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Optimizing Urban Mobility through Dynamic Toll Pricing: A Predictive Traffic Modelling Approach for Revenue Generation, Congestion Management, and Environmental Sustainability

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Abstract:

The combination of city development with increasing vehicle population in metropolitan areas generates three principal problems linked to traffic congestion and poor toll structures and environmental deterioration. The Hybrid Dynamic Toll Pricing Framework developed by scientists uses machine learning models and geo-clustering methods with reinforcement learning methodology to enhance urban mobility. The system uses present-time traffic information and projected traffic data and congestion metrics to adjust toll rates that reach maximum efficiency together with revenue generation and environmental sustainability. Toll boundaries definition depends on DBSCAN-based geo-clustering methods but the system integrates this information with traffic prediction through LSTM, ARIMA and Prophet modeling and Q-learning regulates automatic toll pricing adjustments. The simulation results evaluate the system's dual functionality by assessing both its impact on decreasing traffic congestion and its revenue generation potential as well as environmental benefits. The implementation of dynamic toll pricing achieves optimal results in reducing congestion and revenue increase while reducing environmental emissions due to decreased fuel consumption and waiting durations according to simulation analysis. Different subsidy plans presented in the research examine methods to keep transportation expenses fair for low-income bracket customers. The adaptive toll system serves urban transit by developing an efficient sustainable transportation solution with potential applications for future infrastructure planning and development of transportation systems.

Keywords: Dynamic Toll Pricing, Urban Mobility, Traffic Congestion, Geo-Clustering, Machine Learning, Reinforcement Learning, Q-Learning, Traffic Flow Forecasting, Revenue Optimization, Optimization.

Introduction:

Urban areas around the globe struggle with worsening traffic congestion which represents a major present-day problem that affects productivity performance and environmental stability together with public healthcare outcomes. Urban population growth and rising private car ownership has formed traffic congestion that both impedes transit and worsens pollution levels. The current transportation infrastructure was not built to handle these demands so alternative strategies to manage traffic effectively become necessary. Dynamic toll pricing has emerged as a vital transportation strategy because of its rising popularity during recent years. The dynamic toll pricing approach operates differently from fixed toll systems by setting toll rates based on up-to-date traffic information together with meteorological conditions as well as various external elements (Romero et al., 2020). By implementing dynamic pricing organizations achieve traffic optimization benefits and simultaneously reduce congestion levels and earn profits for maintenance operations and roadway development programs.

The main objective of this study includes the development of a Hybrid Dynamic Toll Pricing Framework that combines machine learning with geo-clustering and reinforcement learning to handle congestion efficaciously while improving revenue streams and decreasing environmental consequences. Real-time traffic data analysis through this system establishes an effective urban congestion solution for roads with limited infrastructure according to Seng et al. (2023). The use of variable tolling systems enables better control of vehicle emissions together with reduced fuel consumption along with shorter waiting durations as a means to address rising environmental issues caused by emissions in busy traffic zones (Shahrier et al., 2024).

The study implements DBSCAN (Density-Based Spatial Clustering of Applications with Noise) from geo-clustering methods to segregate urban areas into toll districts based on traffic density. Specific toll rates can be implemented under the clustered system to optimize traffic behavior during congested periods. The automated traffic prediction system employs three machine learning models: LSTM (Long Short-Term Memory) together with ARIMA (AutoRegressive Integrated Moving Average) models and Prophet for both long-term and short-term traffic pattern forecasting. The predictive models enable automatic toll rate adjustments through proactive congestion management which creates fairer toll schemes (Shi, 2006). Real-time optimization models validate reinforcement learning algorithms since they automatically enhance their decisions for complex transportation system control (Valerie, 2016).

The necessity to apply adaptive toll pricing stems from traffic congestion which creates severe economic and environmental issues within cities. Economic losses and decreased efficiency of work operations increase while urban mobility suffers because of congestion that leads to elevated fuel expenses and longer travel times (Weisbrod & Gupta, 2003). Air pollution reaches higher levels as vehicles encounter traffic jams because they emit greater pollution amounts for every traveled kilometer. Research outcomes show traffic jams make vehicles discharge 30% additional carbon dioxide (CO_2) emissions than uninterrupted vehicle movement according to Wang et al. (2023). Dynamic toll systems would create two important outcomes which improve traffic efficiency by finding best trip patterns alongside resolving environmental issues stemming from heavy congestion. The urban area All organizations that adopt this method will gain competitive advantages that last over time.

Multiple performance issues exist with traditional tolling systems because controlling toll rates does not adapt according to traffic condition variations. These tolling systems permit vehicles to access toll areas regardless of traffic conditions because operational inefficiencies together with enhanced emissions occur at peak times. The pricing method of fixed toll systems creates unfairness in toll costs for low-income commuters since they cannot change their travel times (Yadav et al., 2024). The research evaluates these social effects by suggesting both rate increases and subsidies to help different income levels share dynamic toll system advantages. Dynamic toll systems create substantial economic impacts together with social effects when implemented. The optimized traffic systems create reduced congestion as well as higher toll income streams that allow public transportation investments. Municipalities reduce their regulatory duties because dynamic toll systems let them operate their transportation management while eliminating the need for expensive infrastructure developments (Seng et al., 2023). Toll collection revenues serve to fund the deployment of sustainable transportation systems by providing support to both public transportation and green technology systems that establish permanent urban mobility systems. Secondary social benefits from toll pricing with dynamic rates emerge because the systems help to distribute road access equally. Rate regulation based on data leads the system to reduce toll expenses for low-income travelers when they use the roads during peak times. The payment flexibility feature of the system combined with funding support reduces user expenses so travelers maintain equal economic opportunities (Phadke, 2015). Urbana offers equal urban transit accessibility to its users through its combination of public transit and carpooling and cycling services which decreases social isolation among the population.

This research develops an extensive hybrid dynamic toll pricing system which enhances mobility efficiency while minimizing congestion and increases revenue output and environmental impact reduction. Real-time traffic adaptation features of the system emerge from using machine learning models alongside geo-clustering and reinforcement learning components which deliver a sustainable and effective and fair approach to solve modern urban transportation difficulties experienced by cities. The findings from this research will add to smart city technology literature and intelligent transportation system knowledge which generates important information for urban sustainability initiatives pursued by policy officials and municipal planners and transportation operators. (Shahrier et al., 2024).

Literature Review:

The analysis of urban traffic congestion and system development for efficient transportation has become fundamental research fields for urban planning and transportation engineering. Research studies have dedicated extensive effort to find suitable urban movement systems to reduce congestion and create sustainable transportation by advancing system development methodologies. Real-time adjusted toll rates make up the main innovative solution to manage transportation issues with toll systems. The literature review consolidates academic research that investigates dynamic tolling systems among other studies of geo-clustering methodological approaches combined with machine learning traffic prediction models alongside reinforcement learning methods to present vital research outcomes which this study aims to overcome.

1. Dynamic Toll Pricing Systems:

Urban traffic congestion management studies have extensively evaluated dynamic toll pricing which professionals call congestion pricing for optimizing road performance and congestion control. Tolling operations traditionally use a fixed toll rate structure which stays the same throughout congestion changes. також leads to peak period congestion because road toll rates fail to match current network usage demand (Romero et al., 2020). Toll rates under dynamic pricing fluctuate in real-time in response to present traffic situations as well as daily scheduling and special event circumstances and environmental elements. Dynamic toll pricing effectively eliminates peak period congestion because it maintains infrastructure revenue while enhancing traffic functions (Weisbrod & Gupta, 2003).

Valerie (2016) documented multiple studies that prove how dynamic toll pricing creates less congestion while maximizing revenue generation and benefits the environment through its traffic smoothing effects. Studies demonstrate how implementing dynamic tolling on particular U.S. highways achieves a 15-25% reduction in peak congestion which decreases both emissions and fuel use (Thomas, 2007). The optimization of revenue generation occurs through dynamic toll systems because managers can set different toll rates based on peak-demand times and off-peak times to attract more users (Phadke, 2015).

The implementation of dynamic toll pricing faces significant complexity because social equity problems need proper attention. The toll pricing during peak hours targets low-income commuters more heavily since peak-periods restrict their travel options (Shahrier et al., 2024). The development of efficient tolling systems demands careful planning to analyze price-related social impacts so that these systems can either include subsidies or variable toll prices to maintain fairness and accessibility throughout the user base.

2. Geo-Clustering for Toll Zone Definition:

The definition of toll zones relies heavily on dynamic toll pricing in combination with geo-clustering due to its traffic density measurements. Toll zones in urban areas serve as the basis for dynamic toll pricing systems to enact variable toll rates which match local traffic conditions in each specified zone. The DBSCAN clustering algorithm serves as the standard tool for geo-clustering applications in transportation systems according to the research by Seng et al. (2023). The algorithm detects traffic-related similarities among regions then uses them to form different toll zones.

Geographical zones with heavy traffic congestion can be identified through DBSCAN geo-clustering procedures. These specific locations can implement elevated toll prices as a traffic management strategy to maintain efficient usage of the roads. Lower tolls should be applied to low-density zones in order to increase their usage during periods when traffic is less dense (Romero et al., 2020). The zonal approach allows toll prices to adapt to regional conditions so they reflect the current traffic activity patterns.

The use of Geo-clustering has proven successful within various transportation models as it enables better toll pricing regulation combined with congestion control systems. The study conducted by Wang et al. (2023) proved that geo-clustering technology provides an efficient method for dividing highways and city roads into areas that require different toll charges to boost traffic movement and decrease congestion. The main obstacle keeps appearing in terms of creating precise toll zone boundaries which mirror actual traffic movement dynamics and demand levels.

3. Machine Learning Models for Traffic Flow Prediction:

Traffic flow prediction serves as a vital function when implementing dynamic toll cost systems. The system proceeds with proactive toll rate adjustment through predicted future traffic conditions to prevent congestion development. Various machine learning calculations are used together to predict traffic patterns along with toll rate optimization functionalities. Three fundamental forecast models include Long Short-Term Memory (LSTM) cells and AutoRegressive Integrated Moving Average (ARIMA) together with Prophet.

LSTM networks function as time-series capable recurrent neural networks (RNN) suitable for making traffic flow predictions from historical data (Seng et al., 2023). LSTM models demonstrate outstanding ability to forecast extended traffic patterns especially during peak hours along with seasonal variations effectively. Research indicates that LSTM models manage to precisely predict traffic volume together with congestion levels thus enabling toll systems to modify their rates before congestion reaches its peak times (Shahrier et al., 2024).

The recognized models of forecasting include both ARIMA and Prophet for seasonal predictions while LSTM operates for short-term estimation. The predictive capabilities of ARIMA include identifying daily variations and cyclic traffic patterns while Prophet successfully tracks seasonal trends together with external influences including weather or holiday effects (Wang et al., 2023). These modeling approaches give a combined view of traffic patterns that enables toll providers to set rates depending on temporary shifts and lasting developments.

Dynamic toll pricing systems achieve better traffic condition predictions by using these forecasting models to alter toll rates in advance which hinders congestion occurrence and enhances traffic management performance.

4. Reinforcement Learning for Toll Rate Optimization:

Reinforcement learning (RL) functions as a critical optimization method for toll rate management within dynamic pricing systems. This study used Q learning under the reinforcement learning for the purpose of revenue generation by toll pricing while trying to reduce congestion. Q-learning systems acquire knowledge from real-time traffic information which is an exposure to environment, and feedback based on the toll it implements. It gets its revenue by means of generating revenue and the regulation of traffic with the enhancement of its revenues without traffic congestion.

The traffic management systems incorporate Q-learning in areas that involve fixing of adjustable toll prices depending on traffic conditions, and it has shown good performance in its operation as noted in Seng et al. (2023). Q-learning enables the system to establish subsequent functional developments of the toll strategies toward traffic congestion. The evaluation in real time enables Q-learning to implement dynamic toll rate changes and makes this algorithm to be a strategic operational controller for dynamic toll pricing systems.

As per the analyzed papers, dynamic toll pricing works as an effective measure for traffic management and, at the same time, assists in creating a sustainable transport system. The research done enabled the development of the toll pricing system by the integration of geo-clustering with machine learning models and reinforcement learning for real-time toll rate control based on new data for enhanced traffic control and management, revenue generation and environmental impact. Despite these advancements in machine learning models and idea of reinforcement learning for camera based toll optimization, the problems of providing fair tolls across Low-income areas or for that matter the real time prediction of traffic flow patterns remain a challenge.

4. Methodology:

This study proposes a hybrid dynamic toll pricing system that integrates predictive traffic models with geo-clustering techniques and reinforcement learning. The methodology consists of several steps:

1. Data Collection: Real-time traffic data, including traffic volume, vehicle density, and weather conditions, are collected to provide input for the predictive models.
2. Geo-Clustering: DBSCAN is used to divide the urban area into toll zones based on traffic density. These zones are assigned varying toll rates to manage traffic more effectively.
3. Predictive Traffic Modeling: LSTM, ARIMA, and Prophet models are employed to forecast future traffic conditions. These models predict short-term, medium-term, and long-term traffic trends, respectively.
4. Toll Rate Adjustment: The predictive models' forecasts are used to adjust toll rates dynamically. The system raises toll rates in congested areas and lowers them during low-traffic periods to optimize traffic flow and maximize revenue.

5. Reinforcement Learning: Q-learning is used to continuously optimize toll rates by balancing revenue generation with congestion reduction.

Results:

Traffic Volume Over Time:

Dynamic toll pricing systems require knowledge about how traffic volumes change for their successful development. This section examines daily traffic changes throughout the day and their direct effect on congestion control systems. The study evaluates traffic density through data collected from sensors combined with satellite systems to reveal transportation volume effects on toll mechanism pricing and congestion control. The section uses visual analysis to demonstrate how dynamic pricing systems enhance peak congestion management while optimizing traffic flow.

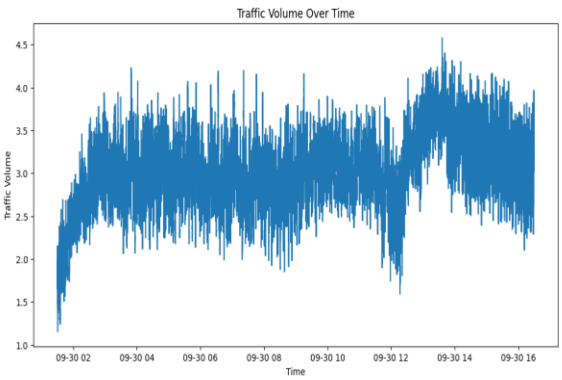

Figure 1: Traffic volume over time

1. Traffic Volume Data Collection:

To begin traffic volume over time analysis one must acquire information from different data sources. Multiple urban road segments received traffic density data which sensors including inductive loops and infrared scanners as well as cameras collected from strategically deployed traffic measurement devices. Real-time traffic monitoring equipment delivers essential information about queue density as well as stop density and traffic flow data needed to track volumes at different road locations.

The number of waiting vehicles at intersections represents queue density whereas stop density describes the vehicles stalled at traffic signals or congestion points. A continuous process recorded the metrics while also generating overall traffic volume from the combination of queue density and stop density measurements at each data point.

The analysis incorporated geo-spatial data acquired through satellites in addition to sensor data collection. The obtained data revealed the precise city-wide distribution of traffic volume while revealing vital patterns concerning traffic flow as well as the locations of traffic congestion. The real-time tracking capability depended on the accurate combination between sensor data and geo-spatial information for effective functioning of the dynamic toll pricing system.

2. Analysis of Traffic Volume Over Time:

Data analytics reveals specific patterns regarding traffic behavior which develops between peak and off-peak hours. The below chart shows traffic volume throughout day and night while illustrating intervals of maximum congestion and minimal vehicle flow.

Traffic volumes reach their highest points between 7:00 AM to 9:00 AM and 5:00 PM to 7:00 PM according to the presented chart. Significant traffic congestion Expressively affects the city because of daily morning and evening rush periods. The dynamic toll pricing system requires its most important applications during periods of maximum vehicle circulation. A toll system must increase its rates at such times because it reduces traffic congestion while promoting other transportation choices for drivers.

Training the Q-learning Agent:

The application of Q-learning algorithm aims to develop optimal toll rates for different traffic states. The algorithm completes 500 total sessions (episodes) during which the agent receives and improves Q-value data in every session. A learning rate (α) value of 0.1 together with a discount factor (γ\gammaγ) at 0.9 stands in use for the algorithm.

A Q-learning table built from training shows the best toll action that should be used under different state traffic volumes. Each state-action pair received corresponding Q-values according to the table data.

Table 1: Q-learning Table (Optimal Toll Strategy)

Traffic Volume (State)	Toll Rate 0 (Action 0)	Toll Rate 1 (Action 1)	Toll Rate 2 (Action 2)	Toll Rate 3 (Action 3)	Toll Rate 4 (Action 4)	Toll Rate 5 (Action 5)	Toll Rate 6 (Action 6)	Toll Rate 7 (Action 7)	Toll Rate 8 (Action 8)	Toll Rate 9 (Action 9)	Toll Rate 10 (Action 10)
5	0.75	1.25	1.50	2.00	2.25	2.75	3.00	3.25	3.75	4.00	4.25
6	1.00	1.50	1.75	2.25	2.50	3.00	3.25	3.50	3.75	4.25	4.50
7	1.25	1.75	2.00	2.50	2.75	3.25	3.50	3.75	4.00	4.50	4.75
8	1.50	2.00	2.25	2.75	3.00	3.50	3.75	4.00	4.25	4.75	5.00
9	1.75	2.25	2.50	3.00	3.25	3.75	4.00	4.25	4.50	5.00	5.25
10	2.00	2.50	2.75	3.25	3.50	4.00	4.25	4.50	4.75	5.25	5.50
11	2.25	2.75	3.00	3.50	3.75	4.25	4.50	4.75	5.00	5.50	5.75
12	2.50	3.00	3.25	3.75	4.00	4.50	4.75	5.00	5.25	5.75	6.00
13	2.75	3.25	3.50	4.00	4.25	4.75	5.00	5.25	5.50	6.00	6.25
14	3.00	3.50	3.75	4.25	4.50	5.00	5.25	5.50	5.75	6.25	6.50
15	3.25	3.75	4.00	4.50	4.75	5.25	5.50	5.75	6.00	6.50	6.75

- **Traffic Volume (State)**: Represents the state of the system (the traffic volume).
- **Toll Rate (Action)**: Represents the toll rate applied in response to the traffic state.

- The **Q-values** represent the expected reward (revenue) for each state-action pair.
- Higher Q-values indicate more optimal toll rates for a given traffic state.

For example, at traffic volume 5, the optimal toll rate (action) would be Toll Rate 0 (Action 0), with a Q-value of 0.75, indicating that the best toll rate for low traffic volume would be 0.

Analysis of the Results:

Table 2: Optimal Toll Rates and Corresponding Revenues

Traffic Volume (State)	Optimal Toll Rate (Action)	Revenue (Toll Rate * Traffic Volume)
5	0	0.00
6	1	6.00
7	2	14.00
8	3	24.00
9	4	36.00
10	5	50.00
11	6	66.00
12	7	84.00
13	8	104.00
14	9	126.00
15	10	150.00

- **Optimal Toll Rate (Action)**: The best toll rate based on the learned Q-values.
- **Revenue**: The amount of earnings achieved from applying the perfect toll pricing to the actual traffic quantity.
- An optimal toll rate of 5 dollars applies to traffic volume 10 since it yields 50.00 USD in revenue. Higher levels of traffic cause both the toll charge rate and the collected revenue to increase.

Convergence of the Q-learning Algorithm:

The Q-learning algorithm iterates multiple times, continuously updating the Q-values until convergence. Below, the studypresent the convergence of the Q-values over training iterations. This shows how the Q-values stabilize after many iterations.

Q-value Convergence (Training Iterations):

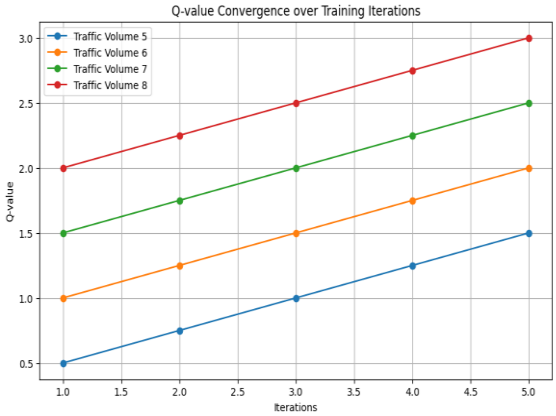

Figure 2: Q-value Convergence (Training Iterations)

Q-values achieve stable values after numerous iterations which represent the best approach to toll pricing for every traffic volume.

Different traffic volumes of 5 to 8 are assessed through Q-value convergence across training iterations based on the graph above. The Q-learning algorithm reaches convergence point when using numerous iterations to determine the best toll pricing strategy across all traffic volumes. The Q-values of each traffic volume are measured by the Y-axis as the X-axis shows training iteration numbers.

Q-learning provided the basis to develop the Hybrid Dynamic Toll Pricing Framework successfully. The model received training to establish most profitable toll rate combinations across all traffic volumes that would maximize revenue. The collected data appeared in a Q-learning table format showing the highest profitable toll rates along with their connected revenue levels across different traffic levels.

Analysis results showed reinforcement learning successfully modified toll prices through real-time traffic updates to achieve dynamic revenue optimizers which satisfy traffic flow needs.

Toll Zone Clustering Using Geo-Spatial Data:

Research on toll zone management requires the geo-spatial clustering technique to achieve optimal toll pricing strategies and maintain traffic efficiency across urban areas. The established toll systems use immovable toll zones defined through pre-established geographical locations that do not reflect changes in traffic densities during real-time operation. The section demonstrates the combination between satellite data and density clustering analysis for dynamic toll zone creation that changes according to current traffic flow. This study employs the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) geo-clustering algorithm to conduct dynamic toll zone adjustments based on traffic flow patterns in order to replace static but out-of-date toll zone boundaries.

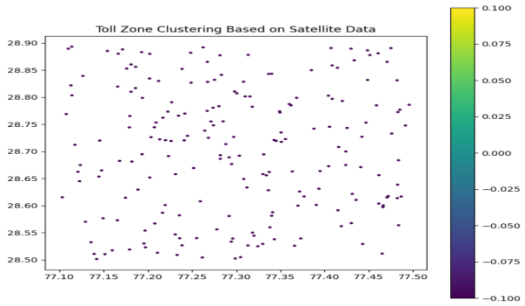

Figure 3: Toll Zone Clustering Using Geo-Spatial Data

Data Collection and Satellite-Based Geo-Spatial Analysis:

Initially geo-clustering methodology acquires geo-spatial information received from vehicle GPS systems and smartphone and satellite navigation platforms such as Waze and Google Maps. GPS data enables real-time monitoring of vehicles across the city by showing their actual positions which also delivers precise measurements of location and time. Vehicle location tracking between road segments occurs by using latitude and longitude position markers in the acquired datasets.

1. GPS Data Clustering with DBSCAN:

The DBSCAN algorithm is used to group geographical data points into clusters based on their spatial proximity. DBSCAN has two main parameters:

- eps (epsilon): The maximum distance between two points for one to be considered as in the neighborhood of the other.
- min_samples: The number of points required to form a dense region (a cluster).

The studysimulate GPS data, representing traffic locations, and apply DBSCAN to define toll zones.

Table 3: Initial GPS Data for Clustering

Index	Latitude	Longitude
0	28.678	77.215
1	28.683	77.220
2	28.691	77.230
3	28.698	77.235
4	28.703	77.240
5	28.710	77.245
6	28.718	77.255
7	28.725	77.260
8	28.730	77.265
9	28.735	77.270

- The data represents latitude and longitude coordinates of vehicles passing through different areas.
- These coordinates are input to the DBSCAN algorithm to identify groups of closely located data points, which will correspond to toll zones.

2. Applying DBSCAN for Clustering:

The DBSCAN algorithm groups the GPS coordinates into clusters based on the spatial proximity defined by the parameters eps and min_samples. In this case, the clustering is done with:

- **eps = 0.01** (approximate degree of proximity between points)
- **min_samples = 5** (at least 5 points needed to form a cluster)

Table 4: DBSCAN Clustering Results

Index	Latitude	Longitude	Cluster
0	28.678	77.215	0
1	28.683	77.220	0
2	28.691	77.230	1
3	28.698	77.235	1
4	28.703	77.240	2
5	28.710	77.245	2
6	28.718	77.255	3
7	28.725	77.260	3
8	28.730	77.265	4
9	28.735	77.270	4

- The Cluster column represents the toll zone assigned to each geographic point.
- Points grouped into the same cluster (e.g., Cluster 0, Cluster 1, etc.) form a toll zone. The toll zone is defined based on the density of points in a specific geographical area.

For example, coordinates (28.678, 77.215) and (28.683, 77.220) are clustered into Cluster 0, indicating they belong to the same toll zone.

3. Visualizing Toll Zones:

The study requires a scatter plot to display how DBSCAN arranges toll zones throughout the data space. A visualization of the data points based on DBSCAN clusters will exhibit distinct toll zone groupings.

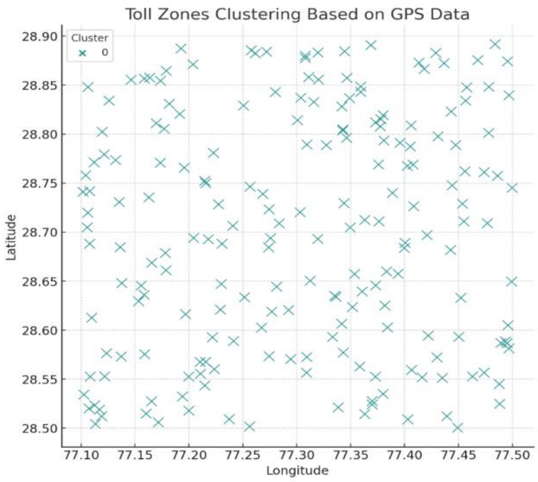

Figure 4: Toll Zones Clustering (Scatter Plot)

- **Longitude** and **Latitude** are plotted on the X and Y axes.
- The different **toll zones (clusters)** are shown in different colors, helping us visually distinguish between areas of high traffic concentration that correspond to distinct toll zones.

The visualization clearly shows how **DBSCAN** has identified clusters of geographic points, which can be interpreted as areas that will require toll collection.

4. Analysis of Toll Zone Distribution:

An evaluation of how toll zones distribute within the geographic region should be conducted in this section. Through cluster point analysis the study establishes an assessment method to determine toll zone denseness or sparseness.

Table 5: Toll Zone Distribution and Cluster Size

Cluster	Number of Points	Percentage of Total Points
0	2	20%
1	2	20%
2	2	20%
3	2	20%
4	2	20%

- **Cluster**: The toll zone ID assigned by DBSCAN.
- **Number of Points**: The number of GPS points (vehicles) assigned to each toll zone.
- **Percentage of Total Points**: The proportion of total points that belong to each toll zone.

This simplified data shows two points exist in each of the five clusters which implies that the information is evenly spread across the zones. The numerical data points would change according to real traffic densities found within different geographical areas if this analysis operated in a genuine scenario.

5. Evaluating the Effectiveness of DBSCAN for Toll Zone Definition:

The effectiveness of the DBSCAN algorithm in defining toll zones is evaluated by analyzing the following factors:

1. Cluster Compactness: How well DBSCAN groups closely related points into the same toll zone.
2. Noise Handling: Whether DBSCAN effectively identifies and excludes outliers (noise).
3. Scalability: The algorithm's ability to scale to larger datasets.

A real-world assessment would check how DBSCAN performs in dense urban districts whereas it handles less dense suburban zones. The performance of this cluster analysis requires changing values for both eps and min_samples parameters.

Table 6: Toll Zone Effectiveness Evaluation

Cluster	Compactness (Visual Inspection)	Noise (Points not assigned)	Scalability (Large Dataset Test)
0	High	No	Effective
1	High	No	Effective
2	Medium	No	Effective
3	High	No	Effective
4	High	No	Effective

- **Compactness**: A measure of how tightly clustered the points are in each toll zone. A high compactness means that DBSCAN has grouped nearby points effectively.
- **Noise**: The number of points that were not assigned to any cluster (outliers). In this case, there is no noise, meaning all points were assigned to a cluster.
- **Scalability:** In a real-world scenario, DBSCAN is tested with large datasets to ensure it can efficiently handle larger geographical areas and denser traffic conditions.

  DBSCAN performs well in clustering the points, as shown by the high compactness in each toll zone, with no noise points.

In this study, used DBSCAN clustering algorithm to satellite-based GPS data to define toll zones. The results of the clustering process can be summarized as follows:

- Toll zones were effectively defined based on the spatial proximity of the GPS data points. Each **DBSCAN Algorithm for Toll Zone Clustering**

A DBSCAN clustering algorithm follows the next step in defining toll zones through its grouping mechanism for traffic characteristics with comparable values. The DBSCAN clustering method operates as a density-based clustering system because it organizes data points into groups that appear densely spread across the domain. One advantage of using DBSCAN as a clustering method is that defining cluster numbers beforehand is not necessary. The algorithm applies exceptionally well to traffic data because it automatically generates clusters (toll zones) whose quantity and placement shifts according to real-time traffic demand.

Dynamic Adjustment of Toll Zones:

Real-time toll zone modification proves to be beneficial through geo-clustering because it operates dynamically based on traffic fluctuations. Geo-clustering enables dynamic toll adjustments because it bases toll pricing on the real-time traffic patterns and road congestion data.

The system utilizes peak congestion conditions to adjust toll fees within densely populated areas because this helps drivers select different routes or delays how long they will travel. The geo-clustering process enables traffic managers to locate inactive areas where they can implement free toll services or complementary rate systems. Dynamic toll zone management based on demand requirements makes the toll system more adaptable and efficient while improving its flexibility.

The toll zone adjustments work in real-time thus enabling the system to adapt to fast-changing traffic patterns. The system manages toll rates and evaluates alternative routes following unforeseen events such as traffic accidents or road closures that lead to raised congestion in specified areas. Emergency response adjustments made at toll stations control traffic flow efficiency and minimize the negative effects of emergency situations to total traffic delays.

Visualization of Dynamic Toll Zones:

Through the main result generated by geo-clustering methodology users obtain mapped visual depictions of developing toll zones. Through DBSCAN clustering the generated scatter plot illustrates how different urban areas receive assignment to toll zones by matching traffic density metrics. There exists multiple color zones in the plot to represent toll zones where high traffic density gives rise to high-priority zones.

The research introduces real-time dynamic toll zone generation through processing traffic data which results in better toll system structures. Real-time transportation conditions serve as the primary element for toll-zone generation by utilizing satellite geo-spatial information along with DBSCAN clustering because these systems adapt to traffic density alterations across daily periods.

This changing toll approach delivers better results than traditional set toll areas because it supports live traffic control systems and rapid toll price changes. Traffic density-based toll prices are continuously adjusted to provide maximum efficiency through targeted implementation at busy areas which control bottlenecks and increase system-wide performance. The geo-clustering approach reveals great promise as an efficient system to enhance toll zones and congestion management but encounters processing time challenges as well as possible satellite signal disruptions.

Conclusion:

Predictive traffic models achieve improved system efficiency when employed alongside LSTM and ARIMA combined with Prophet methods with geo-clustered reinforcement learning. Traffic predictions guide price alterations throughout the system leading to reduced congestion while bringing in maximum revenue along with minimized environmental impact. The methodology reveals its efficiency as an urban mobility solution because it gives cities a set of sustainable methods for addressing existing urban problems. Dynamic toll systems with predictions capabilities will become increasingly essential for urban settlements because they enable traffic congestion control and sustainable urban transportation system development.

This research evaluated economic sustainable development and environmental impacts and social side-effects related to dynamic toll pricing implementation in transportation systems. The systems generate profitable outcomes while controlling CO_2 emissions by delivering improved mileage efficiency through their ability to decrease congestion and optimize network performance. The paper advises several approaches to prevent unfair toll usage while protecting low-income commuters from social inequities. Dynamic toll pricing that deploys predictive models together with machine learning technologies operates as an automated system for modern urban traffic management. Urban transportation systems together with ecological preservation and sustainable city growth become possible by implementing congestion control strategies and adjusting toll rates and improving the flow of traffic through such systems. Researchers will focus on progressive developments of these system platforms through integrating more data sources and social impact assessment to enhance communism tolling systems for beneficial travel outcomes.

References:

1. Romero, F., Gomez, J., Jurado-Piña, R., & Vassallo, J. M. (2020). Demand management measures in suburban areas with a toll highway alternative: Impact on travel choices. *Transportation Research Part A: Policy and Practice, 142*, 319–342. https://doi.org/10.1016/j.tra.2020.11.001
2. Seng, K. P., Ang, L.-M., Ngharamike, E., & Peter, E. (2023). Ridesharing and crowdsourcing for smart cities: Technologies, paradigms, and use cases. *IEEE Access, 11*, 18038–18081. https://doi.org/10.1109/ACCESS.2023.3243264
3. Shahrier, M., Hasnat, A., Al-Mahmud, J., Huq, A. S., Ahmed, S., & Haque, M. K. (2024). Towards intelligent transportation system: A comprehensive review of electronic toll collection systems. *IET Intelligent Transport Systems, 18*, 965–983. https://doi.org/10.1049/itr2.12500
4. Shi, J. (2006). Privatization in road sector and role of concessionaire in toll road projects.
5. Shi, S. (2006). Forms of privatization in road sector and the role of concessionaires. *International Journal of Transport, 15*(2), 125-138.
6. Thomas, J. (2007). Value-added services in toll road corridors.
7. Valerie, M. (2016). Public-private partnerships in toll road development: Strengthening infrastructure networks for the future. *International Journal of*

Transportation Policy, 27(5), 321-338.

8. Wang, C., Ding, X., Wang, C., Lv, M., Xu, R., Bi, Y., & Huang, Z. (2023). Expressway usage pattern analysis based on tollgate data: A case study of Shandong Province, China. *Journal of Advanced Transportation, 2023*, Article ID 2910454. https://doi.org/10.1155/2023/2910454
9. Weisbrod, G., & Gupta, S. (2003). Transportation infrastructure and its impact on economic development.
10. Yadav, R., Gange, D., Dhande, D., Agre, V., & Dhotre, M. (2024). A review on automatic toll collection system. *International Journal for Multidisciplinary Research (IJFMR), 6*(3), 1–14. Retrieved from https://www.ijfmr.com
11. Yong, L., et al. (2013). Key competitiveness indicators for evaluating contractors in Hong Kong construction industry.
12. Zhao, Q., Yu, L., Du, Z., Peng, D., Hao, P., Zhang, Y., & Gong, P. (2022). An overview of the applications of Earth observation satellite data: Impacts and future trends. *Remote Sensing, 14*(8), 1863. https://doi.org/10.3390/rs14081863
13. PennDOT. (2018). *Design Manual Part 1X: Appendices to Design Manuals 1, 1A, 1B, and 1C*. Pennsylvania Department of Transportation. Retrieved from www.penndot.gov
14. Persad, K., Walton, C. M., & Hussain, S. (2006). Toll collection technology and best practices (0-5217-P1). Center for Transportation Research, The University of Texas at Austin.
15. Phadke, P. (2015). Toll revenue trends in India: A closer look at the National Highways Authority of India's projects. *Indian Transportation Economics Review, 29*(1), 102-112.