UDC 621.37
DOI https://doi.org/10.32782/2663-5941/2025.6.1/60

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ELECTRONIC TRAFFIC MONITORING SYSTEM BASED ON BLUETOOTH TECHNOLOGY

*The article presents an approach to the development of urban **electronic** traffic monitoring systems based on Bluetooth Low Energy (BLE) technology. The purpose of the study is to design and experimentally validate a hardware and software complex capable of providing marked tracking of traffic participants without using or transmitting users' personal data. Unlike traditional monitoring methods (GPS, Wi-Fi, cellular networks, computer vision), BLE combines informativeness with privacy protection, energy efficiency, and the possibility of autonomous operation. The research was carried out by simulating an urban transport environment in the SUMO software with Bluetooth systems that register user device signals on a "reachability" basis at discrete time steps. To eliminate redundant MAC address records caused by users possessing multiple Bluetooth devices, Siamese neural networks with LSTM blocks and Batch Normalization were applied, enabling accurate grouping of signals belonging to the same user. The achieved grouping accuracy is 94.69%, while testing on different areas of Berlin and with other geographical coordinates (Madrid) showed a decrease in accuracy within 6–10%, confirming the model's generalization ability and robustness. To optimize the number of sensors and reduce infrastructure costs, the NSGA-II evolutionary multi-criteria algorithm was used, determining the optimal placement of Bluetooth systems and constructing a Pareto front of compromise solutions. The hardware implementation is based on an ESP32 microcontroller with integrated BLE and GSM modules and an MPPT controller, ensuring autonomous power supply, data acquisition, and reliable transmission to cloud storage. The obtained results provide a solid foundation for the practical deployment of BLE-based electronic traffic monitoring systems with predictable costs and controllable observation quality.*

Key words: *BLE, neural network, LSTM, NSGA-II, SUMO, traffic monitoring, MAC address grouping, electronic system.*

Formulation of the problem. Electronic systems for traffic monitoring and control are widely used in modern urban infrastructure, mobility management, and transport planning. They play a key role in collecting and processing primary data on the movement of road users. Their main function is to register signals through electronic nodes, integrate heterogeneous data sources, and perform computational processing for mobility analysis.The development of intelligent traffic management systems has led to the emergence of a wide range of technical solutions [1]. Extensive networks of measuring units, known as Roadside Units [2], are used to monitor traffic density, speed, and flow dynamics in real time. Monitoring systems based on GPS, cellular networks, Wi-Fi, Bluetooth, and video surveillance technologies are also widely implemented [3]. Each of these approaches has its own limitations in terms of accuracy, cost, and infrastructure requirements. Scientific efforts are directed toward improving existing systems and developing new, more efficient methods capable of enhancing technical performance, reducing deployment costs, and protecting users' personal data, which may be exposed through unsecured communication channels.

This research is devoted to the development of an **electronic traffic monitoring system** based on passive Bluetooth scanning technology. Such an approach enables the collection of labeled mobility data without accessing or processing personal information, combining informativeness with confidentiality.

The article is structured as follows: Section 2 presents a review and comparison of modern data collection methods for traffic monitoring and justifies the use of Bluetooth technology. Section 3 describes the research methodology and the design of the electronic system for data acquisition and transmission. Section 4 covers the simulation of the urban infrastructure, the neural network architecture for data processing, and the obtained results. Section 5 discusses the optimization of Bluetooth system placement using the NSGA-II multi-objective algorithm, which determines the compromise between the number of sensors and classification accuracy.

The novelty of the work lies in the integration of three components: BLE-based labeled data collection, grouping of MAC addresses using Siamese neural networks with LSTM blocks, and optimization of sensor placement using the NSGA-II algorithm.

Analysis of recent research and publications. One of the most common approaches to traffic flow monitoring is the use of GPS data, which provide accurate real-time tracking of object locations. In studies [4, 5] clustering and Bayesian methods were proposed to identify modes of transport from anonymized trajectories. To improve classification accuracy, convolutional neural networks, autoencoders, and semi-supervised learning techniques are applied [6, 7]. Wi-Fi and Bluetooth data are used for passive monitoring based on signal analysis within coverage areas. Deep learning methods, such as ResNet [8], as well as velocity correction according to signal strength [9, 10], insure high accuracy in detecting movement modes. Cellular network data make it possible to assess large-scale mobility patterns, while route-matching algorithms [11] and LSTM (Long Short-Term Memory) models [12] improve accuracy under low sampling frequency. Inertial sensors of smartphones (accelerometers, gyroscopes) are used to recognize user activity (walking, running, cycling, or driving) based on motion analysis with deep and recurrent neural networks [13]. Computer vision methods, including aerial imaging within pNEUMA projects [14] achieve the highest spatial precision but require substantial computational resources and continuous spatial coverage.

A common feature of modern monitoring systems is the integration of artificial intelligence algorithms–primarily neural networks–which automatically extract informative features from heterogeneous data and ensure high classification accuracy even in complex urban environments.

The comparison of reviewed approaches shows that the high precision of GPS- or vision-based systems is associated with significant energy and infrastructure costs, whereas inertial smartphone sensors lack spatial reference. At the same time, most methods rely on personalized user data–GPS coordinates, network records, or device telemetry–which creates the risk of identifying individual trajectories and limits the scalability of such systems. European regulators, including the European Data Protection Supervisor, emphasize the **Privacy by Design** principle, which requires ensuring data confidentiality already at the system development stage [15] [16].

Thus, in addition to technical requirements for accuracy and scalability, one of the key criteria of modern transport monitoring systems is privacy protection. This highlights the need for technologies capable of maintaining data label integrity while avoiding the identification of individual users.

A promising solution to the described limitations is **BLE** technology, which records only MAC addresses and signal parameters, significantly reducing the amount of sensitive data. Although even temporary addresses do not guarantee complete anonymity [17], BLE provides the best balance between traceability and privacy protection. Its passive nature allows data collection without user involvement or the installation of dedicated applications, making BLE a suitable foundation for urban monitoring systems.

At the same time, passive BLE scanning introduces the problem of redundant records, when the number of detected devices exceeds the actual number of users. Unlike Bluetooth Classic, which relies on direct connections, BLE only captures broadcast signals, so a single user may appear as multiple MAC addresses. In Europe and North America, more than 90% of users have smartphones, about 20% own smartwatches, and over 30% use wireless headphones, which can generate up to three independent signals [18]. This leads to data fragmentation that requires **grouping of BLE signals belonging to devices of the same user**. Such grouping enables an accurate estimation of the number of traffic participants without direct access to their devices.

The accuracy of this process depends not only on the applied algorithms but also on the network configuration – namely, the number and spatial distribution of BLE nodes. An excessive number of sensors increases costs and data volume, whereas insufficient coverage reduces observation completeness and grouping accuracy.

Task statement. Therefore, this study aims to develop an electronic traffic monitoring system that combines BLE-based data collection, signal grouping using Siamese neural networks with LSTM blocks, and infrastructure optimization through the NSGA-II multi-objective algorithm. The goal is to determine the optimal configuration of BLE nodes that ensures sufficient accuracy of user grouping while minimizing the number of sensors and data redundancy. The proposed system was evaluated in the SUMO simulation environment [24], which models realistic traffic processes in urban conditions.

Methodology

The traffic monitoring study was carried out by modeling an urban infrastructure and simulating transport flows in the SUMO environment [19]. Bluetooth systems were placed on the map to serve as receivers of signals from users' Bluetooth devices. The simulation did not explicitly model radio-wave propagation. Instead, a simplified approach was implemented: at each simulation step, the Euclidean distance between a Bluetooth receiver and a user was calculated. If this distance was less than the device's operating radius, the signal was considered detected. This method made it possible to emulate the "transmit–receive" process without complex physical modeling while maintaining sufficient accuracy for urban scenarios. The placement of antennas was automated using a custom script that calculated installation coordinates and inserted them into the simulation map. Each traffic participant was assigned a random number of Bluetooth devices with a specified detection radius, allowing various user behavior patterns to be represented. During the simulation, registered MAC addresses were recorded in a database together with timestamps and the identifiers of the detecting antennas for further processing.

Description of the Structural Scheme. The core of the Bluetooth monitoring system (Fig. 1) is a high-performance ESP32 microcontroller [20] that supports Wi-Fi 802.11 b/g/n, dual-mode Bluetooth 4.2, and multiple peripheral interfaces. Compared with the previous ESP8266, it features a dual-core processor with a clock frequency of up to 240 MHz (depending on the model). ESP32 supports both Bluetooth Classic and BLE: the former offers higher data rates but greater energy consumption, while BLE provides lower throughput yet enables energy-efficient, connection-free communication suitable for IoT and short-range mobile devices.

The controller's power consumption during active operation is 95–130 mA [21]. For autonomous deployment, the system uses a 3.7 V Li-Po battery (20 Ah) charged by a solar panel via an MPPT (Maximum Power Point Tracking) controller. A temperature sensor with a resistive heater maintains the battery within its operating range. Data transmission to the cloud is handled by the SIM800C GSM module (350–500 mA in transmission mode) [22]. The system performs adaptive scanning – increasing the frequency of Bluetooth detections during peak traffic and reducing it when activity is low. Data are transmitted periodically based on the accumulated volume and battery level, ensuring energy efficiency and several days of autonomous operation even under low solar conditions.

Depending on the deployment environment, the system can operate in three configurations:

- **Autonomous:** solar-powered with GSM data transmission via SIM800C;
- **Connected:** powered by the city grid with data transmission over LAN or the ESP32 Wi-Fi module;
- **Upgraded:** integration of existing Bluetooth-equipped devices through firmware updates for unified network operation.

Collected data in JSON format include the MAC address, timestamp, and ID of the detecting node. Depending on configuration, transmission occurs via GSM or local networks; in the cloud, system IDs are converted to geographic coordinates. The processed

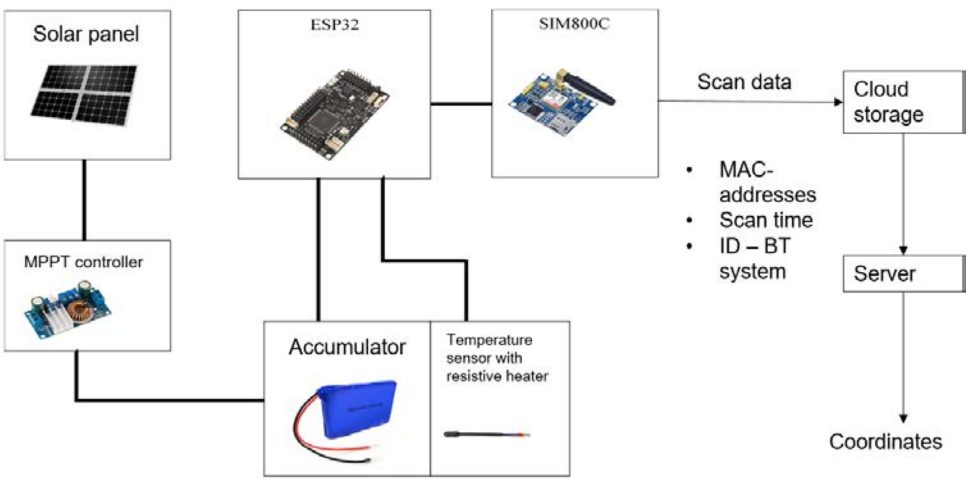

Fig. 1. Structural diagram of an autonomous Bluetooth system for monitoring road users

data are then supplied to the neural network for further grouping. The system's operation algorithm was validated through urban-traffic simulation in the SUMO software environment.

Description of the SUMO Simulation. Eclipse SUMO is an open-source traffic simulation package that models multimodal transport systems, including vehicular, public, and pedestrian flows. Developed by the German Aerospace Center, SUMO provides a comprehensive set of tools for importing road networks, route generation, visualization, and traffic-impact analysis. A key feature of SUMO is its extensible architecture that allows user-defined models and API integration with external systems [19].

For the simulated Bluetooth systems, an XML configuration file was generated containing the coordinates and identifiers of each receiver. These systems do not affect vehicle behavior in the simulation but act as reference points for registering Bluetooth devices, enabling the collection of additional mobility data. A fragment of the simulated city map with deployed Bluetooth systems is shown in Figure 2.

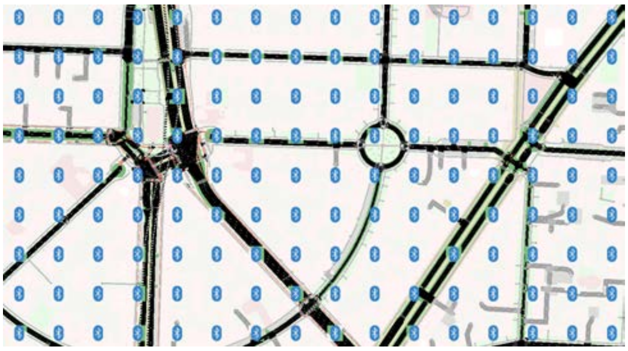

Fig. 2. Placement of Bluetooth systems in the SUMO simulation environment

Simulation results were exported in CSV format for subsequent processing by the neural network.

Artificial Neural Network for Data Processing. To process Bluetooth scanning data, several neural network architectures were developed and tested using a Siamese configuration [23]. Each Siamese model consists of two identical subnetworks sharing weights that generate feature vectors for two MAC addresses. The Euclidean distance between these vectors is computed, and the output neuron with a sigmoid activation evaluates the probability that both signals belong to devices of the same user [24].

Two model groups were designed: fully connected networks (NN1–NN4) and LSTM-based networks (LSTM1–LSTM4), each receiving 1,200 input features (400 time steps × three parameters – scan indicator and antenna coordinates).

The fully connected models differ in preprocessing and optimization methods:

- NN1: standardized input data with the Adam optimizer;
- NN2: same as NN1, but with additional L2 regularization;
- NN3: without data standardization, preserving spatial context.
- NN4: identical to NN3 but trained with the RMSprop optimizer.

The LSTM-based variants incorporate 64 recurrent neurons in different configurations:

- LSTM1: standard unidirectional LSTM layer;
- LSTM2: bidirectional LSTM, processing sequences in both temporal directions;
- LSTM3: one-dimensional convolutional layer (Conv1D) followed by MaxPooling, reducing dimensionality while preserving key temporal features;
- LSTM4: similar to LSTM1 but followed by Batch Normalization, improving training stability and reducing overfitting.

All models end with 32 dense neurons, a layer computing the Euclidean distance, and a single output neuron with a sigmoid activation. The LSTM4 model achieved the highest classification accuracy among all tested architectures.

Training was conducted on data simulated for an 8 km² fragment of Berlin with a 50 m grid step (Fig. 2). The model included 3,100 objects (1,440 vehicles and 1,660 pedestrians), each assigned 1–5 unique MAC addresses with transmission ranges of 10–30 m. The simulation lasted 2,000 seconds with a 5 s scanning step, producing 1,200 input features per record (scan indicator and antenna coordinates).

Balanced 1:1 positive–negative MAC address pairs were formed to prevent model bias: positive pairs corresponded to devices of the same user, negative pairs – to different users. Model performance was evaluated using the confusion matrix (TP, TN, FP, FN) and the classification accuracy metric:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}.$$

The classification accuracy metric of neural networks is displayed in Table 1.

The **LSTM4** configuration, which integrates Batch Normalization after the LSTM layer, demonstrated the best accuracy of 0.9469, confirming its superior generalization and training stability.

To further test robustness, the trained LSTM4 model was evaluated under three simulation scenarios:(1) the same Berlin area with antennas spaced **100 m apart**, which reduced accuracy due to lower spatial coverage (**0.89**); (2) another Berlin district (same

Table 1

Performance accuracy of neural networks

NN version	NN1	NN1	NN1	NN1	LSTM1	LSTM1	LSTM1	LSTM1
Accuracy	0.8718	0.8718	0.9114	0.8132	0.9416	0.9437	0.9448	0.9469

Table 2

Results of neural network accuracy under different simulation conditions

Distance between BT systems and the city	50 m, Berlin	100 м, Berlin	100 m, Berlin (different area)	100 m, Madrid (different coordinates)
Accuracy	0.9469	0.89	0.85	0.88

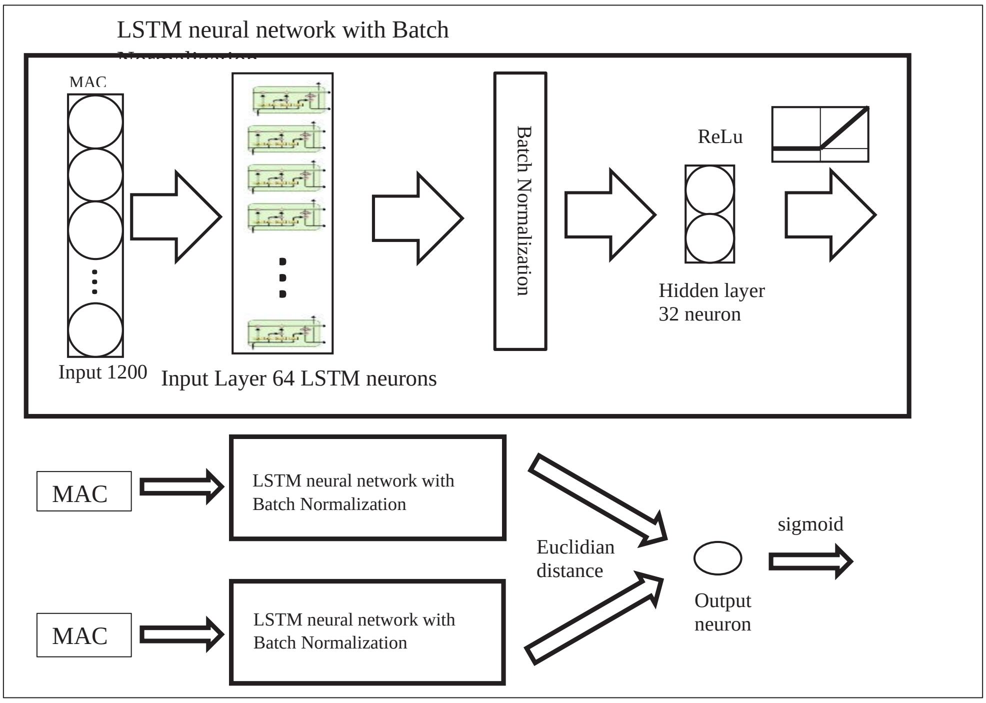

Fig. 3. Siamese neural network model with LSTM neurons and BatchNormalization

parameters, **0.85** accuracy), showing stability under local topology changes; and (3) **Madrid**, a different city with 14 km² area and 100 m spacing, achieving **0.88 accuracy**, confirming cross-city generalization. The results of all tests are shown in Table 2.

These results show that classification accuracy depends not only on model architecture but also on sensor density and placement. Reducing node density decreases the number of simultaneously detected devices, limiting temporal correlation patterns and overall accuracy. This emphasizes the need for optimal sensor placement to balance coverage, cost, and data quality.

Optimization of Bluetooth System Placement Using NSGA-II. Initial modeling in SUMO was carried out with Bluetooth systems uniformly placed on a grid with a 50 m spacing over an 8 km² area, resulting in 3,360 nodes (≈400 per km²). Although this configuration provided full coverage, more than half of the systems registered less than 1% of scans, making it economically inefficient and motivating placement optimization.

The problem was formulated as a multi-objective optimization:

$$\vec{F}(\theta)=\left(f_1(\theta),-f_2(\theta)\right), min\vec{F}(\theta),$$

where θ – vector of filtering parameters (activity, distance), f_1 – number of Bluetooth systems, f_2 – grouping accuracy. Optimization was performed using the NSGA-II (Non-dominated Sorting Genetic Algorithm II) [25], which enables simultaneous minimization of sensor count and accuracy loss. The algorithm constructs a Pareto front of compromise solutions between conflicting objectives – minimizing infrastructure while maximizing classification accuracy.

For each configuration, a two-step filtering was applied:

- **Activity filtering** – removing low-activity systems according to

$$\frac{q}{q_{max}} < q_f,$$

where q is the scan count of the current system, q_{max} is the maximum, and q_f is the activity threshold.

- **Distance filtering** – eliminating systems located too close:

$$D = d_{base} - \alpha \cdot \left(\frac{q}{q_{max}}\right),$$

where D is the minimum allowed distance, d_{base} is the base spacing, and α is the sensitivity coefficient. If two systems are closer than D, the one with higher activity is retained. If two systems are closer than D, the one with higher activity is retained.

The parameters were varied as follows:

- d_{base} = 50–500 m (step 50 m);
- α = 0–450 m (step 50 m);
- q_f = 0–0.3 (step 0.01).

The resulting Pareto front (Fig. 4) includes configurations that balance **sensor density and grouping accuracy**.

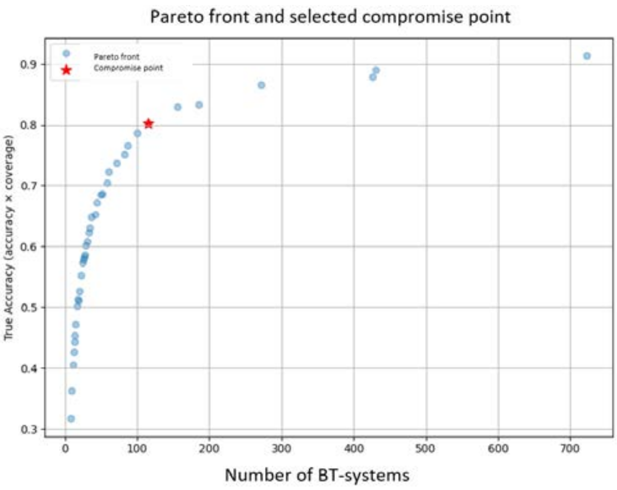

Fig. 4. Optimization result with Pareto front and compromise point

The compromise point, closest to the ideal (minimum number of systems at maximum accuracy), corresponds to 115 Bluetooth systems (~14 per km²) with an accuracy of 0.803.This means the number of antennas was reduced by 96.6% (from 3,360 to 115), while grouping accuracy decreased only by ≈15% (from 0.9469 to 0.803).

Thus, applying the NSGA-II algorithm enabled a substantial reduction in the hardware infrastructure without significant degradation of performance, achieving an effective balance between sensor count, deployment cost, and grouping accuracy of BLE signals.

Conclusions. The study confirmed the feasibility of using BLE technology for urban electronic traffic monitoring systems. BLE enables tagged tracking of mobility without accessing personal data, combining informativeness with privacy compliance. The key issue of users having multiple devices, which leads to redundant detections, was addressed through MAC-address grouping using Siamese neural networks with LSTM blocks and Batch Normalization, achieving a grouping accuracy of 94.69%. Testing in different simulated environments, including various geographical coordinates, showed only a 6–10% decrease in accuracy, confirming the model's generalization capability. Simulation in SUMO validated the applicability of the proposed approach for system-level evaluation. To optimize sensor deployment, the NSGA-II multi-objective evolutionary algorithm reduced the number of Bluetooth systems from 3,360 to 115 (≈14 per km²) while maintaining acceptable accuracy (0.803), equivalent to a 96.6% reduction in infrastructure with only a 15% quality loss. The proposed integration of BLE data acquisition, neural grouping, and multi-criteria optimization provides a foundation for scalable, cost-predictable urban traffic monitoring systems with controllable observation quality.

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Штикало О.В., Ямненко Ю.С. ЕЛЕКТРОННА СИСТЕМА МОНІТОРИНГУ ДОРОЖНЬОГО ТРАФІКУ НА БАЗІ ТЕХНОЛОГІЇ BLUETOOTH

У статті розглянуто підхід до побудови міських електронних систем моніторингу дорожнього трафіку на основі технології Bluetooth Low Energy (BLE). Метою дослідження є розроблення апаратно-програмного комплексу, здатного забезпечити марковане відстеження переміщення учасників руху без залучення персональних даних користувачів. На відміну від традиційних методів (GPS, Wi-Fi, стільникові мережі, комп'ютерний зір), BLE поєднує інформативність із вимогами конфіденційності та низьким енергоспоживанням. Дослідження виконано шляхом симуляції міського середовища у програмі SUMO з розміщенням Bluetooth-систем, які реєструють сигнали пристроїв користувачів за принципом «досяжності» у часових кроках. Для усунення надлишкових записів MAC-адрес, зумовлених наявністю у користувачів кількох пристроїв, застосовано нейронні мережі сіамського типу з LSTM-блоками та Batch Normalization, що дозволило ідентифікувати приналежність сигналів одному користувачеві. Досягнута точність групування становить 94,69%, а тестування для різних ділянок міста Берлін та інших географічних координат (Мадрид) показало зниження точності в межах 6–10%, що підтверджує здатність моделі узагальнювати інформацію. Для оптимізації кількості сенсорів і скорочення вартості інфраструктури використано еволюційний багатокритеріальний алгоритм NSGA-II, який визначає оптимальне розміщення Bluetooth-систем і формує Парето-фронт компромісних рішень. Апаратна частина системи реалізована на мікроконтролері ESP32 із модулями BLE, GSM та контролером MPPT, що забезпечує автономне живлення, збір даних і передавання результатів у хмарне сховище. Отримані результати становлять основу для практичного впровадження BLE-базованих електронних систем моніторингу дорожнього руху з прогнозованими витратами та контрольованою якістю спостережень.

Ключові слова: *BLE, SUMO, NSGA-II, LSTM, сіамські нейронні мережі, групування MAC-адрес, міські системи моніторингу трафіку, багатокритеріальна оптимізація.*

Дата надходження статті: 27.10.2025
Дата прийняття статті: 16.11.2025
Опубліковано: 30.12.2025