BAREKENG: Journal of Mathematics and Its Applications
September 2025 Volume 19 Issue 3 Page 1865-1878
P-ISSN: 1978-7227 E-ISSN: 2615-3017
https://doi.org/10.30598/barekengvol19iss3pp1865-1878

ANALYSIS OF REAL RELATIVE ASYMMETRY IN URBAN TRANSPORTATION NETWORK PROBLEMS USING SPACE SYNTAX, REDS, AND MACHINE LEARNING CONCEPTS

Robiatul Adawiyah[1], Fitriyatul Mardiyah[2], Dafik[3*], Ika Hesti Agustin[4], Excelsa Suli W. Jannah[5], Marsidi[6]

[1,2]*Department of Mathematics Education, Faculty of Teacher Training and Education, Universitas Jember*
[3,4]*Department of Mathematics, Faculty of Mathematics and Natural Science, Universitas Jember*
[1,3,4,5]*PUI-PT Combinatorics and Graph, CGANT, Universitas Jember*
Jln. Kalimantan Tegalboto No.3, Sumbersari, Kabupaten Jember, Jawa Timur, 68121, Indoenesia

[6]*Department of Mathematics Education, Universitas PGRI Argopuro Jember*
Jln. Jawa No.10, Tegal Boto Lor, Sumbersari, Kabupaten Jember, Jawa Timur, 68121, Indonesia

Corresponding author's e-mail: * **d.dafik@unej.ac.id**

ABSTRACT

Article History:

Received: 22nd November 2024
Revised: 20th February 2025
Accepted: 8th April 2025
Published: 1st July 2025

Keywords:

Machine Learning;
REDS;
Space Syntax;
Urban Transportation.

In the context of urban growth and increasing population density, urban transportation networks face significant challenges such as traffic congestion, infrastructure limitations, and traffic law violations. This study integrates three analytical approaches—Space Syntax, Resolving Efficient Dominating Set (REDS), and Graph Neural Networks (GNN)—to identify strategic locations for the deployment of mobile Electronic Traffic Law Enforcement (ETLE) units and to forecast potential traffic violations. The research focuses on Malang City, Indonesia, and utilizes spatial data and ETLE violation records. Results show that Laksamana Martadinata Street, which has the lowest Real Relative Asymmetry (RRA) value, is a key strategic location for monitoring. The REDS analysis yields a resolving efficient domination number that determines the optimal quantity and placement of mobile ETLE units. GNN-based multi-step time series forecasting successfully predicts traffic violation trends across 29 road segments with a Mean Squared Error (MSE) equal to 0.0173. The novelty of this research lies in the integration of spatial configuration analysis, graph theoretical optimization, and machine learning-based forecasting, offering a comprehensive approach not previously combined in related studies. However, limitations include the use of a single urban case study and constraints in the availability and granularity of violation data, which may affect the generalizability of the findings.

How to cite this article:

R. Adawiyah, F. Mardiyah, Dafik, I. H. Agustin, E. S. W. Jannah and Marsidi., "ANALYSIS OF REAL RELATIVE ASYMMETRY IN URBAN TRANSPORTATION NETWORK PROBLEMS USING SPACE SYNTAX, REDS, AND MACHINE LEARNING CONCEPTS," *BAREKENG: J. Math. & App.*, vol. 19, no. 3, pp. 1865-1878, September, 2025.

Journal homepage: *https://ojs3.unpatti.ac.id/index.php/barekeng/*
Journal e-mail: *barekeng.math@yahoo.com; barekeng.journal@mail.unpatti.ac.id*

Research Article · Open Access

1. INTRODUCTION

Urban Transportation Network (UTN) is a complex network system, which is formed by a physical road network and traffic demand network [1]. Urban development and rapid population growth result in serious problems in urban transportation management, including traffic congestion, deficient transportation infrastructure, and traffic law violations. Electronic Traffic Law Enforcement (ETLE) is an effective law enforcement system to overcome these problems. ETLE is a technology-based traffic law enforcement system that uses cameras and artificial intelligence to automatically detect and document traffic violations [2]. The system aims to improve traffic safety by reducing violations and accidents on the roads [3]. ETLE has been implemented in various regions of Indonesia, including Makassar, Jakarta, and many other major cities [4]. The system employs static, mobile, and portable cameras installed at strategic vertices to identify violations such as not wearing helmets, using mobile phones while driving, and violating road markings [5]. ETLE not only enhances the effectiveness of law enforcement by reducing the need for direct interaction between officers and violators, but also supports transparency and accountability through the digitization process [6]. Data on number of traffic violations recorded 1,191 traffic violators in Malang City in the first two months 2024. Statistics on the reduction of traffic accidents before and after ETLE show that in 2024, the number of traffic accidents in Malang City decreased by 43.39% compared to 2023, namely from 439 cases to 246 cases. The number of fatalities also decreased from 61 people (2023) to 50 people (2024). The number of road users or the growth of motorized vehicles from year to year continues to increase, for example from 152,052,805 in 2022 to 159,134,167 in 2023 [7].

The violation data collected by ETLE cameras can be directly accessed by authorities for electronic ticketing, which is then sent to vehicle owners via mail or digital messages [8]. Furthermore, the implementation of ETLE also demonstrates the Indonesian government's commitment to applying e-government to improve public services and good governance [9]. One type of ETLE is ETLE mobile. ETLE mobile is a new method of implementing traffic discipline that allows police officers to use mobile phone cameras and cameras mounted on the roof of police cars on duty to take photographic evidence of traffic violations [10]. The implementation of mobile ETLE requires the right approach in determining its strategic location in order to operate effectively and efficiently. Some approaches that can be used are the Space Syntax and Resolving Efficient Dominating Set (REDS) concepts. Space syntax is a technique used in urban planning, architecture, and social sciences to understand the relationship between the physical structure of urban spaces such as streets, buildings, and open spaces, and how people interact and move within them [11]. Space syntax analysis is performed by modeling the road network as a graph where each road segment is a vertex connected by lines representing the physical relationship between them. The measures used in space syntax research can be local or global [12]. Space syntax analysis can reveal the Real Relative Asymmetry (RRA) value in an urban environment.

According to Deng, et al [13], the set can be said to be efficient dominating set if every vertex $v \in V(G) - D$ is dominated by exactly one dominator and no two vertices in D are neighbors. The minimal cardinality of efficient dominating set is called efficient dominating number which is symbolized by $\gamma_e(G)$. According to Hakim, et al [14], the set W is called REDS if it has satisfied the efficient dominating set requirement. In the concept of REDS, the representation of vertices $v \in V(G)$ in W must be distinct. The minimal cardinality of REDS is called resolving dominating number which is symbolized by $\gamma_{re}(G)$. In this research, the graph operation used is the vertex amalgamation operation [15]. According to Estuningsih, et al [16], the vertex amalgamation operation is denoted by $G = Amal(G, v, n)$ which is graph G has v as terminal vertex, and n denotes the number of graphs of G that are amalgamated.

Previous research in urban transportation network analysis has often relied on isolated methods, such as traditional statistical models, static spatial assessments, or manual surveillance placement, which fail to fully capture the complex interplay between spatial configuration, optimal monitoring placement, and predictive violation trends [17]. These approaches typically lack the ability to model how urban form influences traffic behavior, do not optimize surveillance deployment using graph-theoretic principles, and are limited in forecasting accuracy due to linear assumptions [18]. In contrast, the integration of Space Syntax, REDS, and Graph Neural Networks (GNN) in this study offers a comprehensive and data-driven framework that addresses these limitations. Space Syntax reveals the spatial accessibility patterns influencing movement; REDS determines the minimal and most effective monitoring nodes; while GNN enables accurate multi-step forecasting by modeling both spatial and temporal dependencies within the road network. This interdisciplinary approach is novel and urgent as it bridges theoretical foundations with practical applications, supports proactive traffic law enforcement, and provides scalable solutions for smart urban planning.

After the location of mobile ETLE is determined using the concept of space syntax and REDS, forecasting is carried out to predict the number of violations that may occur on each road [19]. GNN provides the ability to handle data that has a more complex structure and is not limited to spatial representation, making it suitable for a variety of graph analysis tasks and understanding of complex relationship patterns [20]. GNN can be applied to the concept of multi- step time series forecasting, which is used to predict future values or data in a sequence of time series. This research takes the Malang city area focusing on densely populated areas and areas with high population activity. This research will discuss solving the urban transportation network problem by analyzing the Real Relative Asymmetry value using the concept of space syntax and REDS. The problem is the problem of determining the location of the implementation of mobile ETLE in Malang City. Furthermore, forecasting will be carried out using one type of machine learning, namely GNN.

Malang City was selected as the focus of this research due to its unique urban characteristics and growing transportation challenges. As one of the largest cities in East Java, Malang experiences rapid urban development, population growth, and increased motor vehicle usage, particularly in densely populated and high-activity areas such as education centers, markets, and tourist zones [21]. These conditions contribute to complex traffic dynamics, including frequent congestion, high rates of traffic violations, and limitations in transportation infrastructure [22]. Moreover, Malang's urban layout, which combines historical road networks with modern development, presents a diverse spatial configuration that is ideal for analysis using the Space Syntax approach [23]. The presence of numerous small and irregularly connected streets creates asymmetries in accessibility, making the city a strategic case study for applying the REDS method to optimize the placement of mobile ETLE units. Additionally, Malang has already begun adopting electronic traffic law enforcement technologies, offering real-world data for evaluating and forecasting traffic violations. These factors make Malang not only a relevant but also a representative urban environment for testing the effectiveness of the integrated approach combining Space Syntax, REDS, and GNN.

2. RESEARCH METHODS

2.1 Research Instruments

In this study, several research instruments were employed to analyze the urban transportation network in Malang City. ArcMap was used as a Geographic Information System (GIS) tool to process and convert spatial road network data from shapefiles (SHP) into DXF format, which is compatible with further analysis tools. DepthmapX, a specialized software for spatial network analysis based on Space Syntax theory, was then used to calculate the RRA values, helping identify areas with low or high spatial accessibility. These RRA values served as a basis for determining strategic locations for mobile ETLE deployment. In addition, Python programming language was utilized to model the road network as a graph and to compute key graph-theoretic parameters such as Total Depth (TD), Mean Depth (MD), Relative Asymmetry (RA), and RRA at each vertex. Python was also used in implementing the GNN algorithm to perform multi-step time series forecasting of traffic violations. These instruments collectively supported a comprehensive spatial, structural, and predictive analysis of the urban transportation network.

2.2 Study Area and Data Collection

This study focuses on the urban transportation network of Malang City, specifically targeting densely populated areas and regions with high traffic activity. The data required for the analysis includes spatial road network data, traffic flow information, and traffic violation data captured by Electronic Traffic Law Enforcement (ETLE) systems, particularly mobile ETLE units. Data on traffic violations, including the types and frequency of violations, will be obtained from the ETLE system deployed in Malang City. Additionally, GIS data will be used to create a comprehensive road network map for space syntax and REDS analysis.

2.3 Space Syntax Analysis

The first phase of analysis involves applying Space Syntax to assess the structure of Malang City's urban transportation network. The road network will be modeled as a graph where each road segment is represented as a vertex, and intersections or connections between road segments are represented as edges. Using space syntax measures such as integration, choice, and RRA, the analysis will identify strategic vertices in the road network that have high or low accessibility. These results will be critical for determining suitable locations for mobile ETLE deployment, as areas with high RRA values indicate regions that may be less accessible and therefore more prone to violations.

$$TD = \sum step\ depth \tag{1}$$

$$MD = \frac{TD}{n-1} \tag{2}$$

$$RA = \frac{2(MD-1)}{n-2} \tag{3}$$

$$G_L = 2\frac{L(L)^{\frac{1}{2}} - 2L + 1}{(L-1)(L-2)} \tag{4}$$

$$RRA = \frac{RA}{G_L} \tag{5}$$

2.4 Resolving Efficient Dominating Set (REDS) Analysis

Following the space syntax analysis, the REDS concept will be used to further refine the selection of strategic locations for mobile ETLE units. The REDS approach involves calculating the efficient dominating set and resolving dominating set of the urban road network graph. By identifying the minimal cardinality of REDS, the research will determine the most effective set of roads where mobile ETLE cameras should be installed to monitor traffic violations efficiently. The vertex amalgamation graph operation will be employed to amalgamate key vertices in the network, optimizing the positioning of mobile ETLE units.

Definition 1. REDS is a combination of the concept of efficient dominating set and metric dimension. The lower bound of resolving efficient dominating set is $\gamma_{re} \geq max\{\gamma_e(G), dim(G)\}$.

2.5 Machine Learning Forecasting using Graph Neural Networks (GNN)

Once the optimal locations for mobile ETLE deployment have been identified, a forecasting model will be developed to predict the number of traffic violations at each location. This step will utilize Graph Neural Networks (GNN) due to their ability to analyze complex graph structures and relationships in the urban transportation network. GNN will be applied to perform multi-step time series forecasting, predicting future traffic violations based on historical data collected by ETLE systems. The model will be trained using past traffic violation data and traffic flow information from Malang City. GNN will enable the research to forecast violations with higher accuracy compared to traditional methods, providing insight into potential future trends in traffic violations across the city. Neural Message Passing allows graph nodes to exchange information by calculating messages based on node and edge features. Neural Message Aggregation combines these messages using functions like sum, mean, or max to iteratively update node representations, capturing local and global graph structures.

$$h_v^0 = x_v \tag{6}$$

$$h_v^{(k+1)} = \sigma\left(W_k \sum_{u \epsilon N(v)} \frac{h_u^{(k)}}{|N(v)|} + B_k h_v^{(k)}\right), \forall k \in \{0, \dots, K-1\} \tag{7}$$

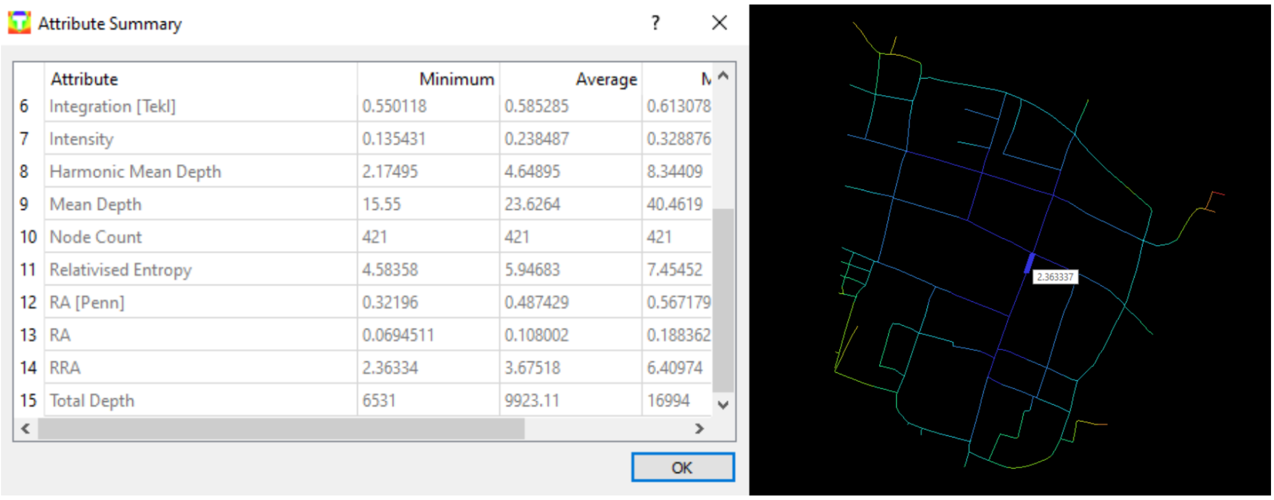
$$z_v = h_v^{(K)} \tag{8}$$

3. RESULTS AND DISCUSSION

This section describes the results of research on local and global RRA analysis, theorems related to resolving efficient dominating sets, and a multi-step time series forecasting model scheme for traffic violations based on ETLE data using the GNN technique.

3.1 Analysis of Local Real Relative Asymmetry

Local RRA analysis was conducted using ArcMap and DepthmapX software. Determination of local RRA values begins with downloading SHP (Shapefile) files on Google to be exported with the help of ArcMap. The export process will produce a DXF file that can be used for further analysis. Next is to analyze the local RRA value using DepthmapX. The DXF file is imported into DepthmapX to determine the value and location of the smallest local RRA. The smallest local RRA value will later be compared with the smallest global RRA value to be used in determining the location of traffic monitoring posts. The value of the smallest local RRA on the Malang city road map is 2.363337, namely on the Laksamana Martadinata street. The results of the local RRA analysis can be seen in **Figure 1**.



	Attribute	Minimum	Average	M
6	Integration [Tekl]	0.550118	0.585285	0.613078
7	Intensity	0.135431	0.238487	0.328876
8	Harmonic Mean Depth	2.17495	4.64895	8.34409
9	Mean Depth	15.55	23.6264	40.4619
10	Node Count	421	421	421
11	Relativised Entropy	4.58358	5.94683	7.45452
12	RA [Penn]	0.32196	0.487429	0.567179
13	RA	0.0694511	0.108002	0.188362
14	RRA	2.36334	3.67518	6.40974
15	Total Depth	6531	9923.11	16994

Figure 1. Results of Local RRA Analysis of Malang City Road Map

3.2 Analysis of Local Real Relative Asymmetry

This research produces a global value of RRA of Malang city based on the space configuration on the road map. The research object used is a graph of the representation of the road map of Malang city (G_A). The global RRA analysis is done by modeling the road as a vertex and the relationship between one road and another as an edge. In this case each road is initialized x_i as with $1 \leq i \leq 29$, thus obtained as shown in **Table 1**.

Table 1. Labels of Street Names

Label	Name of Street	Label	Name of Street
x_1	Arif Rahman Hakim	x_{16}	Muharto
x_2	Basuki Rachmat	x_{17}	Zaenal Zakse
x_3	Mgr. Sugiyopranoto	x_{18}	Pasar Besar
x_4	Aries Munandar	x_{19}	Ade irma Suryani
x_5	Merdeka Utara	x_{20}	Sutan Syahrir
x_6	Merdeka Barat	x_{21}	Kapten Piere Tendean
x_7	Kauman	x_{22}	Nusakambangan
x_8	Merdeka Selatan	x_{23}	Halmahera
x_9	S. W. Pranoto	x_{24}	Kyai Tamin
x_{10}	Merdeka Timur	x_{25}	Prof. Moh. Yamin
x_{11}	Agus Salim	x_{26}	Irian Jaya

Label	Name of Street	Label	Name of Street
x_{12}	Zainul Arifin	x_{27}	Sartono, S.H.
x_{13}	K. H. Ahmad Dahlan	x_{28}	Laksamana Martadinata
x_{14}	Gatot Subroto	x_{29}	Kebalen Wetan
x_{15}	Ir. H. Juanda		

So that the graph representation of the road map of Malang city can be seen in **Figure 2**. Furthermore, the calculation of Total Depth (TD), Mean Depth (MD), Relative Asymmetry (RA), and Real Relative Asymmetry (RRA) at each vertex is carried out with the help of Python software. The data inputted in the program is in the form of step depth data or distance 1 between one vertex and another starting at vertex 1 which is replaced with vertex 0, vertex 2 which is replaced with vertex 1, and so on. The step depth data or distance 1 on a graph of the representation of the road map of Malang city inputted in the python program.

After the data is inputted in the program, a road graph visualization of the Malang city map is generated. Furthermore, the TD, MD, RA, and RRA values generated with the help of Python software at each vertex can be seen in **Table 2**.

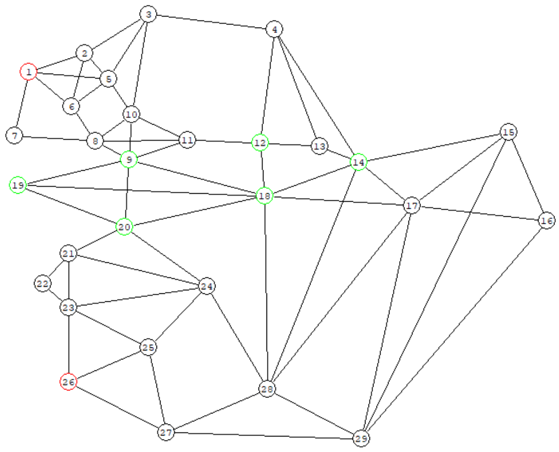


Figure 2. Graph of Malang City Road Map Representation Results G_A

Table 2. Labels of Street Names

Vertex	TD	MD	RA	RRA
x_1	514	18.35714286	1.28571429	4.90068651
x_2	260	9.28571429	0.61375661	2.33942237
x_3	139	4.96428571	0.29365079	1.11929260
x_4	157	5.60714286	0.34126984	1.30079951
x_5	168	6.00000000	0.37037037	1.41172039
x_6	159	5.67857143	0.34656085	1.32096694
x_7	166	5.92857143	0.36507937	1.39155296
x_8	109	3.89285714	0.21428571	0.81678108
x_9	113	4.03571429	0.22486772	0.85711595
x_{10}	115	4.10714286	0.23015873	0.87728339
⋮	⋮	⋮	⋮	⋮
x_{26}	338	12.07142857	0.82010582	3.12595230
x_{27}	141	5.03571429	0.29894180	1.13946003
x_{28}	106	3.78571429	0.20634921	**0.78652993**
x_{29}	270	9.64285714	0.64021164	2.44025954

From the table, the smallest RRA value is obtained at vertex x_{28} which means it is located at vertex 27 in the python visualization. The smallest global RRA value will later be compared with the smallest local RRA value to be used in determining the location of traffic monitoring posts. The smallest global RRA value is 0.78652993 or 0.79, which is on the Laksamana Martadinata Street. Visualization of road graph of Malang city map and the result of global RRA analysis of Malang city road map can be seen in

Figure 3. Identification of Laksamana Martadinata Street as the location with the smallest RRA suggests that it is one of the most accessible and spatially integrated roads in Malang's urban network. This could explain its high traffic flow, which potentially increases the likelihood of traffic violations due to constant vehicular movement and interaction. However, this spatial advantage may also result in traffic bottlenecks if not properly regulated, highlighting the need for strategic law enforcement.

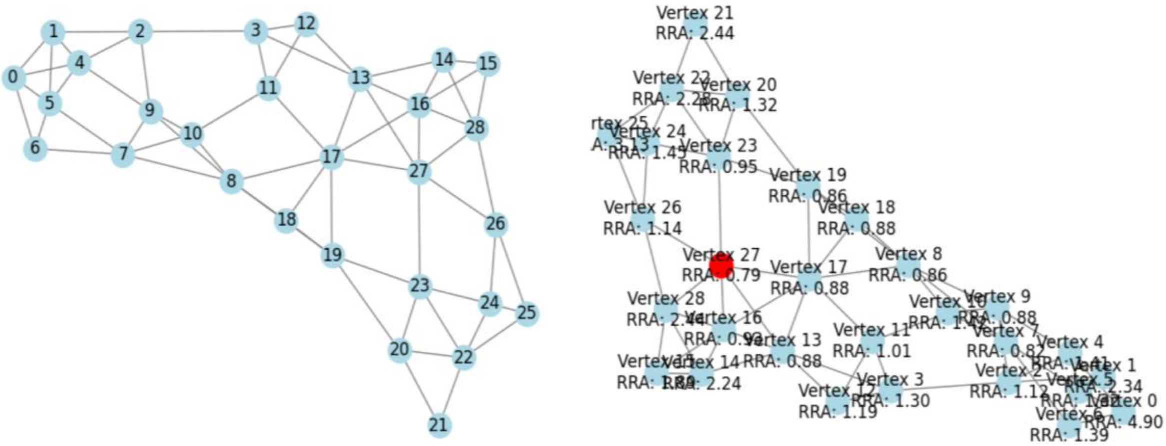


Figure 3. Graph Visualization and Global RRA Analysis Results of Malang City Road Map

3.3 Resolving Efficient Dominating Set

This research produces a theorem about the Resolving Efficient Dominating Set (REDS) on the graph resulting from the amalgamation operation of the graph resulting from the representation of the road map of Malang city $Amal\ (G_A, x, n)$. For $\gamma_{re}\big(Amal\ (G_A, x, n)\big)$ with $n = 2$ can be seen in **Figure 4**.

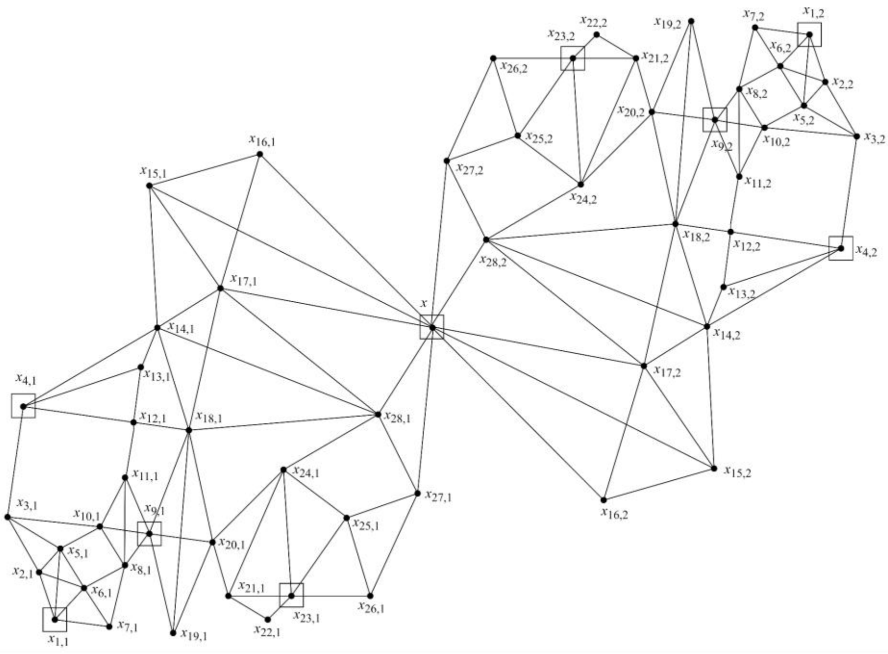


Figure 4. $\boldsymbol{\gamma_{re}\big(Amal\ (G_A, x, 2)\big)}$

Theorem 1. *Efficient Domination Number of graph* $Amal\,(G_a, x, n)$, *for every integer* $n \geq 2$ *is* $\gamma_e\big(Amal\ (G_A, x, n)\big) = 4n + 1$.

Proof. Graph $Amal\ (G_A, x, n)$ has $V\big(Amal\ (G_A, x, n)\big) = \{x\} \cup \{x_{i,j}; 1 \leq\ i \leq 28, 1 \leq j \leq n\}$ and $E\big(Amal\ (G_a, x, n)\big) = \{xx_{i,j}; 15 \leq\ i \leq 17, 1 \leq j \leq n\} \cup \{x_{1,j}x_{i,j}; 5 \leq\ i \leq 7, 1 \leq j \leq n\}$
$\cup \{x_{2,j}x_{i,j}; i = 3,5,6; 1 \leq j \leq n\} \cup \{x_{3,j}x_{i,j}; i = 4,5,10; 1 \leq j \leq n\} \cup \{x_{4,j}x_{i,j}; 12 \leq i \leq 14; 1 \leq j \leq n\}$
$\cup \{x_{5,j}x_{i,j}; i = 6,10; 1 \leq j \leq n\} \cup \{x_{6,j}x_{i,j}; i = 7,8; 1 \leq j \leq n\} \cup \{x_{8,j}x_{i,j}; 9 \leq i \leq 11; 1 \leq j \leq n\}$

$\cup \{x_{9,j}x_{i,j}; 18 \leq i \leq 20; 1 \leq j \leq n\} \cup \{x_{12,j}x_{i,j}; i = 13,18; 1 \leq j \leq n\}$
$\cup \{x_{14,j}x_{i,j}; i = 15,17,18,28; 1 \leq j \leq n\} \cup \{x_{15,j}x_{i,j}; i = 16,17; 1 \leq j \leq n\}$
$\cup \{x_{17,j}x_{i,j}; i = 18,28; 1 \leq j \leq n\} \cup \{x_{18,j}x_{i,j}; i = 19,20,28; 1 \leq j \leq n\}$
$\cup \{x_{20,j}x_{i,j}; i = 21,24; 1 \leq j \leq n\} \cup \{x_{21,j}x_{i,j}; i = 22 \leq i \leq 24; 1 \leq j \leq n\}$
$\cup \{x_{23,j}x_{i,j}; 24 \leq i \leq 26; 1 \leq j \leq n\} \cup \{x_{24,j}x_{i,j}; i = 25,28; 1 \leq j \leq n\}$
$\cup \{x_{25,j}x_{i,j}; i = 26,27; 1 \leq j \leq n\} \cup \{xx_{27,j}; 1 \leq j \leq n\} \cup \{xx_{28,j}; 1 \leq j \leq n\} \cup \{x_{1,j}x_{2,j}; 1 \leq j \leq n\}$
$\cup \{x_{7,j}x_{8,j}; 1 \leq j \leq n\} \cup \{x_{9,j}x_{10,j}; 1 \leq j \leq n\} \cup \{x_{9,j}x_{11,j}; 1 \leq j \leq n\} \cup \{x_{10,j}x_{11,j}; 1 \leq j \leq n\}$
$\cup \{x_{11,j}x_{12,j}; 1 \leq j \leq n\} \cup \{x_{13,j}x_{14,j}; 1 \leq j \leq n\} \cup \{x_{16,j}x_{17,j}; 1 \leq j \leq n\} \cup \{x_{19,j}x_{20,j}; 1 \leq j \leq n\}$
$\cup \{x_{22,j}x_{23,j}; 1 \leq j \leq n\} \cup \{x_{26,j}x_{27,j}; 1 \leq j \leq n\} \cup \{x_{27,j}x_{28,j}; 1 \leq j \leq n\}$.
The cardinality of graph $Amal\ (G_A, x, n)$, is $|V(Amal\ (G_A, x, n))| = 1 + 28n$ and $|E(Amal\ (G_A, x, n))| = 64n$.

This theorem is proved by determining the upper and lower bound. $\gamma_e(Amal\ (G_A, x, n)) = 4n + 1$ is proved by showing the lower bound $\gamma_e(Amal\ (G_A, x, n)) \geq 4n + 1$ and the upper bound $\gamma_e(Amal\ (G_a, x, n)) \leq 4n + 1$. First, we prove the lower bound of efficient domination number of graph $Amal\ (G_A, x, n)$ is $\gamma_e(Amal\ (G_A, x, n)) = 4n + 1$. We choose $\gamma_e(Amal\ (G_A, x, n)) \leq 4n + 1$. Assume that $\gamma_e(Amal\ (G_A, x, n)) = 4n$. If $\gamma_e(Amal\ (G_A, x, n)) = 4$, then there are several cases, they are:

i. Suppose we select $4n$ vertices in graph $Amal\ (G_A, x, n)$, are $W = \{x_{4,n}, x_{5,n}, x_{16,n}, x_{20,n}\}$, then there are some vertices which are not dominated by W, that is vertex $x_{10,n}, x_{11,n}, x_{22,n}, x_{23,n}, x_{25,n}, x_{27,n}, x_{28,n}$. Thus the set of W is not a dominating set.

ii. Suppose we select $4n$ vertices in graph $Amal\ (G_A, x, n)$ with the largest degree, are $W = \{x_{6,n}, x_{17,n}, x_{18,n}, x_{23,n}\}$, then there are vertices in W are neighbors, in $x_{17,n}$ they are $\{x_{7,n}, x_{8,n}, x_{11,n}, x_{13,n}, x_{27,n}\}$ and some vertices that are dominated by two vertices in W, they are $x_{14,n}$ and $x_{28,n}$. Thus the set of W is not a dominating set.

Thus, the assumption that $\gamma_e(Amal\ (G_A, x, n)) \leq 4n + 1$ is a contradiction. Therefore $\gamma_e(Amal\ (G_A, x, n)) \geq 4n + 1$ is true. Next, we prove the upper bound of efficient domination number of the graph $Amal\ (G_A, x, n)$. If we choose $W = \{x\} \cup \{x_{i,j}x_{i,j}; i \in \{1,4,9,23\}; 1 \leq j \leq n\}$ then the vertices dominated by W are in Table 3.

Table 3. Vertices Dominated by *W*

W	The Dominated Vertex
x	$\{x_{15,n}, x_{16,n}, x_{17,n}, x_{28,n}\}$
$x_{1,n}$	$\{x_{2,n}, x_{5,n}, x_{6,n}, x_{7,n}\}$
$x_{4,n}$	$\{x_{3,n}, x_{12,n}, x_{13,n}, x_{14,n}\}$
$x_{9,n}$	$\{x_{8,n}, x_{10,n}, x_{11,n}, x_{18,n}, x_{19,n}, x_{20,n}\}$
$x_{23,n}$	$\{x_{21,n}, x_{22,n}, x_{24,n}, x_{25,n}, x_{26,n}\}$

So that obtained $|W| = 4n + 1$. We have proved the lower bound $\gamma_e(Amal\ (G_A, x, n)) \geq 4n + 1$ and the upper bound $\gamma_e(Amal\ (G_A, x, n)) \leq 4n + 1$. So, it can be concluded that the efficient domination number of graph $Amal\ (G_A, x, n)$ is $\gamma_e(Amal\ (G_A, x, n)) = 4n + 1$. So, it is proved that $4n + 1 \leq \gamma_e \leq 4n + 1$.

Theorem 2. *The metric dimension of graph $Amal\ (G_A, x, n)$, for every integer $n \geq 2$ is $dim(Amal\ (G_A, x, n)) = 3n + 1$.*

Proof. $dim(Amal\ (G_A, x, n)) = 3n + 1$ is proved by showing the lower bound $dim(Amal\ (G_A, x, n)) \geq 3n + 1$ and the upper bound $dim(Amal\ (G_A, x, n)) \leq 3n + 1$. First, we prove the lower bound of the metric dimension of the graph $Amal\ (G_A, x, n)$ is $dim(Amal\ (G_A, x, n)) \geq 3n + 1$. We choose

$dim(Amal\ (G_A, x, n)) \leq 3n+1$. Assume that $dim(Amal\ (G_A, x, n)) = 3n$. If $dim(Amal\ (G_A, x, n)) = 3n$, then there are several cases, they are:

i. Suppose we select $3n$ vertices in graph $Amal\ (G_A, x, 2)$, they are $W = \{x_{7,1}, x_{11,1}, x_{15,1}, x_{20,1}, x_{3,2}, x_{6,2}\}$, then there are 2 vertices that have the same vertex representation on W, they are $x_{19,2}$ and $x_{20,2}$. Thus the set of W is not a resolving set.

ii. Suppose we select $3n$ vertices of graph $Amal\ (G_A, x, 3)$, they are $W = \{x_{7,1}, x_{11,1}, x_{15,1}, x_{20,1}, x_{3,2}, x_{6,2}, x_{19,2}, x_{3,3}, x_{6,3}\}$, then there are 6 vertices which have the same vertex representation on W, they are $x_{2,3}$ and $x_{5,3}$; $x_{8,3}$ and $x_{11,3}$; $x_{19,3}$ and $x_{20,3}$. Thus the set of W is not a resolving set.

Thus, the assumption that $dim(Amal\ (G_A, x, n)) \leq 3n$ is a contradiction. So, $dim(Amal\ (G_A, x, n)) \geq 3n+1$ is true. Next, we prove the upper bound of the metric dimension of graph $Amal\ (G_A, x, n)$. If we choose $W = \{x_{7,1}, x_{11,1}, x_{15,1}, x_{20,1}, x_{3,2}, x_{6,2}, x_{19,2}\}$ on graph $Amal\ (G_A, x, 2)$, then each vertex has a different representation on W. So that obtained $|W| = 3n+1$. We have proved the lower bound of $dim(Amal\ (G_A, x, n)) \geq 3n+1$ and the upper bound of $dim(Amal\ (G_A, x, n)) \leq 3n+1$. So it can be concluded that the metric dimension of graph $Amal\ (G_A, x, n)$ is $dim(Amal\ (G_A, x, n)) = 3n+1$. It is proved that $3n+1 \leq dim \leq 3n+1$.

Theorem 3. *Resolving efficient domination number of graph $Amal\ (G_A, x, n)$, for every integer $n \geq 2$ is $\gamma_{re}(Amal\ (G_A, x, n)) = 4n+1$.*

Proof. $\gamma_{re}(Amal\ (G_A, x, n)) = 4n+1$ is proved by showing the lower bound $\gamma_{re}(Amal\ (G_A, x, n)) \geq 4n+1$ and the upper bound $\gamma_{re}(Amal\ (G_A, x, n)) \leq 4n+1$. First, we prove the lower bound of resolving efficient domination number of graph $Amal\ (G_A, x, n)$ is $\gamma_{re}(Amal\ (G_A, x, n)) \geq 4n+1$. Based on **Definition 1**, the lower bound of the resolving efficient domination number of graph $Amal\ (G_A, x, n)$, is obtained as:

$$
\begin{aligned}
\gamma_{re} &\geq max\{\gamma_{re}(Amal\ (G_A, x, n)), dim(Amal\ (G_A, x, n))\} \\
&= max\{4n+1, 3n+1\} \\
&= 4n+1
\end{aligned}
$$

Next, the upper bound of the resolving efficient domination number of graph $Amal\ (G_A, x, n)$, we choose $W = \{x\} \cup \{x_{i,j} x_{i,j}; i \in \{1,4,9.23\}, 1 \leq j \leq n\}$ so as obtain $W = 4n+1$. As the result, there are several conditions:

i. All vertices in $v \in V(Amal\ (G_A, x, n)) - W$ are dominated by vertices in W and no vertices in W are neighbors, indicating that W is an efficient dominating set.

ii. The vertices in $Amal\ (G_A, x, n) - W$ have different representations in W. So W is a resolving set.

Based on the above conditions, it can be concluded that the upper bound of the resolving efficient domination number of graph $Amal\ (G_A, x, n)$ is $\gamma_{re}(Amal\ (G_A, x, n)) \leq 4n+1$.

We have proved the lower bound $\gamma_{re}(Amal\ (G_A, x, n)) \geq 4n+1$ and the upper bound $Amal\ (G_A, x, n)$ is $\gamma_{re}(Amal\ (G_A, x, n)) \leq 4n+1$. So, we can conclude that the resolving efficient domination number of graph $Amal\ (G_A, x, n)$ is $Amal\ (G_A, x, n)$ is $\gamma_{re}(Amal\ (G_A, x, n)) = 4n+1$. So, it is proved that $4n+1 \leq \gamma_{re} \leq 4n+1$.

This theorem is used to determine how many mobile ETLE's are required for the electronic traffic law enforcement system to operate more efficiently and effectively. The vertices in W are the starting vertices of the ETLE mobile and the vertices dominated by W are the vertices where the ETLE mobile operates. The representation of vertices on graph $Amal\ (G_A, x, n)$ is used as the code of the ETLE mobile itself to send violation data to the RTMC. Thus, the placement and use of mobile ETLE can be optimized to increase road safety and improve compliance with traffic rules.

3.4 Scheme Analysis of Multi-step Time Series Forecasting Model of Traffic Violations Based on ETLE Data Using Graph Neural Network Techniques

Observation 1. *Given a graph G for order n. Supposed that set of vertices and edges $V(G) = \{x_1, x_2, x_3, \dots, x_{n-1}, x_n\}$ and $E(G) = \{x_i x_j | x_i x_j \in V(G)\}$. Given vertex features as:*

$$H_{xi} = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,m} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n,1} & s_{n,2} & \cdots & s_{n,m} \end{bmatrix}$$

Embedding at a vertex can be determined using message passing from a vertex that is neighboring $h_x^l = AGG^l\{m_u^{l-1}, u \in N(v)\}$ under aggregation $\boldsymbol{sum}(\cdot)$, so $h_x^l = SUM^l\{m_u^{l+1}, u \in N(v)\}$ with respect to matrix $B = A + I$ where A, I are adjacency matrix and identity matrix respectively.

Proof. Based on the graph *G*, we get the adjacency matrix *A*. However, considering the neighborliness of the vertices of graph *G* to itself, it is necessary to add *A* with the identity matrix *I* and obtain the matrix *B* as:

$$B = A + I = \begin{bmatrix} b_{1,1} & b_{1,2} & \cdots & b_{1,n} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n,1} & b_{n,2} & \cdots & b_{n,n} \end{bmatrix}$$

According to the layer one GNN algorithm, it is necessary to initialize the weights as.

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,m} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m,1} & w_{m,2} & \cdots & w_{m,m} \end{bmatrix}$$

This weight will be used to obtain the value of m_{xi} and update the new weight in the next iteration. The vertex embedding process of GNN is done in two stages, namely message passing and aggregation. In the first step, perform a message passing $m_u^l = MSG^l(h_u^{l-1})$. For the linear layer $m_u^l = W_g^l(h_u^{l-1})$, which is $l = 0,1,2, \dots, k$. Furthermore, it can start the calculation with the following iteration.

$$m_{v_l}^l = H_{vi}^0 \times W^0 \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,m} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ s_{n,1} & s_{n,2} & \cdots & s_{n,m} \end{bmatrix} \times \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,m} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m,1} & w_{m,2} & \cdots & w_{m,m} \end{bmatrix}$$

The next step is aggregation by looking at the neighbors of vertex x. By applying aggregation $\boldsymbol{sum}(\cdot)$, for $h_x^l = AGG^l\{m_u^{l-1}, u \in N(v)\}$ we get $h_x^l = SUM^l\{m_u^{l+1}, u \in N(v)\}$ with respect to the matrix $B = A + I$. The embedding vector h_{xi} can be written as:

$$h_{vi}^{l+1} = \begin{bmatrix} m_{v_{1,1}}^{l+1} & m_{v_{1,2}}^{l+1} & \cdots & m_{v_{1,m}}^{l+1} \\ m_{v_{2,1}}^{l+1} & m_{v_{2,2}}^{l+1} & \cdots & m_{v_{2,m}}^{l+1} \\ \vdots & \vdots & \ddots & \vdots \\ m_{v_{n,1}}^{l+1} & m_{v_{n,2}}^{l+1} & \cdots & m_{v_{n,m}}^{l+1} \end{bmatrix}$$

Then, it needs to calculate the error value that shows how close the two vertices are to each other adjacent in the embedding space. The smaller the error value, the closer the distance between the two vertices. The error value can be formulated as: $error^l = \frac{\left\| h_{x_i}^l - h_{x_j}^l \right\| inf}{|E(G)|^2}$ which is $i, j \in \{1,2,3, \dots, n\}$. Next, we need to check whether the $error \le \epsilon$. If no, it is necessary to update W^l using h_{vi}^l in the previous iteration. In this iteration the weights need to be updated by using $W^{l+1} = W^l + \alpha \times error^l \times \left(h_{vi^l}\right)^T \times h_{vi}^{l+1}$ until $error \le \epsilon$.

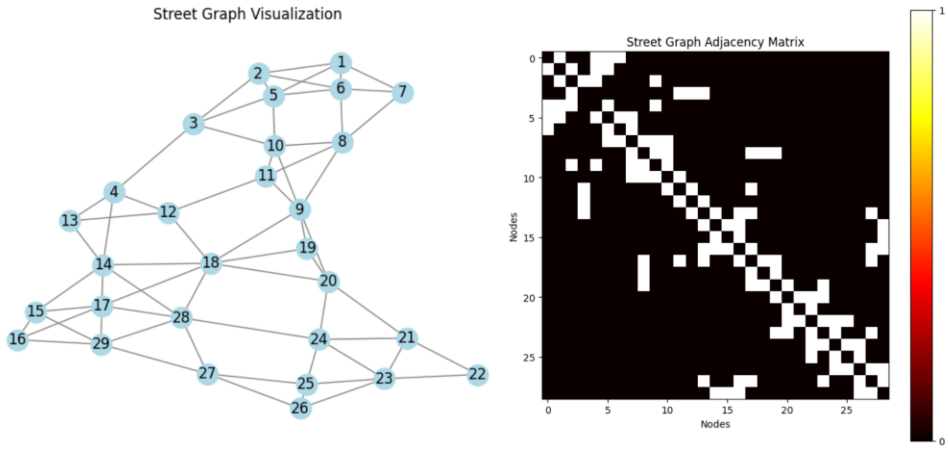


Figure 5. Neighborhood Matrix of Graph G_A

Furthermore, computer simulations will be conducted on the GNN architecture for training, testing, and forecasting traffic violation data using the one-layer GNN algorithm. The graph used is the representation graph of Malang city road map (G_A) which is derived from **Theorem 3** with $n = 1$. Furthermore, traffic violations are analyzed at 29 vertices on graph G_A. The first stage of this research performed vertex embedding process from one layer of GNN on graph was provided with 3 data features, namely violations of traffic signs and road markings, riders not wearing helmets, and riders not wearing seat belts from 29 roads. The observations use an hourly time scale and are observed for 10 effective working days for 12 hours from 06.00 - 18.00, so there are 120 hours of observations. Overall, the data used was $29 \times 3 \times 120 = 10{,}440$.

After performing above algorithm, the neighborhood matrix of graph G_A can be seen in **Figure 5**. The distribution graphs of violations of traffic signs and road markings, riders not wearing helmets, and riders not wearing safety belts for 120 hours are shown in **Figure 6**.

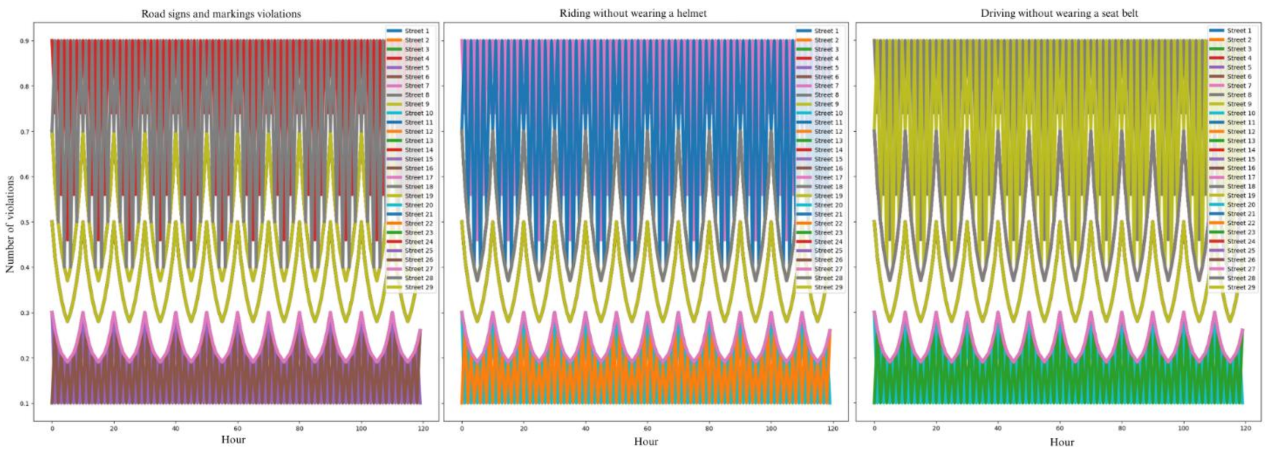
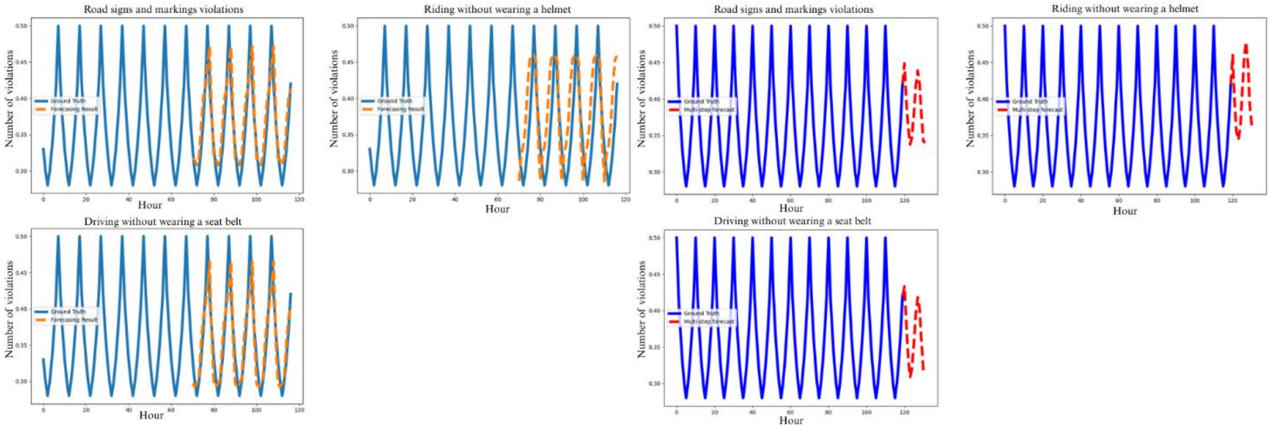


Figure 6. Distribution Chart of Violations at 29 Vertices for 120 Hours

Furthermore, all data will be subjected to training and testing where the division is 60% training data, 72 hours and 40% testing data, 48 hours. The results of training, testing, and forecasting traffic violations in 120 hours are shown in **Figure 7** (a). The results of training and testing, obtained Mean Squared Error or $MSE = 0.0173$. Furthermore, multi-step time series forecasting is carried out on all dominators, obtaining a graph of multi-step time series forecasting results for the next 12 hours on Arif Rahman Hakim Street or at dominator vertex x_i shown in **Figure 7** (b). It shows that the next highest violation occurs on the 121^{st} hour. The analysis reveals that traffic violations are not uniformly distributed across time; instead, they exhibit clear temporal patterns. Notably, higher violation rates are observed during peak hours—specifically between 06:00–08:00 and 16:00–18:00—corresponding with the start and end of daily work and school activities. These findings suggest that traffic congestion during these periods may contribute to increased infractions. Conversely, violation rates decline significantly during midday and late evening hours. Based on these insights, it is recommended that mobile ETLE units prioritize deployment during peak hours at high-risk locations such as Laksamana Martadinata Street, where both local and global RRA values are low, indicating high accessibility and traffic volume. Implementing time-aware traffic law enforcement strategies can enhance effectiveness and efficiency, reduce violations, and support safer urban mobility.



(a) (b)

Figure 7. (a) Forecasting Results of Training and Testing Data for 120 hours, (b) Multi-step Time Series Forecasting Results for 12 hours ahead

Table 4 presents a performance comparison between the Graph Neural Network (GNN) and several conventional models using a traffic violation dataset. The results indicate that GNN outperforms traditional approaches in terms of prediction accuracy and data processing efficiency. This superiority is attributed to GNN's ability to simultaneously capture both spatial and temporal relationships within complex graph structures, making it a more effective solution for analyzing and forecasting patterns in urban transportation networks.

Table 4. Performance Comparison of GNN and Another Models (Traffic Violations Dataset)

Model	RMSE↓	MAE↓	R^2↑	Training Time (s)↓
GNN (Ours)	**4.87**	**3.45**	**0.93**	**40.2**
GCN	5.76	4.12	0.88	38.4
GAT	5.21	3.88	0.90	50.7
GRU	6.02	4.53	0.86	42.6
Informer	5.33	3.91	0.91	58.3

4. CONCLUSIONS

The conclusion of this study are as follows:

1. The integration of Space Syntax, REDS, and Machine Learning provides a robust analytical framework for understanding urban transportation networks, highlighting the relationship between spatial configurations and urban mobility.
2. Space Syntax effectively identifies structural patterns and connectivity within urban layouts, revealing how spatial configurations influence movement, accessibility, and traffic flow. REDS quantifies asymmetries in urban networks, pinpointing inefficiencies and imbalances in accessibility that may hinder optimal transportation performance.
3. Machine Learning enhances predictive capabilities, enabling the identification of mobility patterns and trends, which supports proactive urban transportation planning and decision-making.
4. The combined application of these methodologies offers critical insights into traffic flow dynamics, congestion points, and overall network performance, paving the way for data-driven urban planning.

5. Addressing asymmetries and optimizing urban network designs can significantly improve accessibility, reduce traffic congestion, and enhance the overall functionality of transportation systems.
6. This interdisciplinary approach not only advances theoretical understanding of urban networks but also provides practical solutions for creating more sustainable, efficient, and accessible urban environments.
7. One identified limitation of this study is its focus on a single case study—Malang City—which may restrict the generalizability of the findings to other urban areas with different spatial structures and traffic dynamics.

ACKNOWLEDGMENT

We gratefully acknowledge the support from PUI-PT Combinatorics, Graph Theory and Network Topology (CGANT), Research Group University of Jember. We also would like to thank LP2M-University of Jember for the research support for the year 2025.

REFERENCES

[1] H. Feng, F. Bai and Y. Xu, "IDENTIFICATION OF CRITICAL ROADS IN URBAN TRANSPORTATION NETWORKS BASED ON GPS TRAJECTORY DATA," vol. 535, 2019. doi: https://doi.org/10.1016/j.physa.2019.122337

[2] E. S. W. Jannah, Dafik and A. I. Kristiana, "RESEARCH-BASED LEARNING AND STEM LEARNING ACTIVITIES: THE USE OF RAINBOW ANTIMAGIC COLORING TO IMPROVE THE STUDENTS' INFORMATION LITERACY IN SOLVING ELECTRONIC TRAFFIC LAW ENFORCEMENT PROBLEMS," *CGANT Journal of Mathematics and Applications,* vol. 5, no. 1, pp. 35-46, 2024. doi: https://doi.org/10.25037/cgantjma.v5i1.118

[3] E. S. W. Jannah, Dafik and A. I. Kristiana, "THE DEVELOPMENT OF RBL-STEM LEARNING MATERIALS TO IMPROVE STUDENTS' INFORMATION LITERACY IN SOLVING RAINBOW ANTIMAGIC COLORING PROBLEM FOR ETLE TECHNOLOGY," vol. 7, no. 1, 2024. doi: https://doi.org/10.47191/ijcsrr/V7-i1-16

[4] B. Irfan, "ELECTRONIC GOVERNANCE IN THE IMPLEMENTATION OF ELECTRONIC TRAFFIC LAW ENFORCEMENT (ETLE) IN THE CITY OF MAKASSAR," *KnE Social Sciences,* 2023. doi: https://doi.org/10.18502/kss.v8i17.14139

[5] Yuliantoro, "THE EFFECTIVENESS AGAINST TRAFFIC VIOLATIONS WITH ELECTRONIC TRAFFIC LAW ENFORCEMENT," *International Journal of Law Society Services,* 2020. http://dx.doi.org/10.26532/ijlss.v3i2.35391

[6] E. Nasali, "THE BREAKTHROUGH IN ENFORCING THE TRAFFIC LAW THROUGH E-TICKET," *Proceedings from the 1st International Conference on Law and Human Rights (ICLHR),* 2021. doi: https://doi.org/10.33506/js.v10i3.3319

[7] B. P. Statistik, LAND TRANSPORTATION STATISTICS 2023, Indonesia: BPS - Statistics, 2024.

[8] A. Bagasatwika, "ELECTRONIC TRAFFIC LAW ENFORCEMENT: IS IT ABLE TO REDUCE TRAFFIC VIOLATIONS?," *Unnes Law Journal,* vol. 6, no. 1, p. 73–96, 2020. doi: https://doi.org/10.15294/ulj.v5i1.28642

[9] W. Narendroputro and E. Z. Rusfian, "THE INNOVATION CAPACITY OF THE ELECTRONIC TRAFFIC LAW ENFORCEMENT (ETLE) OF THE INDONESIAN NATIONAL POLICE VIEWED BY THE OBSERVATORY OF PUBLIC SECTOR INNOVATION (OPSI) FRAMEWORK," *Jurnal Public Policy,* vol. 9, no. 4, pp. 262-269, 2023. doi: https://doi.org/10.35308/jpp.v9i4.7890

[10] A. M. Putri and Z. Rusli, "EFFECTIVENESS OF MOBILE ELECTRONIC TRAFFIC LAW ENFORCEMENT (ETLE) IMPLEMENTATION IN PEKANBARU CITY," *Jurnal Pendidikan Tambusai,* vol. 7, no. 2, p. 15828–15836, 2023. doi: https://doi.org/10.32832/jurmayustisi.v1i2.574

[11] Golshan, H. Hamedani, G. Motalebi and Most, "THE RELATIONSHIP BETWEEN SPATIAL CONFIGURATION AND SOCIAL INTERACTION IN TEHRAN RESIDENTIAL AREAS: BRIDGING THE SPACE SYNTAX THEORY AND BEHAVIOR SETTINGS THEORY," *International Journal of Architectural Engineering & Urban Planning,* vol. 31, p. 4, 2021. doi: https://doi.org/ 10.22068/ijaup.31.4.539

[12] M. J. Dawes, M. J. Ostwald and J. H. Lee, "EXAMINING CONTROL, CENTRALITY AND FLEXIBILITY IN PALLADIO'S VILLA PLANS USING SPACE SYNTAX MEASUREMENTS," *Frontiers of Architectural Research,* vol. 10, no. 3, p. 467–482, 2021. doi: https://doi.org/10.1016/j.foar.2021.02.002

[13] Y. P. Deng, Y. Q. Sun, Q. Liu and H. C. Wang, "EFFICIENT DOMINATING SETS IN CIRCULANT GRAPHS," *Discrete Mathematics,* vol. 340, no. 7, pp. 1503-1507, 2017. doi: https://doi.org/10.1016/j.disc.2017.02.014

[14] R. A. Hakim, I. M. Tirta, R. M. Prihandini and I. H. Agustin, "ON RESOLVING EFFICIENT DOMINATION NUMBERS OF COMB PRODUCTS OF SPECIAL GRAPHS," *Journal of Physics: Conference Series,* vol. 1832, no. 1, p. 12018, 2021. doi: https://doi.org/10.1088/1742-6596/1832/1/012018

[15] M. I. N. Annadhifi, R. Adawiyah, Dafik and I. N. Suparta, "RAINBOW VERTEX CONNECTION NUMBER OF BULL GRAPH, NET GRAPH, TRIANGULAR LADDER GRAPH, AND COMPOSITION GRAPH (P_n [P_1])," *BAREKENG: Jurnal Ilmu Matematika dan Terapan,* vol. 18, no. 3, pp. 1665-1672, 2024. doi: https://doi.org/10.30598/barekengvol18iss3pp1665-1672

[16] N. Estuningsih, T. W. Damayanti and L. Susilowati, "THE DOMINANT METRIC DIMENSION ON THE VERTEX AMALGAMATION PRODUCT GRAPH," *AIP Conference Proceedings,* vol. 2975, no. 1, 2023. doi: https://doi.org/10.1063/5.0181059

[17] R. Zhang, "SPATIAL ANALYSIS OF TRANSPORTATION NETWORKS FOR URBAN PLANNING," *Int. J. New Dev. Eng. Soc,* vol. 7, pp. 1-5, 2023. doi: https://doi.org/10.25236/IJNDES.2023.070801

[18] R. Patel, P. K. Singh and S. Saw, "TRAFFIC NOISE MODELING UNDER MIXED TRAFFIC CONDITION IN MID-SIZED INDIAN CITY: A LINEAR REGRESSION AND NEURAL NETWORK-BASED APPROACH," *International Journal of Mathematical, Engineering & Management Sciences,* vol. 9, no. 3, 2024. doi: https://doi.org/10.33889/IJMEMS.2024.9.3.022

[19] R. M. Prihandini, M. R. Rahmadani and Dafik, "ANALYSIS OF RESOLVING EFFICIENT DOMINATING SET AND ITS APPLICATION SCHEME IN SOLVING ETLE PROBLEMS," *BAREKENG: Jurnal Ilmu Matematika dan Terapan,* vol. 18, no. 3, pp. 1615-1628, 2024. doi: https://doi.org/10.30598/barekengvol18iss3pp1615-1628

[20] M. Graña and I. Morais-Quilez, "A REVIEW OF GRAPH NEURAL NETWORKS FOR ELECTROENCEPHALOGRAPHY DATA ANALYSIS," *Neurocomputing,* vol. 126901, 2023. doi: https://doi.org/10.1016/j.neucom.2023.126901

[21] H. A. N. Pratiwi, A. Rachmansyah, A. Efani, F. C. Wardana and F. R. Dhana, "FIRE DISASTER MITIGATION STRATEGY IN MALANG CITY USING A GEOGRAPHIC INFORMATION SYSTEM (GIS) APPROACH," *urnal Pendidikan Geografi: Kajian, Teori, dan Praktek dalam Bidang Pendidikan dan Ilmu Geografi,* vol. 29, no. 2, p. 9, 2024. doi: https://doi.org/10.17977/um017v29i22024p224-239

[22] A. K. Kayisu, M. El-Bahnasawi, M. Alsisi, K. Egbine, W. V. Kambale, P. N. Bokoro and K. Kyamakya, "SYSTEM DYNAMICS FOR A HOLISTIC MANAGEMENT OF ROAD TRAFFIC CONGESTION–A COMPREHENSIVE OVERVIEW WITH SOME SELECTED SIMPLE USE-CASES RELATED TO THE TOWN OF KINSHASA," *WSEAS Transactions on Environment and Development,* vol. 20, pp. 1032-1044, 2024. doi: https://doi.org/10.37394/232015.2024.20.94

[23] P. Tutuko, N. Bonifacius, D. Yuniawan, N. Aini, Z. Shen, E. Mohamad and A. G. Sulaksono, "THE PATTERN OF LAND USE INTEGRATION IN HISTORIC AREAS IN THE CBD ZONE: COMPARATIVE STUDY OF SPACE SYNTAX ATTRIBUTES OF MALANG, MELAKA, AND KANAZAWA," *International Review for Spatial Planning and Sustainable Development,* vol. 10, no. 3, pp. 148-169, 2022. doi: https://doi.org/10.14246/irspsd.10.3148