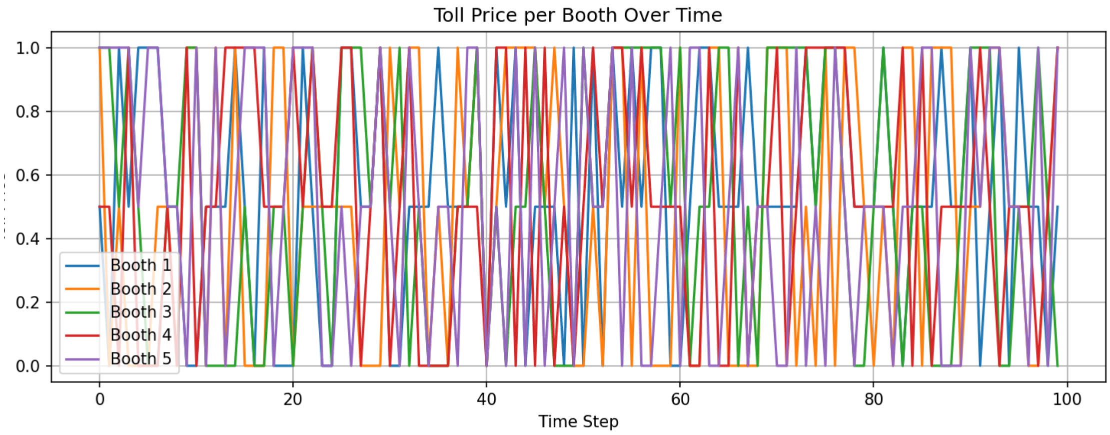

Figure 1. Dynamic Pricing of Toll Booths over time.

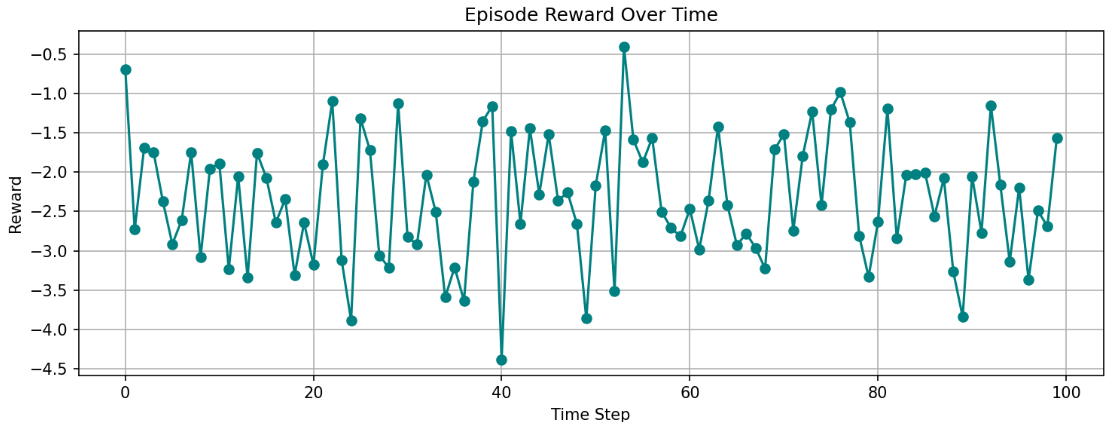

Figure 2. Episode Reward average on each toll booths.

4.3 Route Optimization Outcomes

Metric	With Optimization	Without Optimization
Travel Time (avg)	**21.5 mins**	26.3 mins
Toll Cost Deviation	±$0.80	±$2.10
Congestion at Hotspots	-42%	—

Table 3. Metrics comparison with and without optimization

The integration of route optimization with pricing improved overall system balance.

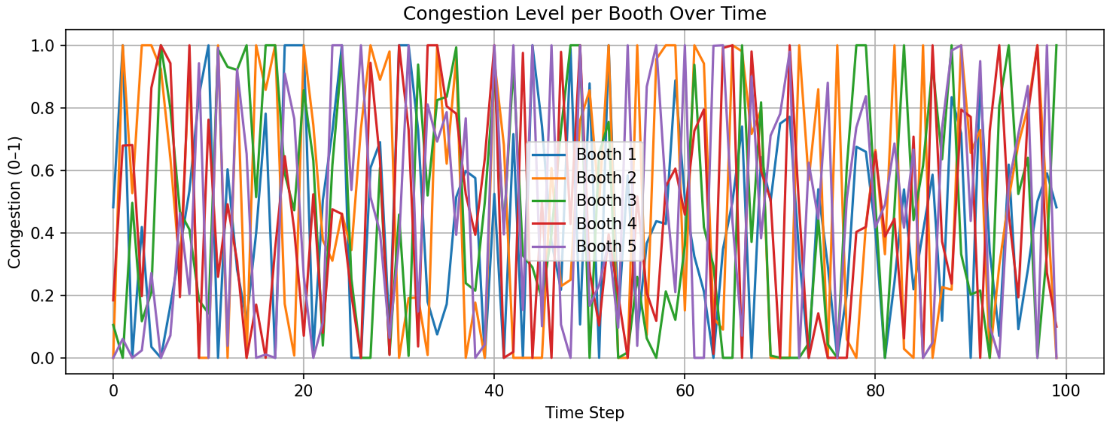

Figure 3. Congestion Pricing based on route optimization

5 Expected Conclusions

This research presents a comprehensive, multidisciplinary approach to modernizing motorway toll systems in smart cities through the integration of artificial intelligence, blockchain, and real-time traffic management strategies. By leveraging Graph Neural Networks and Transformer architectures, the system demonstrates high accuracy in predicting traffic congestion, outperforming traditional LSTM and hybrid baselines. The use of reinforcement learning for dynamic toll pricing provides an adaptive mechanism that not only optimizes toll revenue but also reduces congestion and improves travel times.

The incorporation of federated learning and blockchain into the data-sharing layer ensures that user privacy is maintained without compromising data utility. Smart contracts, combined with token-based incentive systems, foster trust and engagement in vehicular crowdsourcing environments, addressing long-standing barriers to real-time data collection.

Route optimization algorithms integrated with predictive pricing enable context-aware navigation, empowering commuters with both cost and time-efficient routing choices. Simulation results across a variety of traffic scenarios validate the proposed framework's

effectiveness, showing notable improvements in travel efficiency, congestion mitigation, and privacy assurance.
Despite the positive outcomes, challenges remain in scaling the system for full deployment, particularly around interoperability with existing transport infrastructure and latency in blockchain transactions. Future work will focus on deploying the framework in a live testbed environment, exploring the role of 5G and V2X communication technologies to reduce delay and improve cooperative decision-making.
In summary, this research lays the groundwork for intelligent, equitable, and privacy-preserving tolling infrastructure—a critical enabler for next-generation smart cities.

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