

Scalable Parking Demand Forecasting Using Bidirectional XLSTM and Temporal Attention Networks

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Abstract— Urban parking systems face inefficiencies due to unpredictable vehicle inflow and poor utilization of available spaces. A hybrid forecasting framework is developed by extending the XLSTM-Informer model with a Bidirectional LSTM layer to improve temporal feature learning. This enhancement enables the model to capture patterns from both forward and backward time sequences, strengthening its ability to model complex dependencies in parking data. The architecture combines convolutional layers for feature extraction, XLSTM for long-term sequence learning, and Informer attention for capturing global relationships across time steps. The model is trained on a real-world parking dataset with proper preprocessing and normalization. Performance evaluation is carried out using R² score, MAE, MAPE, and RMSE. The extended model demonstrates higher prediction accuracy and lower error compared to traditional LSTM and baseline XLSTM approaches, providing a more effective solution for real-time parking demand forecasting in smart city environments.

Keywords— Urban Parking, Bidirectional LSTM, Deep Learning, Hybrid Model

I. INTRODUCTION

Urbanization has significantly increased the number of vehicles in cities, creating serious challenges in managing limited parking resources. Inefficient parking systems contribute to traffic congestion, increased fuel consumption, and environmental pollution. A large portion of urban traffic is often caused by drivers searching for available parking spaces, which highlights the need for intelligent and data-driven parking management solutions. Accurate forecasting of parking demand has become a critical requirement for improving space utilization and reducing unnecessary vehicle movement.

Time-series forecasting techniques have been widely used to analyze historical parking data and predict future demand patterns. Traditional statistical models such as ARIMA rely on linear assumptions and often fail to capture complex, nonlinear relationships present in real-world data. With the advancement of machine learning, models like Support Vector Machines and Random Forest have been applied, but they still face limitations in handling temporal dependencies effectively. Deep learning approaches, particularly Recurrent Neural Networks and Long Short-Term Memory networks, have shown better performance due to their ability to learn sequential patterns over time.

Despite these improvements, forecasting urban parking demand remains challenging due to dynamic factors such as daily traffic variations, seasonal trends, and external influences like holidays or weather conditions. These factors introduce high variability and complexity into the data, making accurate prediction difficult. In addition, real-world datasets often contain noise, missing values, and imbalanced patterns, which further complicate model performance. Therefore, developing robust and scalable forecasting techniques is essential for enabling efficient parking management systems and supporting the broader goals of smart city infrastructure.

II. RELATED WORK

Research in demand prediction and dynamic systems laid the groundwork for modern forecasting approaches. The work of E. P. Wigner (1965) introduced fundamental concepts of sequential system behavior, which later influenced time-series modeling techniques. Building on statistical foundations, D. Chen (2011) applied the ARIMA model to predict automobile demand, demonstrating its capability in capturing linear temporal trends. However, such models struggled with nonlinear and highly dynamic data, which is common in real-world transportation scenarios.

Research in intelligent transportation systems further explored parking-related challenges. A. Klappenecker (2010) proposed early smart parking frameworks that focused on detecting and sharing available parking spaces, emphasizing real-time data usage. Similarly, S. D. Boyles (2015) introduced the concept of parking search equilibrium, highlighting how driver behavior and network conditions affect parking demand. These studies established the importance of predictive and adaptive systems to reduce congestion and inefficiencies.

With the advancement of machine learning, more sophisticated models were introduced to improve prediction accuracy. Y. Wu (2015) utilized multilinear analysis and K-nearest neighbor regression to capture nonlinear traffic patterns, showing improved performance over traditional statistical methods. In parallel, M. H. Amini (2015) extended ARIMA by incorporating probabilistic modeling for electric vehicle parking demand, addressing uncertainty in forecasting. Furthermore, E. I. Vlahogianni (2016) developed a real-time

parking prediction system, demonstrating the effectiveness of combining historical and real-time data for enhanced accuracy.

Recent studies have focused on deep learning and hybrid architectures to handle complex spatial-temporal dependencies. F. Zhang (2022) proposed a weather-aware LSTM model that integrates external factors such as weather and events, significantly improving prediction performance. Y. Feng (2022) introduced a hybrid deep learning framework for zone-wise parking prediction, combining multiple models to strengthen feature extraction. More recently, C. Ma (2025) developed an EMD-LSTM-BiLSTM model, demonstrating the advantage of bidirectional learning and signal decomposition in achieving higher forecasting accuracy. These advancements highlight a clear shift toward hybrid and deep learning approaches for efficient parking demand prediction.

Table: Summary of Key Literature Contributions and Their Impact on Current Research:

Author (Year)	Contribution	Impact on Research
E. P. Wigner (1965)	Explained basic concepts of dynamic systems and sequences.	Helped in developing time-series forecasting methods.
A. Klappenecker (2010)	Proposed early smart parking system using real-time data.	Showed importance of real-time parking information.
D. Chen (2011)	Used ARIMA model for demand prediction.	Proved statistical models can predict trends but have limits.
S. D. Boyles (2015)	Studied driver behavior in parking search.	Helped understand parking demand patterns.
Y. Wu (2015)	Applied machine learning for traffic prediction.	Showed ML models handle complex data better than traditional methods.
M. H. Amini (2015)	Added probability-based forecasting for parking demand.	Improved prediction under uncertain conditions.
E. I. Vlahogianni (2016)	Developed real-time parking prediction system.	Improved accuracy using live and past data together.
F. Zhang (2022)	Used LSTM with weather and events.	Showed external factors improve prediction results.
Y. Feng (2022)	Proposed hybrid deep learning model.	Improved accuracy by combining models.
C. Ma (2025)	Used BiLSTM with LSTM for prediction.	Showed bidirectional learning gives better accuracy.

III. PROPOSED APPROACH

Forecasting of parking demand requires a structured pipeline that can handle noisy, time-dependent data while capturing both short-term variations and long-term trends. The approach begins with collecting real-world parking data containing time-stamped vehicle entry records. Data preprocessing is carried out to remove inconsistencies, handle missing values, and normalize features so that the model can learn stable patterns. Exploratory analysis is performed to identify temporal trends, periodic behavior, and feature relationships that influence parking demand.

Feature engineering plays a key role by introducing time-based attributes such as hour of the day, day of the week, and seasonal indicators. These features help the model understand recurring patterns in parking usage. The dataset is then divided into training and testing sets, typically using an 80:20 ratio, to ensure reliable performance evaluation.

A hybrid deep learning architecture is designed to improve prediction capability. The initial layer uses convolutional operations to extract local patterns and reduce noise in the input sequence. This is followed by an Extended Long Short-Term Memory (XLSTM) layer, which is capable of learning long-range dependencies more effectively than traditional sequence models. To further enhance temporal learning, a Bidirectional LSTM layer is integrated, allowing the model to process information from both past and future contexts within the sequence.

An attention mechanism is applied to focus on the most relevant time steps, improving the model's ability to handle long sequences and complex dependencies. Finally, fully connected layers generate the predicted parking demand values. The model is trained using optimized parameters, and its performance is evaluated using standard metrics such as R² score, MAE, MAPE, and RMSE to ensure accuracy and reliability.

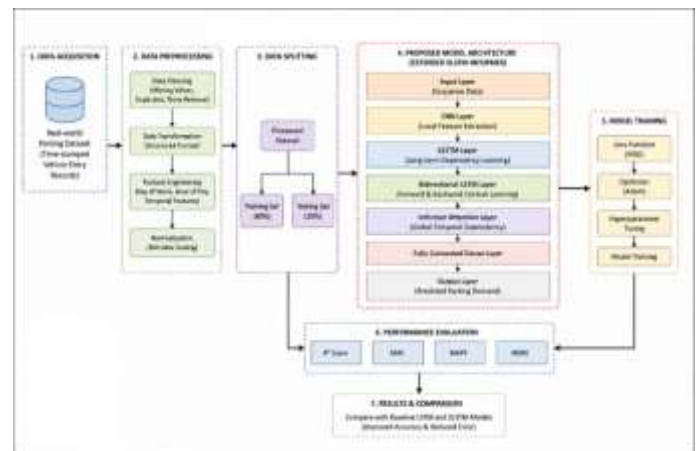


Figure 1: Parking demand forecasting framework

IV. METHODOLOGIES

Algorithm: Extended Parking Demand Forecasting Model

Input:

- D ← Raw parking dataset (time-series)
- T ← Sequence length
- E ← Number of epochs
- B ← Batch size

Output:

- Y_pred ← Predicted parking demand

Begin

1. Data Preprocessing

Load dataset D

Remove missing and duplicate values

Normalize features using Min-Max scaling

Generate time-based features (hour, day, etc.)

2. Sequence Creation

Convert D into sequences of length T

Split dataset into:

Train_Set (80%)

Test_Set (20%)

3. Model Initialization

Initialize CNN layer parameters

Initialize XLSTM layer parameters

Initialize Bidirectional LSTM parameters

Initialize Informer Attention parameters

Initialize Dense layer weights

4. Model Architecture

For each input sequence X :

$F1 \leftarrow \text{CNN}(X)$ // Local feature extraction

$F2 \leftarrow \text{XLSTM}(F1)$ // Long-term dependency learning

$F3 \leftarrow \text{BiLSTM}(F2)$ // Forward + backward context learning

$F4 \leftarrow \text{Informer_Attention}(F3)$ // Global temporal attention

$Y_{\text{pred}} \leftarrow \text{Dense}(F4)$ // Final output prediction

5. Training Phase

For epoch = 1 to E :

For each batch in Train_Set:

Forward pass using steps in Model Architecture

Compute Loss using MSE:

$\text{Loss} = \text{mean}((Y_{\text{true}} - Y_{\text{pred}})^2)$

Backpropagate error

Update weights using Adam optimizer

6. Testing Phase

For each sequence in Test_Set:

Generate prediction Y_{pred}

Store results

7. Performance Evaluation

Compute metrics:

$R2_score$

$\text{MAE} = \text{mean}(|Y_{\text{true}} - Y_{\text{pred}}|)$

$\text{MAPE} = \text{mean}(|(Y_{\text{true}} - Y_{\text{pred}}) / Y_{\text{true}}|)$

$\text{RMSE} = \text{sqrt}(\text{mean}((Y_{\text{true}} - Y_{\text{pred}})^2))$

8. Output Results

Display predicted values

Compare with actual values

Plot performance graphs

End

Data Collection

The process begins with collecting a real-world parking dataset containing time-stamped records of vehicle entries. Since direct

datasets used in earlier studies are not publicly available, an alternative dataset is obtained from open sources such as Kaggle. The dataset includes attributes such as date, time, and parking count, which are essential for time-series forecasting. The quality and consistency of data are carefully verified before further processing.

Data Cleaning and Preprocessing

Raw data often contains missing values, noise, and inconsistencies that can affect model performance. These issues are handled by removing duplicate entries, filling or interpolating missing values, and correcting irregular data points. The dataset is then transformed into a structured format suitable for sequential modeling. Proper preprocessing ensures that the model learns meaningful patterns rather than noise.

Exploratory Data Analysis (EDA)

Exploratory analysis is performed to understand the behavior of parking demand over time. Visualization techniques such as line graphs and correlation heatmaps are used to identify daily, weekly, and seasonal patterns. This step helps in detecting trends, periodic fluctuations, and relationships among variables, which are critical for designing an effective forecasting model.

Feature Engineering

Additional features are generated from the timestamp to improve prediction accuracy. These include day of the week, hour of the day, and other temporal indicators that capture recurring patterns. Feature engineering enhances the model's ability to understand time-based variations and improves its generalization capability.

Data Normalization

To ensure stable training, numerical values are normalized using scaling techniques such as Min-Max normalization. This transforms all features into a common range, preventing large values from dominating smaller ones during learning. Normalization also speeds up convergence and improves model performance.

Dataset Splitting

The processed dataset is divided into training and testing sets, typically using an 80:20 ratio. The training set is used to learn patterns, while the testing set evaluates the model's performance on unseen data. This step ensures that the model is not overfitting and can generalize well.

Baseline Model Implementation (LSTM)

A standard Long Short-Term Memory (LSTM) model is implemented as a baseline. This model captures sequential dependencies in time-series data and provides a reference for

comparison. Performance metrics such as R^2 score, MAE, MAPE, and RMSE are calculated to evaluate its effectiveness.

Proposed XLSTM Model Development

An Extended LSTM (XLSTM) model is developed to overcome limitations of traditional LSTM. XLSTM incorporates additional temporal features and enhanced memory representation, allowing it to better capture long-term dependencies. This improves the model's ability to handle complex and large-scale time-series data.

Integration of Bidirectional Layer

To further enhance performance, a Bidirectional LSTM layer is integrated into the XLSTM architecture. Unlike standard models, this layer processes the sequence in both forward and backward directions, enabling the model to capture contextual information from both past and future time steps. This significantly improves feature extraction and prediction accuracy.

Attention Mechanism Integration

An Informer-based attention mechanism is applied to focus on the most relevant time steps in the sequence. This reduces computational complexity while maintaining high accuracy. The attention layer helps the model prioritize important temporal features and ignore irrelevant information.

Model Training and Optimization

The complete model is trained using the training dataset with optimized hyperparameters such as learning rate, batch size, and number of epochs. Optimization techniques such as Adam optimizer are used to minimize loss. During training, the model learns patterns and adjusts weights to improve prediction accuracy.

Performance Evaluation and Comparison

The trained model is evaluated on the test dataset using performance metrics including R^2 score, MAE, MAPE, and RMSE. Results are compared with baseline LSTM and original XLSTM models. The extension model demonstrates higher accuracy and lower error rates, confirming the effectiveness of bidirectional learning and hybrid architecture in parking demand forecasting.

indicating moderate prediction accuracy, with relatively higher error values such as MAPE = 0.1034, MAE = 0.0277, and RMSE = 0.0659. From the output graphs and code execution screens, it is evident that the predicted values do not closely follow the actual parking demand, showing noticeable gaps between the curves.

The proposed XLSTM model significantly improves performance, achieving an R^2 score of 0.9927, which is very close to perfect prediction. Error metrics are also reduced, with MAPE = 0.0630, MAE = 0.0123, and RMSE = 0.0166. The visualization results confirm that the predicted and actual values overlap more closely compared to LSTM, indicating better learning of temporal patterns.

The extension model, which integrates Bidirectional LSTM, achieves the best performance among all models. It records an R^2 score of 0.9959, with further reduced errors such as MAPE = 0.0496, MAE = 0.0095, and RMSE = 0.0124. The output plots from the implementation show almost complete overlap between predicted and actual values, demonstrating highly accurate forecasting. These results confirm that incorporating bidirectional learning enhances feature extraction and improves prediction reliability, making the extended model more effective for real-world parking demand forecasting.

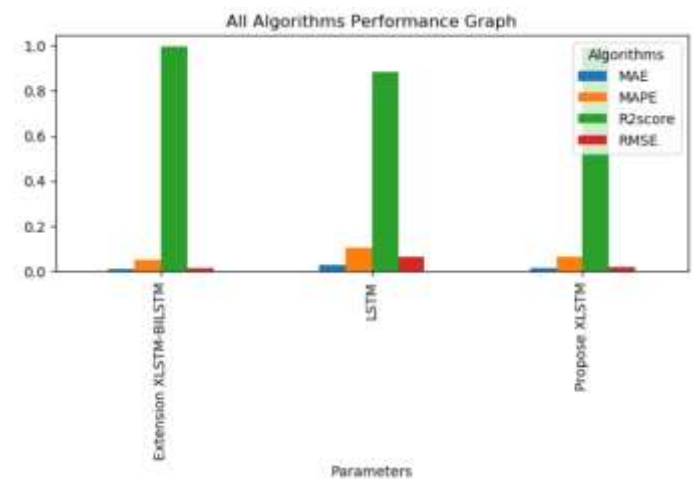


Figure 2: All Algorithms Performance Graph

The results highlight a clear progression in model capability as the architecture becomes more expressive. The baseline LSTM underperforms because it processes sequences in a single direction and relies on limited memory representation, which makes it sensitive to noise and weak at capturing long-range dependencies. This is visible in the higher error values and the gap between predicted and actual trends. The XLSTM model improves performance by strengthening temporal feature learning and handling longer sequences more effectively. Its lower error metrics indicate that it captures recurring patterns and seasonality with better stability.

The extension with a bidirectional layer further refines this behavior. Processing sequences in both directions gives the

VI RESULTS & DISCUSSION

	Algorithm Name	R2Score	MAPE	MAE	RMSE
0	Existing LSTM	0.883935	0.103498	0.027764	0.065965
1	Propose XLSTM	0.992679	0.063048	0.012325	0.016568
2	Extension XLSTM-BILSTM	0.995911	0.049613	0.009546	0.012382

The experimental results clearly show the improvement achieved by the extended model over the baseline approaches. The existing LSTM model produced an R^2 score of 0.8839,

model access to additional context, which reduces ambiguity in time-dependent patterns. This directly translates into tighter alignment between predictions and actual values and consistently lower errors. The attention mechanism also contributes by focusing the model on relevant time steps instead of treating all inputs equally. Overall, the improvement is not marginal; it reflects a structural advantage. The combined architecture handles complexity, variability, and temporal dependencies more effectively, which explains the consistent gains across all evaluation metrics.

VII. CONCLUSION

Parking demand forecasting depends on models that can capture complex temporal behavior and adapt to dynamic urban conditions. Conventional approaches such as LSTM struggle with long-term dependencies and often produce higher prediction errors. The enhanced framework addresses these limitations by improving temporal feature learning and reducing variability in predictions. Experimental results confirm consistent gains across all evaluation metrics, with predictions closely aligning to actual demand patterns.

The improved accuracy and stability make the model suitable for real-time smart parking applications, where efficient allocation of spaces and reduction of traffic congestion are critical. Better forecasting directly supports informed decision-making in urban planning and transportation management. The approach also provides a scalable foundation for future enhancements. Incorporating additional external factors such as weather conditions, special events, and traffic flow data can further strengthen prediction reliability and adaptability across different urban environments.

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