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Yurii Matseliukh,
Vasyl Lytvyn,
Myroslava Bublyk

DEVELOPMENT OF A NEURAL NETWORK FOR FORECASTING PASSENGER FLOWS IN SMART CITY PUBLIC ELECTRIC TRANSPORT

The research object is a hybrid deep learning model for passenger flow forecasting. These passenger flows constitute complex time series, influenced by a combination of temporal, spatial, and operational factors. The study addresses the fundamental mismatch between stochastic passenger demand and the static supply of transport services. This disparity results in operational inefficiency and a reduced quality of service for passengers. A lack of accurate forecasting tools hinders the optimal daily allocation of rolling stock, thereby limiting the efficiency of transport operators.

A hybrid deep learning model was developed and validated to predict daily passenger flows with high accuracy (R^2 = 0.91). The findings significantly outperform the baseline models and approaches described in scientific sources. This performance is attributed to a sophisticated strategy combining advanced feature engineering. This included the use of cyclic, lagged, and moving average features. This approach was paired with residual modelling, enabling the neural network to capture complex non-linear deviations. Furthermore, robust data preparation methods enhanced the model's high generalization capabilities.

The findings demonstrate that the proposed hybrid approach is an effective tool for operational planning. The results of the neural network work facilitate the optimization of the distribution of rolling stock allocation and improve resource utilization. Consequently, it enhances passenger comfort, contributing to the sustainable development of urban mobility. For practical applications, the model requires reliable historical passenger flow data. It enables operators to mitigate economic losses from underutilized vehicles and prevent overcrowding on high-demand days.

Keywords*: passenger flow, neural network, LSTM, public transport, smart city, residuals modelling.*

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1. Introduction

The challenge of rapid urbanization creates several significant problems in the field of urban passenger transport, which, in turn, also lead to increased congestion, higher emissions of carbon compounds and a general decline in quality of life [1, 2]. Sustainable urban development is intended to address these issues by creating an efficient, reliable and convenient public transport system, in which electric transport plays a key role [3, 4]. In the paradigm of sustainable development, electric transport is recognized as an alternative to private vehicles powered by hydrocarbon fuels.

The efficiency of electric transport during operation is directly determined by the relationship between the supply of services and passenger demand. An imbalance between them results in overcrowded vehicles during peak hours and economic inefficiency due to underutilized vehicles during off-peak hours [5, 6]. This negatively impacts the quality of transport services, passenger comfort and urban life. Therefore, the problem of accurately forecasting passenger demand is becoming increasingly pressing for building modern intelligent transport systems in line with the smart city concept.

Studies [7, 8] demonstrate that traditional statistical approaches, such as ARIMA, effectively model linear trends and seasonality in traffic flow forecasting [9]. However, forecasting the nonlinear and stochastic nature of passenger demand remains an unresolved issue. This is due to the models' fundamental inability to capture complex, nonlinear dependencies influenced by external factors. Machine learning models present a viable option for overcoming these limitations.

In [10], LSTM and GRU deep learning architectures were successfully applied to traffic flow forecasting. However, as [11] point out in their large-scale study, for many time series tasks, ensemble methods, such as XGBoost, can achieve comparable or even better results with lower computational costs and greater interpretability. This gives rise to a discussion about the feasibility of using complex neural network architectures [12, 13].

On the other hand, research [14, 15] shows that LSTM networks are a powerful tool for traffic flow forecasting, since they are able to learn long-term dependencies. This approach was developed in works where various LSTM-based architectures were used for passenger flow analysis [16, 17]. Hybrid models have been proposed to address this problem [18, 19], as standard recurrent networks by their nature process data sequentially. In [20], the issues of effectively considering spatial dependencies and external factors remained unresolved. In [21], neuro-fuzzy networks were proposed for forecasting, which is also a promising direction. However, the integration of additional modules, such as attention mechanisms [22] or convolutional blocks, often leads to a significant complication of the model and an increase in the cost of its training and implementation.

The most modern option for overcoming spatial limitations is the use of graph neural networks (GNN), as described in detail in the review [23]. Models [24, 25] directly model the topology of the transport network. However, their practical application is complicated by high computational complexity and the need for detailed, precisely structured graph data, which makes such studies extremely expensive for many transport operators.

All this allows to argue that there is a significant trade-off between the accuracy of architecturally complex models (GNN) and their resource requirements. On the other hand, more accessible architectures such as standard LSTMs, while capturing temporal patterns well [26], are often unable to fully overcome the noise and complex nonlinearities of real-world data. It is worthwhile to conduct research dedicated to the development of a robust and practical model that achieves high accuracy not at the expense of architectural complexity, but thanks to advanced data preparation and modelling techniques.

The aim of this research is to develop and evaluate a hybrid deep learning model, which combines advanced feature engineering with a Bidirectional LSTM architecture and a residual modelling approach, to accurately forecast daily passenger flows in urban electric transport. The practical application of this model will provide transport operators and city authorities with an effective data-driven tool for operational planning. This enables optimized rolling stock allocation, improving economic efficiency and the passenger experience. It therefore boosts the transport system's attractiveness and reliability, a vital smart city objective. The methodology [27] in substantiates this, linking the success of new transport technologies to public perception.

To achieve this aim, it is necessary to complete the following objectives:

1. To develop a hybrid deep learning architecture, utilising a Bi-LSTM structure and a residual modelling approach.
2. To design and implement an advanced feature engineering process to enrich the input data.
3. To rigorously evaluate the developed model's performance on a realistic dataset.

2. Materials and Methods

The object of research is a hybrid deep learning model for passenger flow forecasting. This process is treated as a complex stochastic time series, characterized by fluctuations, patterns, and a temporal structure with complex, non-linear dependencies. Its functioning is influenced by a combination of temporal (day of the week, seasonality), and spatial (the route network), all examined within the context of the smart city and sustainable development concepts.

The demand data for electric vehicles is temporal in nature with pronounced weekly seasonality, making LSTM networks an excellent candidate for modeling.

The methodology for this study is founded upon a comprehensive strategy, integrating advanced data preparation with a sophisticated deep learning architecture and a robust training process. This approach was structured around three key areas: extensive feature engineering (including Advanced Feature Engineering), a hybrid residual modelling architecture (Residual Model and Bi-LSTM Layers), and an optimized learning process.

A critical component of the methodology was advanced feature engineering to provide the model with a rich contextual understanding of the time-series data. To capture the inherent cyclicality of temporal data, features such as the day of the week, day of the month, and month of the year were transformed into two-dimensional representations using sine and cosine functions. This allows the model to understand the proximity of sequential periods, such as Sunday to Monday.

To model short-term autocorrelation, lagged features were created, notably *Pass_Flow_Lag1* (previous day) and *Pass_Flow_Lag7* (same day last week), with the latter serving as a strong baseline for the forecast. Furthermore, to provide the model with a sense of local trends, moving averages over a 7-day window and an Exponentially Weighted Moving Average (EWM) with a smoothing parameter $\alpha = 0.3$ were introduced. All temporal features were carefully grouped by route to prevent data leakage between distinct transport lines. A seasonal feature indicating the quarter of the year was also included.

This rich feature set was then utilized within a hybrid residual modelling framework. Rather than tasking the network with predicting the absolute passenger flow, a residual modelling approach was adopted. The model was trained to predict only the residual – the difference between the actual passenger flow and the baseline forecast provided by the 7-day lag feature. This significantly simplifies the learning task, allowing the model to focus its capacity on capturing complex, non-linear deviations.

The core of the architecture is a stack of two bidirectional LSTM (Bi-LSTM) layers. Unlike a standard LSTM which processes data chronologically, a Bi-LSTM analyses the sequence in both forward and reverse directions. This provides each time step with a richer context derived from both past and future points within the input sequence, significantly improving the model's ability to capture intricate patterns.

The specific model architecture is as follows (Fig. 1). It begins with an input layer configured for sequences of 7 time steps with 28 features each. The first Bi-LSTM layer contains 128 neurons and is set with *return_sequences = True* to pass its full output sequence to the next layer. This is followed by a second Bi-LSTM layer with 64 neurons, which compresses the information and outputs only the final hidden state (*return_sequences = False*). To prevent overfitting, dropout layers with a rate of 0.3 are applied after each Bi-LSTM layer. The architecture concludes with an intermediate dense layer of 32 neurons and a final dense output layer with a single neuron and a linear activation function to produce the unconstrained regression forecast. The Rectified Linear Unit (ReLU) activation function is used throughout the hidden layers.

The model was trained using the Adam optimizer with an initial learning rate of 0.001. To ensure robust convergence and prevent overfitting, a dynamic learning process was established. A *ReduceLROnPlateau* callback was implemented to automatically decrease the learning rate if the validation loss (*val_loss*) did not improve for 7 consecutive epochs.

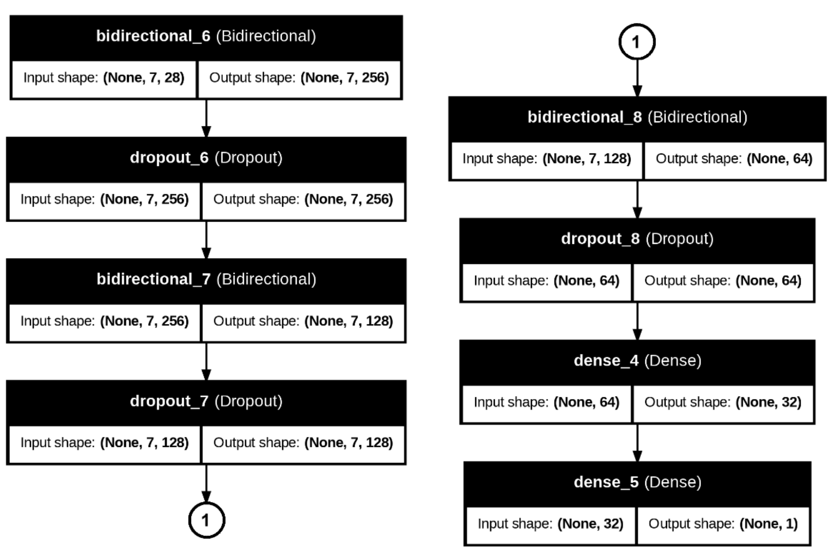


Fig. 1. Architecture of the developed LSTM network

Furthermore, an *EarlyStopping* callback was used to halt the training process if the validation loss failed to improve for 30 epochs, thereby ensuring the model's best-performing state was retained. The model was trained with a maximum of 150 epochs and a *batch_size* of 64. This combination of a powerful architecture, a sophisticated modelling strategy, and an adaptive learning process was instrumental in achieving the high accuracy reported in this study.

3. Results and Discussion

3.1. Dataset analysis and pre-processing

The results of an initial inspection of the dataset structure indicate that it contains 1638 records, the data type of which was integer (int64), except for the number of races (*Race_Count*), which was a real floating-point number (float64). *Route_ID* was from 1 to 18, which corresponds to the expected number of routes. *WeekDay_ID* was in the range from 1 (Monday) to 7 (Sunday). The first 5 rows of data are given in Table 1. The statistical description of the numeric columns is given in Table 2. *Race_Count* and *Pass_Flow* have a very wide range of values, indicating a significant difference between routes.

Table 1

View of the studied dataset (First 5 rows of data)

ID	*Day_ID*	*Month_ID*	*WeekDay_ID*	*Route_ID*	*Race_Count*	*Pass_Flow*
0	1	9	7	1	57.5	3799
1	2	9	1	1	61.5	4852
2	3	9	2	1	61.0	4518
3	4	9	3	1	58.0	4137
4	5	9	4	1	62.5	4612

Table 2

Statistical description of numeric columns

ID	*Day_ID*	*Month_ID*	*WeekDay_ID*	*Route_ID*	*Race_Count*	*Pass_Flow*
count	1638.00	1638.00	1638.00	1638.00	1638.00	1638.00
mean	15.67	10.00	4.00	9.50	66.79	4990.88
std	8.76	0.81	2.00	5.18	29.53	3819.66
min	1.00	9.00	1.00	1.00	0.00	0.00
25%	8.00	9.00	2.00	5.00	52.00	2622.50
50%	16.00	10.00	4.00	9.50	64.00	4038.50
75%	23.00	11.00	6.00	14.00	82.00	7134.75
Max	31.00	11.00	7.00	18.00	136.50	59385.00

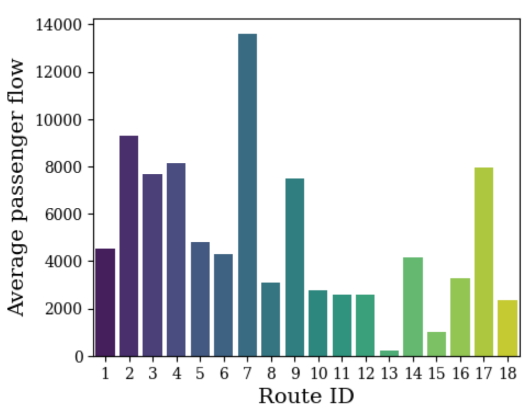
During anomaly detection and data cleaning, it is possible to found rows with an abnormally high *Pass_Flow* > 20000 value, which was 59385. Since the passenger flow on this route usually fluctuates in the range of 7000–8000.

The value of 59385 is an obvious outlier. So, to correctly train the model, such anomalies were corrected by replacing them with the average value for this route on this day of the week. In real projects [28, 29], the strategy for handling outliers can be more complex (removal, median replacement, use of models resistant to outliers), but replacing with the average value is a reasonable compromise [30, 31].

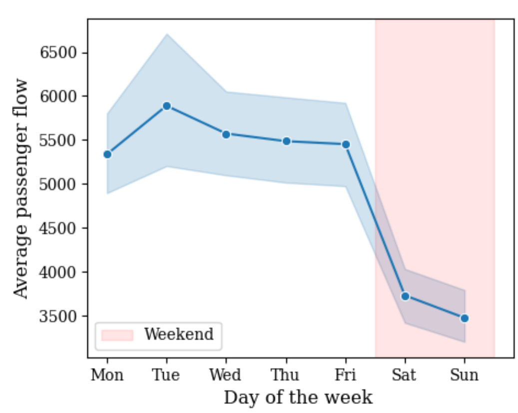
Fig. 2, *a* shows visualized data on the average passenger flow per day on each route to better understand the existing dependencies. As can be seen from Fig. 2, *a,* the routes are very uneven in terms of traffic. Routes 7, 17, 2, 3, 4 are the leaders, then 13, 8, 18, 10 are the least busy. This is critically important for the model, after which it is necessary to learn to distinguish the dynamics of each route. Fig. 2, *b* shows the dependence of passenger traffic on the day of the week, which indicates the tendency that passenger traffic is significantly higher on weekdays (1–5) and drops sharply on weekends (6–7). This is a key feature that the developed model should learn.

Fig. 3, *a* shows a visualization of the dynamics of passenger traffic over time for several typical routes, for example, with medium, high and low traffic load, respectively (1, 7, 13).

The graphs in Fig. 3, *a* clearly show the weekly cyclicality (peaks on weekdays, declines on weekends) for each route. Route 7 (the most popular) has significantly higher passenger traffic than route 1, and route 13 has the lowest. This confirms that the model should consider *Route_ID* as one of the most important features. Fig. 3, *b* visualizes the correlation between the number of races and passenger traffic in the form of a correlation matrix. The correlation between *Race_Count* and *Pass_Flow* is 0.83 (Fig. 3, *b*). This is a strong positive relationship: the more races are operated on a route, the greater the passenger flow it carries, which makes *Race_Count* a very important input feature. Thus, the data has a clear structure and strong dependencies, the key influencing factors are *Route_ID*, *WeekDay_ID*, *Race_Count*. The data is temporal in nature with pronounced weekly seasonality, which makes LSTM networks an excellent candidate for modelling. However, the data requires scaling due to the large difference in values between different features and routes.

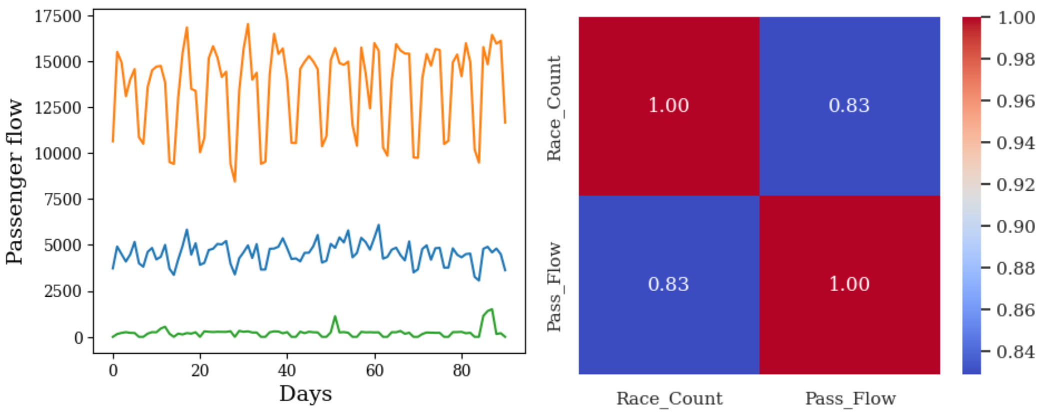


a



b

Fig. 2. Dependence of average passenger flow: *a* – by routes; *b* – by weekdays



a *b*

Fig. 3. Visualization of the passenger flow dynamics: *a* – for each route; *b* – correlation matrix between the number of races and passenger flow

Since the LSTM model requires data in a specific format: [number_of_samples, number_of_time_steps, number_of_features], sequences were created where the model looked at data for N previous days to predict the $(N+1)$ day. To train the features, the One-Hot Encoding method was used for categorical features: *Month_ID*, *WeekDay_ID*, *Route_ID*. This allowed the model to perceive these features not as ordinal, but as separate categories. Neural networks work better with data scaled in the range [0, 1], so separate scalers were created for the features and the target variable (*MinMaxScaler*). To create time sequences, the *create_sequences* function was used, which transformed the flat data set into sequences for the LSTM model. The data is split into training and testing in a ratio of 70/30 for each route and this is a key requirement. For each unique route and the data was selected only for the current route, determining the split point (70%). At the final stage of data splitting, the indices were split, and the data was added to the corresponding lists, which were combined into a single data frame. Only after this did the process of training scalers on the training data and transforming both sets take place. When forming the final sequences, data from the last week was used for prediction, and sequences were created for the training set and the test set.

3.2. Model performance and results interpretation

The efficient and popular Adam optimization algorithm was used to compile the model, as well as the Mean Squared Error (MSE) – a loss function that is best suited for regression problems. *EarlyStopping* was added to automatically stop training if the quality on the validation set did not improve within a certain number of epochs. Model training was limited to a maximum number of epochs of 150, the number of samples processed in one step (*batch_size*) was 64, and the training progress was displayed for each epoch. During the visualization of the learning process, losses on the training set and losses on the test (validation) set were monitored (Fig. 4).

During the forecasting on the test data, the forecast was returned to the original scale. Visualization of the results allowed comparing the actual values with the forecasted ones (Fig. 5). When assessing the quality of the model using metrics, the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and R^2 score indicators were used. A robust version of the model was obtained with the following results: RMSE = 1050.73, MAE = 656.36, R^2 = 0.91. The model is wrong by 1050.73 passengers (RMSE), the absolute average error is 656.36 passengers (MAE), and the model also explains approximately 91% of the data variability.

The developed LSTM model demonstrates a good ability to forecast passenger traffic. It successfully captures the main dependencies, such as weekly cyclicality and differences between routes. The R^2 score (0.91) shows that the model explains a significant part of the variability of the data. This high accuracy is explained by a comprehensive development strategy. The key to this success was the use of a residuals model. Instead of forecasting the entire passenger flow from scratch, the model learned to predict only the error (residual) of a simple baseline. This significantly simplified the task for the neural network, allowing it to focus on complex, nonlinear deviations.

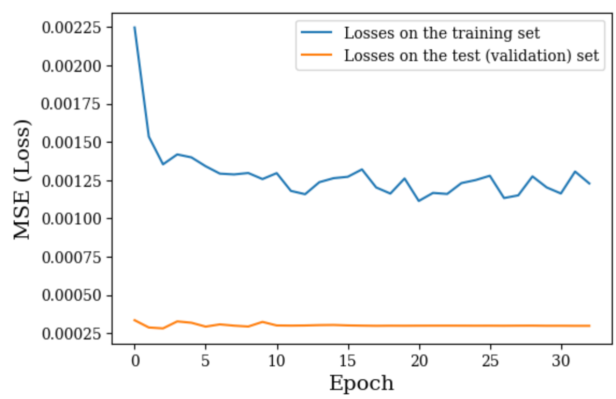


Fig. 4. Loss graph during model training

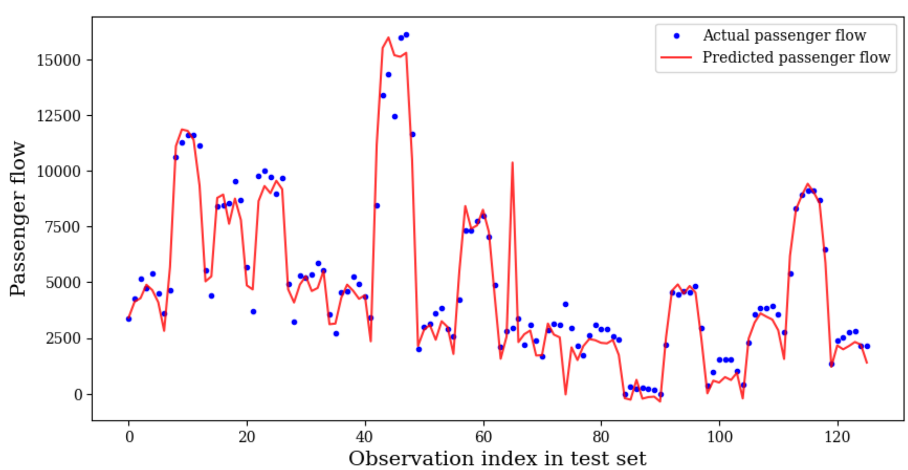


Fig. 5. Comparison of actual and predicted values on the test set

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Additionally, significant improvements were made through advanced feature engineering. The extraction of cyclical and lag features gave the model more context, helping it sees not only what happened yesterday (Lag) but also how the current day fits into weekly, monthly, and annual cycles. Features based on exponential smoothing and moving averages were also added to help our model understand short-term and medium-term trends. Adaptive learning with optimization of the process and an increased model capacity allowed for the effective use of these new features to achieve higher prediction accuracy.

3.3. Contextualizing the contribution: a discussion of findings, implications, and limitations

The developed Bi-LSTM model has much higher performance due to Bi-LSTM layers allow for a much deeper analysis of patterns within the weekly sequence. However, this may not be enough if not enough attention is paid to preparing the data for the model, carrying out serious work on the features, and thoroughly working on dividing the data into training and test sets.

The use of exponential smoothing as a feature engineering technique is a crucial distinction. While smoothing the target variable *Pass_Flow* would make the model learn an ideal curve, it would fail on real, noisy data. Instead, creating smoothed versions of *Pass_Flow* as new input features, as was done in this study, provides the model with trend information without losing critical details about daily peaks and fluctuations.

The implementation of a method where sequences are created only from continuous blocks of data (gold standard) is a significant methodological advantage. It ensures that the model never sees an artificially glued sequence from two different time periods, which is a potential flaw in simpler data preparation approaches. This robust and methodologically correct approach to data preparation, from scaler training to sequence generation, is a fundamental prerequisite for achieving the highest results in modelling and is often a distinguishing feature from studies that may overlook these nuances.

The developed deep learning model accurately forecasts next-day passenger flows ($R^2 > 0.9$), providing operators with a tool for operational planning. It enables the optimization of daily rolling stock allocation to prevent underutilized services and overcrowding. This improves resource efficiency, service reliability, and passenger comfort, contributing to the sustainable development goals of a smart city.

The model's primary limitation is its daily, rather than hourly, forecast granularity, precluding its use for real-time service adjustments. Its generalizability is constrained by a dataset limited to a specific season and city. Furthermore, the model currently excludes external factors known to influence demand, such as weather and public events.

3.4. Impact of martial law conditions

This research was conducted under the conditions of martial law in Ukraine, which imposed challenges related to power supply disruptions, difficulties in data processing and collection, limited access to resources, and changes in passenger behavior patterns due to curfews and air raid alerts. However, these circumstances do not in any way limit the applicability of its results; on the contrary, they make the study interesting and unique by taking the wartime context into account. The developed model is representative for forecasting demand both in the unique circumstances of war and in stable, peaceful conditions.

3.5. Prospects for further research

Further research should be aimed at overcoming the identified limitations by transitioning to hourly forecasting using automatic passenger counting data and integrating external factors like weather and public events. Model enhancements should involve systematic hyperparameter tuning, exploring alternative architectures such as GRU, and incorporating attention mechanisms. Finally, research into more complex architectures could allow for the modelling of spatial relationships between all routes simultaneously, bringing the system closer to a full-fledged digital twin of the city's transport network.

4. Conclusions

1. A hybrid deep learning architecture was successfully developed, integrating two Bidirectional LSTM layers with a residual forecasting methodology. The architecture proved highly effective, as the model was not required to predict the absolute passenger flow but rather the deviation from a reliable baseline, simplifying the learning task. This structure, combined with adaptive learning rate optimization (*ReduceLROnPlateau*), formed a robust framework for the forecasting task.

2. An advanced feature engineering process was designed and implemented, which was critical to the model's success. By transforming temporal data into cyclical features (*sine/cosine*) and creating lagged and exponentially smoothed moving average features, the model was provided with a rich, multi-dimensional context. This allowed it to discern not only immediate day-to-day dependencies but also underlying weekly and seasonal trends.

3. The final model was evaluated on a constructed realistic dataset and demonstrated high predictive accuracy. The key performance metrics were excellent: R^2 Score of 0.91 indicates that the model explains 91% of the data's variability. These results validate the model as a highly effective and reliable tool for next-day operational planning in urban transport both in the unique circumstances of war and in stable, peaceful conditions.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

Financing

The research was performed without financial support.

Data availability

Manuscript has no associated data.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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Yurii Matseliukh, *PhD Student, Department of Information Systems and Networks, Lviv Polytechnic National University, Lviv, Ukraine, ORCID: https://orcid.org/0000-0002-1721-7703*

Vasyl Lytvyn, *Doctor of Technical Sciences, Professor, Department of Information Systems and Networks, Lviv Polytechnic National University, Lviv, Ukraine, ORCID: https://orcid.org/0000-0002-9676-0180*

✉***Myroslava Bublyk,*** *Doctor of Economic Sciences, Professor, Department of Management and International Business, Lviv Polytechnic National University, Lviv, Ukraine, ORCID: https://orcid.org/0000-0003-2403-0784*

✉*Corresponding author*