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Evaluating the Robustness of Bidirectional LSTM Models for Traffic Volume Prediction Under Travel Demand Disruptions: A Melbourne, Australia Case Study

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Highlights

What are the main findings?

- BiLSTM achieved lower forecasting errors than LSTM in all traffic directions, forecasting horizons and test periods, and across all five training runs, reducing RMSE by 5.2–19.6%.
- Under changing travel demand, the errors of both neural models rose by 4–21% while persistence errors were largely unchanged, and by June–July a simple weekly seasonal-naive forecast outperformed BiLSTM on some longer horizons.

What are the implications of the main findings?

- Higher forecasting accuracy should not be equated with robustness: deep-learning traffic forecasting models should be assessed by how their accuracy changes when conditions depart from those seen in training, and compared with simple benchmarks.
- The decline in accuracy over time suggests that periodic retraining may be needed to keep the advantage of deep-learning models over simple forecasting methods as traffic patterns evolve.

Abstract

Accurate traffic volume forecasting is important for Intelligent Transport Systems (ITS), but the reliability of forecasting models under disrupted travel-demand conditions has received limited attention. This study evaluates the robustness of a Bidirectional Long Short-Term Memory (BiLSTM) model for short-term traffic volume forecasting under changing demand conditions associated with external economic and policy factors. Using 15 min traffic volume data from 31 monitoring sites along Melbourne's Tullamarine Freeway (M2) in Australia, the study examines traffic conditions from January to July 2026, including a period of rising fuel prices and temporary fare-free public transport. Average traffic volumes decreased by approximately 6% in April and 5% in May compared with February, while morning peak reductions reached approximately 15% in the selected periods. The models were trained using traffic volume observations collected during January–February 2026 and evaluated across three separate test periods: Test1 (1–30 March 2026), representing pre-disruption (reference) conditions; Test2 (31 March–31 May 2026), representing the period of changing travel demand associated with rising fuel prices and

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temporary fare-free public transport; and Test3 (1 June–27 July 2026), representing post-disruption conditions. Both models were evaluated for northbound and southbound traffic at forecasting horizons of 15, 30, 45, and 60 min. To assess model robustness and training variability, each experiment was repeated using five random seeds (26, 42, 100, 123, and 2026). Forecasting performance was assessed using RMSE, MAE, MAPE, WAPE, and R^2, with mean performance, standard deviation, and 95% confidence intervals calculated across repeated runs. Additional comparisons against persistence, daily seasonal-naive, and weekly seasonal-naive benchmarks were conducted to evaluate the models' predictive advantages under changing traffic-demand conditions. BiLSTM achieved lower RMSE than LSTM in all 24 combinations of direction, horizon and test period, and in every one of the five seeds, with mean RMSE reductions of 5.2–19.6%. During the disruption period, BiLSTM also outperformed the persistence, daily seasonal-naive and weekly seasonal-naive benchmarks at all horizons. The errors of both neural models increased by 4–21% relative to the pre-disruption period, while persistence errors were largely unchanged. The results indicate that BiLSTM provides more accurate short-term forecasts than LSTM under abrupt demand changes. However, the accuracy of both models declines as traffic conditions deviate from those observed during training. This suggests that model retraining may be beneficial for maintaining forecasting accuracy amid evolving traffic demand.

Keywords: traffic volume prediction; short-term traffic prediction; neural networks; bidirectional LSTM; unidirectional LSTM; deep learning; persistence baseline; seasonal naive; travel demand disruption

1. Introduction

1.1. Background and Motivation

Accurate traffic volume forecasting is a critical component of ITS, supporting traffic management, network optimisation, infrastructure planning, and real-time operational decision-making [1]. Traffic conditions can be broadly classified as recurrent, such as regular peak-period congestion, and non-recurrent, such as disruptions caused by crashes, road maintenance, and other unexpected events [2]. While recurrent patterns can often be predicted from historical observations, non-recurrent and externally driven changes can cause traffic demand to vary from established patterns. Traffic forecasting research has therefore progressed from statistical approaches towards machine learning and deep learning methods that are capable of modelling complex traffic patterns [3].

Recent advances in artificial intelligence (AI) and deep learning have improved traffic forecasting by enabling models to capture complex nonlinear relationships and temporal dependencies within transportation datasets [4-6]. Long Short-Term Memory (LSTM) networks have been widely adopted because of their ability to capture long-term temporal dependencies in sequential traffic data [4,7]. Bidirectional LSTM (BiLSTM) models extend this approach by processing temporal information in both directions, providing a more comprehensive representation of temporal patterns [8]. Previous studies have demonstrated the effectiveness of LSTM and BiLSTM models for short-term traffic forecasting [9].

However, many traffic forecasting approaches are evaluated under relatively stable demand conditions, where historical observations provide a consistent basis for future predictions. In practice, urban mobility can be influenced by external economic, social, and policy-related factors that introduce uncertainty into traffic demand [10]. One important source of uncertainty is fuel price variation. Changes in fuel prices can change the

operating cost of private vehicles and influence trip frequency, car dependency, and transport mode choice, particularly where alternative transport modes are available [11].

Public transport pricing can similarly influence travel behaviour by changing the relative attractiveness of public and private transport [12,13]. Melbourne provides an important real-world case study because rising fuel prices in 2026 coincided with a temporary Victorian Government initiative providing free public transport. Free travel on metropolitan trains, trams, and buses was introduced from 31 March 2026 through the end of April and was subsequently extended through the end of May 2026 [14]. The occurrence of these external changes provides relevant context for examining traffic forecasting performance during a period when private vehicle demand may vary from previously observed patterns.

Such changes create a challenging forecasting environment because models trained primarily on historical observations may experience reduced predictive performance when traffic demand changes from previously established temporal patterns. Although BiLSTM models have demonstrated strong predictive performance for traffic forecasting, their ability to generalise from established traffic conditions to a period of changing and disrupted demand has not yet been sufficiently evaluated. Evaluating whether BiLSTM can maintain accurate short-term traffic predictions when a model trained on reference-period traffic conditions is applied to a subsequent period of changed demand is therefore important for developing more reliable and resilient ITS applications.

1.2. Research Objectives

Most existing traffic forecasting studies assess model performance under relatively stable traffic conditions. Previous research has demonstrated the effectiveness of BiLSTM models for short-term traffic prediction [6,15-18]. However, less attention has been given to their robustness when external factors coincide with significant changes in traffic demand.

This study investigates the robustness of a BiLSTM model for short-term traffic volume prediction during a period of changing travel demand associated with increased fuel prices and temporary free public transport in Melbourne, Australia. To evaluate model generalisation across different traffic-demand conditions, BiLSTM and conventional LSTM models are trained using traffic observations from January–February 2026 and independently evaluated across three chronologically separated periods: Test1 (1–30 March 2026), representing pre-disruption (reference) conditions; Test2 (31 March–31 May 2026), representing the disruption period; and Test3 (1 June–27 July 2026), representing post-disruption conditions.

The study evaluates forecasting performance for both northbound and southbound traffic across prediction horizons of 15, 30, 45, and 60 min. To ensure a reliable assessment, a leakage-controlled historical input window of 96 observations (24 h) is adopted, and each model is independently trained using five random seeds to examine performance variability and consistency. In addition to comparing BiLSTM with conventional LSTM, the study incorporates persistence, daily seasonal-naive, and weekly seasonal-naive forecasting benchmarks to determine whether the deep-learning models provide improvements over simpler historical forecasting approaches.

The primary aim is to determine whether BiLSTM can maintain its predictive advantage during sudden travel-demand disruptions and subsequent post-disruption conditions without retraining. Particular attention is given to identifying whether forecasting performance deteriorates over time and whether conventional baseline methods become competitive with, or outperform, BiLSTM as traffic patterns evolve. The findings are intended to provide insights into the robustness, generalisation capability, and potential need for periodic retraining of deep-learning traffic forecasting models.

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The specific objectives of this study are to

- Evaluate short-term forecasting performance: Assess the prediction accuracy of BiLSTM across 15, 30, 45, and 60 min forecasting horizons for northbound and southbound traffic.
- Compare BiLSTM and conventional LSTM: Investigate differences in prediction accuracy and consistency between BiLSTM and LSTM models across pre-disruption, disruption, and post-disruption periods.
- Assess generalisation under changing demand conditions: Examine the ability of models trained exclusively on January–February 2026 traffic observations to maintain forecasting performance across three chronologically separated periods without retraining.
- Evaluate performance against conventional forecasting baselines: Compare BiLSTM with persistence, daily seasonal-naive, and weekly seasonal-naive methods to determine its predictive advantage and identify conditions under which simpler forecasting approaches become competitive or outperform the deep-learning model.
- Examine model robustness: Evaluate prediction variability across five independent training runs using different random seeds, reporting mean performance, standard deviation, and 95% confidence intervals.

1.3. Scope and Boundaries

This study focuses on short-term traffic volume forecasting using BiLSTM and LSTM models, based on an open-access traffic volume dataset from the Transport Victoria Open Data Portal [19]. The case study considers a section of the Tullamarine Freeway (M2) between the Western Ring Road (M80) interchange and Sunbury Road in Melbourne, Australia.

The analysis uses 15 min traffic volume observations from 31 monitoring sites in both northbound and southbound directions between January and July 2026. Model performance is evaluated for forecasting horizons of 15, 30, 45, and 60 min. To assess model robustness and generalisation under changing travel-demand conditions, the BiLSTM and conventional LSTM models were trained exclusively on traffic observations from January–February 2026 and subsequently evaluated across three chronologically separated periods: Test1 (1–30 March 2026), representing pre-disruption conditions; Test2 (31 March–31 May 2026), representing the disruption period associated with increased fuel prices and the temporary fare-free public transport initiative in Victoria; and Test3 (1 June–27 July 2026), representing post-disruption conditions. This chronological evaluation framework enables an assessment of the models' ability to maintain forecasting accuracy across different demand conditions without retraining. It also allows the investigation of whether the predictive advantage of BiLSTM over conventional LSTM and seasonal-naive forecasting methods diminishes over time, providing insights into the potential need for periodic model updating to maintain forecasting reliability.

1.4. Global Context

Traffic demand disruptions represent a broader challenge for transportation systems worldwide. Fuel price instability, public transport pricing, economic changes, government policies, major events, and other external factors can influence travel behaviour and cause traffic conditions to vary from historical patterns [10,11]. As AI-based forecasting systems become increasingly integrated into ITS, their reliability under such changing conditions becomes increasingly important.

Deep learning models can achieve high prediction accuracy under conventional traffic conditions because of their ability to learn complex temporal relationships from historical data [4,5,7]. However, high prediction accuracy under historical conditions does not

necessarily guarantee robustness when traffic-demand patterns change. The Melbourne case, therefore, represents a broader challenge for transportation systems: determining whether AI-based traffic forecasting models can maintain reliable performance when models trained under reference-period conditions are applied to traffic conditions influenced by external economic and policy factors.

This study addresses this challenge by training BiLSTM and conventional LSTM models using traffic observations from January–February 2026 and evaluating their forecasting performance across three chronologically separated periods: pre-disruption (March 2026), disruption (31 March–May 2026), and post-disruption (June–July 2026). The findings provide empirical evidence on how the accuracy of BiLSTM and LSTM changes when traffic demand departs from the conditions represented in the training data, and when simple benchmarks become competitive, contributing to the broader development of more reliable AI-based forecasting approaches for ITS applications.

2. Literature Review

Accurate traffic prediction is fundamental to ITS, particularly where traffic demand is dynamic and subject to disruption. Conventional traffic forecasting research has addressed both recurrent and non-recurrent traffic conditions, with early approaches including the California Algorithm, ARIMA, and Kalman Filters [20]. Although these approaches remain useful for structured traffic conditions, their ability to represent nonlinear and rapidly changing traffic behaviour is limited [21].

Machine learning and deep learning approaches have therefore become increasingly important because they can learn complex relationships directly from traffic data. However, the key challenge for the present study is not simply improving prediction accuracy but determining whether forecasting models remain reliable when traffic demand changes in response to external disruptions.

2.1. Parametric Approaches

Parametric approaches, such as ARIMA and Kalman Filters, use predefined mathematical structures to represent relationships between traffic variables [22-25]. ARIMA has been widely applied to traffic speed and volume prediction [26], while Kalman Filters have been used for real-time traffic estimation and monitoring [27]. However, these approaches can have limitations when traffic exhibits nonlinear and highly dynamic behaviour [2,3].

Kalman-filter-based approaches have also been applied to incident detection by analysing changes in traffic flow before and after incidents [28]. More recently, traffic incident detection methods have increasingly employed changes and anomalies in traffic-flow characteristics to identify disruptions [29], incorporating approaches such as deep learning, Bayesian modelling and spatiotemporal feature extraction [28,30-32]. More broadly, conventional parametric models can become less effective when the statistical characteristics of traffic change over time [2,33]. These limitations have contributed to the increasing use of more flexible machine-learning and non-parametric approaches for traffic prediction.

2.2. Non-Parametric and Machine Learning Approaches

Non-parametric approaches do not require a fixed functional relationship and can therefore represent nonlinear traffic patterns in a more flexible manner [2,34,35]. Neural Networks (NNs) and Support Vector Regression (SVR) have demonstrated their ability to learn complex relationships from traffic data [3,36]. Neural networks have been applied to traffic speed and volume prediction using large datasets and have demonstrated advantages in complex traffic environments [4,20,26,33,34].

Despite their flexibility, machine-learning models can still experience reduced performance when future traffic conditions change significantly from those represented in the training data. Recent reviews have identified model generalisation, changing traffic conditions, and robustness as continuing challenges in deep-learning-based traffic forecasting [2,37]. This issue is particularly relevant when external economic or policy changes affect travel demand.

2.3. LSTM Models for Traffic Prediction

LSTM networks were developed to address the difficulty of learning long-term dependencies in conventional Recurrent Neural Networks through memory cells and gating mechanisms [38]. Their ability to capture temporal dependencies has made LSTM networks widely applicable to traffic speed, flow, volume, and travel-time prediction [21,39].

[21] demonstrated the effectiveness of LSTM for traffic prediction, while [40] applied LSTM to irregular travel-time prediction. LSTM models have also been applied across different road hierarchies to predict traffic speed and flow [15]. Other studies have investigated LSTM-based approaches to transportation behaviour and vehicle dynamics [21,26].

The recent literature continues to identify LSTM as an important architecture for traffic forecasting, although graph-based and Transformer-based approaches are increasingly being investigated [2,37,41,42]. Importantly, much of the existing literature continues to emphasise prediction accuracy under historical traffic conditions, with comparatively less attention given to the stability of forecasting performance when the underlying demand conditions change.

2.4. BiLSTM Models for Traffic Prediction

BiLSTM extends the conventional LSTM architecture by processing sequential information in both the forward and backward directions during model learning. This allows the model to develop a representation of temporal patterns and has led to its application in traffic flow and speed prediction.

[15] demonstrated the effectiveness of BiLSTM for traffic flow prediction, while [6] compared LSTM and BiLSTM models using traffic speed and volume data from Hoddle Street, Melbourne. Their findings demonstrated the potential of BiLSTM for short-term traffic prediction. Other studies have investigated hybrid BiLSTM architectures and combinations with convolutional, attention, and optimisation techniques, primarily to improve prediction accuracy.

These studies demonstrate the strong predictive capability of BiLSTM architectures. However, their evaluation has generally focused on conventional accuracy measures under observed traffic conditions. Therefore, whether BiLSTM prediction performance remains reliable when the underlying traffic-demand pattern changes due to external economic or policy factors needs to be investigated.

2.5. External Economic and Policy Factors Affecting Travel Demand

Traffic forecasting models typically depend on historical traffic observations; however, travel demand can also be affected by factors external to the traffic time series [43]. Fuel prices and public transport pricing are particularly relevant because they can change the relative cost and attractiveness of private and public transport [44-46].

2.5.1. Fuel Price Changes and Travel Behaviour

Fuel price increases raise the operating cost of private vehicles and can influence trip frequency, car dependency, and transport mode choice. Previous research has demonstrated that fuel price variation can influence travel behaviour, particularly where alternative transport modes are available [11,47].

From a forecasting perspective, a significant change in fuel prices can act as an external factor influencing travel demand. When fuel prices change, overall travel behaviour may shift, and traffic patterns may also change from those observed in the historical data used to train the forecasting model. This makes fuel price variation a useful context for assessing how well forecasting models perform when travel demand changes.

2.5.2. Public Transport Pricing and Travel Behaviour

Public transport pricing can similarly influence mode choice by changing the relative cost of public and private transport. Fare reductions can increase the attractiveness of public transport and potentially encourage modal shifts [12,13,48,49]. However, the scale of such responses depends on factors including accessibility, travel time, convenience, and established travel behaviour.

The relationship between mobility demand and public-transport service provision is an important consideration when examining changes in urban travel conditions. [50] proposed a model and an accompanying tool (DORAM) for comparing public transport demand with the service offered, allowing what-if scenarios in which service or demand changes to be evaluated, for example, to identify the causes of overcrowding at stops and on vehicles. Their work, validated with real data from the Tuscany region, highlights the value of considering demand and transport supply together when assessing changing mobility conditions. In the context of traffic forecasting, such changes provide relevant background for evaluating whether models maintain predictive performance when traffic patterns differ from those observed during training. In the present study, the period of temporary fare-free public transport provides an opportunity to examine forecasting performance during a period of observed traffic-volume change; however, the available analysis does not establish a causal relationship between the fare policy and the observed changes in traffic volume.

The Victorian Government's temporary free public transport initiative in 2026 provides a real-world example of such a policy intervention. Free metropolitan trains, trams, and buses were introduced from 31 March 2026 through the end of April and subsequently extended through the end of May 2026 [14]. The timing of this intervention provides an opportunity to examine traffic forecasting performance during a period of changing travel-demand conditions.

2.5.3. Traffic Forecasting Under Combined Fuel Price and Free Public Transport Effects

The combination of higher fuel prices and free public transport may influence user choice between private and public transport. Recent traffic forecasting studies have highlighted changing traffic conditions, model generalisation, and model robustness as important challenges [2,37]. High prediction accuracy under conventional conditions should not necessarily be interpreted as evidence of model robustness.

Therefore, in this study, the period of rising fuel prices and free public transport provides a real-world setting for examining this issue. The main question is whether the BiLSTM model can maintain reliable predictive accuracy when traffic patterns change from those observed in the historical data used to develop the model.

2.6. Research Gap

The literature demonstrates a clear progression from conventional parametric approaches, such as ARIMA and Kalman Filters, towards flexible machine learning and deep learning approaches. LSTM and BiLSTM models have demonstrated strong capability in learning temporal traffic patterns and producing accurate short-term predictions of traffic speed and volume.

However, three key gaps remain. First, most traffic forecasting studies evaluate models under relatively stable demand conditions rather than during externally disrupted demand conditions. Second, although fuel prices and public transport pricing have been widely examined in travel-behaviour and mode-choice research [11,12], their implications for the robustness of traffic forecasting models remain underexplored. Third, although BiLSTM models have demonstrated high prediction accuracy, their ability to maintain forecasting performance when traffic demand deviates from historical patterns needs to be evaluated.

Therefore, this study investigates the robustness of BiLSTM for short-term traffic volume forecasting under changing travel-demand conditions associated with increased fuel prices and temporary free public transport. Using a section of the Tullamarine Freeway (M2) between the Western Ring Road (M80) interchange and Sunbury Road in Melbourne, this study trains the models using traffic observations from January–February 2026 and evaluates their forecasting performance across three chronologically separated periods: pre-disruption (March 2026), disruption (31 March–May 2026), and post-disruption (June–July 2026). The models are evaluated without retraining to examine their generalisation and robustness under evolving traffic-demand conditions, with additional comparisons against persistence, daily seasonal-naive, and weekly seasonal-naive forecasting benchmarks to assess whether their predictive advantages are maintained over time. Model performance is examined across different forecasting horizons and traffic directions. It is compared with a conventional LSTM model to assess the robustness of BiLSTM when traffic demand deviates from the conditions represented in the training data.

3. Data Collection and Description

3.1. Traffic Volume Data

The traffic volume data used in this research were obtained from the open-access TIRTL Traffic Counts dataset available through the Transport Victoria Open Data Portal [19]. The data were collected using Infra-Red Traffic Logger (TIRTL) devices developed by CEOS Pty Ltd. and deployed at locations across the Victorian road network. TIRTL devices use non-invasive infrared sensing technology to detect passing vehicles and provide information on traffic volume, direction, vehicle classification, and speed.

The TIRTL Traffic Counts dataset provides traffic observations aggregated into 15 min intervals across more than 400 sites in Victoria. The dataset includes traffic volume, direction of travel, vehicle class based on the Austroads vehicle classification scheme, speed in 5 km/h increments, and geographic location represented by latitude and longitude coordinates.

This study focuses on a section of the Tullamarine Freeway (M2) between the Western Ring Road (M80) interchange and Sunbury Road in Melbourne, Victoria, Australia (Figure 1). The Tullamarine Freeway is a major urban motorway connecting Melbourne's central business district, Melbourne Airport, and the northern and western metropolitan regions. The corridor experiences significant traffic demand and recurrent peak-period congestion and therefore provides an appropriate case study for evaluating short-term traffic volume forecasting under changing travel-demand conditions.

A total of 31 TIRTL sites were selected along the study corridor. The TIRTL dataset reports traffic volumes aggregated into 15 min intervals for each site and direction. For each direction, the 15 min volumes were averaged across the selected sites to form a single corridor-level series representing the average traffic volume per site. No missing intervals were present for the selected sites during the study period. The analysis covers the period from 1 January 2026 to 27 July 2026, providing approximately seven months of traffic observations. The final dataset contained 19,968 15 min observations for the northbound direction and 19,968 for the southbound direction, for a total of 39,936 observations.

Figure 1 presents the spatial distribution of the selected TIRTL sites along the Tullamarine Freeway. The map was generated in QGIS 3.44.12, with site locations geocoded using the latitude and longitude coordinates from the Transport Victoria Open Data Portal [19].

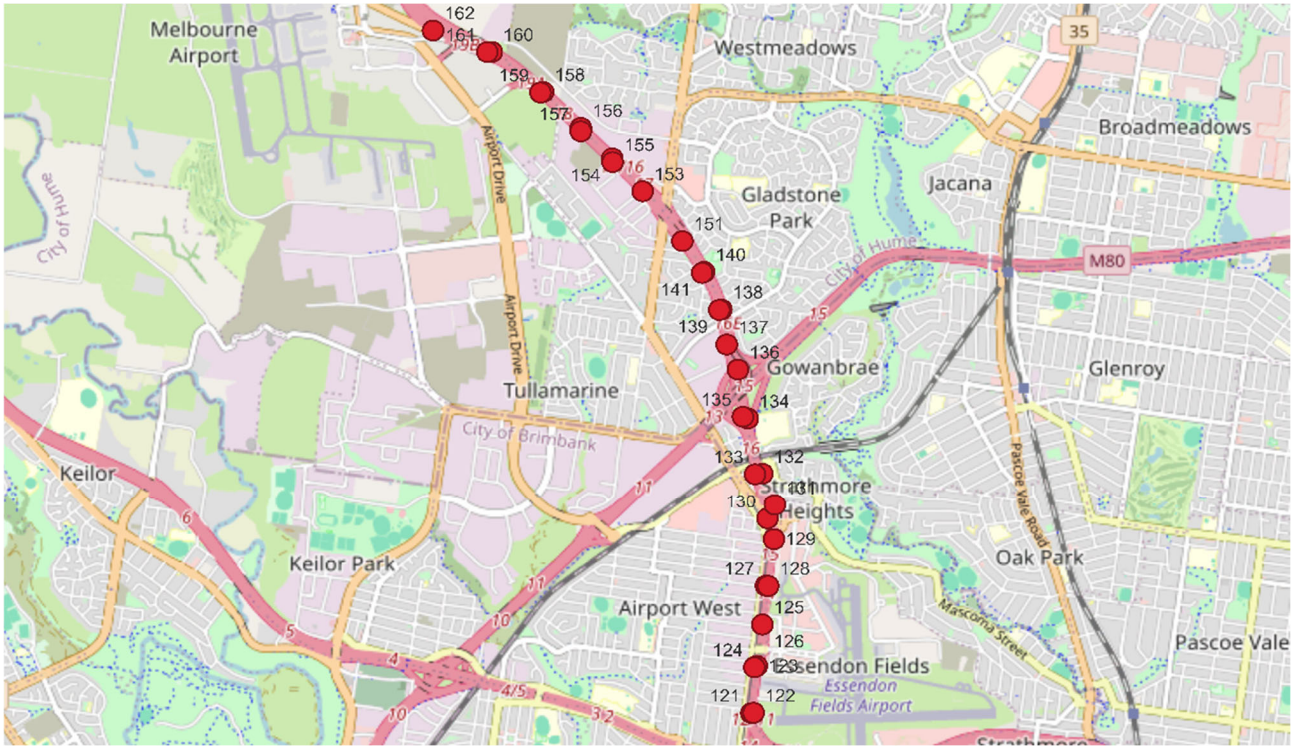


Figure 1. Spatial distribution of selected TIRTL sites along the Tullamarine Freeway, Australia. Source: Authors using Transport Victoria Open Data and QGIS 3.44.12.

For model development, the traffic-volume observations were divided chronologically into a reference-period training dataset and a disruption-period evaluation dataset. The models were trained using observations from January–February 2026 and were evaluated for their forecasting performance across these chronologically separated periods: pre-disruption (March 2026), disruption (31 March–May 2026), and post-disruption (June–July 2026). This design prevents observations from the disruption period from being used during model training. It provides an independent assessment of whether the models can generalise from established traffic-demand conditions to a period of changing demand.

The BiLSTM and LSTM models were evaluated separately for the northbound and southbound directions and for forecasting horizons of 15, 30, 45, and 60 min ahead. The resulting datasets used for model development and disruption-period evaluation are summarised in Table 1.

Table 1. Traffic volume data used for model development and disruption-period evaluation.

Dataset	Period	Number of Observations	Description
Training	1 January–28 February 2026	5664	Input data used for model training
Testing 1	1–30 March 2026	2880	Pre-disruption (reference) period
Testing 2	31 March–31 May 2026	5952	Disruption period
Testing 3	1 June–27 July 2026	5472	Post-disruption period
Total	1 January–27 July 2026	19,968	Total training and testing sets

Data source: Transport Victoria, TIRTL Traffic Counts and Classification, Transport Victoria Open Data Portal. Note: The first 96 intervals (24 h) of each test period were used only as model input; forecasts were therefore evaluated for 2–30 March (Test1), 1 April–31 May (Test2) and 2 June–27 July (Test3), giving 2784, 5856 and 5376 forecasts, respectively, at the 15 min horizon and one fewer for each additional step of horizon.

3.2. Traffic Demand Conditions During the Study Period

The study period encompasses significant changes in observed traffic demand during 2026. These changes provide an opportunity to evaluate the forecasting performance of BiLSTM when traffic conditions change from previously observed patterns.

The monthly average daily traffic volumes shown in Figure 2 indicate a reduction in traffic demand from February onwards. The average daily volume increased from approximately 46,234 vehicles in January to 50,596 in February, then declined slightly to approximately 50,267 in March. A significantly larger reduction occurred in April, when the monthly average decreased to approximately 47,674 vehicles per day, representing a 2922-vehicle-per-day reduction (6%) compared with February. Traffic volumes remained below the February level in May, at approximately 47,930 vehicles per day, representing a reduction of approximately 2666 vehicles per day (5%). Traffic demand partially recovered in June to approximately 48,519 vehicles per day, remaining approximately 4% below the February level. July recorded a further reduction to approximately 45,550 vehicles per day; however, as the dataset covers only the first 27 days of July, this figure is not directly comparable to the complete-month averages reported for the other months and should be interpreted with caution.

To further assess whether traffic volumes in the disruption period differed from those in the reference period, daily traffic volumes (average per site) were compared between March (Test1) and April–May (Test2) for weekdays, excluding public holidays. In the southbound (city-bound) direction, mean weekday volume was 4.4% lower in April–May than in March (95% confidence interval: 1.8% to 7.0% lower; Welch's *t*-test, $p = 0.001$). In the northbound direction, the difference was −0.3% (95% confidence interval: −3.4% to +2.7%; $p = 0.82$). Because daily volumes are serially correlated, the comparison was repeated using weekly mean weekday volumes, which gave consistent results (southbound −4.9%, $p = 0.016$; northbound −0.8%, $p = 0.67$), as did excluding the school holidays (southbound −4.1%, $p = 0.006$; northbound +1.1%, $p = 0.53$). These results indicate a statistically detectable reduction in southbound weekday volumes during the disruption period, but no detectable change in northbound volumes. They describe a change in the level of observed traffic rather than establishing a formal structural break or its causes.

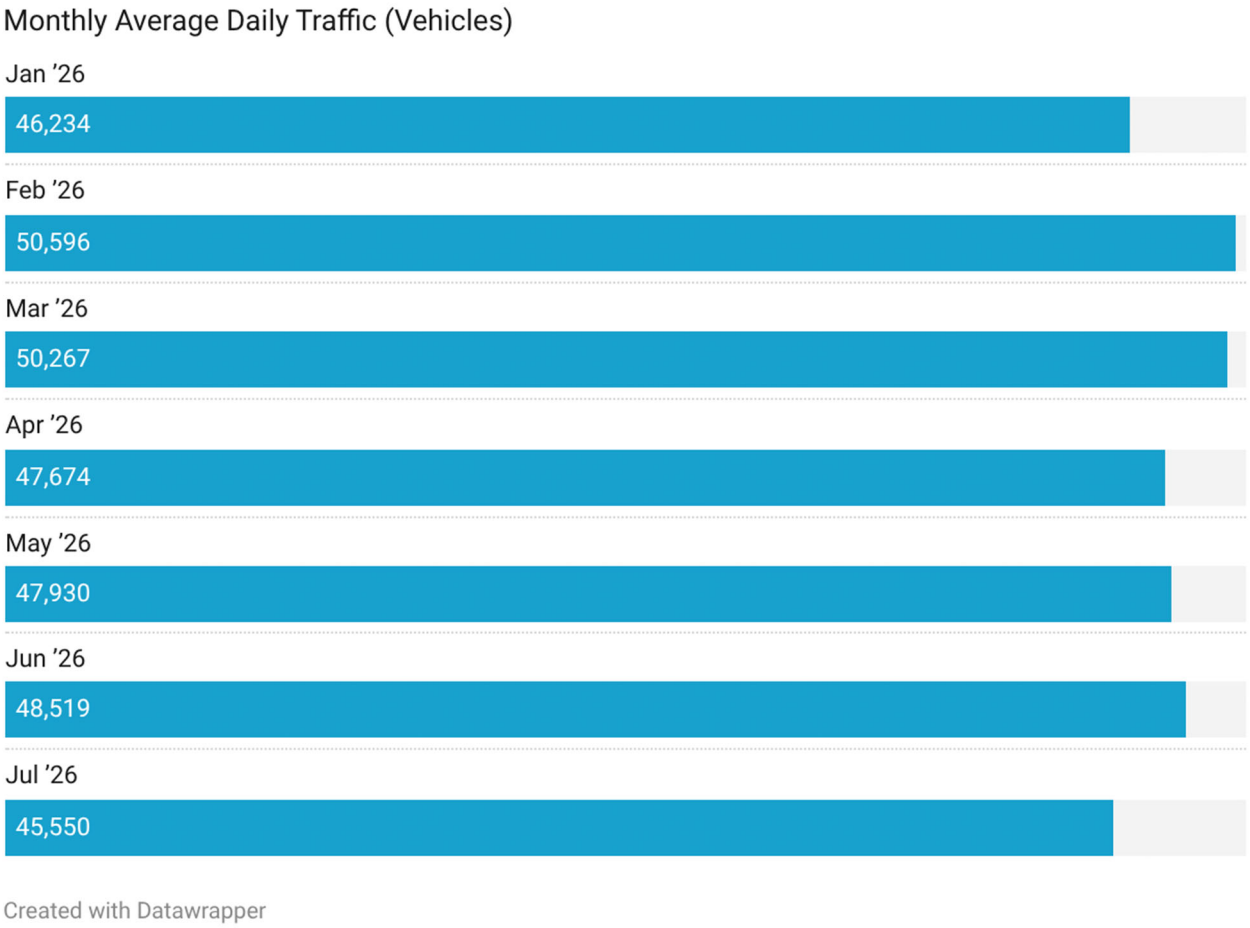


Figure 2. Monthly average daily traffic volumes on the Tullamarine Freeway. Data source: Transport Victoria, TIRTL Traffic Counts and Classification, Transport Victoria Open Data Portal.

The reduction observed from April onwards coincides with a period of increased fuel prices and the introduction of temporary free public transport in Victoria. The Victorian Government initiative provided free travel on metropolitan trains, trams, and buses from 31 March 2026 and was subsequently extended through May 2026 [14]. These changes may have altered the relative attractiveness of private and public transport and potentially contributed to changes in private vehicle demand. However, the observed traffic data alone cannot establish a direct causal relationship between these factors and the reduction in traffic volumes.

Figure 3 provides further evidence of changes in traffic demand. It presents the weekday inbound traffic volume profile during the morning peak period (7:00 AM to 9:00 AM) for February to June 2026. The largest reduction occurred in April, with traffic volume at 7:45 AM decreasing by approximately 15% compared with February. Although traffic demand partially recovered in May, volumes remained approximately 3–9% below the February baseline. A further reduction was observed in June, with traffic volumes approximately 4–13% below February levels during the morning peak period.

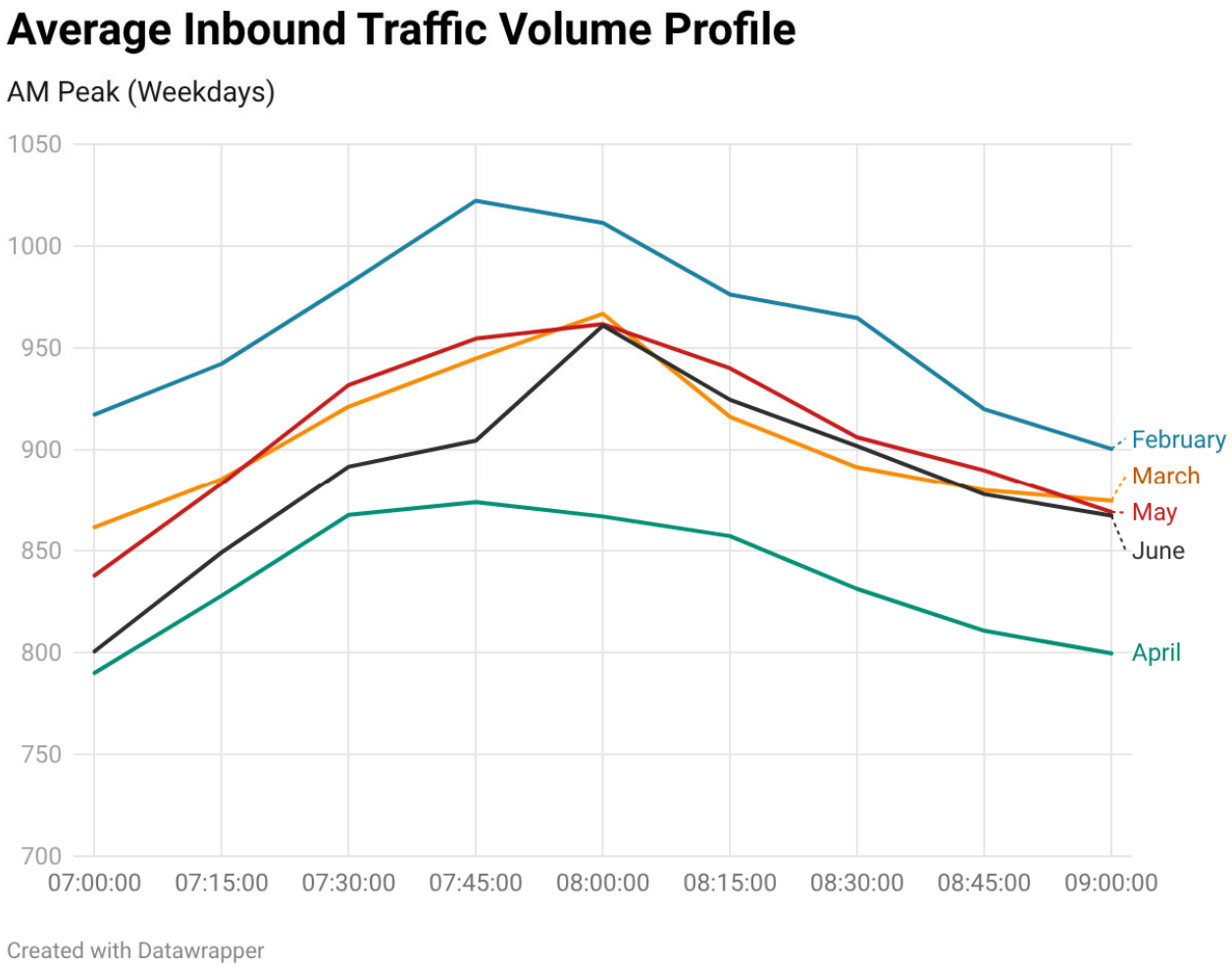


Figure 3. Weekday inbound traffic volume profile during the morning peak period. Data source: Transport Victoria, TIRTL Traffic Counts and Classification, Transport Victoria Open Data Portal.

These variations demonstrate that traffic demand did not remain constant throughout the study period. In particular, the reductions observed in April and May provide useful real-world context for assessing whether the BiLSTM model can maintain prediction accuracy when traffic volumes change from those of the reference period. The differences in traffic volume reductions between the two directions can be attributed to their directional travel characteristics. Southbound (SB) traffic represents inbound movements towards Melbourne CBD, whereas northbound (NB) traffic represents outbound movements away from the city. These directional differences may result in varying responses to changes in transport conditions, with inbound traffic potentially being more sensitive to changes in public transport availability and commuting behaviour. This may explain the more pronounced reduction observed in the southbound direction, as illustrated in Figures 2 and 3. Although the northbound direction did not experience a statistically significant reduction in average traffic volumes, this does not necessarily indicate that traffic demand remained unchanged. Rather, it represents a less disrupted demand condition than in the southbound direction. Therefore, evaluating both directions enables assessment of forecasting robustness to different magnitudes of traffic demand change within the same study period, providing a broader understanding of the models' ability to generalise under changing traffic conditions.

3.3. Training and Test Periods

To assess model robustness under changing traffic-demand conditions, the study period was divided into a training period and three chronologically separated test periods (Table 1).

In this study, robustness is assessed in a specific and limited sense: as the change in forecasting accuracy when models trained on January–February data are applied, without retraining, to later periods with different traffic conditions. Because the evaluation covers a single freeway corridor and a single observed demand shift, the results describe temporal generalisation under these conditions and should not be interpreted as evidence of robustness across other locations or types of disruption.

January–February 2026 was used as the training period. January was retained to increase the size of the training dataset and to provide a broader representation of normal traffic-demand conditions. The lower volumes observed in January may be associated with the Australian summer holiday period and are therefore treated as part of the natural variation in normal conditions rather than excluded as atypical observations.

Test1 (1–30 March 2026) was used as the reference test period, representing pre-disruption traffic-demand conditions. Traffic volumes in February and March were comparatively high and relatively stable before the reductions observed from April onwards.

Test2 (31 March–31 May 2026) was considered the disruption period, during which average daily traffic volumes were 5–6% lower than in February. This period coincided with increased fuel prices and the temporary free public transport initiative, which commenced on 31 March 2026.

Test3 (1 June–27 July 2026) was considered the post-disruption period. Average daily volumes in June partially recovered but remained approximately 4% below the February level, and volumes in the first 27 days of July were lower again. Test3 therefore represents a later period whose traffic conditions differ from both the training period and the disruption period.

The models were trained only on January–February observations and were evaluated, without retraining, on each of the three test periods. No test observations were used for model training or hyperparameter selection. This design allows the change in forecasting accuracy between the reference, disruption, and post-disruption periods to be assessed for models trained under normal traffic conditions.

Forecasting performance was evaluated using five statistical metrics: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Weighted Absolute Percentage Error (WAPE), and the Coefficient of Determination (R^2). The evaluation is considered across the four forecasting horizons and for both NB and SB traffic. The same evaluation framework was applied to both BiLSTM and LSTM models to provide a consistent basis for comparison.

4. Model Development and Evaluation

A BiLSTM network was developed to forecast traffic volume at four prediction horizons: 15, 30, 45, and 60 min ahead. BiLSTM was selected because it extends the conventional LSTM architecture by processing sequential information in both forward and backward directions, allowing temporal dependencies within traffic-volume observations to be captured [51]. The model was implemented using MATLAB and the Deep Learning Toolbox, version R2026b [52,53].

A BiLSTM model was developed for short-term traffic volume prediction along Melbourne's Tullamarine Freeway. The proposed architecture consists of a single BiLSTM layer with 300 hidden units, followed by a fully connected layer and a regression output layer. Unlike conventional LSTM networks, which process sequential information in a single direction, BiLSTM networks incorporate forward and backward recurrent

processing to capture temporal dependencies in both directions. This bidirectional structure enables the model to extract temporal relationships within the historical traffic observations, potentially improving its ability to represent complex traffic patterns and fluctuations in travel demand.

The model applies a fixed historical input window comprising 96 consecutive traffic volume observations recorded at 15 min intervals, representing 24 h of historical traffic conditions. For each forecasting instance, the input sequence contains only observations available up to the forecast origin, while the target corresponds to the traffic volume at the specified prediction horizon. This window-based approach ensures that predictions use only historical observations available at the forecast origin, preventing information leakage from future observations. Four separate BiLSTM models were developed for forecasting horizons of 15, 30, 45, and 60 min, corresponding to one, two, three, and four time steps ahead, respectively. Input data were normalised using statistical parameters derived exclusively from the training dataset to avoid information leakage from the testing periods.

The BiLSTM model was trained using the Adam optimisation algorithm over 300 epochs, with an initial learning rate of 0.005 and a gradient threshold of 0.90. A piecewise learning-rate schedule was adopted, with the learning rate reduced by a factor of 0.2 every 125 epochs, as shown in Table 2. To evaluate the model's ability to generalise under changing travel-demand conditions, training was conducted exclusively using traffic volume observations from January–February 2026. The trained model was subsequently evaluated across three chronologically separated periods: Test1 (1–30 March 2026), representing pre-disruption conditions; Test2 (31 March–31 May 2026), representing the disruption period associated with increased fuel prices and temporary fare-free public transport in Victoria; and Test3 (1 June–27 July 2026), representing post-disruption conditions. Separate experiments were conducted for northbound and southbound traffic, and the trained models were evaluated without retraining across the three testing periods. The adopted architecture is consistent with the use of recurrent deep-learning models for short-term traffic forecasting [6,15-17]. Forecasting accuracy was evaluated using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Weighted Absolute Percentage Error (WAPE), and the Coefficient of Determination (R^2) as described in Section 5. Additionally, the BiLSTM model was compared against a conventional LSTM model and three statistical forecasting benchmarks, namely persistence, daily seasonal-naive, and weekly seasonal-naive methods. These comparisons were conducted across all forecasting horizons and testing periods to investigate whether the predictive advantage of BiLSTM was maintained under evolving traffic-demand conditions. All models were trained and evaluated on CPU-based cloud computing instances (Amazon Web Services EC2, c6i.2xlarge).

Table 2. Model hyperparameters for LSTM and BiLSTM.

Parameters	Values
Number of input features	1
Number of BiLSTM hidden units	300
Gradient threshold	0.90
Initial learning rate	0.005
Mini-batch size	128
Maximum epochs	300
Trainable parameters	362,701 (LSTM); 725,401 (BiLSTM)
Training optimiser	Adaptive moment estimation optimiser
Learning rate schedule	Piecewise
Learning rate drop period	125

Learning rate reduction factor	0.2
Number of responses	1

Figure 4 illustrates the modelling framework used in this study. Unlike the previous study from which the modelling configuration was adapted, the present analysis does not incorporate weather variables or other external predictors. Traffic volume is used as the model input, so the analysis specifically examines whether a traffic-history-based BiLSTM model can maintain its forecasting performance when the underlying traffic demand changes during a period of fuel price increases and free public transport.

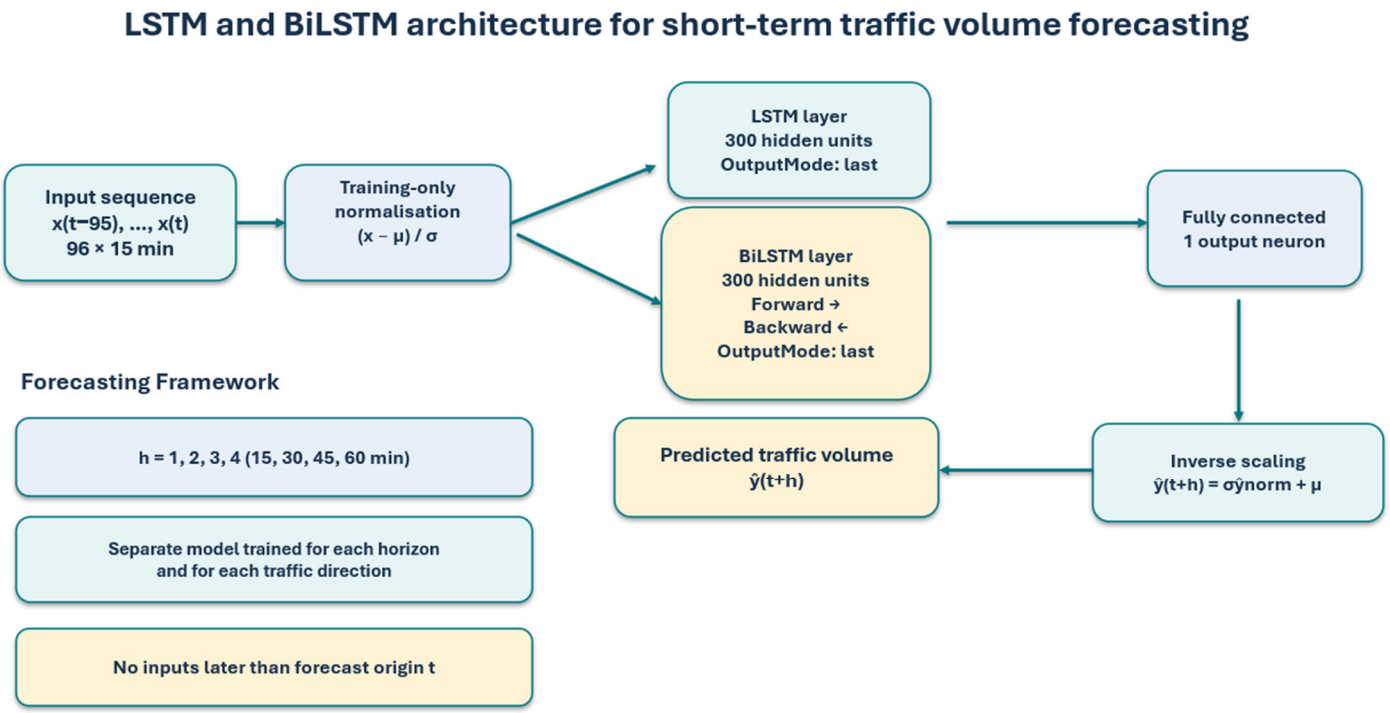


Figure 4. Overview of the modelling framework for comparing LSTM and BiLSTM models for northbound and southbound traffic-volume prediction at 15-, 30-, 45-, and 60 min forecast horizons. Source: authors.

5. Prediction Performance Results

5.1. Prediction Performance Evaluation

The predictive performance of the BiLSTM and LSTM models was evaluated using five statistical measures: RMSE, MAE, MAPE, WAPE, and R^2. RMSE and MAE measure the magnitude of prediction errors, with RMSE assigning greater weight to larger errors; both are expressed in vehicles per 15 min interval (average per site). MAPE expresses prediction error as a percentage of the observed traffic volume in each interval, while WAPE expresses the total absolute error as a percentage of the total observed volume, which makes it less sensitive to intervals with low traffic volumes. R^2 measures the proportion of variance in the observed traffic volumes explained by the prediction model.

The mathematical formulations of the evaluation measures are given in Equations (1) to (5).

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

$$\mathrm{MAPE}\ (\%) = \left(\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|\right) \times 100 \quad (3)$$

$$\mathrm{WAPE}\ (\%) = \left(\frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{\sum_{i=1}^{n}|y_i|}\right) \times 100 \quad (4)$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (5)$$

where

y_i = observed traffic volume, $\hat{y}_i$ = predicted traffic volume, $\bar{y}$ = mean observed traffic volume, n = number of observations, Σ = summation over all observations.

5.2. Prediction Performance of BiLSTM and LSTM Models

The forecasting results are presented for NB and SB traffic over four prediction horizons (15, 30, 45 and 60 min) and three chronologically separated test periods: Test1 (1–30 March 2026), Test2 (31 March–31 May 2026) and Test3 (1 June–27 July 2026). The models were trained on January–February observations and evaluated without retraining. All neural-network results reported below are the means of five independent random-seed runs. Lower RMSE, MAE, MAPE and WAPE indicate better accuracy, whereas higher R^2 indicates better fit. Confidence intervals refer to uncertainty in the five-run mean, not a prediction interval for individual observations.

To account for variability from model training, each model was trained 5 times with different random seeds (26, 42, 100, 123, and 2026) as shown in Table 3. The mean RMSE and standard deviation (SD) were calculated across the five runs. The 95% confidence intervals were calculated using Student's *t*-distribution with four degrees of freedom. Paired two-sided *t*-tests were conducted using seed-matched RMSE results to compare the performance of LSTM and BiLSTM models. The resulting *p*-values were adjusted for multiple comparisons using the Benjamini–Hochberg procedure.

Table 3. Mean RMSE (95% confidence interval) across five seeds and percentage RMSE reduction in BiLSTM relative to LSTM.

Direction	Test	Horizon (min)	BiLSTM RMSE ± SD (95% CI)	LSTM RMSE ± SD (95% CI)	Reduction	Paired *p*-Value [1]
NB	Test1	15	32.75 ± 0.25 (32.44–33.06)	38.95 ± 0.52 (38.31–39.59)	15.9%	<0.001
		30	42.24 ± 1.34 (40.58–43.90)	45.78 ± 0.32 (45.37–46.18)	7.7%	0.005
		45	45.67 ± 2.03 (43.14–48.19)	50.76 ± 0.46 (50.19–51.33)	10.0%	0.004
		60	49.99 ± 1.63 (47.96–52.01)	54.93 ± 1.02 (53.66–56.20)	9.0%	0.005
	Test2	15	35.03 ± 0.27 (34.70–35.36)	40.38 ± 0.57 (39.67–41.08)	13.2%	<0.001
		30	48.36 ± 1.68 (46.27–50.44)	51.00 ± 0.61 (50.24–51.76)	5.2%	0.026
		45	52.42 ± 2.78 (48.96–55.87)	58.65 ± 0.85 (57.60–59.71)	10.6%	0.013
		60	55.10 ± 1.89 (52.76–57.44)	64.40 ± 1.22 (62.88–65.92)	14.4%	0.004
	Test3	15	39.28 ± 0.84 (38.24–40.32)	45.46 ± 0.51 (44.83–46.08)	13.6%	<0.001
		30	54.64 ± 2.01 (52.14–57.14)	57.77 ± 0.89 (56.66–58.88)	5.4%	0.026
		45	59.71 ± 2.48 (56.62–62.79)	64.74 ± 1.12 (63.34–66.13)	7.8%	0.004
		60	63.76 ± 3.92 (58.89–68.62)	70.94 ± 1.90 (68.58–73.30)	10.1%	0.030
SB	Test1	15	41.86 ± 0.14 (41.69–42.04)	52.09 ± 0.31 (51.70–52.47)	19.6%	<0.001
		30	56.24 ± 1.11 (54.87–57.62)	65.67 ± 0.57 (64.96–66.37)	14.4%	<0.001

	45	62.43 ± 2.32 (59.55–65.30)	72.22 ± 1.20 (70.73–73.71)	13.6%	0.002
	60	66.32 ± 1.95 (63.90–68.74)	77.71 ± 1.57 (75.76–79.67)	14.7%	<0.001
Test2	15	45.16 ± 0.58 (44.44–45.88)	54.35 ± 0.16 (54.15–54.54)	16.9%	<0.001
	30	67.50 ± 1.71 (65.37–69.62)	71.90 ± 0.39 (71.42–72.37)	6.1%	0.006
	45	73.99 ± 2.06 (71.43–76.54)	81.31 ± 1.40 (79.57–83.04)	9.0%	0.003
	60	79.98 ± 1.86 (77.68–82.28)	88.99 ± 1.35 (87.32–90.67)	10.1%	0.003
Test3	15	46.02 ± 0.75 (45.08–46.95)	56.01 ± 0.62 (55.25–56.78)	17.8%	<0.001
	30	69.41 ± 1.50 (67.55–71.27)	74.91 ± 0.47 (74.32–75.50)	7.3%	0.002
	45	78.07 ± 2.37 (75.12–81.01)	83.60 ± 0.81 (82.60–84.60)	6.6%	0.012
	60	83.28 ± 2.28 (80.44–86.11)	89.40 ± 1.97 (86.95–91.84)	6.8%	0.004

Note: Results shown are mean RMSE ± standard deviation (SD), followed by the 95% confidence interval of the mean. Each value was calculated across five independent runs (seeds: 26, 42, 100, 123, 2026); 95% CI = mean ± $t_{0.975,4}$ × SD/√5 ($t_{0.975,4}$ = 2.776). The reduction is 100 × (LSTM RMSE—BiLSTM RMSE)/LSTM RMSE, where the mean is used. [1] Paired *p*-values are from two-sided paired *t*-tests of five seed-matched RMSE differences (LSTM minus BiLSTM), adjusted for 24 comparisons using the Benjamini–Hochberg false discovery rate procedure. All adjusted *p*-values are < 0.05.

For northbound traffic, BiLSTM achieved lower RMSE than LSTM in all 12 test–horizon combinations, with relative reductions ranging from 5.2% to 15.9%. The largest improvement occurred in Test1 at 15 min.

For southbound traffic, BiLSTM achieved lower RMSE than LSTM in all 12 test–horizon combinations, with relative reductions ranging from 6.1% to 19.6%. The largest improvement occurred in Test1 at 15 min.

Across both directions, BiLSTM outperformed LSTM in all 24 comparisons. Paired statistical comparisons confirmed that these improvements were statistically significant across all 24 comparisons (adjusted $p < 0.05$). The relatively small standard deviations across the five independent training runs indicate generally consistent model performance, although some variability was observed at longer forecasting horizons. These findings show that the accuracy advantage of BiLSTM over LSTM is consistent across training runs. This consistent advantage supports the usefulness of bidirectional processing within the available historical input window, although the magnitude of improvement varied with direction, horizon and test period.

Forecast-Horizon Sensitivity and Temporal Change for BiLSTM

For northbound traffic in Test1, BiLSTM RMSE increased from 32.75 at 15 min to 49.99 at 60 min (an increase of 52.6%).

For northbound traffic in Test2, BiLSTM RMSE increased from 35.03 at 15 min to 55.10 at 60 min (an increase of 57.3%).

For northbound traffic in Test3, BiLSTM RMSE increased from 39.28 at 15 min to 63.76 at 60 min (an increase of 62.3%).

For southbound traffic in Test1, BiLSTM RMSE increased from 41.86 at 15 min to 66.32 at 60 min (an increase of 58.4%).

For southbound traffic in Test2, BiLSTM RMSE increased from 45.16 at 15 min to 79.98 at 60 min (an increase of 77.1%).

For southbound traffic in Test3, BiLSTM RMSE increased from 46.02 at 15 min to 83.28 at 60 min (an increase of 81.0%).

The increase in absolute error with forecasting horizon is consistent across both directions and all test periods (Figure 5). However, comparisons of RMSE between periods should be interpreted alongside WAPE and R^2 because the volume distributions and variability may differ. The increase in post-disruption error does not, by itself, establish a causal effect of fuel prices, fare-free transport or time elapsed since training.

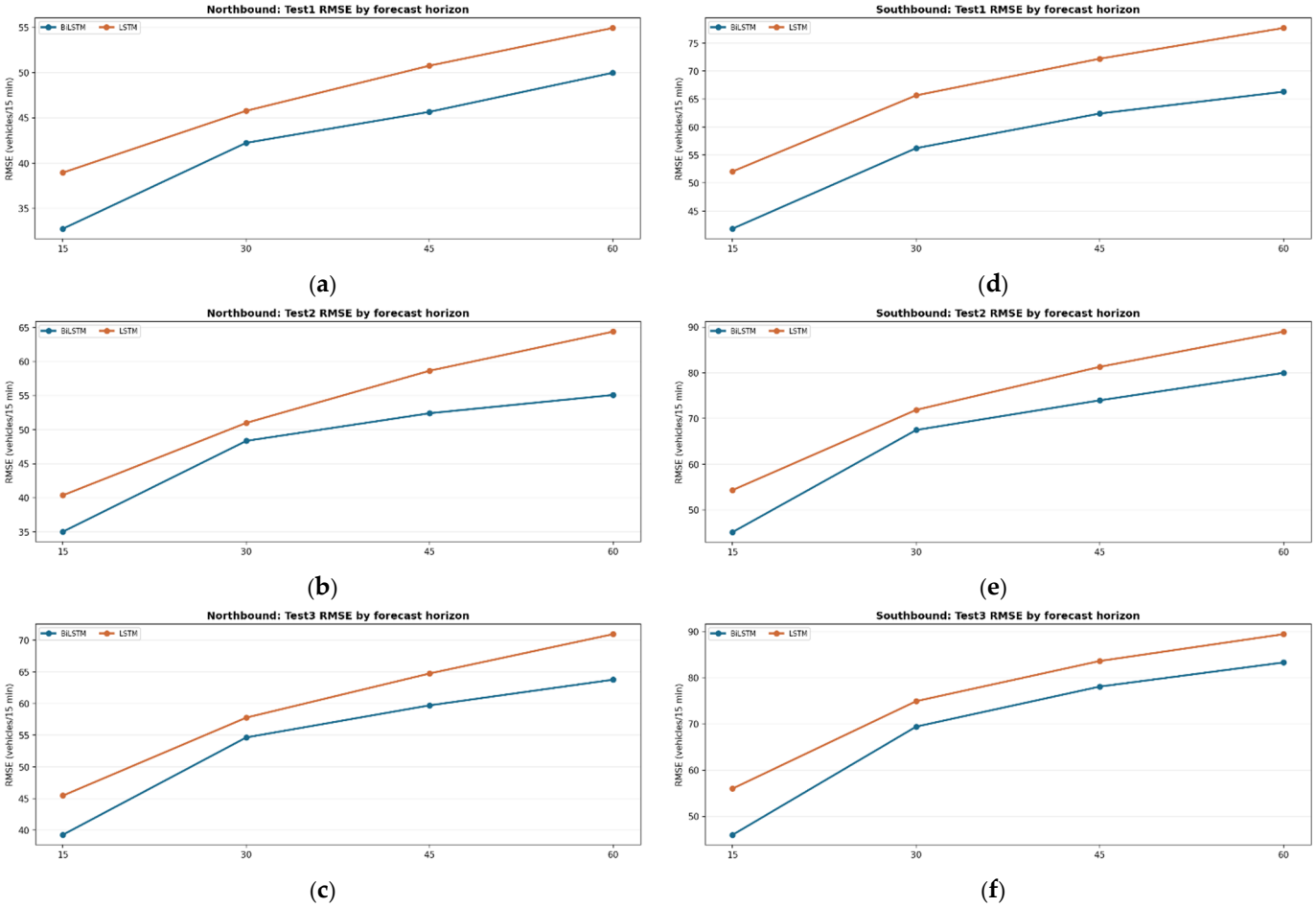


Figure 5. Forecasting RMSE across prediction horizons for northbound (**a**–**c**) and southbound (**d**–**f**) traffic under Test1, Test2 and Test3, respectively. Values represent the mean RMSE across five random seeds.

5.3. Prediction Performance Across All Settings

High R^2 values are expected in this setting because traffic volumes follow a strong and regular daily cycle; R^2 is therefore interpreted alongside the benchmark comparisons in Table 4, which show the improvement achieved over simple forecasts that also capture this cycle.

Table 4. BiLSTM accuracy across all settings, with LSTM WAPE for comparison (five-seed means).

Direction	Test	Horizon (min)	MAE	MAPE (%)	WAPE (%)	R^2	LSTM WAPE (%)
NB	Test 1	15	23.74	7.05	5.14	0.9810	6.09
		30	30.66	9.71	6.64	0.9684	7.24
		45	33.39	10.78	7.22	0.9630	8.10
		60	36.31	11.33	7.85	0.9557	8.84
	Test 2	15	25.71	7.85	5.63	0.9797	6.51
		30	35.79	11.35	7.84	0.9613	8.27
		45	39.16	13.06	8.57	0.9544	9.50
		60	41.10	14.04	9.00	0.9497	10.53
	Test 3	15	28.68	7.50	5.76	0.9768	6.73
		30	40.30	11.13	8.09	0.9550	8.59
		45	44.85	13.69	9.00	0.9463	9.72
		60	47.60	14.74	9.55	0.9386	10.74
SB		15	31.69	8.86	6.04	0.9775	7.51

Test 1	30	42.65	12.80	8.12	0.9593	9.45
	45	47.26	14.15	9.00	0.9498	10.35
	60	49.89	15.15	9.50	0.9434	11.03
Test 2	15	34.19	10.84	6.87	0.9734	8.25
	30	51.75	18.02	10.39	0.9405	10.91
	45	56.69	20.63	11.38	0.9285	12.45
	60	61.06	23.13	12.26	0.9165	13.58
Test 3	15	34.78	10.72	7.09	0.9689	8.66
	30	53.14	17.58	10.84	0.9291	11.56
	45	60.01	20.91	12.24	0.9103	13.01
	60	63.76	22.49	13.00	0.8979	13.91

Northbound, Test1: BiLSTM WAPE increased from 5.14% (15 min) to 7.85% (60 min), indicating that the higher absolute errors at longer horizons also represent a larger share of observed volume.

Northbound, Test2: BiLSTM WAPE increased from 5.63% (15 min) to 9.00% (60 min), indicating that the higher absolute errors at longer horizons also represent a larger share of observed volume.

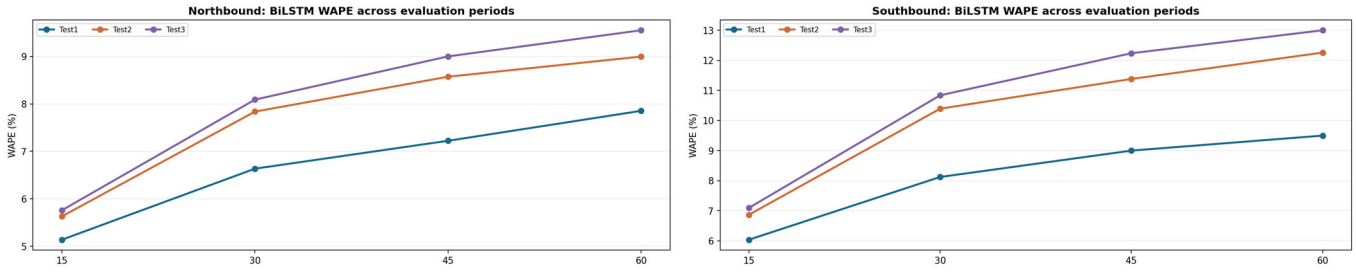
Northbound, Test3: BiLSTM WAPE increased from 5.76% (15 min) to 9.55% (60 min), indicating that the higher absolute errors at longer horizons also represent a larger share of observed volume.

Southbound, Test1: BiLSTM WAPE increased from 6.04% (15 min) to 9.50% (60 min), indicating that the higher absolute errors at longer horizons also represent a larger share of observed volume.

Southbound, Test2: BiLSTM WAPE increased from 6.87% (15 min) to 12.26% (60 min), indicating that the higher absolute errors at longer horizons also represent a larger share of observed volume.

Southbound, Test3: BiLSTM WAPE increased from 7.09% (15 min) to 13.00% (60 min), indicating that the higher absolute errors at longer horizons also represent a larger share of observed volume.

WAPE is particularly useful because it normalises aggregate absolute error by the sum of observed volumes. MAPE and WAPE need not yield identical rankings because MAPE weights each time interval equally in percentage terms, whereas WAPE weights errors according to the aggregate observed volume. The results should therefore be discussed using several complementary metrics rather than a single error measure (Figure 6).



(**a**) (**b**)

Figure 6. BiLSTM WAPE across prediction horizons for (**a**) northbound and (**b**) southbound traffic under the three test periods, illustrating horizon-dependent changes in relative forecasting error.

5.4. Comparison with Persistence and Seasonal-Naive Methods

BiLSTM generally achieved lower RMSE than the persistence and daily seasonal-naive methods. Nevertheless, the weekly seasonal-naive benchmark was competitive at

longer horizons, particularly in the post-disruption test period. The weekly naive approach repeats the volume observed at the corresponding 15 min interval one week earlier and may therefore benefit from stable weekly traffic patterns (Table 5, Figures 7 and 8).

Table 5. RMSE comparison against statistical forecasting benchmarks (five-seed means; matched evaluation timestamps within each baseline-comparison file).

Direction	Test	Horizon (min)	BiLSTM	LSTM	Persistence	Daily Naive	Weekly Naive
NB	Test1	15	32.75	38.95	41.69	97.33	59.23
		30	42.24	45.78	63.12	97.32	59.24
		45	45.67	50.76	83.02	97.32	59.25
		60	49.99	54.93	103.17	97.33	59.26
	Test2	15	35.03	40.38	41.15	92.66	71.32
		30	48.36	51.00	62.10	92.67	71.32
		45	52.42	58.65	81.77	92.68	71.33
		60	55.10	64.40	100.80	92.68	71.33
	Test3	15	39.28	45.46	44.72	97.33	58.48
		30	54.64	57.77	67.28	97.34	58.48
		45	59.71	64.74	87.49	97.34	58.49
		60	63.76	70.94	107.02	97.35	58.49
SB	Test1	15	41.86	52.09	51.95	130.87	84.44
		30	56.24	65.67	80.84	130.89	84.46
		45	62.43	72.22	104.08	130.91	84.45
		60	66.32	77.71	125.48	130.93	84.46
	Test2	15	45.16	54.35	52.76	121.48	92.83
		30	67.50	71.90	82.03	121.49	92.84
		45	73.99	81.31	104.75	121.50	92.84
		60	79.98	88.99	125.68	121.51	92.85
	Test3	15	46.02	56.01	53.22	115.18	79.71
		30	69.41	74.91	82.68	115.18	79.72
		45	78.07	83.60	104.60	115.19	79.72
		60	83.28	89.40	124.30	115.20	79.73

Only BiLSTM consistently outperformed persistence at the 15 min horizon. LSTM RMSE was higher than persistence RMSE in all three southbound test periods and in northbound Test3, indicating that the advantage over simple short-horizon benchmarks was achieved by the bidirectional model rather than by recurrent modelling in general.

Notably, in northbound Test3 at 45 min, weekly seasonal-naive RMSE was 58.49, compared with 59.71 for BiLSTM (weekly naive 2.0% lower).

Notably, in northbound Test3 at 60 min, weekly seasonal-naive RMSE was 58.49, compared with 63.76 for BiLSTM (weekly naive 8.3% lower).

Notably, in southbound Test3 at 60 min, weekly seasonal-naive RMSE was 79.73, compared with 83.28 for BiLSTM (weekly naive 4.3% lower).

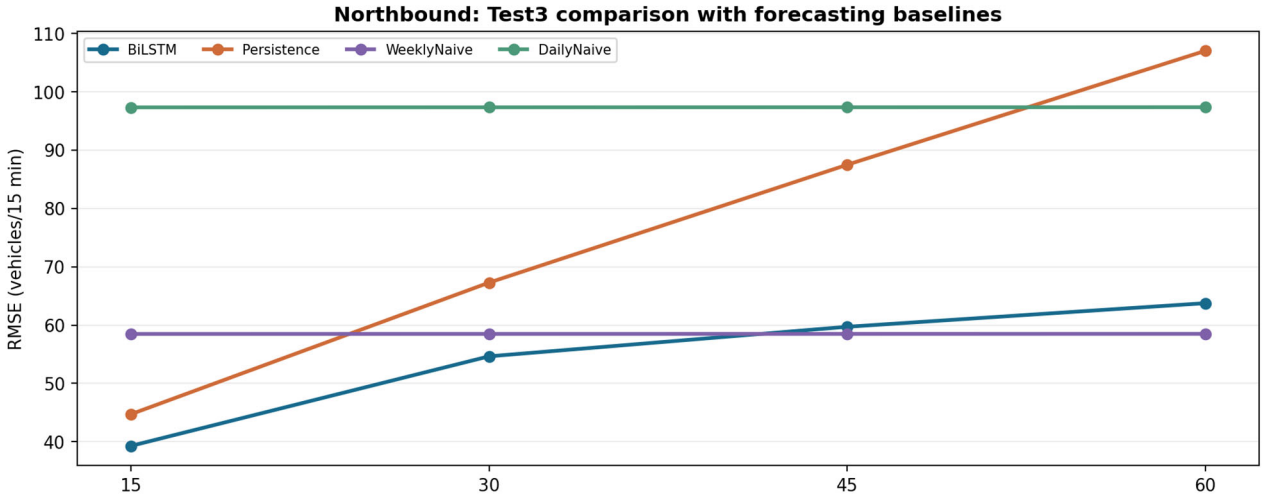


Figure 7. Northbound Test3 RMSE compared with persistence and seasonal-naive baselines; values are means across five seeds.

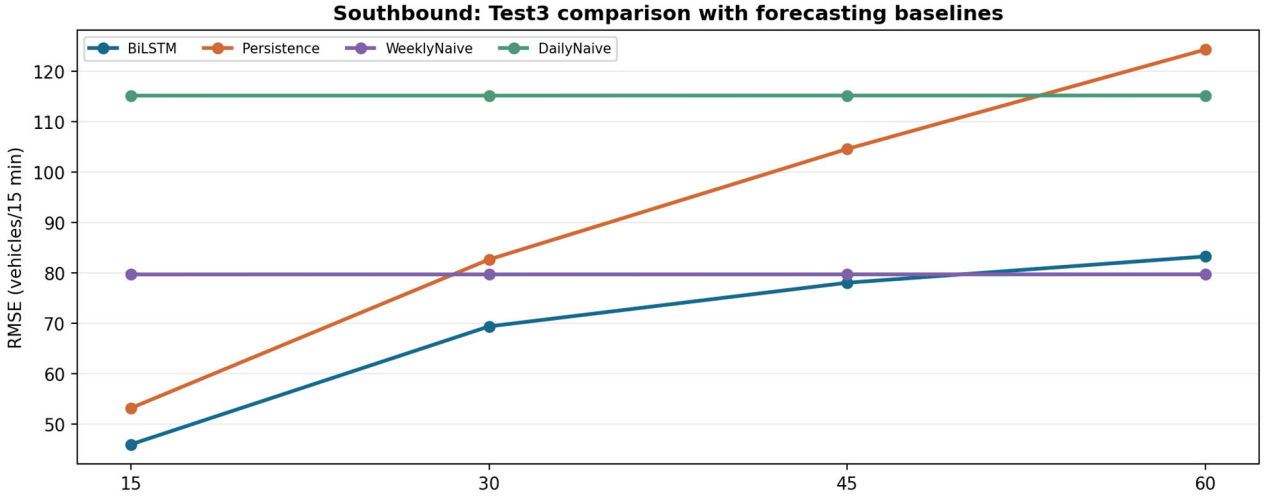


Figure 8. Southbound Test3 RMSE compared with persistence and seasonal-naive baselines; values are means across five seeds.

5.5. Change in Forecasting Accuracy Across Test Periods

Table 6 reports the ratio of each method's mean RMSE in Test2 and Test3 to its RMSE in Test1. A ratio above 1 indicates a higher error than in the pre-disruption period. During the disruption period, BiLSTM RMSE increased by 7–21% and LSTM RMSE by 4–17%, whereas persistence RMSE changed by less than 3% and daily seasonal-naive RMSE decreased by 5–7%. Weekly seasonal-naive RMSE increased by 10–20% in Test2, largely because its forecasts for early April were based on pre-disruption traffic observed one week earlier. In the post-disruption period, BiLSTM and LSTM RMSE were 10–31% and 8–29% higher than in Test1, respectively, while persistence RMSE changed by between −1% and +7% and the seasonal-naive errors were at or below their Test1 levels. The increase in neural-network error therefore does not appear to be explained by greater short-term variability in the test periods and more likely reflects differences between the training and test conditions.

Table 6. Ratio of mean RMSE in Test2 and Test3 to RMSE in Test1 (five-seed means for BiLSTM and LSTM).

Direction	Horizon (min)	Test2/Test1: BiLSTM	LSTM	Persis-tence	Daily Naive	Weekly Naive	Test3/Test1: BiLSTM	LSTM	Persis-tence	Daily Naive	Weekly Naive
NB	15	1.07	1.04	0.99	0.95	1.20	1.20	1.17	1.07	1.00	0.99
	30	1.14	1.11	0.98	0.95	1.20	1.29	1.26	1.07	1.00	0.99
	45	1.15	1.16	0.98	0.95	1.20	1.31	1.28	1.05	1.00	0.99
	60	1.10	1.17	0.98	0.95	1.20	1.28	1.29	1.04	1.00	0.99
SB	15	1.08	1.04	1.02	0.93	1.10	1.10	1.08	1.02	0.88	0.94
	30	1.20	1.09	1.01	0.93	1.10	1.23	1.14	1.02	0.88	0.94
	45	1.19	1.13	1.01	0.93	1.10	1.25	1.16	1.00	0.88	0.94
	60	1.21	1.15	1.00	0.93	1.10	1.26	1.15	0.99	0.88	0.94

6. Discussion

The results demonstrate that the BiLSTM model achieved consistently higher short-term traffic-volume forecasting accuracy than the conventional LSTM model across the three evaluation periods examined in this study. Both models were trained using January–February 2026 traffic observations and subsequently evaluated without retraining during the pre-disruption (Test1), disruption (Test2), and post-disruption (Test3) periods. This evaluation framework provides an opportunity to examine how models trained under reference-period traffic conditions generalise to subsequent changes in travel demand. Across both NB and SB traffic, BiLSTM achieved lower RMSE than LSTM in all 24 combinations of forecasting horizon, traffic direction, and testing period. The relative RMSE reductions ranged from 5.2% to 15.9% for NB traffic and from 6.1% to 19.6% for SB traffic. These findings indicate that BiLSTM maintained a consistent predictive advantage over conventional LSTM, although the magnitude of this advantage varied according to traffic direction, forecasting horizon, and evaluation period.

The forecasting results also demonstrate a clear relationship between prediction horizon and forecasting accuracy. As the forecasting horizon increased from 15 to 60 min, prediction errors generally increased for both traffic directions and across all three testing periods. For NB traffic, BiLSTM RMSE increased from 32.75 to 49.99 during Test1, from 35.03 to 55.10 during Test2, and from 39.28 to 63.76 during Test3. These changes correspond to increases of approximately 52.6%, 57.3%, and 62.3%, respectively. A similar pattern was observed for SB traffic, where RMSE increased from 41.86 to 66.32 during Test1, from 45.16 to 79.98 during Test2, and from 46.02 to 83.28 during Test3. The corresponding increases were approximately 58.4%, 77.1%, and 81.0%. These findings suggest that forecasting becomes increasingly challenging as the prediction horizon extends, particularly under the changing traffic conditions represented by the later evaluation periods. Nevertheless, BiLSTM continued to outperform conventional LSTM across all forecasting horizons, demonstrating a consistent advantage in modelling short-term traffic-volume dynamics.

The changes in traffic volume observed during the study period should be interpreted in the context of several potentially interacting influences. Although the reduction from April onwards coincided with rising fuel prices and the introduction of temporary fare-free public transport on 31 March 2026, it cannot be attributed to these developments alone. The test periods also include public holidays (Labour Day on 9 March in Test1; Good Friday and Easter Monday on 3 and 6 April and Anzac Day, a Saturday, on 25 April in Test2; and the King's Birthday on 8 June in Test3), as well as the school holidays from 3 to 19 April and from 27 June to 12 July. Seasonal changes in travel between the summer training period and the autumn and winter test periods may also have contributed. The

available traffic-volume data do not allow the separate contribution of these factors to be quantified. The test periods were therefore retained in full, including holidays, and are treated as periods of observed change in traffic conditions rather than as periods in which the causal effect of any single intervention has been established.

The superior performance of BiLSTM may be associated with its ability to extract temporal information through forward and backward recurrent processing within the available historical input sequence. Unlike conventional LSTM, which processes sequential observations in a single direction, BiLSTM incorporates information from both directions to develop a more comprehensive representation of historical temporal dependencies. This mechanism may help the model identify recurring traffic patterns and complex relationships within the 24 h historical input window. The results therefore provide empirical evidence that the BiLSTM architecture can offer advantages over conventional LSTM under the forecasting configuration adopted in this paper.

The repeated-training experiments showed that the results were stable across training runs: BiLSTM achieved lower RMSE than LSTM in every one of the five seeds for all 24 combinations of direction, horizon and test period, and the standard deviation of RMSE across seeds remained below 4.0 vehicles per interval. However, higher accuracy should not be equated with greater robustness. Relative to the pre-disruption period (Test1), BiLSTM RMSE increased by 7–21% during the disruption period (Test2), compared with 4–17% for LSTM, so BiLSTM errors increased proportionally more than LSTM errors in six of the eight direction–horizon combinations. Over the same periods, persistence errors changed by less than 2.5%, suggesting that short-term variability in the traffic series did not increase during the disruption and that the increase in model error more likely reflects differences between training and test conditions. Errors increased further in the post-disruption period (Test3), where the weekly seasonal-naive benchmark outperformed BiLSTM at 45 and 60 min in the northbound direction and at 60 min in the southbound direction. Overall, the findings indicate that BiLSTM provides more accurate forecasts than conventional LSTM under the evaluated conditions, but the accuracy of both models declines as traffic conditions deviate from those observed during training. This suggests that periodic model retraining may be beneficial for maintaining forecasting accuracy as traffic demand conditions evolve. However, the effectiveness and optimal frequency of such retraining require further investigation through experiments with different model-updating strategies.

7. Conclusions

This study investigated the robustness of a BiLSTM model for short-term traffic volume forecasting under changing travel-demand conditions in Melbourne, Australia. An open-access TIRTL traffic dataset from the Transport Victoria Open Data Portal was used to analyse traffic volumes along a section of the Tullamarine Freeway (M2), between the Western Ring Road (M80) interchange and Sunbury Road. The dataset comprised 39,936 15 min traffic-volume observations covering January to July 2026.

A key focus of the study was to examine forecasting performance under changing traffic-demand conditions. Traffic volumes varied during the study period, with a noticeable reduction in April and May coinciding with increased fuel prices and temporary free public transport in Victoria. Although the study does not establish a causal relationship between these external factors and the observed traffic-volume changes, their occurrence provides a relevant real-world context for evaluating model performance when travel demand changes from previously observed patterns. To directly assess this aspect, the models were trained exclusively using traffic observations from January–February 2026 and evaluated without retraining across three chronologically separated periods: pre-disruption (March), disruption (31 March–May), and post-disruption (June–July). Forecasting

performance was assessed for NB and SB traffic across prediction horizons of 15, 30, 45, and 60 min. Comparisons were conducted against a conventional LSTM model and three statistical forecasting benchmarks, namely persistence, daily seasonal-naive, and weekly seasonal-naive methods. Five independent training runs were performed to assess the consistency and reproducibility of the results.

The findings demonstrate that BiLSTM consistently outperformed conventional LSTM across all 24 combinations of forecasting horizon, traffic direction, and testing period, achieving reductions in RMSE ranging from 5.2% to 19.6%. Although prediction errors generally increased with longer forecasting horizons, BiLSTM maintained its relative advantage over LSTM throughout the evaluation. These results indicate that the bidirectional architecture provides a promising approach for capturing temporal traffic patterns and generating short-term predictions under conditions that differ from those represented in the training dataset.

The findings highlight the importance of distinguishing prediction accuracy from prediction robustness. BiLSTM remained the most accurate method during the disruption period, outperforming LSTM and all three benchmarks at every horizon in both directions. However, the errors of both neural models increased by 4–21% relative to the pre-disruption period, whereas persistence errors were largely unchanged, and in the post-disruption period a simple weekly seasonal-naive forecast outperformed BiLSTM at some longer horizons. The BiLSTM advantage over LSTM was generally largest at the 15 min horizon. These results suggest that BiLSTM can provide useful short-term forecasts under abrupt demand changes but that its advantage is not maintained indefinitely without retraining. This is particularly relevant to ITS applications, where short-term traffic forecasts support congestion monitoring, operational planning, traveller information and network management.

Several limitations should be acknowledged. The analysis is limited to a single freeway corridor and a single observed demand shift in 2026, so the results describe temporal generalisation under these conditions and do not establish robustness across other corridors, seasons or types of disruption. The study considers the combined occurrence of increased fuel prices and temporary fare-free public transport but does not identify their causal contributions to the observed traffic changes, which may also reflect seasonal variation, public and school holidays and other external factors. In addition, traffic volumes from 31 monitoring sites were averaged into a single time series for each direction to represent corridor-level traffic demand. While this approach captures overall demand patterns, spatial aggregation may smooth local traffic fluctuations and reduce variability, potentially influencing the reported forecasting accuracy. It may also mask localised congestion and differences in traffic conditions between individual monitoring sites. Therefore, the reported forecasting accuracy reflects aggregated corridor-level conditions rather than performance at individual locations. Future research should examine forecasting performance at individual monitoring sites to assess how spatial aggregation affects model accuracy and the models' ability to capture localised traffic variations. The models were trained once on January–February data and were not retrained, so the results do not show how quickly accuracy would recover with periodic updating. The benchmark comparison is limited to persistence and seasonal-naive methods; classical statistical models such as ARIMA and non-recurrent machine-learning approaches were not evaluated. In addition, both models used 300 hidden units, so the BiLSTM model had approximately twice as many trainable parameters as the LSTM model (725,401 compared with 362,701); part of its advantage may therefore reflect greater model capacity rather than bidirectional processing alone. Future research should extend the benchmarking framework to include these approaches to provide a more comprehensive assessment of the predictive advantages of recurrent neural network architectures, particularly BiLSTM, under changing

traffic demand conditions. Future research could extend the analysis to multiple corridors and disruption events, evaluate retraining strategies, include additional benchmarks such as ARIMA, and incorporate external variables such as fuel prices, public transport demand and major events.

Overall, the study shows that BiLSTM provided more accurate short-term traffic volume forecasts than LSTM under the changing demand conditions examined, although the accuracy of both models declined as conditions moved away from those represented in the training period. More broadly, the findings emphasise that AI-based traffic forecasting models should be evaluated not only under conventional traffic conditions but also under situations where real-world travel-demand patterns change. Also, the models were trained once using January–February data and were not subsequently retrained. Therefore, the results do not establish how quickly forecasting accuracy could recover through periodic model updates or the optimal retraining frequency. Future research should investigate different retraining strategies to assess their effectiveness in maintaining forecasting accuracy under evolving traffic demand conditions.

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Data Availability Statement: The traffic volume data used in this study are openly available from the Transport Victoria Open Data Portal (TIRTL Traffic Counts and Classification dataset; Transport Victoria, 2026). Code Availability: The MATLAB scripts used to prepare the data, train the BiLSTM and LSTM models, and compute the forecasts, as well as benchmark predictions and evaluation metrics, are publicly available at https://doi.org/10.5281/zenodo.24237018.

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