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# Algorithmic Congestion Pricing in Smart Cities: Adapting Ethereum’s EIP-1559 Mechanism for Dynamic Urban Traffic Management

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***Abstract*— This paper aims to examine the possibility of using blockchain resource allocation mechanisms in controlling urban road traffic congestion. In modern Intelligent Transport Systems (ITS) systems, there exists a problem of resource scarcity, where existing fixed price and first-price auction methods have demonstrated inefficiencies due to high price variability and lack of predictability. A new algorithmic framework for urban road traffic congestion pricing is proposed, inspired by the Ethereum EIP-1559 protocol. A digital twin of road capacity is created as a block space on a blockchain network, with a base fee adjustment mechanism designed to support a target utilization. A normalization process using median demand values and a price stability mechanism, referred to as Price Freeze, is incorporated for urban logistics applications. Simulation results using historical Ethereum values show that the modified algorithm maintains a stable traffic flow despite high fluctuations in traffic demand, resulting in a state of “bounded instability.”**

**Keywords— Algorithmic Congestion Pricing, Blockchain, Urban Logistics, Intelligent Transport Systems (ITS)**

## I. INTRODUCTION

### *A. Study Background*

Modern infrastructure management systems—encompassing both physical and digital assets—are characterized by the fundamental problem of resource scarcity. In the context of urban logistics, these resources include, for example, finite road capacity (Wardrop, 1954) and the associated implementation of restricted access zones. Similarly, within the blockchain ecosystem, this scarcity is manifested as limited block space (Min et al., 2016).

Traditionally, blockchain networks utilized first-price auctions, which exhibited significant inefficiencies compared to alternative substitution mechanisms. The primary challenges included extreme price volatility coupled with often unpredictable transaction fees (Matheus et al., 2021), substantial intra-block disparities (Leonardos et al., 2025), and vulnerability to external attacks (Landis and Schwartzbach, 2023). In the context of urban logistics and access management, no such bidding mechanism exists; instead, residents simply decide whether to pay or forgo the entry fee for city centers (Cipriani et al., 2019) or parking charges (Inci, 2015). This approach generates issues analogous to those found in blockchain networks. However, it should be noted that urban logistics typically does not suffer from price volatility or transaction fee unpredictability, as these costs are generally fixed and disclosed in advance (e.g., flat rates for entry or hourly parking). Nevertheless, the static nature of these rates significantly exacerbates another problem -network congestion characterized by an uneven distribution of flows over time, which peak during rush hours and diminish during off-peak periods (De Palma et al., 1983). Furthermore, in urban logistics systems governing area accessibility, the issue of external attacks is either non-existent or exceedingly rare, rendering it negligible for the purpose of this analysis.

The implementation of alternative mechanisms allows for the mitigation of these issues within blockchain networks by decoupling revenue from block size constraints and ensuring resilience against validator manipulation (Lavi et al., 2022). For instance, dynamic posted-price mechanisms facilitate demand satisfaction while maintaining price stability (Matheus et al., 2021). Similarly, the EIP-1559 protocol significantly reduces price volatility and enhances user experience through the continuous and dynamic adjustment of the base fee; consequently, the deviation of actual block size from the target size has decreased to approximately 1% (Leonardos et al., 2025). A comparable mechanism could be utilized in urban

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logistics to optimize resource allocation. This approach is particularly compelling as the Ethereum network could serve as a digital twin of urban infrastructure.

It must be noted, however, that the implementation of the discussed mechanisms in blockchain networks does not simultaneously satisfy all desired properties, namely dominant-strategy incentive compatibility (DSIC), miner incentive compatibility (MIC), and collusion resistance (Roughgarden, 2024). In the context of urban logistics, this does not pose a significant challenge, as issues related to external attacks and validator manipulation are virtually non-existent. Consequently, one can seamlessly adopt a core element of these models: the dynamic adjustment of a base fee relative to network load. In the field of traffic engineering, this allows for road capacity to be treated as a specific resource aimed at achieving optimal utilization; in such a framework, prices only begin to rise once a predefined threshold of transportation system efficiency is exceeded. The adaptation of algorithms derived from the Ethereum network theoretically enables the creation of a stable transport environment that automatically responds to capacity breaches, thereby preempting the development of traffic congestion.

### *B. Algorithmic dynamic pricing mechanisms for urban infrastructure and congestion management*

First and foremost, it should be noted that the implementation of dynamic pricing mechanisms consistently enables the reduction of urban traffic congestion, particularly when compared to fixed-pricing strategies. The scale of potential improvement varies depending on the context; studies on traditional road networks have observed delay reductions ranging from 8.4% to 50% (Pandey et al., 2020). The most significant effects, however, were achieved in mobility-on-demand systems, where queue lengths were shortened by up to 200-fold (Turan et al., 2020). Furthermore, emphasis should be placed on approaches based on machine learning—specifically deep reinforcement learning and the application of neural networks—which allow for substantially greater improvements than traditional optimization methods (Liu et al., 2022). Nevertheless, the effectiveness of these methods depends primarily on the degree to which the algorithm is calibrated to the complexity of the optimized network and the prevailing demand dynamics (Aboudina et al., 2016).

A prerequisite for the implementation of dynamic pricing mechanisms is a sophisticated technological infrastructure, specifically concerning IoT sensors, real-time data transmission systems, and frameworks capable of high-frequency price adjustments. Furthermore, it should be emphasized that the primary constraints on the scalability of these systems are the quality of the collected data and the available computational power (Gosipathala, 2025).

It is also noteworthy that geographic demand patterns significantly influence the optimal pricing structure. Networks characterized by spatially dispersed demand yield the greatest benefits from price differentiation, as they allow for the specific targeting of zones experiencing congestion—an approach that is unattainable under a uniform pricing model (Torrico et al., 2024).

It should also be noted that several key mediating factors significantly influence the effectiveness of these solutions—most notably the behavioral response of users to the implemented pricing algorithm and, consequently, its public acceptance and specific network characteristics. Furthermore, issues of social equity are paramount; dynamic pricing may lead to perceived injustices and further social segmentation, particularly impacting low-income users. In this context, however, it is worth highlighting that spatial price differentiation (area-based pricing) can facilitate a higher level of social welfare across all demographic groups residing within a given area (Torrico et al., 2024).

Studies have demonstrated significant variation in congestion indices and the magnitude of improvement when implementing dynamic price adjustments relative to fixed pricing. Among the most frequently measured performance metrics were the reduction in supply time, the mitigation of delays, shifts in traffic volume, and the overall lowering of congestion indices (Table 1).

TABLE 1. EFFECTS OF DYNAMIC PRICING ON CONGESTION LEVELS

| Study | Primary congestion metric |
|---|---|
| Triantafyllos et al., 2019 | Traffic delay time, NOx emissions |
| Rodríguez et al., 2022 | Average queuing, fuel consumption, delay time, travel time |
| Turan et al., 2020 | Queue lengths |
| Gosipathala et al., 2025 | Average travel time, throughput |
| Sabarshad et al., 2021 | Average delay, waiting costs |
| Liu et al., 2023 | Total travel time |
| Pandey et al., 2020 | Total system travel time |
| Peyravi et al., 2025 | Congestion, waiting time, peak load demand |
| Genser et al., 2021 | Total time spent |
| Solé-Ribalta et al., 2016 | Median congestion level, travel times |
| Source: own elaboration based on provided studies | |

In summary, the implementation of dynamic pricing mechanisms demonstrates clear positive effects regarding the reduction of network-wide congestion. Nevertheless, the direct translation of theoretical and often highly complex algorithms into the urban fabric is primarily constrained by the level of infrastructural development, concerns regarding user privacy, and the necessity of achieving broad social acceptance (Zoeter et al., 2014).

### *C. Technical Architectures and Performance Trade-offs in Blockchain-Enabled Intelligent Transport Systems*

Dynamic price adaptation mechanisms tailored to fluctuating demand levels—implemented within Intelligent Transportation Systems (ITS) and underpinned by blockchain technology—exhibit significant technical heterogeneity, which is directly correlated with the specific requirements of various applications. The requisite computational architecture can range from minimal throughput requirements (Knirsch et al., 2018) to the necessity of high-performance configurations, frequently utilizing Graphics Processing Units (GPUs) (Shukla et al., 2020). Consequently, network connectivity specifications span from basic low-bandwidth protocols (250 kbps) to 5G networks for applications requiring ultra-low latency (Tanwar et al., 2022).

Dynamic price adaptation mechanisms—tailored to fluctuating demand levels, implemented within Intelligent Transportation Systems (ITS), and underpinned by blockchain technology—exhibit significant technical heterogeneity. This diversity is directly correlated with the specific requirements of various applications. The requisite computational architecture may range from minimal throughput requirements (Knirsch et al., 2018) to the necessity of high-performance configurations, frequently utilizing Graphics Processing Units (GPUs) (Shukla et al., 2020). Consequently, network connectivity specifications span from basic low-bandwidth protocols (250 kbps) to 5G networks for applications requiring ultra-low latency (Tanwar et al., 2022).

It should also be emphasized that the selection of a specific platform type determines the performance of a given solution; private blockchains achieve significantly higher throughput—measured in transactions per second (TPS) (Liang, 2025)—than public networks, which frequently contend with substantial scalability constraints and network congestion (Bhangale et al., 2025). Regarding the consensus mechanism, implementations range from Proof-of-Stake (PoS) (Liang, 2025), which prioritizes energy efficiency, to advanced specialized solutions such as PhDPoR. The latter is specifically optimized for vehicular networks by integrating a Practical Byzantine Fault Tolerance (PBFT) algorithm with a hierarchical delegated Proof-of-Reputation (Shen et al., 2026).

Notably, Proof-of-Work (PoW) mechanisms are excluded from Intelligent Transportation Systems (ITS) implementations due to their excessive energy consumption. Furthermore, the data storage infrastructure typically combines on-chain and off-chain components (the latter utilizing the InterPlanetary File System (IPFS)), enabling a strategic balance between transparency and scalability (Shukla et al., 2020).

The utilization of blockchain-based solutions also presents significant implementation challenges, which are primarily contingent upon the specific application context. For instance, electronic toll collection (ETC) solutions require ultra-low latency—often below 50 ms (Shukla et al., 2020)—whereas electric vehicle (EV) charging systems can effectively operate with longer confirmation times of up to 15 seconds (Farhoumandi et al., 2025). To address scalability constraints, strategies based on off-chain storage integration may be employed, facilitating up to a 90% reduction in latency during the consensus process (Vishwakarma & Das, 2022). Another approach involves the deployment of dedicated consensus protocols, which can reduce processing times to less than 1.5% of the baseline value (Li et al., 2023).

Regarding the preservation of user privacy within the network, these mechanisms encompass techniques based on zero-knowledge proofs (Fiege et al., 1987) and oblivious transfer protocols (Kong et al., 2021). The implementation of such methods enables the achievement of the required level of anonymity within a given network environment (Bhangale et al., 2025).

In the implementation of blockchain-based solutions, potential integration challenges may include infrastructure compatibility issues (necessitating hardware modernization), regulatory barriers, and low levels of user acceptance (Bhangale et al., 2025). Successful deployment must be predicated on flexibility; rather than adopting a "one-size-fits-all" approach, solutions must be precisely tailored to specific operational requirements.

Given the aforementioned requirements and constraints, the application of blockchain technology within Intelligent Transportation Systems (ITS) may encompass, inter alia:

- autonomous driving (Ramnekk, Pack, 2022; Olivier et al., , 2025),
- data trading in IoV (Liu et al., 2019) and spectrum sharing in IoV (Shen et al., 2026),
- digital Twin services for ITS (Siyi et al., 2022),
- EV charging (Li et al., 2023; Knirsch et al., 2018; Pustišek et al., 2016; Farhoumandi et al., 2025; Kakkar et al., 2022b; Kakkar et al., 2024;Tanwar et al., 2022;Pan et al., 2025;Amamra, 2025),
- Mobility as a Service (MaaS) (Kong et al., 2021),
- parking (Reebadiya et al., 2021; Kakkar et al., 2022a),
- task offloading for smart transportation (Liang, 2025),
- Tolling system (Shukla et al., 2020; Babloee et al., 2019; Gao, Zhang, 2025),
- traffic management (Bhangale et al., 2025; Vishwakarma, Das, 2022) and trafffic monitoring (Guo et al., 2022),
- usage-based insurance (Lin et al., 2023).

This article proposes an adaptation of the EIP-1559 algorithm, which represents a natural progression in the evolution of dynamic pricing mechanisms. This model integrates operational transparency with the automated maintenance of price stability through a base fee mechanism. Notably, it leverages the target utilization principle—inherent to the Ethereum protocol—thereby transposing digital resource management onto the physical constraints of urban infrastructure. By implementing this framework via Layer-2 solutions or specialized consortium blockchains, EIP-1559 can function as an urban digital twin. Consequently, it mitigates the inefficiencies associated with traditional first-price auctions while ensuring the predictability essential to modern urban logistics. Furthermore, this approach not only systematizes pricing structures but also provides municipal authorities with a highly adaptive tool that is better aligned with user requirements.

## II. The Model

### A. *Ethereum as a Digital Twin*

Ethereum represents a highly viable research and experimental testing ground for solutions dedicated to urban logistics. Despite being seemingly disparate domains, numerous points of convergence exist between them; following appropriate modifications, these intersections can be leveraged to develop a digital twin of the transportation network.

In urban transportation, when addressing infrastructure occupancy, the scarce resource is road capacity—defined as the maximum number of vehicles a given roadway can accommodate. Similarly, within the Ethereum network, the scarce resource is the available block space. When network traffic becomes excessive, urban environments experience traffic congestion, whereas the Ethereum network sees an accumulation of pending transactions in the mempool. Table 2 presents the systemic characteristics that validate the feasibility of utilizing the Ethereum network as a digital twin of the urban transportation grid.

TABLE 2. ETHEREUM AS A DIGITAL TWIN OF THE URBAN NETWORK

| | Transportation System | Blockchain System | Common Denominator |
|---|---|---|---|
| Scarce Resource | Road capacity | Block space (gas limit) | Inelastic supply |
| Unit of Measurement | PCE (Passenger Car Equivalent) | Gas used | Demand heterogeneity |
| Waiting Buffer | Traffic congestion (jams) | Mempool | External cost |
| Regulation Mechanism | Proposed model (dynamic pricing) | EIP-1559 | Negative feedback loop |
| Prioritization | None (FIFO) | Auction | Utility-based allocation |
| Source: own elaboration based on provided studies | | | |

The model proposed in this study leverages identified analogies between transportation systems and the Ethereum blockchain ecosystem. The model introduced in the following subsection adapts the EIP-1559 mechanism—an algorithm that automatically prices this scarce resource by utilizing a negative feedback loop to stabilize traffic flow.

### B. *Model Specification*

1) Variable Definitions

The following key variables are defined within the proposed model:

- Qmax – the maximum physical capacity of the infrastructure (number of vehicles per unit of time); the blockchain equivalent is the Block Gas Limit.
- Qtarget – the target traffic flow ensuring the assumed level of fluidity; the blockchain equivalent is the Target Block Size.
- Qspot – the measured, real-time traffic volume at time ; the blockchain equivalent is the current number of transactions awaiting validation (mempool).
- Φ – the utilization coefficient, representing the targeted capacity threshold to be achieved on a given network (expressed as a percentage of maximum capacity); the blockchain equivalent is the maximum block occupancy.
- PCE – Passenger Car Equivalent; the unit of measure for road occupancy (different vehicle classes impact capacity to varying degrees; e.g., passenger vehicles have a smaller impact than heavy goods vehicles); the blockchain equivalent is the transaction weight encoded within a given block.

These defined variables allow for the adaptation of the EIP-1559 algorithm to the requirements of urban traffic control

2) Noise Filtration

One of the problems that must be resolved within the urban network is the issue of noise. For example, a temporary stop at a red light could be misinterpreted by the algorithm, which could consequently result in an abrupt price change:

$$Q_{smooth,t} = \alpha \times Q_{spot,t} + (1 - \alpha) \times Q_{smooth,t-1}$$

Where:
Qsmooth,t – smoothed demand value at time,
Qspot,t – raw reading at time ,
Qsmooth,t-1 – smoothed value from the previous period,
α – smoothing factor.

The proposed noise filtration based on the Exponential Moving Average (EMA) allows the system to ignore momentary fluctuations in traffic and react to real and persistent congestion trends.

3) Base Price

The foundation of the proposed model is the adaptation of the EIP-1559 algorithm for the purposes of urban traffic control. The price in the subsequent period depends on the extent to which the current traffic deviates from the assumed target (Qtarget):

$$Q_{target} = \Phi \times Q_{max}$$

$$P_{base,t} = P_{base,t-1} \times \left(1 + \delta \times \frac{Q_{smooth,t} - Q_{target}}{Q_{target}}\right)$$

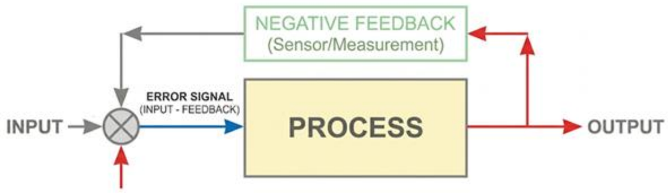
Where:
Pbase,t – new base fee per unit of time spent in the zone,
Pbase,t-1 – fee applicable in the previous period,
Qsmooth,t – current, smoothed road load,
Qtarget – desired road load (optimum),
δ – elasticity coefficient.

If the traffic exceeds the assumed target, the value of the fraction in the parentheses is positive and the price increases; conversely, if the traffic is lower—the price decreases. The delta parameter determines the sensitivity of the system, thereby achieving a "thermostat" effect—it allows for the "cooling" of demand when the entire system overheats, i.e., in situations where demand reaches the assumed target (limit).

4) Negative Feedback

The entire model operates on the principle of a negative feedback loop, as illustrated in Figure 1.

FIGURE 1. NEGATIVE FEEDBACK LOOP




Source: own elaboration

This relationship can also be represented mathematically. When traffic congestion occurs, the price increases exponentially:

$$\frac{Q_{smooth} - Q_{target}}{Q_{target}} > 0$$

Conversely, when traffic congestion does not occur, the price decreases exponentially:

$$\frac{Q_{smooth} - Q_{target}}{Q_{target}} < 0$$

The system therefore strives for equilibrium at the Qtarget point. The price serves solely as a tool to achieve this capacity objective.

5) Price Guarantee

It should also be noted that, in contrast to financial exchanges, urban logistics requires budgetary predictability. Consequently, a price guarantee has been introduced to the model:

$$TC_i = PCE_i \times P_{base,t-entry} \times T_{duration}$$

where:

TCi – total entry cost for vehicle,

PCEi – passenger car equivalent (road load conversion unit),

Pbase,t-entry – market price "frozen" at the moment of entering the zone at time,

Tduration – duration of stay within the zone.

This approach allows the system to freeze the rate at the moment of entry into the zone. Even if traffic congestion subsequently develops and the market price increases, a vehicle already inside the zone pays the original rate. Such a guarantee is crucial for the social acceptance of the proposed model.

### C. Model Adaptation

1) Data Source

The presented model has been empirically verified. Data from the Ethereum network was utilized, which serves as an experimental testing ground where millions of entities bid for access to a limited resource: block space. The characteristics of the data source are presented in Table 3.

TABLE 3. CHARACTERISTICS OF THE EXPERIMENTAL DATA SOURCE

| | |
|---|---|
| Source | Ethereum public ledger (indexed by Google BigQuery) |
| Time Range | August 5, 2021 (The Merge) – December 31, 2024 (29,868 observations) |
| Proxy | Transaction fee volatility (Gwei) adopted as a proxy for demand volatility in a fixed-supply system |

TABLE 3. CHARACTERISTICS OF THE EXPERIMENTAL DATA SOURCE

| | |
|---|---|
| Source | Ethereum public ledger (indexed by Google BigQuery) |
| Calibration / Assumption | Historical median of fees corresponds to the base urban rate (β) |

Source: own elaboration

The data range limited to the end of 2024 appears to have a solid justification, as it encompasses the entire period of a key technological shift in the Ethereum network, known as **The Merge**. It was during this time that it became possible to more accurately verify the **EIP-1559 algorithm** within the more stable environment of **Proof-of-Stake**. This specific dataset provides a comprehensive picture of demand volatility—from periods of relative stagnation to situations of rapid load spikes. Such a set of information can be considered sufficient to confirm the hypothesis regarding the "bounded instability" of the mechanism and its ability to precisely achieve the network load target. The objective of this text is not based on an analysis of current market conditions, but rather on presenting the universal mechanics of the model and its reactions in extreme situations when resources become scarce. Consequently, this period can be treated as a representative and closed dataset that allows for reliable simulations of behavior in transportation systems without the need to reference the most recent data.

2) Model Normalization

In the first step, the model was normalized to better reflect the realities known from transportation systems. It was assumed that the historical median load on the network corresponds to the standard urban fee (β):

$$P(t) = \frac{BaseFee(t)}{Median(BaseFee)} \times \beta$$

where:

P(t) – dynamic price expressed at time,

BaseFee(t) – base fee value (load indicator) from the digital twin at time,

Median(BaseFee) – long-term load median (reference point),

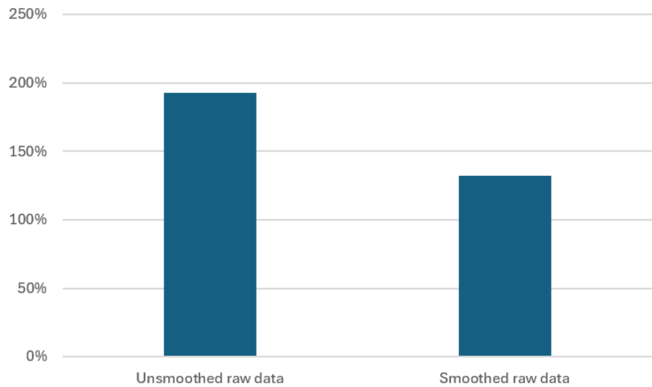
β – reference base rate.

The relation presented in this manner enables a direct mapping of Ethereum network load indicators onto monetary amounts used in traffic network analysis. At the same time, the non-linear nature of the system's reaction to increasing congestion is preserved. The result is that the model becomes highly controllable. This allows for the precise determination of the equilibrium point at which the dynamic fee begins to function as a demand regulator when the optimal infrastructure capacity is exceeded.

3) Raw Model

In the first instance, a comparison was made between the raw base model (without adjusting the data to urban realities) and its smoothed version, as shown in Figure 2.

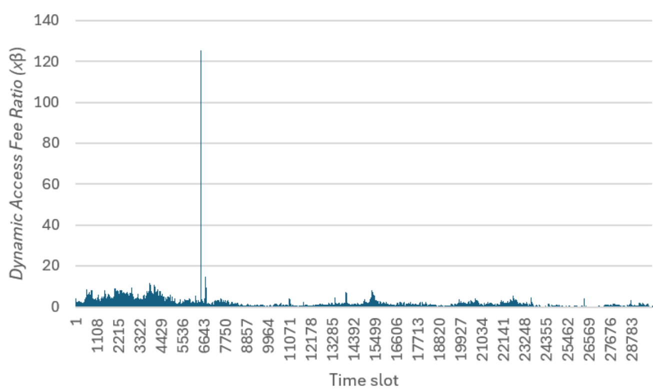
FIGURE 2. RAW MODEL VOLATILITY




Source: own elaboration

As can be seen, the application of a moving average (smoothed raw data) reduces the volatility of the pricing system, making it more acceptable while maintaining its effectiveness. Figure 3 presents the result of the simulation conducted for all observations.

FIGURE 3. RAW MODEL RESULTS

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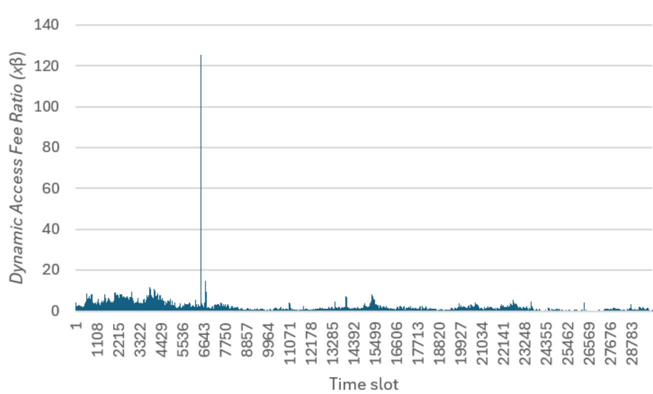
Attention should be drawn to the characteristic "spikes"—for the majority of the time, the system remains inexpensive and stable. However, there are moments of critical overload during which the algorithm continues to react instantaneously, increasing the price manifold to "cut off" excess demand. These are precisely the moments where a fixed base fee fails, while the proposed algorithm maintains throughput at the assumed level, as shown in Figure 4.

FIGURE 4. MAINTAINING THROUGHPUT IN THE RAW MODEL



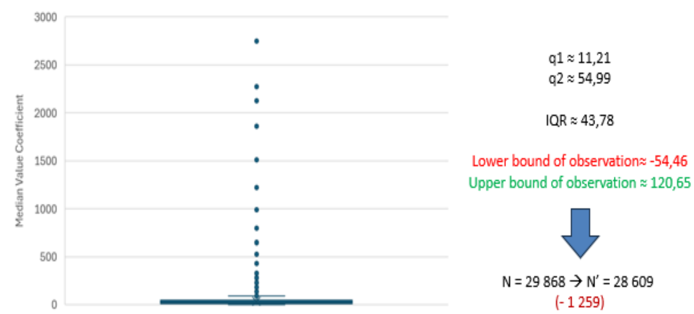

Source: own elaboration

The presented Figure 4 is evidence of the model's effectiveness, even during critical situations (the spikes from Figure 3). What is shown on the graph is the infrastructure load, which oscillates around the target (in Ethereum, this target is 50% of maximum capacity; however, in the case of a transportation system, it can be set to any range—this is the utilization factor (Φ) in the proposed model).

4) Model Calibration

The situation presented in the previous section, however, requires calibration, as such large, sudden spikes in network demand are unlikely to occur in a real urban network—a situation where the number of vehicles planning to enter the network increases by several orders of magnitude in a single period is impossible. To adapt the data originating from the digital twin, which is Ethereum, the model was calibrated by removing outliers, as shown in Figure 5.

FIGURE 5. MODEL CALIBRATION BY REMOVING OUTLIERS




Source: own elaboration

The boundaries for outliers were determined using the IQR (Interquartile Range) method. The lower bound for observations was calculated at -54.46—since this value is less than 0, no observations were removed based on this limit. The upper bound was set at 120.65, resulting in the removal of all observations above this value. In total, 1,259 observations were removed from the dataset. This procedure allowed the data to be made more realistic in relation to actual data originating from a transport network.

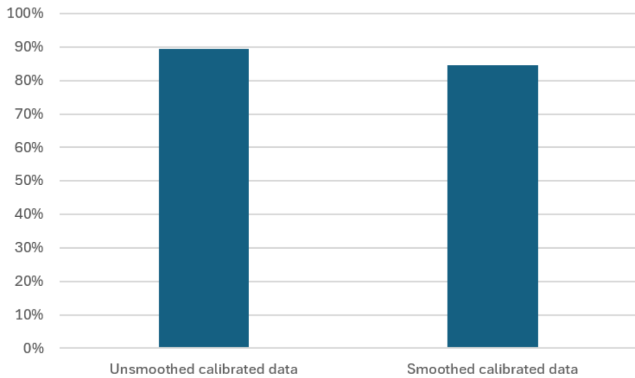
5) Corrected Model

In the case of the corrected model, the volatility of both versions of the model is at a significantly lower level. Furthermore, smoothing still functions, although it is no longer as essential since extreme outliers have been removed from the data. Nevertheless, the noise reduction mechanism (smoothing) has been retained in the model to safeguard against unexpected, random changes in the network. The volatility results for the corrected model are presented in Figure 6.

In the presented corrected model, price volatility is at a significantly more acceptable level—ranging from values below the base rate during periods of no network load to values reaching a maximum of six times the base rate during peak demand (commuter peaks). Such price volatility is not exceptionally high; however, social research would need to be conducted to assess its level of acceptability. It should be noted, though, that any actions related to increasing transportation fees are generally not well-received by the public.

Despite the significant reduction in fee volatility, the model continues to react correctly to changes in demand and allows for the achievement of the assumed target, as shown in Figure 8

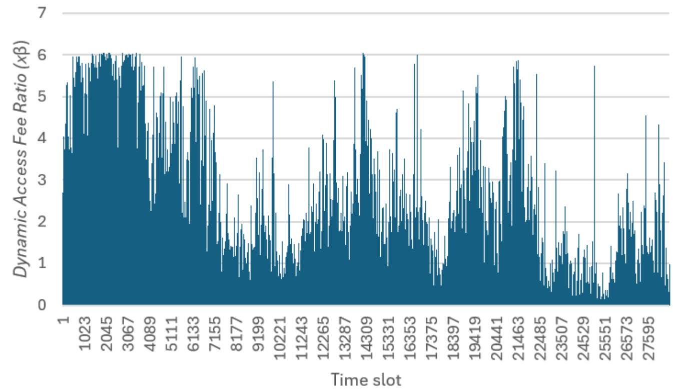
FIGURE 6. VOLATILITY OF THE CORRECTED MODEL




Source: own elaboration

The corrected data were introduced into the proposed model, as shown in Figure 7.

FIGURE 7. RESULTS OF THE CORRECTED MODEL




Source: own elaboration

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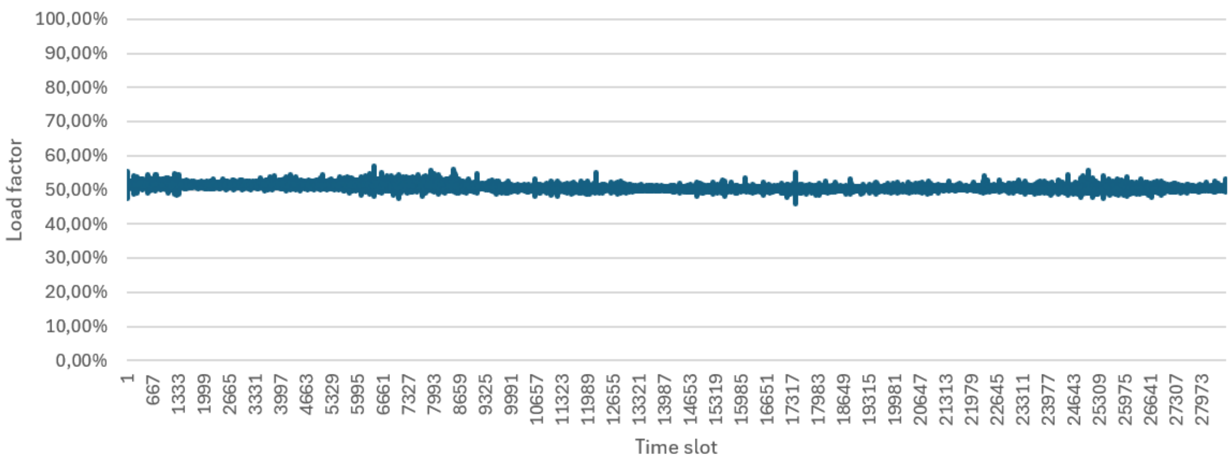
FIGURE 8. MAINTAINING THROUGHPUT IN THE CORRECTED MODEL




Source: own elaboration

The presented figure unequivocally confirms that the application of dynamic pricing allows for the continuous achievement of a constant, assumed level of capacity utilization. It should be noted, however, that in the case of real urban networks, the upper limit may be set significantly higher to permit a greater number of vehicles onto the network. Furthermore, during hours of negligible network load (e.g., at night), this value will drop significantly below the assumed target, even reaching levels near 0%—this is a natural phenomenon on the road network that does not generate any problems; the problem is traffic congestion during peak hours, not the lack of traffic during off-peak hours.

## III. DISCUSSION

This article has unequivocally demonstrated that innovative and highly rigorous resource allocation mechanisms developed for blockchain networks can serve as effective tools for managing modern urban infrastructure. The simulation conducted in this work proved that the adaptation of the EIP-1559 protocol allows for the simple and consistent maintenance of the assumed level of road capacity utilization, striving toward a designated equilibrium point even under conditions of extreme demand fluctuations. It can also be noted that this model, following appropriate modifications, could be applied to other urban challenges, such as parking fee management or resolving congestion at electric vehicle charging stations.

It should also be noted that the proposed model can also be used for other applications. A good example of its alternative use would be the optimization of access to electric vehicle chargers. Charging electric vehicles at stationary charging points that are connected to the network generates a unique transaction event that can be verified and stored in a distrib-uted blockchain ledger (Sarkar et al., 2025). The implementation of blockchain technology to manage EV charging infrastructure indicates measurable improvements in transaction efficiency, cost reduction, and security improvements. It should be noted, however, that this performance differs significantly from the architecture of a given platform and the deployment context, in particular in terms of the achieved bandwidth (Dorokhova et al., 2021; Lasla et al., 2020).

In the case of cost reduction, this phenomenon occurred most often in the context of energy trading (Huang et al., 2021) and dynamic vehicle charging pricing (Chen et al., 2024), where a significant improvement over traditional centralized systems was observed in both cases. The use of blockchain also allows for the reduction of charging costs (Chen et al., 2024), translation costs (Lasla et al., 2020) verification costs (Yang et al., 2024), or communication costs (Kim et al., 2019). A reduction in energy consumption itself has also been observed (Kumar et al., 2024).

Another important aspect is the security of authentication and stored data, where the use of blockchain together with homomorphic encryption allows for a 100% reduction in data exposure, which raises privacy to very high levels (Aldweesh and Alangari, 2025). Moreover, cryptographic mechanisms are effective in preventing hacking attacks (Sybil, MITM, DDoS) (Kumar et al., 2024). The verifications carried out confirmed the effectiveness of blockchain in the context of protection against external attacks (Kim et al., 2019).

The described benefits are strongest in a situation where the implementation of blockchain architecture was carried out along with integration with already existing public utility infrastructure. It should also be noted that blockchain, despite the presented benefits for charging a vehicle directly from the network, provides the greatest benefits during peer-to-peer trading (Lasla et al., 2020).

The model proposed in this work addresses one of the fundamental dilemmas of modern congestion pricing transportation systems: the lack of flexibility in fixed fees. Thanks to the proposed smoothing mechanism and price guarantee, the model becomes not only a highly efficient traffic regulator but also a transparent and predictable economic instrument, ready for integration with modern Intelligent Transportation Systems (ITS).

Future research directions should focus on both the empirical verification of the proposed model and its social acceptability. Studies may also encompass the technical aspects of model implementation, both in a centralized architecture and directly on a blockchain (whether on a base Layer-1 in a dedicated network or in systems based on Layer-2 or side-chains of already existing networks). Such an approach will ensure the low transaction latency required in urban logistics, as well as data security and the privacy of the system's users.

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Data Availability Statement

The data supporting the findings of this study are publicly available and were sourced directly from the Ethereum blockchain ledger. The dataset, comprising historical transaction fees and network utilization metrics (2021–2024), can be accessed and verified through public blockchain explorers (e.g., Etherscan) or by querying an Ethereum full node. The processed datasets and simulation parameters used in this research are available from the author upon request.

Conflicts of Interest

No potential conflicts of interest was reported by the author.

Declaration of the use of generative AI

This work was prepared with the assistance of advanced artificial intelligence models, which were utilized solely for the purpose of precise translation from Polish to English and professional linguistic proofreading. AI tools supported the editorial process, ensuring terminological consistency and stylistic accuracy, while the entire substantive concept, the selection of experimental data, the conducted analyses, and the formulated conclusions are the result of the author's original research.

Abbreviations

The following abbreviations are used in this manuscript:

DDoS Distributed Denial of Service
DSIC Dominant-Strategy Incentive-Compatibility
EIP Ethereum Improvement Proposal
EV Electric Vehicles
FIFO First In, First Out
GPU Graphics Processing Units
Gwei Giga-wei,- one billion of wei (0.000000001 ETH)
IoV Internet of Vehicles
IPFS InterPlanetary File System
ITS Intelligent Transportation Systems
kWh Kilowatt-hour
MaaS Mobility as a Service
MIC Miner Incentive Compatibility
MITM Man-in-the-Middle attack
NOx nitric oxide and nitrogen dioxide
PCE Passenger Car Equivalent