

URBAN TRAFFIC FLOW SIMULATION IN VARIOUS WEATHER CONDITIONS USING LONG SHORT-TERM MEMORY-BASED MACHINE LEARNING

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Highlights:

- created a weather-aware short-term urban traffic flow prediction framework combining SUMO microscopic simulation with LSTM-based ML.
- integrated weather-dependent driver-behaviour parameters such as speed factor, reaction time, acceleration, deceleration, driver imperfection, and minimum gap to reflect realistic traffic dynamics under 5 weather scenarios: normal, light rain, heavy rain, fog, and snow.
- the best LSTM model uses 3 recurrent layers and achieves validation RMSE = 0.1056 with validation loss = 0.0652 with moderate amount of data.
- results show that the model captures the overall temporal traffic pattern and preserves the relative traffic intensity ordering across weather conditions, where prediction accuracy is best in normal weather (RMSE \approx 0.21 veh/min) and worst in snow (RMSE \approx 2.5 veh/min), with heavy rain also causing high error.
- the study concludes that the SUMO–LSTM framework is a promising tool for weather-adaptive traffic forecasting and intelligent traffic management, with future improvements suggested through richer features and broader real-world calibration.

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Abstract. This study proposes a weather-aware short-term urban traffic prediction framework that combines microscopic traffic simulation with Long Short-Term Memory (LSTM) based Machine Learning (ML) for forecasting vehicle flow at selected urban junctions. The research is motivated by the need to improve traffic-state prediction under varying environmental conditions, since weather disturbances such as rain, fog, and snow significantly affect driver-behaviour, vehicle speed, spacing, and intersection throughput. The simulation environment was developed in the Simulation of Urban Mobility (SUMO) platform using an urban road segment derived from geographic map data and traffic-flow information from the Vilnius city traffic database. 2 monitored junctions were selected as observation points, and traffic behaviour was simulated under 5 weather scenarios: normal conditions, light rain, heavy rain, fog, and snow. Weather-dependent driver parameters, including speed factor, reaction time, acceleration, deceleration, driver imperfection, and minimum gap, were incorporated into the simulation in order to reproduce realistic traffic dynamics. The generated simulation data, including vehicle count, speed, waiting time, temporal features, and encoded weather conditions, were used to train and evaluate multiple LSTM models through an AutoML-based tuning procedure. Among different configurations, the best-performing model consisted of 3 recurrent layers and achieved a validation RMSE of 0.1056 with a validation loss of 0.0652. The results show that the proposed framework is capable of reproducing the general temporal structure of urban traffic flow and preserving the relative ordering of traffic intensity across weather scenarios. Prediction quality was highest under normal conditions, with RMSE of approximately 0.21 veh/min, while the poorest accuracy was observed under snow conditions (about 2.5 veh/min). The model captured dominant traffic trends effectively, although it tended to smooth short-term local oscillations, especially under more unfavourable weather conditions. Overall, the study demonstrates that integrating SUMO-based simulation with LSTM forecasting provides an effective and flexible approach for short-term urban traffic prediction under varying meteorological conditions and may support future intelligent traffic management and weather-adaptive mobility applications.

Keywords: traffic flow simulation, machine learning, traffic flow prediction, weather condition simulation, SUMO.

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Notations

AutoML – automated ML;

CNN – convolutional neural network;

CSV – comma separated values;

IoT – Internet of things;

J1, J2 – monitored junctions in the study;

JUDU – Vilnius city mobility/traffic data source referenced in the article (<https://judu.lt>);

LSTM – long short-term memory;

MAE – mean absolute error;

ML – machine learning;

OpenStreetMap – open geographic map platform used for road-network generation (<https://www.openstreetmap.org>);

RL – reinforcement learning;

RMSE – root mean square error;

RNN – recurrent neural network;

SUMO – simulation of urban mobility;

TraCI – traffic control interface;

UM-DS – urban mobility – digital shadow;

V2X – vehicle-to-everything;

YOLO – you only look once.

1. Introduction

Mobility is becoming an increasingly important issue as cities gain in importance, with more than 56% of the world's population living in them. Urban planning principles have traditionally been developed to promote urban efficiency and increase productivity. The emergence of “smart mobility” has provided researchers with new ways to understand and plan cities (Allam, Sharifi 2022). In this context, intelligent transportation systems have become a key component of modern urban development, since they enable traffic processes to be monitored, analysed, and optimized in real-time. The growing availability of traffic data, simulation tools, and ML methods has created new opportunities for predicting traffic conditions and supporting more efficient traffic management strategies.

For instance, the analysis of theoretical concepts and models in the field of urban transport and smart cities shows the relevance and importance of this problem. Sustainable urban transport helps to achieve the Sustainable Development Goals and supports transformation processes towards more sustainable economic development, an ecologically minded society, and smart cities (Mavlutova *et al.* 2023). Recent smart city mobility innovations, such as intelligent transport systems, electric vehicles, autonomous vehicles, on-demand transport, shared transport, and mobility as a service, are constantly being hailed as a panacea for many of the economic, social and environmental impacts associated with private transport, including road congestion, social exclusion, increased costs, accidents, emissions and environmental degradation (Butler, Yigitcanlar 2020). One of the many strategies of smart city mobility policy is a sustainable approach to the transport system, aiming to reduce negative impacts and improve its performance. Nevertheless, given the rapid technological progress in the transport sector, it is necessary to identify and assess key innovations in smart mobility from a sustainability perspective. Testing intelligent transport systems on a city scale is expensive, requiring significant funding and planning. Using combined traffic simulations can help reduce initial costs and make it easier to adjust parameters to find real-world needs. Schweppenhäuser *et al.* (2026) presents a simulation-based evaluation that uses the open-source collaborative modelling framework Eclipse MOAIC, along with a new application.

Some connected vehicle-based approaches are limited by low penetration or limited real-time performance, which limits their engineering applicability. To overcome these problems, Wang *et al.* (2026a) proposes a microscopic, driver-behaviour-oriented queue prediction method for traffic light-controlled intersections based on roadside traffic data. The classical intelligent driver model is extended here by introducing a traffic light remaining time adjustment term to explicitly integrate drivers' anticipated braking during red phases and speed adaptation near the end of green phases into longitudinal acceleration. Recent studies have emphasized the relationship between urban traffic flow and ambient noise (Danilevičius *et al.* 2025). Danilevičius *et al.* (2025) examined instantaneous traffic noise levels through experimental observations combined with theoretically estimated traffic volumes derived from a discrete road traffic flow model. Traffic volume and the functioning of signalized intersections significantly affect noise levels, according to their findings.

On the other hand, road networks constitute a vital infrastructural element for the enduring operation of urban environments. Nevertheless, these networks frequently experience disruption due to urban flooding, thereby extending travel durations and impeding emergency response efforts. The research presented by Li *et al.* (2026) proposes a novel dynamic flood and response modelling framework designed for urban transport, with the aim of evaluating the effects of precipitation and flooding on traffic systems. This framework emphasizes the integration of an urban flood model, and an urban mobility model implemented within the SUMO software. The study concentrates on vehicular movement within urban areas and explores how cities can facilitate this movement through more intelligent planning. The essential elements for sustainable urban planning and management within SUMO are outlined as follows (Lopez *et al.* 2018):

- real-time data systems that optimize traffic flows and public transport schedules;
- smart public transport with digital ticketing, dynamic routes and live updates;
- shared mobility services such as electric scooters-, bicycles- and car-sharing fleets;
- smart charging networks integrate electric and low-emission vehicles;
- connected infrastructure, including sensors, cameras, and IoT devices, monitors and manages mobility and other.

Urban transport systems are increasingly at risk of climate-induced disasters and infrastructure disruptions. Wang *et al.* (2026b) presents a resilience-oriented assessment framework that integrates microscopic traffic modelling using SUMO to investigate both structural and functional performance of urban road networks under 4 different emergency scenarios. The simulation results highlight spatial and temporal vulnerabilities in urban transport systems and provide practical insights into emergency traffic management, climate change adapta-

tion planning, and resilient infrastructure design in rapidly urbanizing regions. The Chen *et al.* (2026) study revealed a dynamic “flow chain” characterized by changing roles of actors and complex interrelationships. While the increasing diversity of participants increased the stability of the ecosystem and mutualistic relationships encouraged cooperation, commensal and especially parasitic dynamics arising from competitive pressure and monopolized services posed significant barriers to integration. Serok *et al.* (2026) introduced a new decentralized traffic light control strategy, called the tree method, to mitigate the challenges posed by conflicting traffic flows operating at competing cycle times at certain phases of traffic intersections. This methodology relies on the precise identification of congestion bottlenecks and subsequent prioritization, considering their significant impact on the entire road network.

Urban mobility systems require continuous monitoring and optimization to meet increasing complexity and sustainability requirements. Rodríguez-Gómez *et al.* (2026) article introduces UM-DS, a modular framework that integrates heterogeneous real-time and historical data, such as traffic volume, incidents, weather and public transport, into a unified urban mobility model. UM-DS allows visualization, modelling and analysis through an extensible dashboard connected to the SUMO modelling engine. Petrov *et al.* (2026) proposes a modelling framework that integrates open-source tools such as OMNeT++ (<https://omnetpp.org>) and SUMO, augmented with a comprehensive communication model. Key contributions include extending the Veins framework to support pedestrian interaction variables and demonstrating its application in a simulated environment.

V2X technologies are widely considered a cornerstone of cooperative and automated driving, but their large-scale deployment in the real-world remains limited. Most existing performance assessments rely on synthetic traffic scenarios generated by simulators, however not fully reflecting real-world traffic characteristics. Vehicle trajectories obtained from highway drone and intersection drone datasets are converted into simulation-ready formats and combined with a standardized V2X network package to enable message-level performance analysis for all traffic groups (Arockiasamy, Vinel 2026).

Traffic light control is one of the main tools for reducing congestion, and recent studies have increasingly applied RL due to its adaptive capabilities (Chang *et al.* 2026). An adaptive traffic light control method is proposed by Deng *et al.* (2026) uses deep Q-network and proximal policy optimization to optimize signal timing by integrating variable cell length and multi-channel state representation. Simulation results using SUMO – Tensor Flow – Python demonstrate the cross-band portability evaluation and show that the proposed variable cell length and multi-channel state representation method is superior to the fixed cell length method in optimization performance.

Ahiska (2026) article examines multi-agent RL-based autonomous driving techniques and deep learning-based

comprehensive cooperative driving solutions. Intermediate autonomous navigation synthesis schemes are examined, in particular transformer-based connected and cooperative autonomous vehicles collective navigation architectures. A theoretical concept proposed by Rebally *et al.* (2026) identifies the indirect and cascading effects of floods and precipitation on transport when performing flood impact assessments. Conventional sensor-based crash detection systems suffer from high implementation costs and limited contextual awareness. Darla *et al.* (2026) article presents a comprehensive multimodal framework that combines a 6-model YOLO ensemble with image captions to detect and describe vehicle collisions in real-time. The proposed framework features improved interpretability due to natural language captions and efficient implementation scalability, making it a promising step towards autonomous, privacy-enhancing traffic safety systems.

Darla *et al.* (2026) presents a method for extracting information about individual mobility behaviour that ensures data privacy and integrates the data into comprehensive traffic modelling. A Bayesian network is created to capture the dependencies of trip variables, such as trip destination and start time. The network graph is discovered using a genetic algorithm. The conditional distributions obtained from these dependencies are used to generate synthetic, individual trip chains, which serve as input for traffic modelling in the open-source software SUMO.

A major challenge in autonomous vehicle research is reliable object detection in a variety of environmental conditions, such as fog, rain, and low light. Esmail Abbasi (2026) study developed a YOLO-based object detection model to identify vehicles, pedestrian zones or crossings, traffic lights, and road signs on roads. A multi-channel CNN is used to process SUMO environmental map data, including elements such as road edges, traffic light locations, and vehicle distribution. By integrating these features, CNN can dynamically determine optimal routes, considering real-world factors such as traffic density and signal layout.

The problem of sustainable transport in urban areas has been recognized in academic research, searching for suitable models and solutions. After analysing the studies conducted by other researchers, it was possible to systematize the ecosystem and trends of the urban transport concept, as well as mentioning possible future trends.

One of the major challenges in urban mobility one of the biggest problems with getting around in cities is that traffic conditions change a lot depending on the time-of-day, how many people are on the road, the layout of the road network, signal control, and environmental conditions. In particular, weather conditions such as rain, fog, and snow can significantly affect driver-behaviour, vehicle speed, and waiting time at intersections, thereby reducing network efficiency and increasing congestion. For this reason, reliable short-term traffic prediction models must account not only for temporal traffic patterns, but also for external factors that influence traffic dynamics and traffic

planning. Therefore, the main goal of this study is to develop and evaluate a weather-aware short-term traffic prediction framework that combines microscopic traffic simulation and deep learning for forecasting traffic conditions at selected urban junctions. The proposed framework aims to reproduce realistic traffic behaviour under different environmental conditions and to predict future traffic states, such as vehicle count, traffic flow, and average speed. To achieve this goal, the study addresses the following tasks:

- construct a simulation-based traffic environment using the SUMO platform and a real urban road network derived from geographic map data;
- incorporate weather-dependent driver-behaviour parameters into the traffic simulation in order to model the impact of normal weather, light rain, heavy rain, fog, and snow on traffic dynamics;
- generate and validate traffic datasets at selected junctions by comparing simulated traffic behaviour with available real traffic observations;
- prepare sequential traffic datasets containing traffic variables, time-of-day information, and encoded weather conditions for ML;
- train and evaluate LSTM-based forecasting models capable of predicting short-term traffic states under varying weather and demand conditions;
- to identify the optimal architecture for the traffic prediction problem at hand, a comparative analysis of various network configurations and training methodologies is essential;
- the model's ability to predict needs to be assessed using numerical accuracy measures and a visual comparison of the predicted and actual traffic curves.

This research introduces a novel approach by combining a SUMO-based microscopic traffic simulation model with a weather-aware LSTM forecasting model. The goal is to predict short-term urban traffic at specific intersec-

tions. The proposed method combines simulation-based scenario generation with machine-learning prediction. This is different from traditional mechanism-based approaches, which often oversimplify driver-behaviour and ignore the effects of changes in signal control, and from purely data-driven models, which rely heavily on large historical datasets. By including weather-dependent driver factors including speed factor, reaction time, acceleration, deceleration, driver imperfection, and minimum gap, it is possible to mimic realistic traffic behaviour in diverse weather circumstances. The key advantage of the suggested method is that it can create and use realistic traffic datasets even when there aren't many real-world observations available and expands the weather-based traffic prediction on previous research.

2. Methodology of research

The proposed traffic prediction framework integrates real-world traffic information, microscopic traffic simulation, and ML techniques. The overall workflow is illustrated in the methodology diagram in Figure 1.

Initially, traffic-related data are collected from official available traffic databases of Vilnius city routes from JUDU (<https://portal.sisp.lt/portal/apps/experiencebuilder/experience/?id=1741b3ca76c64faab74fe6343723c2ab>) and used to configure the simulation environment. These datasets provide baseline parameters such as traffic demand levels, and typical traffic patterns throughout the workdays. The road network configuration is generated using a digital map using *OpenStreetMaps* platform (Briem *et al.* 2019), which provides detailed information about the road topology, intersections, and connectivity between road segments. The selected study-area focuses on an observable street segment with 2 monitored junctions, as illustrated in Figure 2.

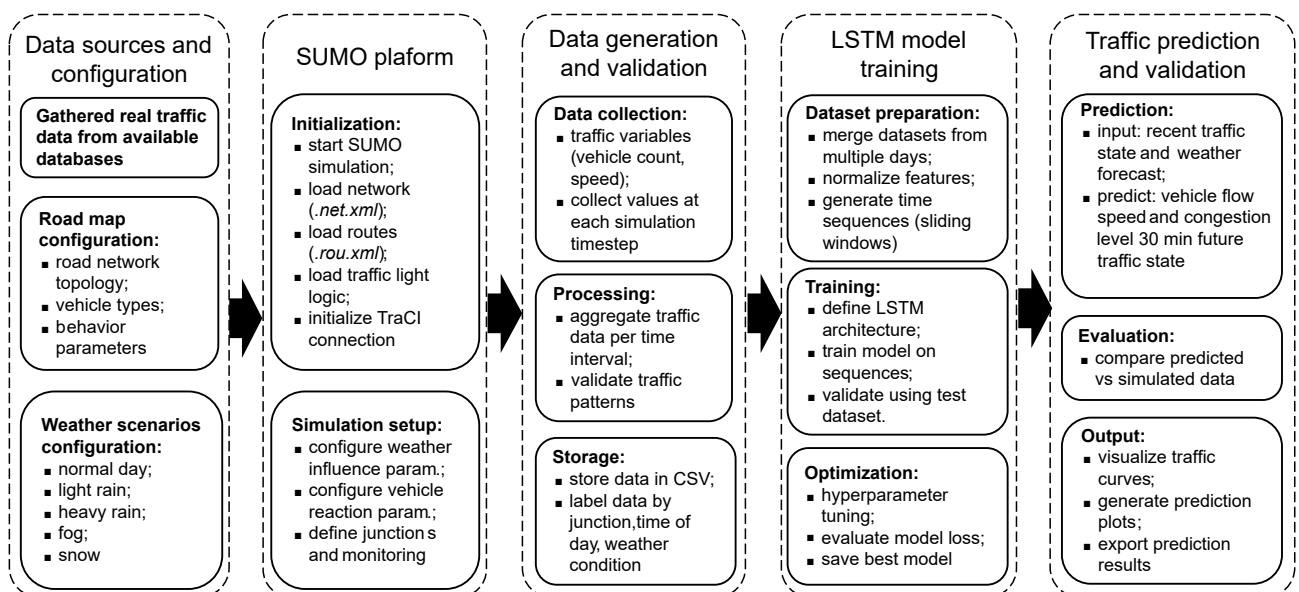
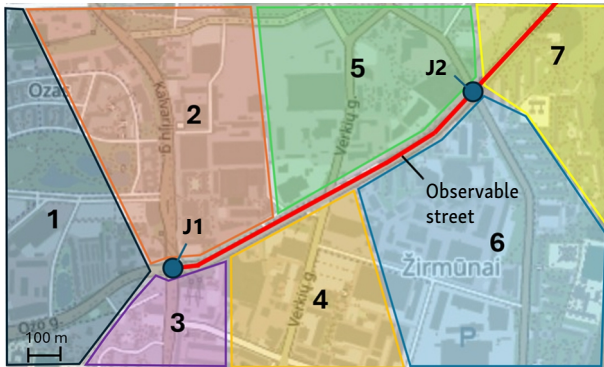


Figure 1. Methodology of the proposed SUMO-LSTM traffic forecasting framework

Table 1. Weather-dependent driver-behaviour parameters adopted in the SUMO simulation for different weather scenarios (Lu, Tettamanti 2018)

Weather condition	Speed factor	Driver reaction time τ [s]	Acceleration [m/s ²]	Deceleration [m/s ²]	Driver imperfection or unpredictability σ_i	Minimum gap [m]
Normal	1.00	1.20	2.6	4.5	0.5	2.5
Light rain	0.90	1.50	2.2	4.0	0.7	2.8
Heavy rain	0.80	1.80	2.0	3.8	0.9	3.2
Fog	0.80	1.70	2.2	4.0	0.8	3.0
Snow	0.70	2.50	1.3	2.8	1.2	3.8

**Figure 2.** Study-area road network with surrounding traffic zones (1...7) and monitored junctions J1 and J2

The analysed traffic map zone, presented in the figure, is divided into 7 surrounding traffic zones (1...7) representing different traffic areas with particular vehicle flow rate per hour, which contributing vehicle flows to the street under investigation is highlighted by a red line. For instance, analysing available information, traffic zones marked 1, 2 and 7 have a greater intensity of vehicles compared to 3, 4, 5 and 6 zones and from where the most vehicles arrive. Correspondingly, the end directions of traffic flow, where vehicles leave, can be monitored and defined for traffic simulations. 2 road intersections (or junctions), labelled J1 and J2, are selected as monitoring points where traffic variables are collected during simulation, representing the beginning and the end of the street. Additionally, these junctions represent bottlenecks where traffic converge from multiple zones.

The road network representation includes intersections, road segments, traffic signal locations, and connectivity relationships between edges. In addition, several parameters describing vehicle behaviour are combined to simulate realistic traffic dynamics within the simulation environment. These parameters include vehicle acceleration and deceleration capabilities, driver reaction time, driver imperfection (which reflects driver variability and randomness), and minimum headway between vehicles. Moreover, in order to model the influence of environmental conditions on traffic flow, several weather-dependent driver-behaviour parameters are introduced. These parameters modify vehicle dynamics and driver responses under different weather scenarios. The adopted parameter values used in the SUMO traffic simulation are summarized in Table 1 defined by Krauss car-following model.

The Table 1 presents the driver's behaviour parameters for 5 different weather conditions: normal weather, light rain, heavy rain, fog, and snow. The parameters include the speed factor, driver reaction time τ , acceleration, deceleration, driver imperfection or unpredictability σ , and minimum gap between vehicles. In unfavourable weather, the model simulates diminished vehicle speeds and acceleration, alongside extended driver reaction times and increased minimum safety gaps. For instance, under snowy conditions, the speed factor is diminished to 0.70, the reaction time is extended to 2.5 s, and the minimum inter-vehicle gap expands to 3.8 m, thereby mirroring more conservative driving practices. Likewise, scenarios involving heavy rain and fog precipitate moderate reductions in speed and increases in reaction time. These parameter modifications enable the simulation to accurately depict the influence of weather on traffic flow dynamics. Additionally, it is known that during summer and winter times these parameters can vary as well, therefore it was chosen to use average values. Nevertheless, parameter transferability is constrained, as driver reactions to snow, rain, and fog may differ based on local traffic culture, road maintenance standards, and seasonal variations.

The traffic simulation uses the SUMO platform. SUMO is a microscopic traffic simulator, which means it can model the movement and interactions of individual vehicles. The simulation environment is set up by following these steps:

- the road network is loaded, as defined in the *.net.xml* file;
- loading traffic routes involves working with *.rou.xml* files. These files hold the details of vehicle trips and the routes they take;
- the traffic light control logic is loaded, which specifies the signal phases and timing for each intersection it controls;
- the TraCI interface is initialized, allowing for real-time external control and monitoring of the simulation.

During the simulation's setup phase, weather-dependent parameters are implemented to influence driver-behaviour, and specific junctions are designated as monitoring points for the measurement of traffic variables throughout the simulation. Subsequently, traffic data are generated via numerous simulation iterations, encompassing diverse weather scenarios and varying traffic demand conditions, facilitated by the TraCI interface.

During the simulation's operation, various traffic-related metrics are documented at each timestep. The main var-

ables recorded encompass the vehicle count at the junction, the average vehicle speed, and the waiting time for vehicles. These variables are specifically gathered for each monitored junction, with a focus on J1 and J2. The resulting data offers a comprehensive temporal perspective on traffic dynamics throughout the simulated day. Each data point is linked to a precise timestamp, facilitating the analysis of traffic flow as a time-series dataset. The raw traffic measurements derived from the simulation undergo processing to generate systematized traffic statistics across predetermined time intervals. For this research, traffic flow values are systematized on an hourly basis to identify daily traffic patterns and peak traffic periods. Subsequently, the processed data undergoes validation to confirm that the simulated traffic patterns align with realistic traffic behaviour observed in the real-world dataset.

To evaluate the accuracy of the simulation model, the simulated traffic data are compared with real traffic observations obtained from the Vilnius city traffic database over a month period in February 2026. The comparison focuses on the number of vehicles passing through junctions J1 and J2 during different times of the day (Figure 3). The figure illustrates the temporal distribution of vehicle numbers throughout a 24-h period for both real and simulated traffic flows. As can be noticed in the figure, the simulated traffic curves closely follow the general trend of the real traffic data validating the simulation accuracy to real life example. Both datasets demonstrate similar traffic patterns characterized by low traffic volumes during nighttime hours, a rapid increase in traffic during the morning rush period between approximately 06:00 and 08:00 (1st traffic peak), and a gradual stabilization during daytime hours. A 2nd traffic peak can be observed during the afternoon and evening period between 16:00 and 18:00, corresponding to typical evening commuter traffic.

After processing and validation, the traffic data are stored in CSV format for further analysis and ML model training. Each dataset entry contains information about the monitored junction, timestamp, weather scenario, and corresponding traffic variables. This structured dataset forms the basis for the further training of the LSTM-based traffic prediction model.

To predict short-term traffic conditions under different environmental scenarios, a LSTM neural network is employed. LSTM networks belong to the class of RNNs and are particularly suitable for modelling sequential data with long-term temporal dependencies, such as traffic flow time series. The proposed model learns the relationship between historical traffic observations, weather conditions, and temporal patterns in order to predict future traffic states. The traffic dataset used for training the model is constructed by combining traffic measurements obtained from multiple simulation runs under different weather conditions. Each data record includes the following variables and are combined into a feature vector representing the traffic state at time t :

$$x_t = \{N_t, v_t, w_t, T_t, Wx_t\}, \quad (1)$$

where: x_t – traffic-state feature vector at time t ; N_t – number of vehicles observed at time t ; v_t – average vehicle speed; w_t – average waiting time, T_t – represents time-dependent features (e.g., hour of day), Wx_t – weather condition encoded as categorical variables.

To capture temporal dependencies, sliding windows are used to transform the dataset into sequences. For a given time, window of length k , the input sequence is defined as:

$$X_t = \{x_{t-k+1}, x_{t-k+2}, \dots, x_t\}, \quad (2)$$

where: X_t – input sequence formed from historical traffic-state vectors within the sliding window.

The model is trained to predict the future traffic state after a prediction horizon h , such as 30 min ahead:

$$\hat{x}_{t+h} = f(X_t), \quad (3)$$

where: \hat{x}_{t+h} – predicted future traffic state after horizon h ; $f(\cdot)$ – representation of the LSTM prediction function. LSTM networks extend traditional RNNs by introducing a memory cell and gating mechanisms that regulate the flow of information through time. At each time step t , the LSTM cell receives traffic-state feature vector at time x_t ; h_{t-1} – hidden state from the previous time step.

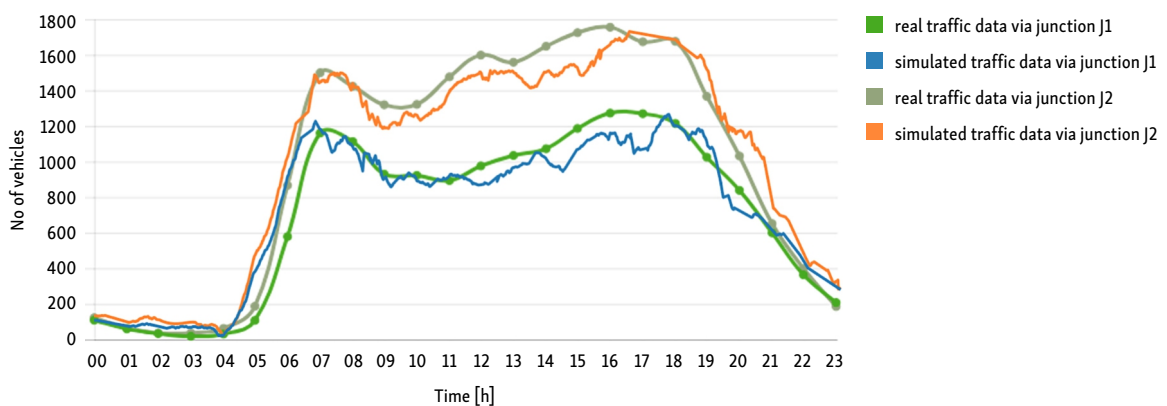


Figure 3. Traffic data comparison between real traffic and simulated referring to the number of vehicles during working days

The internal operations of the LSTM cell are controlled by 3 gates: the forget gate, input gate, and output gate. These gates determine how information flows through the network (Abduljabbar *et al.* 2021). The forget gate determines which information from earlier traffic states should be retained or discarded. This is particularly important because traffic data generated from SUMO contain both persistent patterns and short-term fluctuations. For example, the model may retain recurring daily congestion patterns, such as morning and evening peaks, while suppressing less relevant short-lived disturbances. The forget gate is defined as:

$$f_t = \sigma(W_f \cdot x_t + U_f \cdot h_{t-1} + b_f), \quad (4)$$

where: f_t – forget gate activation vector; σ – activation vector in the LSTM cell; x_t – traffic-state feature vector at time t ; h_{t-1} – hidden state from the previous time step; W_f , U_f – trainable weight matrices; b_f – bias vector.

In practical terms, this gate allows the network to decide how much previously observed traffic information, such as earlier vehicle accumulation or speed reduction, remains relevant for future predictions.

The input gate controls how much new SUMO-generated information should be written into the LSTM memory. Since the traffic state evolves over time as vehicles pass monitored junctions and weather conditions affect driving behaviour, the input gate determines the extent to which newly observed traffic changes are incorporated into the internal memory of the model. It is computed as:

$$i_t = \sigma(W_i \cdot x_t + U_i \cdot h_{t-1} + b_i), \quad (5)$$

where: i_t – input gate activation vector in the LSTM cell; W_i , U_i – trainable weight matrices; b_i – bias vector.

The output gate determines which part of the internal memory should be exposed as the hidden state used for traffic prediction. In other words, it decides which learned temporal patterns are most relevant for estimating the future traffic condition, such as the expected vehicle count or speed 30 min ahead. The output gate o_t is defined as:

$$o_t = \sigma(W_o \cdot x_t + U_o \cdot h_{t-1} + b_o), \quad (6)$$

where: o_t – output gate activation vector in the LSTM cell; W_o , U_o – trainable weight matrices; b_o – bias vector.

In the proposed framework, this output may represent traffic speed, vehicle count, or another selected traffic indicator predicted from the historical SUMO-generated data.

In the present study, the evaluation of multiple LSTM configurations is necessary because of the traffic data exhibited substantial variability across weather conditions, time periods, and monitored junctions. In order to better adapt the LSTM model, several architecture configurations need to be tested. Because of spatial and temporal variations in SUMO generated data, a random single fixed model architecture could not be assumed to be optimal for all cases. The AutoML process was employed to systematically

evaluate various LSTM architectures and training configurations to determine the optimal model for the specified traffic prediction task. The search space encompassed the quantity of recurrent layers, the number of hidden units per layer, dropout rate, dense layer size, learning rate, and batch size, which are the main hyperparameters of such model type (Abduljabbar *et al.* 2021). Model selection was determined by validation loss and validation RMSE, with the search concluding after the completion of a predetermined set of 12 trials. The number of hidden units in the recurrent layers varies between 32, 64, 128, allowing the comparison of models with lower and higher representational capacity. To reduce overfitting and improve generalization, different dropout coefficients were tested, including the ratio of 0.2. In addition, the fully connected layer following the LSTM block is tested with 32, 64, 128 neurons in order to assess the influence of output-layer complexity on prediction performance and training. The models were trained using the Adam optimizer with an initial learning rate of 0.001 and 0.005, which influences the convergence speed and training stability. By systematically comparing these alternative configurations, the study selected the architecture that achieved the best balance between prediction accuracy and model generalization.

Once the LSTM model is trained, the prediction of future traffic states based on recent traffic observations and weather conditions is performed and evaluated by comparing data with real traffic scenarios in different weather conditions. This comparison enables the validation of how accurately the trained model predicts future scenario simulated by traffic dynamics under different traffic and weather conditions. The predictive performance is assessed using standard regression metrics such as the MAE. The model generates forecasts for traffic variables on which it is trained, for example 30 min ahead. In this way, the model provides a short-term estimate of the expected traffic state at the monitored junctions under different environmental scenarios. The prediction process is performed by supplying the trained LSTM model with a sequence of recent traffic observations collected over a predefined input window. These observations include traffic variables for specific period of time extracted from the SUMO simulation, such as vehicle count, speed, and waiting time, together with additional contextual features, including time-of-day indicators and encoded weather conditions.

3. Results

This section presents the results of the proposed LSTM-based traffic prediction framework and evaluates the influence of different model configurations on forecasting performance. The objective of the analysis is to identify the most suitable neural network architecture for short-term traffic prediction under the considered traffic and weather conditions and use it for pattern predictions on unseen data. Model comparison was performed using both the

best validation loss and the validation RMSE. Table 2 summarizes the training performance of a total of 12 trials during AutoML training and evaluated, each corresponding to a different LSTM architecture and training setup. In the present study, validation loss corresponds to the optimization objective recorded during model training, while validation RMSE was used as an additional performance indicator for model comparison. Because these values are not necessarily computed on exactly the same scale or transformation stage, they should not be interpreted as numerically equivalent.

Among the evaluated configurations, the best overall configuration was Trial No 1, which achieved the lowest validation RMSE of 0.1056 and the validation loss of 0.0652. This model used a 3-layer recurrent architecture with 32 neurons in the 1st layer, 96 neurons in the 2nd layer, and 32 neurons in the 3rd layer, without dropout, followed by a dense layer with 32 neurons. The model was trained using a learning rate of 0.001 and a batch size of 32. This result indicates that, for the considered dataset, a moderately deep architecture without dropout was able to capture the temporal traffic dependencies most effectively. Very similar performance was obtained by Trial No 12, which produced a validation RMSE of 0.1058 and a best validation loss of 0.0658. This model consisted of a 2-layer recurrent structure with 128 and 128 neurons, also without dropout, a dense layer with 32 neurons, a learning rate of 0.001, and a batch size of 64. Another competitive configuration was Trial No 8, which used a single recurrent layer with 64 neurons, a dense layer with 64 neurons, and no dropout, achieving a validation RMSE of 0.1069 and a best validation loss of 0.0671.

At the same time, some configurations produced noticeably worse results. For example, trials using dropout of 0.2 with smaller or less balanced recurrent structures generally showed higher validation losses. This suggests that, for the current dataset and forecasting task, excessive regularization may reduce the model’s ability to capture important temporal dependencies in the traffic data. Similarly, the results show that the relationship between model

depth and performance is not monotonic: increasing the number of layers does not necessarily improve prediction accuracy. Instead, model performance depends on the balance between network complexity, training stability, and the representational capacity required by the traffic time series.

The training curve of the best-performing trial is shown in Figure 4. The figure below illustrates the performance of the training and validation losses over 40 epochs. A rapid decrease in both curves can be observed during the initial epochs, indicating that the model efficiently learned the dominant traffic patterns from the training data. After approximately 5...10 epochs, both loss curves begin to stabilize, and only minor improvements are observed in the rest of epochs. This behaviour indicates that the model successfully converged and that the selected number of epochs was adequate for training.

It can be noted from the training history that the validation loss remains consistently below the training loss throughout the learning process. This indicates stable generalization behaviour and suggests that the trained model did not suffer from severe overfitting. The relatively smooth shape of the validation curve also indicates that the optimization process was stable and that the selected

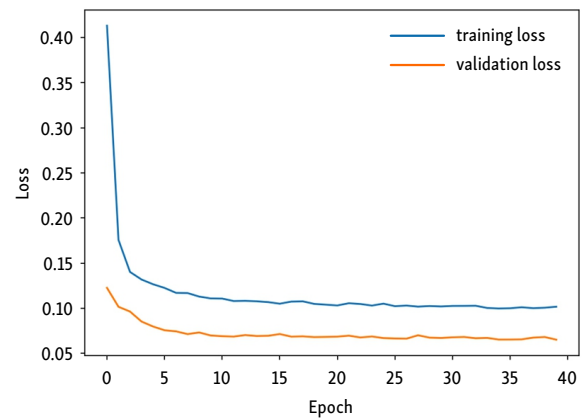


Figure 4. Training and validation loss curves of the best-performing LSTM model

Table 2. Performance comparison of AutoML-tested LSTM configurations

Trial No	Neuron units in 1st layer	Neuron units in 2nd layer	Neuron units in 3rd layer	Dropout ratio	Neuron units in dense layer	Learning rate	Batch size	Best validation loss	Validation RMSE
1	32	96	32	0	32	0.001	32	0.0652	0.1056
12	128	128	–	0	32	0.001	64	0.0658	0.1058
8	64	–	–	0	64	0.001	32	0.0671	0.1069
6	64	128	–	0	32	0.001	32	0.0116	0.1078
3	128	32	96	0.2	128	0.0005	32	0.0119	0.1090
11	64	–	–	0	32	0.0005	32	0.0120	0.1097
7	96	–	–	0	64	0.0005	32	0.0697	0.1098
2	96	–	–	0.2	32	0.001	64	0.0126	0.1120
9	32	–	–	0	128	0.0005	32	0.0129	0.1133
4	64	–	–	0.2	64	0.0005	32	0.0764	0.1151
10	96	–	–	0.2	128	0.0005	64	0.0757	0.1156
5	64	–	–	0.2	64	0.0005	32	0.0751	0.1156

learning rate allowed gradual convergence toward a suitable local optimum. After the analysis of ML models, the best-trained model is integrated into a traffic simulation and prediction pipeline.

Figure 5 shows the short-term traffic prediction results for junction J1 under 5 weather scenarios: normal conditions, light rain, heavy rain, fog, and snow. The solid curves denote the actual traffic values, while the dashed curves represent the predicted traffic over the future forecast interval. The plotted variable is vehicle count per minute, and the displayed time interval extends approximately from 09:00 to 11:30.

From the Figure 5, it can be observed that the traffic level strongly depends on the weather scenario. Under normal conditions, the actual traffic remains in the range of approximately 14...21 veh/min, with most values concentrated around 18–20 veh/min. Under light rain, the traffic varies more significantly, roughly between 14 and 24 veh/min. For heavy rain, the traffic level is generally higher, fluctuating in the interval of about 17...27 veh/min. Under fog, the actual traffic is mainly between 17 and 26 veh/min, whereas under snow the highest traffic intensities are observed, with values reaching approximately 24...28 veh/min and local maxima close to 29 veh/min.

The forecast interval begins near 11:00, as indicated by the vertical marker dashed line. In this interval, the model continues the traffic evolution using coloured dashed lines. For normal conditions, the predicted traffic remains close to the recent observed level, around 17.5...18.0 veh/min, which is consistent with the actual scenario. For light rain, the prediction remains near 17...19 veh/min, while the actual curve shows a stronger fluctuation, including a local decrease to about 15 veh/min before rising again. For heavy rain, the forecast increases from approximately 20 veh/min to about 22...23 veh/min, whereas the actual curve 1st decreases toward 17...18 veh/min and then recovers sharply. In the fog scenario, the predicted traffic remains near 20.0 veh/min, while the actual continuation fluctuates around 19...21 veh/min. Under snow, the prediction rises from approximately 26 veh/min to nearly 29 veh/min, while the actual curve remains between about 24.5 and 27 veh/min.

The most important observation is that the model preserves the relative traffic ordering among weather scenarios. This indicates that the model is not only extrapolating recent temporal behaviour but is also incorporating the weather-dependent structure learned from the training data. At the same time, the forecasted segments are visibly smoother than the measured curves. In quantitative terms, the model reproduces the average traffic level well, but it tends to have a deviation of about 2...4 veh/min. This effect is especially visible in the light rain and heavy rain cases, where the actual traffic exhibits short-term oscillations that are only partially captured by the forecast. Such smoothing behaviour is typical for LSTM-based predictors, which are generally effective in representing the dominant trend but less accurate in reconstructing local fluctuations.

Figure 6 presents the short-term traffic prediction results for another junction J2 under the same weather scenarios. As in the previous figure, the solid curves correspond to the actual traffic values, while the dashed curves indicate the predicted traffic values in the forecast horizon.

Compared with junction J1, the traffic dynamics at J2 exhibit a wider range of fluctuations and stronger sensitivity to weather conditions but also more vehicles as well. Under normal conditions, the actual traffic varies approximately between 16.5 and 26.5 veh/min, with most values lying in the range of 20...24 veh/min. In the case of light rain, the traffic level fluctuates roughly between 17.5 and

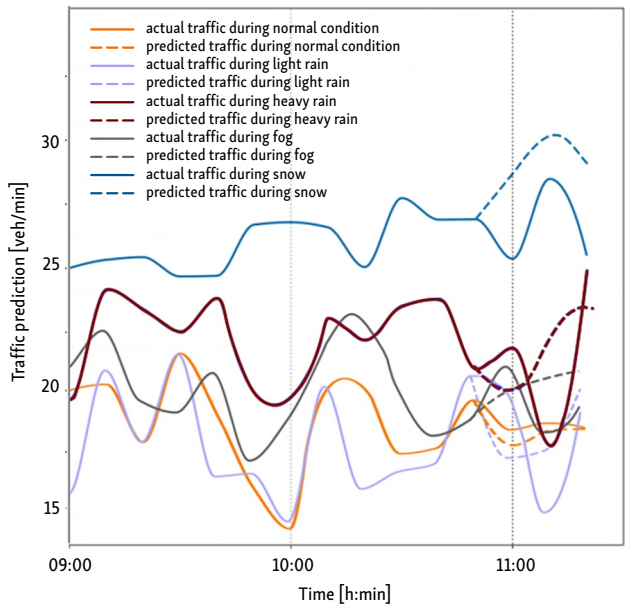


Figure 5. Traffic prediction in J1 evaluating different weather conditions

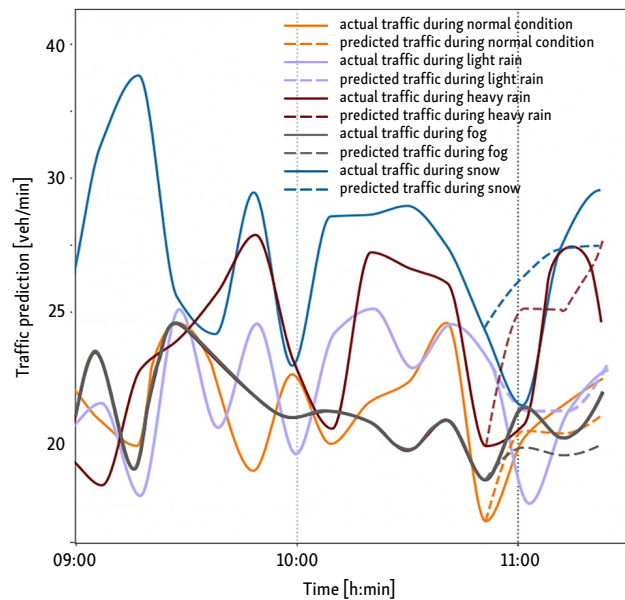


Figure 6. Traffic prediction in J2 evaluating different weather conditions

30.5 veh/min. Under heavy rain, the actual traffic remains mostly in the range of 18...30 veh/min, with several local maxima around 29...30 veh/min. For fog, the traffic is concentrated between approximately 18.5 and 28 veh/min, while under snow the highest traffic levels are observed, reaching about 23...37 veh/min, with a particularly strong peak near 09:20, where the traffic approaches 37 veh/min. Therefore, the overall spread between the lowest and highest observed traffic levels at J2 is on the order of 20 veh/min, which is noticeably larger than that observed at J1.

In traffic forecast region, the dashed curves show how under normal conditions, the predicted traffic remains close to 20...21 veh/min, which is consistent with the actual continuation of the curve. In the light rain case, the forecast remains around 20...23 veh/min, while the actual traffic recovers from a lower level near 17.5 veh/min toward approximately 22...23 veh/min. For heavy rain, the predicted traffic remains near 25 veh/min, which aligns well with the actual future values, remaining in the interval of approximately 24.5...27 veh/min. In the fog scenario, the prediction is close to 19...20 veh/min, while the actual traffic is slightly higher, around 21...22 veh/min, indicating a moderate underestimation. Under snow, the forecast rises from approximately 24 veh/min to nearly 25 veh/min, while the actual curve remains around 22...23 veh/min, indicating that the model slightly overestimates the future traffic under snow conditions. The ML model again preserves the relative effect of weather conditions on traffic intensity, although in comparison to J2, it is more dynamic than at J1. The snow scenario remains the highest overall, especially during the observed period, while heavy rain and light rain also produce elevated traffic levels relative to normal conditions and fog. The model correctly reflects these differences in the prediction interval, demonstrating that it learned the weather-sensitive structure of the traffic data.

At the same time, Figure 6 also confirms a characteristic feature of the LSTM forecasts: the predicted curves are smoother than the corresponding actual trajectories. While the model captures the average traffic level and overall continuation of the process, it tends to reduce the amplitude of short-term oscillations. At J2, these local variations can reach approximately 3...6 veh/min, especially under snow, light rain, and heavy rain, and the model reproduces them only partially. This indicates that the prediction performance is effective in estimating the dominant short-term tendency but less precise in reconstructing abrupt local fluctuations.

Figure 7 presents the summarized box-plot of the distribution of RMSE standard deviation values for traffic-flow prediction under the same weather conditions during the whole workday time and in both junctions J1 and J2. RMSE is expressed in vehicles per minute, and lower RMSE indicates better predictive agreement between the estimated and actual traffic counts.

The box-plot standard deviation distributions were plotted to visualize variability and robustness, where the box centre line shows the median and the green triangle

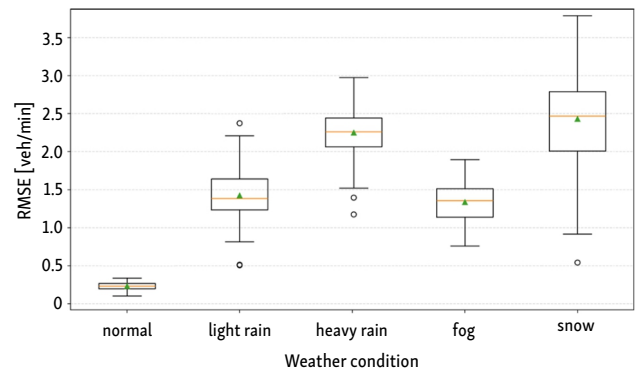


Figure 7. Traffic prediction RMSE values representation of different weather conditions

shows the arithmetic average. Thus, the narrow and low-valued box for normal conditions reflects both high accuracy and low dispersion, whereas the higher and wider boxes for heavy rain and snow indicate larger prediction error and increased uncertainty. The intermediate positions of fog and light rain indicate moderate model degradation under those weather disturbances.

These values indicate that the prediction model performs best under normal traffic conditions, where the error is comparably small ($RMSE \approx 0.21$) to other less predictive weather conditions. This suggests that, in the absence of more unfavourable weather conditions, the predicted traffic flow is closely aligned with the actual measured values, and the prediction error remains highly low and stable. Under fog, the RMSE rises to approximately 1.3 veh/min, indicating a noticeable but still moderate deterioration in performance. A similar effect is observed for light rain, where the RMSE is approximately equal to 1.5 veh/min. Comparing these 2 cases shows that the model prediction quality in fog and light rain is similar.

The poorest prediction is observed during snow condition over the time, where the RMSE reaches almost 2.5 veh/min. For heavy rain, the RMSE is approximately 2.3 veh/min, which is also substantially higher than the values obtained in normal, fog, and light rain conditions. In comparison to normal weather conditions, the snow-related prediction error is roughly 12 times greater, indicating a strong reduction in prediction reliability, indicating big unpredictability of driver's behaviour. These values confirm that adverse weather introduces measurable instability into traffic prediction, and the severity of this impact increases with the intensity of the weather disturbance. In this approximation, snow condition represents the most critical condition for model performance, followed by heavy rain, while normal conditions remain the most predictable traffic regime.

4. Conclusions

This study introduced a weather-aware short-term urban traffic forecasting framework that integrates microscopic traffic simulation in SUMO with LSTM-based prediction. The proposed approach was used on a Vilnius city road

length with 2 monitored intersections, J1 and J2. The simulation results were compared to real traffic data. The comparison demonstrated that the simulated traffic profiles accurately reflected the main daily traffic pattern, encompassing morning and evening peak periods. This proved that the established simulation environment was appropriate for producing training data for the forecasting model.

The trained LSTM models showed that the suggested framework can forecast the main short-term trends in traffic flow in diverse weather conditions. The model that worked best out of all the ones evaluated had 3 recurrent layers and got a validation RMSE of 0.1056 and a validation loss of 0.0652. The results also demonstrated that the accuracy of the predictions depends a lot on the weather. The smallest prediction error was when the weather was normal, with an RMSE of around 0.21 veh/min. The biggest mistakes happened when it was foggy and light rain, and the poorest performance happened when it was heavy rain and snow, with RMSEs of about 2.3 and 2.5 veh/min, respectively. These results show that bad weather makes urban traffic behaviour far more unpredictable and makes it harder to create short-term predictions. The model's tendency to mitigate short-term local fluctuations can be attributed to the characteristics of the LSTM forecasting methodology and the increased variability of traffic during severe weather conditions. The model is designed to identify the prevailing temporal pattern and reduce average prediction error, resulting in a tendency to replicate the overall traffic trend rather than sudden short-term fluctuations. This effect is more noticeable in snowy conditions, where diminished speed, extended reaction time, decreased acceleration, and increased vehicle spacing contribute to more unpredictable traffic behaviour. The model accurately reflects the general trend but fails to account for abrupt local variations, leading to the elevated RMSE noted in snowy conditions.

Similar to earlier research, the present model performed best under more stable traffic conditions and was able to reproduce the general short-term trend reliably. The main practical advantage of the suggested method is that it can give accurate short-term predictions of overall traffic trends, even when there aren't any large, weather-diverse datasets available. The findings indicate that prediction accuracy may be enhanced by incorporating more explanatory variables, including traffic-signal states, wait length, lane occupancy, and a more comprehensive real-world calibration of weather-dependent driving attributes. The study validates and expands on previous research by this SUMO-LSTM framework, which is an effective instrument for weather-adaptive urban traffic forecasting and can facilitate future intelligent traffic management applications.

Future work should focus on extending the model to a larger urban network and other traffic parameters prediction to get better insights, incorporating additional external variables such as traffic signal states, prolonged observation terms including day length and seasonal vari-

ables. This can be done by adding road-surface condition indicators, like wet or low-friction pavement, and visibility-related variables, like fog and snowfall intensity, or reduced sight distance. Additionally, it would be important to improve the calibration with larger real-world datasets and investigate other types of ML models to better capture fluctuations in short- and long-term traffic.

Author contributions

Giedrius Garbinčius and *Mantas Makulavičius* conceived the study and were responsible for the design and development of the data analysis.

Giedrius Garbinčius and *Mantas Makulavičius* were responsible for data collection and analysis.

Mantas Makulavičius was responsible for data interpretation.

Giedrius Garbinčius and *Mantas Makulavičius* visualization.

Giedrius Garbinčius wrote the 1st draft of the article and finalized the article.

Disclosure statement

Authors do not they have any competing financial, professional, or personal interests from other parties.

Declaration on the use of Artificial Intelligence (AI)

During the preparation of this manuscript, the authors did not use generative AI or AI-assisted technologies.

The authors take full responsibility for the content of this manuscript.

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