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Research Paper

Short-Term Prediction of Bus Station Fleet Number using a Combination of BiLSTM Models

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Abstract

Predicting the number of bus station fleets requires a holistic approach, using sophisticated data analysis techniques and appropriate predictive modeling. Short-term predictions of bus station fleet numbers are proposed based on the best MAPE evaluation values from the comparison of the Bi-LSTM, BiLSTM-CNN, BiLSTM-Transformer, BiLSTM-Informer, and BiLSTM-Reformer models. The dataset used is in the form of a CSV consisting of 6 types of arrivals and departures of the Giwangan City Yogyakarta type A bus station fleet from 01/01/2021 to 09/30/2023. The best prediction model was found in BiLSTM-Transformers based on a MAPE value of 0.2211 with a relatively fast time (00:00:52) compared to BiLSTM, BiLSTM-CNN, BiLSTM-Informer, and BiLSTM-Reformer. The BiLSTM-Transformer model can short-term predict 6 types of fleet arrivals and departures at the bus station in the next 30 days. The peak of the bar and curve is at 0 which means the proposed prediction model is very accurate. There is 1 strong positive correlation, 2 weak positive correlations, 2 strong negative correlations, 8 weak negative ones, and 2 uncorrelated ones. Prediction results can be used to support short-term decision making in fleet planning and management based on the dynamics of community mobility.

Keywords: Bus station; Fleet; Short-term; Prediction; BiLSTM

1. Introduction

Bus stations are the center of urban transportation infrastructure that connects various destinations with bus transportation services [1], [2], [3]. Bus stations have a strategic role in increasing connectivity between regions [4]. Effective development and management of bus stations is an important aspect in sustainable urban planning and management [5]. Bus stations is the central point for passengers getting on or off the bus and the meeting of various bus routes for passenger exchange [6]. Bus stations is an important point for setting schedules, operating bus services, as well as managing logistics related to the movement of vehicles and passengers [7]. The number of arrivals and departures of the bus fleet will be recorded every day for reporting [8]. The report covers a number of factors that influence individual travel patterns and mobility needs [9], [10]. Fluctuations are influenced by the activities of economic centers, educational centers, tourist destinations, schedules [11], infrastructure development, special events [5], [12], policies/regulations [4], and connections between modes of transportation [2]. Predictions of the number of fleet arrivals and departures at bus stations [13],

[14], [15] are influenced by travel patterns, demand for transportation services, social and economic dynamics [16]. Understanding historical trends in the number of arrivals and departures at bus stations is an important step in making accurate predictions [17]. Population growth, industrial activities, environmental awareness, work patterns [18], traffic conditions, road conditions [11], technology adoption [13], and infrastructure investment can influence the number of requests for road transportation services at bus stations [19]. Prediction results can help bus terminal managers to plan and manage services more effectively, ensuring adequate availability and accessibility for public transportation users [20].

Prediction of fleet arrival times at bus stations using Route Spatial Temporal Information-Residual Networks (RTSI-ResNet) in Shenzhen can outperform the accuracy of Recurrent Neural Network (RNN)/Long Short-Time Memory (LSTM) and Support Vector Machines (SVM) [20]. Travel time prediction model between bus stations using eXtreme Gradient Boosting (XGBoost) in Guangzhou can outperform K-Nearest Neighbors (KNN), Backpropagation (BP) Neural Network, and Light Gradient Boosting Machine (LightGBM) in terms of fitting, accuracy and stability evaluated by Symmetric Mean Absolute Percentage Error (SMAPE) [13]. Real-time prediction of bus travel times between stations is proposed using Clustering by fast search and Find of Density Peaks-Deep Neural Network (CFDP-DNN) which can effectively increase accuracy compared to Support Vector Machine (SVM), Adaptive Neuro-Fuzzy Inference System (ANFIS), and BP-Neural Network evaluated by Mean Absolute Percentage Error (MAPE) [11]. Bus arrival prediction proposed with LSTM and Artificial Neural Networks (ANN) based on spatial-temporal feature vectors has high accuracy [18]. LSTM and Multilayer Perceptron (MLP) are proposed to predict real weather on buses and stations having reliable performance compared to actual sensing from the Environment Protection Administration (EPA) and Central Weather Bureau (CWB) in Taichung [19]. LSTM is proposed to predict bus arrival times at bus stations to obtain more precise times with increased accuracy and stability of the model compared to AutoNavi and Baidu [17]. Many prediction models at bus stations have been carried out by adopting various models according to the dataset and prediction objectives.

The problem of predicting the number of arrivals and departures of a bus station fleet can include challenges that affect the accuracy and usefulness of predictions [17], [18], [21]. Uncertainty factors make bus station fleet predictions inaccurate [20]. Changes in lifestyle, preferences, transportation policies, and the operational environment of bus station make modeling difficult to predict accurately [14]. The available historical data is incomplete resulting in low accuracy and validity [11], [22]. Prediction models require large data processing, complex statistical models, or technical limitations in data processing and analysis [13], [20], [23]. Predicting bus station fleet numbers requires a holistic approach, using sophisticated data analysis techniques and appropriate predictive modeling. Bus station managers and stakeholders can optimize operations, increase efficiency, and increase user satisfaction of transportation services by improving prediction accuracy. Short-term prediction of the number of bus station fleets using time-series data is proposed based on the results of the best Mean Absolute Percentage Error (MAPE) evaluation values from the comparison of the Bidirectional-LSTM (Bi-LSTM), BiLSTM-Convolutional Neural Network (BiLSTM-CNN), BiLSTM- Transformer, BiLSTM-Informer, and BiLSTM-Reformer. The performance of the short-term prediction model is compared with hidden layer variations to obtain the best model. Selection of the best model to obtain an optimal model for short-term predictions of the number of bus station fleets. The best model will be used to predict the number of 6 types of bus station fleet, the correlation between predictions, and the relationship between predictions for the next 30 days. The proposed prediction model and prediction results have never been carried out at a bus station, so station managers can use it to optimize fleet use, operational planning, cost savings, fleet maintenance, crisis management and short-term planning.

2. Method

Data collection comes from reports on the number of arrivals and departures of the bus station fleet for 3 years at the Giwangan type A bus station, Yogyakarta City, Indonesia. The report is made into a dataset in CSV form consisting of the number of fleet arrivals and departures from inter-city inter-provincial, inter-city within province, and city transport. Google colaboratory on macOS Venture 13.5 is used to run the Python programming language with the Tensor Flow deep learning framework into the proposed prediction simulation environment. Data processing with Minmax feature scaling was first carried out to divide the training and testing segments. Bi-LSTM, BiLSTM-CNN, BiLSTM-Transformer, BiLSTM-Informer, and BiLSTM-Reformer models run a training dataset with different hidden layers to find a prediction model for the number of arrivals and departures of the bus terminal fleet. The prediction and training datasets are compared and MAPE evaluates the prediction accuracy. The best prediction model based on evaluation values and stability testing of model performance to predict the number of arrivals and departures of the bus terminal fleet was produced by the Combination Comparison Architecture Model (**Figure 1**). Lowest evaluation value and relatively fast time for model experiments to find the best model. Different simulation environments are possible to obtain different results.

BiLSTM is a type of neural network designed to process sequence data in a more effective way than conventional LSTM [24], [25]. BiLSTM produces two hidden states, namely one forward LSTM($\overrightarrow{h_t}$) and one backward LSTM ($\overleftarrow{h_t}$) at each time step t which are then combined to produce the final representation $h_t = [\overrightarrow{h_t}, \overleftarrow{h_t}]$ [26], [27], [28] (**Figure 2**). BiLSTM can capture richer context and understand more complex dependencies in data sequences. BiLSTM tends to provide better performance compared to one-way LSTM [26], [28], [29], [30], [31], [32], [33], [34]. BiLSTM and a combination of BiLSTM with CNN, Transformer, Informer, and Reformer are carried out to look for improvements in the accuracy of the prediction model. CNN, Transformer, Informer, and Reformer were chosen to be the BiLSTM combination because of their reliability for predicting time series. The performance of the proposed prediction model will be assessed from the MAPE evaluation matrix. MAPE divides each error based on each request [35], [36] (Eq. (1)). A MAPE value close to 0 is an accurate representation of model performance [37].

$$MAPE = \frac{1}{n}\sum_{i-1}^{n}\left|\frac{\hat{p}_i - p_i}{p_i}\right| \quad (1)$$

$\hat{p}$i represents the predicted price, pi represents the actual price and N is the total number of observations.

3. Result and Discussion

The dataset used contains the number of fleets based on daily arrivals and departures at the type A Giwangan bus station, Yogyakarta City, Indonesia in numerical format on 01/01/2021-09/30/2023. There are 994 CSV file types for preprocessing data. The 7 columns in the dataset consist of DATE, BUS_AKDP_ARR, BUS_AKDP_DEPART, BUS_AKAP_ARR, BUS_AKAP_DEPART, BUS_CITY_ARR, and BUS_CITY_DEPART. DATE contains the date, BUS_AKDP_ARR contains the number of arrivals of inter-city fleets within province, BUS_AKDP_DEPART contains the number of departures of inter-city fleets within province, BUS_AKAP_ARR contains the number of arrivals

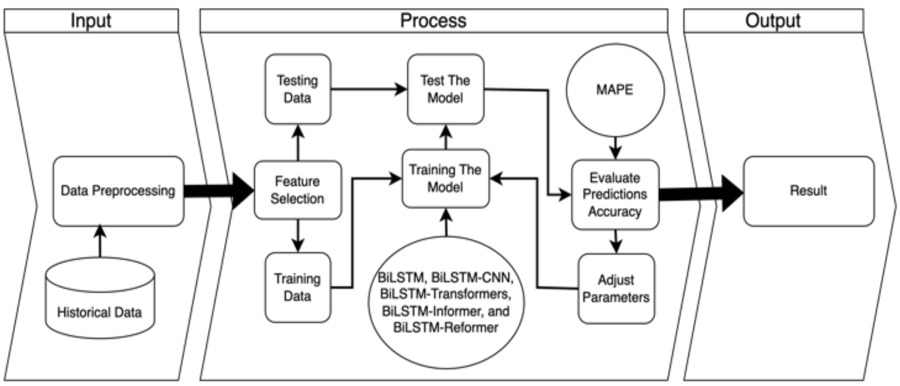

Figure 1. BiLSTM model combination comparison architecture

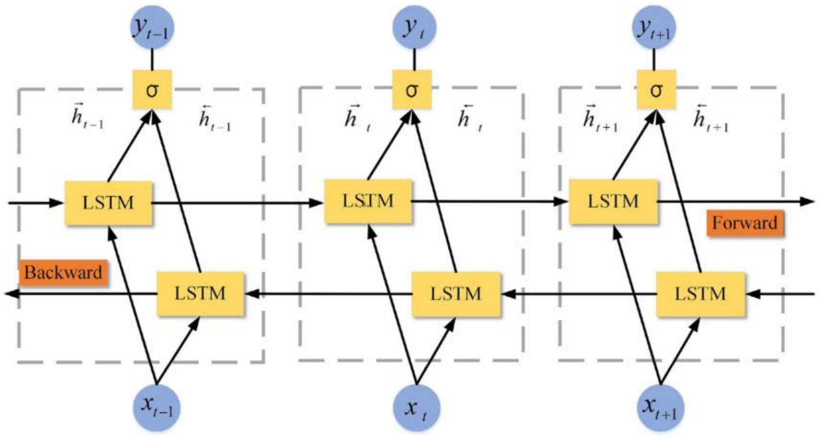

Figure 2. Network stucture of BiLSTM

of inter-city inter-provincial fleets, BUS_AKAP_DEPART contains the number of departures of inter-city inter-provincial fleets, BUS_CITY_ARR contains the number of city transport fleet arrivals, and BUS_CITY_DEPART contains the number of city transport fleet departures (**Figure 3**). The dataset used is private data that cannot be published to the public.

Minmax feature scaling divides 80% for training data and 20% for testing data. The 5 prediction models that were experimented with were BiLSTM, Bi-LSTM-CNN, BiLSTM-Transformer, BiLSTM-Informer, and BiLSTM-Reformer. The LSTM tuning parameters used are activation hyperbolic tangent(tanh), dropout 0.20, epoch 60, batch size 16, verbose 1, and optimizer Adam. Hidden layer variations (0, 2, and 4 layers) significantly impact the evaluation and time of prediction models. The BiLSTM-Informer model is the fastest but has a lower MAPE score, while the BiLSTM-Transformer provides the best prediction accuracy based on MAPE, though it takes slightly longer. Combining BiLSTM with CNN, Transformers, Informer, and Reformer improves the model's evaluation value. The BiLSTM-CNN model requires the longest time, while the BiLSTM-Informer combination is the fastest across all hidden layer variations (**Table 1**).

Sharing training and testing data is commonly used to ensure the model has enough data to learn and can be tested with data not seen during training. The min-max method feature scaling helps normalize data with the results of all features being in the same range. This can accelerate model convergence and increase performance. The parameters used are selected to regulate model complexity, prevent overfitting, and speed up the training process. Experiments

	DATE	BUS_AKDP_ARR	BUS_AKDP_DEPART	BUS_AKAP_ARR	BUS_AKAP_DEPART	BUS_CITY_ARR	BUS_CITY_DEPART
0	2021-01-01	72	84	371	396	168	168
1	2021-01-02	106	114	417	456	167	152
2	2021-01-03	76	103	474	468	170	167
3	2021-01-04	86	82	386	435	167	62
4	2021-01-05	107	109	384	390	166	155
..	...	...	...	...	...	...	...
989	2023-09-26	58	66	394	416	239	232
990	2023-09-27	65	67	396	437	233	240
991	2023-09-28	59	61	465	468	201	274
992	2023-09-29	67	68	424	423	224	217
993	2023-09-30	62	66	455	477	228	220

Figure 3. Dataset

Table 1. Prediction model experiment

No	Model	0 Hidden Layer		2 Hidden Layer		4 Hidden Layer	
		MAPE	Time	MAPE	Time	MAPE	Time
1.	BiLSTM	0.2858	00:00:51	0.2882	00:01:31	0.3037	00:02:01
2.	BiLSTM-CNN	0.3010	00:00:54	0.2832	00:04:12	0.2816	00:04:46
3.	BiLSTM-Transformer	0.2573	00:00:49	0.2211	00:00:52	0.2624	00:01:07
4.	BiLSTM-Informer	0.2616	00:00:45	0.2762	00:00:53	0.2935	00:00:55
5.	BiLSTM-Reformer	0.2706	00:00:51	0.2887	00:01:15	0.2670	00:01:43

with 5 prediction models were conducted to test whether the combination of BiLSTM with other methods could improve prediction performance. The combination of BiLSTM with CNN, Transformer, Informer, and Reformer can improve the performance of prediction models. BiLSTM-Transformer is the best model with prediction accuracy based on MAPE values, although it requires longer computing time. BiLSTM-Informer is the fastest model, but its accuracy is not as good as BiLSTM-Transformer. Hidden layer variations have a significant influence on model performance in terms of time and accuracy [23], [24]. The addition of hidden layers tends to increase computing time because the model becomes more complex and requires more calculations [10], [30]. This can improve the prediction accuracy to a certain extent. Too many hidden layers can cause overfitting which makes the model too complex and does not generalize well to testing data [10], [24]. More complex models with more hidden layers tend to be more accurate, but require more time to train.

Time series decomposition analyzes time series data into simpler components to identify patterns. Observations from January 2021 to September 2023 show fluctuations in daily fleet arrivals and departures. Key trends include declines around July 2021 and sharp drops in May 2021, 2022, and 2023. Rapid increases occurred in September 2021 and August 2023, with peaks in January and May and declines in August. Seasonal patterns show increases early in the month, peaking mid-month, followed by sharp declines. Residual components highlight random fluctuations, confirming the suitability of the decomposition model (**Figure 4**). Significant fluctuations in bus fleet arrivals and departures, driven by outliers, likely reflect the impact of special events or policies influencing public transportation and community mobility.

Fluctuations in the number of arrivals and departures of the bus fleet occurred constantly throughout the period, reflecting the high dynamics of transportation activities. The trend of instability in the number of arrivals and departures

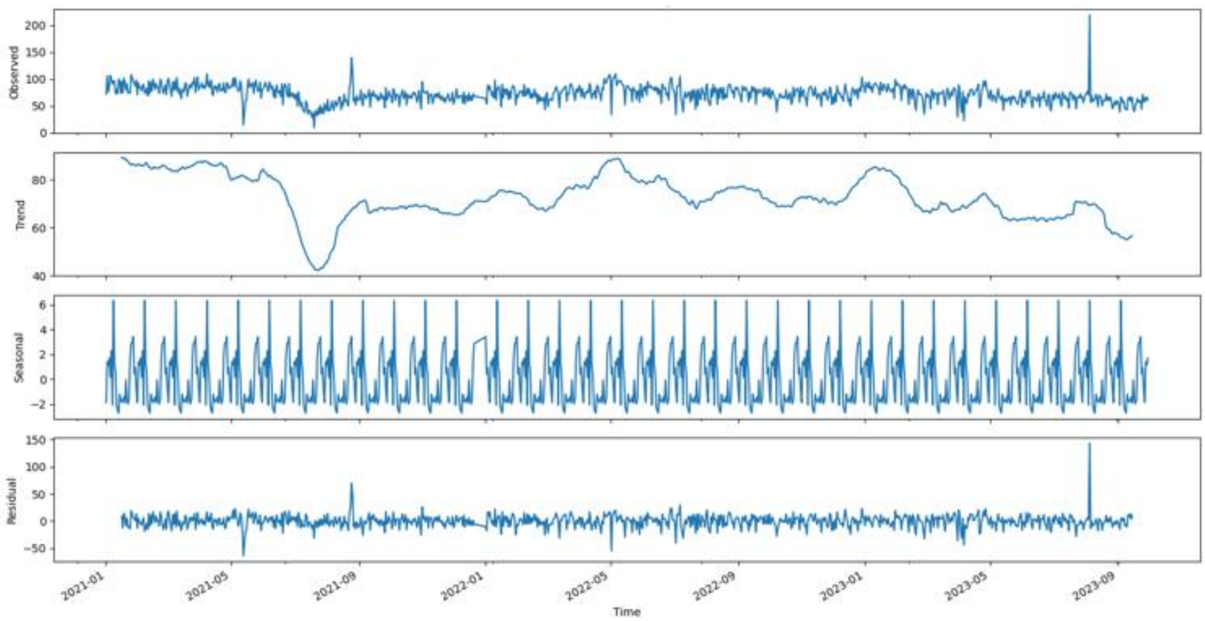

Figure 4. Time series decomposition

of the bus fleet throughout the period illustrates that transportation activities at bus station have high variability [8]. Peak increases and decreases in the number of fleet arrivals and departures may be related to seasonal patterns or external factors such as holidays, agendas, activities or certain policies [9], [11]. Seasonal patterns relate to the existence of monthly cycles in transportation activities which may be influenced by work schedule factors, holidays or certain monthly activities [6]. The unclear pattern in the residual components shows that the decomposition model used is appropriate in identifying and isolating seasonal trends and patterns. Time series decomposition becomes an effective tool for analyzing and understanding the underlying components of complex data such as the number of fleet arrivals and departures. Identification of trends, seasonal patterns, and random fluctuations can gain more insight into transportation dynamics and make better decisions to optimize transportation services [2], [3], [4].

The distribution of dataset errors or the results of the proposed prediction model is shown in the distribution of error graph. Most of the dataset errors are around 0 as seen from the peak of the bar and curve at 0. This is an indication that the proposed prediction model is very accurate because larger errors rarely occur. The prediction model is very close to the actual value or target value for most of the data making the proposed prediction model work very well. The error distribution curve has a long tail to the right as an illustration of the error distribution having positive skewness. Positive skewness means that most of the errors are clustered around low values (close to 0), but there is a significant amount of errors on the right (positive) side of the distribution. The long tail to the right indicates that the proposed prediction prediction model is quite accurate, but there are some predictions that produce errors. This occurs because the model complexity is not sufficient to capture all data patterns (**Figure 5**).

The error distribution shows that the majority of errors are around 0 as an indication that the proposed prediction model is very accurate for most of the data. Positive skewness with a long tail to the right indicates the presence of several large errors that have not fully captured the data pattern in the proposed prediction model. This can be due to data complexity or anomalies that are not captured by the model [18], [29], [31]. The error distribution provides valuable insight into model performance and areas that need improvement to improve overall prediction accuracy [26], [32].

The BiLSTM-Transformers model predicts the number of arrivals and departures for six types of bus fleets over the next 30 days. For city transport fleets, the number of arrivals and departures is expected to remain stable without significant increases or decreases. Meanwhile, arrivals and

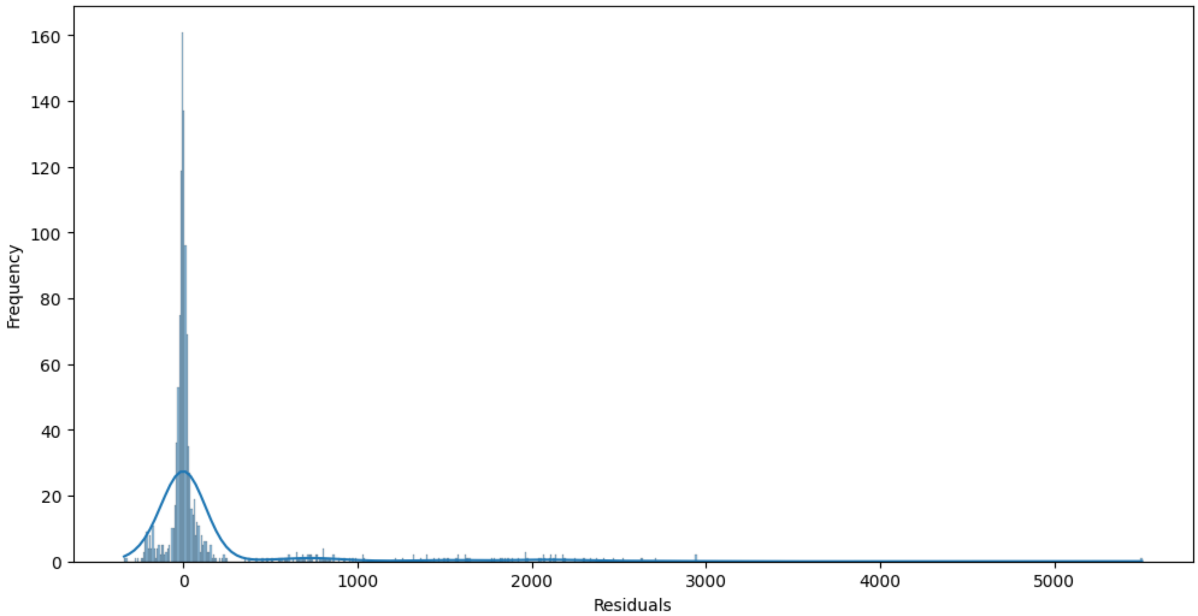

Figure 5. Distribution of errors

departures for inter-city within-province and inter-city inter-provincial fleets are predicted to decline from the 1st to the 16th before stabilizing. On the 4th, a downward intersection occurs between the arrivals and departures of inter-city inter-provincial fleets, with arrivals decreasing more sharply than departures. These predictions highlight distinct trends for each bus fleet category. The number of arrivals and departures of the inter-city within province bus fleet is predicted to be the lowest compared to the others with stability from the 10th to the 30th. This happens even though from the 1st to the 9th there is an insignificant increase (**Figure 6**).

The stability of demand for intra-city transportation is quite consistent due to well-established travel patterns and the lack of seasonal fluctuations or other external factors. Declines in inter-city within province and inter-city inter-provincial can be caused by travel policy factors, seasonal changes, or fluctuations in demand for transportation services. The sharp decline in the number of arrivals compared to departures for inter-city inter-provincial fleets reflects a decline in demand for travel between provinces, or the presence of external factors that influence the number of passengers arriving from outside the province. Predictions show stability in city transport, but a decline in inter-city within province and inter-city inter-provincial. The combination of BiLSTM and Transformers provides the power to capture complex temporal patterns and short-term relationships (daily) in time series data. BiLSTM can deal effectively with temporal patterns, while Transformers can take into account long-term data interactions. The BiLSTM-Transformers combination model provides accurate short-term (daily) predictions regarding the number of bus fleet arrivals and departures. Predictive information is extremely valuable for fleet management, transportation policy, travel schedule optimization, and bus station managers [5], [6]. Prediction results can help bus fleet operators to plan fleet allocations more effectively and deal with temporary decreases in demand on inter-city within province and inter-city inter-provincial routes [2], [14]. Information on sharp declines and stabilization of demand can be used by policy makers to adjust transportation strategies and travel policies, as well as mitigate the negative impacts of temporary declines in demand [3], [13]. Predictions of stability in city transport and temporary decreases in inter-city within province and inter-city inter-provincial can be used to optimize fleet departure and arrival schedules, and allocate resources efficiently.

The correlation matrix heatmap for the predicted number of fleets at the bus station shows varying relationships: 1 strong positive correlation, 2 weak positive correlations, 2 strong negative correlations, 8 weak negative correlations, and 2 uncorrelated pairs. A strong positive correlation exists between city transport

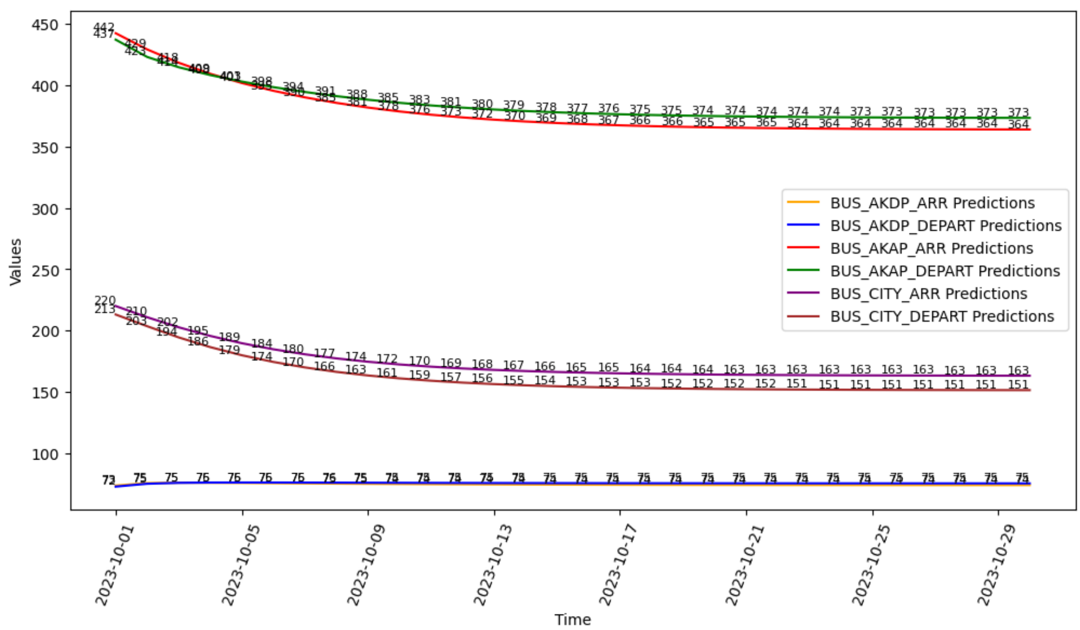

Figure 6. Predictions for the next 30 days

departures and inter-city inter-provincial departures. Strong negative correlations are observed between city transport departures with inter-city within-province arrivals and inter-city inter-provincial departures with inter-city within-province arrivals. No correlation is found between city transport arrivals and inter-city inter-provincial arrivals, as well as city transport departures with city transport arrivals. Inter-city within province arrivals are negatively correlated with city transport and inter-city inter-provincial departures, but inter-city within provincial departures are positively correlated with city transport and inter-city inter-provincial departures (**Figure 7**).

The strong positive correlation between city transport departures and inter-city inter-provincial departures shows that increases in departures in one category tend to be followed by increases in the other category. This is an indication that there are common factors that drive increased demand for transportation, such as holiday seasons or large events that increase mobility both within cities and between provinces [1], [7]. The strong negative correlation between city transport departures and inter-city within province arrivals explains that an increase in the number of city transport fleet arrivals will be followed by a decrease in the number of inter-city within province fleet arrivals. This is because the shift in transportation demand from increasing intra-city travel reduces the need for inter-city travel within provinces [2], [14]. An increase in inter-city inter-provincial departures will be followed by a decrease in inter-city within province arrivals, reflecting changes in travel patterns influenced by factors such as transportation policies or changes in community mobility trends [3], [11], [16]. A strong negative correlation to an increase in one category tends to be followed by a decrease within the category that may be due to shifts in transportation demand or changes in travel patterns.

Weak correlation, positive or negative, means there is a relationship but it is not strong, which may be due to the influence of the variable coming from other factors that have not been identified. Two weak positive correlations have a relationship that is not too strong but remains in the same direction between the variables concerned. Eight weak negative correlations have a relationship that is not too strong but is in the opposite direction between the variables in question. No correlation was found between city transport arrivals and inter-provincial inter-city arrivals, as well as between city transport departures and city transport arrivals [11], [14]. Changes in one variable have no meaningful

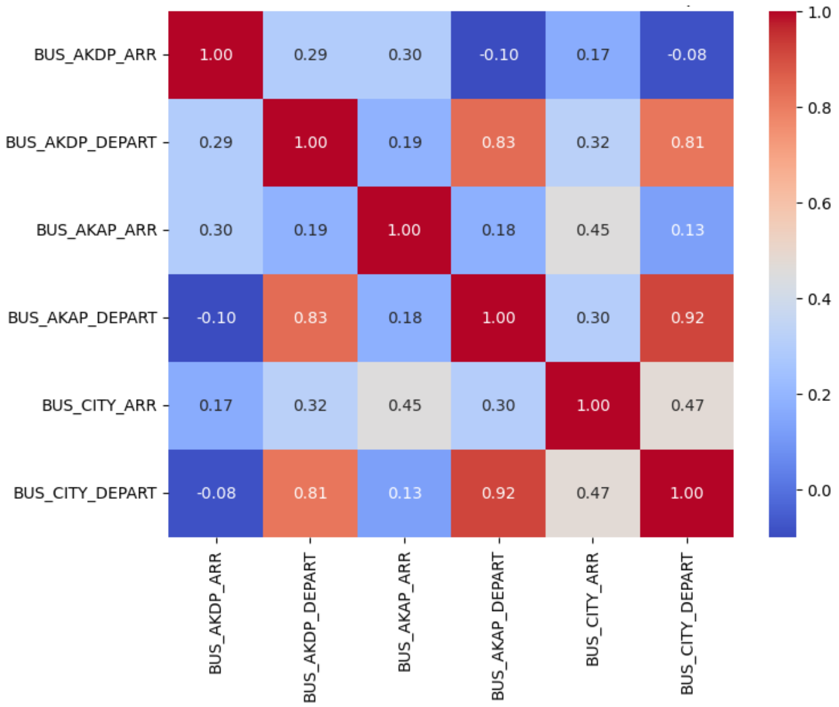

Figure 7. Data and prediction correlation heatmap

relationship with changes in other variables. No correlation indicates these variables are influenced by very different factors. Unrelatedness may be caused by different movement patterns or other operational factors [5]. The correlation of the 6 resulting predictions can be used to support better decision making for fleet planning and management, as well as to understand more deeply the dynamics of community mobility.

4. Conclusion

Short-term predictions of 6 types of fleet arrivals and departures at bus station and correlation between predictions can be carried out by the BiLSTM prediction model and a combination with CNN, Transformers, Informer, and Reformer. The best prediction model was found in BiLSTM-Transformers based on a MAPE value of 0.2211 with a relatively fast time (00:00:52). Short-term predictions of 6 types of fleet arrivals and departures at the bus station in the next 30 days can be carried out simultaneously by the BiLSTM-Transformer model. The peak of the bar and curve is at 0 which is an indication that the proposed prediction model is very accurate because larger errors rarely occur. There was 1 strong positive correlation, 2 weak positive ones, 2 strong negative ones, 8 weak negative ones, and 2 uncorrelated ones. Prediction results can be used to support better short-term decision making in fleet planning and management to understand more in the dynamics of community mobility. Prediction models that can capture all time-series data patterns to minimize error distribution are the next development.

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Author's Declaration

Authors' contributions and responsibilities

Conceived and designed the experiments (J.S, U.R); Performed the experiments (J.S, A.R, N.D.P, M.I.N.H); Analyzed and interpreted the data (J.S, U.R, T.P, I.B.P); Wrote the original paper (A.R, U.R, T.P); and Wrote the revised manuscript (J.S, A.R, U.R, N.D.P, M.I.N.H, T.P, I.B.P).

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Availability of data and materials

All data are available from the authors.

Competing interests

The authors declare no competing interest.

Additional information

No additional information from the authors.

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