Context aware parking occupancy forecasting in urban environment for sustainable smart parking system

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Abstract. The increasing urbanization and car ownership rates are placing a significant strain on urban parking infrastructure, leading to congestion, pollution, and driver frustration. While smart parking systems, leveraging sensors, communication networks, and data analytics, offer a promising solution, existing systems face challenges such as limited accuracy, coverage, and integration. This paper examines the potential of context-aware parking occupancy forecasting to overcome these limitations. By incorporating external factors like traffic flow, weather, and events into forecasting models, this approach aims to improve prediction accuracy and optimize parking resource management. We discuss the current state of smart parking, its challenges, and the benefits of context-aware forecasting. This research contributes to the development of more effective and efficient smart parking solutions for creating sustainable and livable urban environments. The study leverages context-aware forecasting models such as LSTM and ARIMA to address challenges in parking occupancy prediction.

Keywords: smart parking, parking occupancy forecasting, context-aware forecasting, urban mobility

1 Introduction

The increasing number of vehicles on the roads has led to several issues, one of which is finding a parking space in urban environments. The rapid urbanization and increasing population have put a tremendous strain on cities' transportation infrastructure, particularly the parking systems. The increase in the number of

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vehicles on the road has resulted in limited parking spaces, traffic congestion, and increased air pollution. The problem of finding a parking space is particularly challenging in densely populated urban areas, where parking spaces are scarce. In addition, the lack of real-time information on parking availability makes it difficult for drivers to plan their trips and choose the most convenient parking spot. Previous studies, such as [1, 19], have shown limited accuracy due to a lack of real-time context integration. To tackle these challenges, governments and municipalities are looking towards smart parking systems that use technology to optimize parking spaces, reduce traffic congestion, and enhance sustainability. Context-aware parking occupancy forecasting is an essential element of a smart parking system, which uses real-time data and machine learning techniques to predict the availability of parking spaces [20, 21]. Parking occupancy forecasting can help address this problem by providing drivers with information about the availability of parking spaces, reducing congestion, and improving air quality. Context-aware parking occupancy forecasting is an emerging research area that utilizes various sensors and data analysis techniques to provide accurate and reliable parking occupancy predictions. This paper aims to explore the concept of context-aware parking occupancy forecasting in urban environments and its contribution to sustainable smart parking systems.

2 Overview of Smart Parking Systems

A smart parking system is a combination of hardware and software that helps drivers locate an available parking spot quickly. The system comprises various components, including sensors, cameras, communication networks, data processing algorithms, and mobile applications. The sensors and cameras detect the occupancy of parking spots, while the communication networks transmit the information to the data processing algorithms. The algorithms analyze the data and provide real-time parking availability information to the drivers through mobile applications [20]. The primary goal of a smart parking system is to reduce traffic congestion, air pollution, and carbon emissions by guiding drivers to available parking spots efficiently.

Smart parking systems provide real-time information on the availability of parking spaces, which helps drivers to choose the most convenient parking spot and avoid unnecessary traffic congestion. These systems are typically based on wireless sensor networks (WSNs) that detect the presence of vehicles in parking spaces and transmit this data to a central server. The server processes the data and provides real-time information on parking availability to drivers through mobile applications [20] or electronic signage. Sustainable smart parking systems have several benefits, including reducing traffic congestion, improving air quality, and enhancing the overall quality of life in urban environments.

Smart parking systems can benefit urban areas by ensuring every available parking slot is utilized efficiently [1]. Context-aware parking systems analyze previous user's parking spots to discern private places from on-street ones [2]. Smart parking solutions can also direct drivers to vacant parking stalls, reducing the number of cars congesting urban streets [3]. A crowdsourcing-based approach that makes use of a mobile app for facilitating the search for a parking space in the campus environment is also a sustainable smart parking solution[3].

3 Sustainable Smart Parking Systems

Smart parking systems are designed to improve the efficiency of parking operations, reduce traffic congestion, and improve the overall parking experience for drivers. A sustainable smart parking system goes beyond these objectives and aims to reduce the environmental impact of parking operations. A sustainable smart parking system incorporates context-aware parking occupancy forecasting to provide drivers with information about available parking spaces, reducing the amount of time spent on the road searching for a parking space. This, in turn, reduces fuel consumption and emissions, leading to improved air quality.

A sustainable smart parking system can also incorporate other sustainability features, such as the use of renewable energy sources for lighting and electric vehicle charging stations. The system can be designed to encourage the use of electric vehicles by providing preferential parking spaces for electric vehicles or offering discounted parking rates for electric vehicles. The system can also be designed to encourage the use of public transportation by providing information about nearby public transportation options and integrating with public transportation ticketing systems. The Role of Context-Aware Parking Occupancy Forecasting in Sustainable Smart Parking Systems. Smart parking systems are an integral part of sustainable urban transportation as they reduce traffic congestion, emissions, and energy use. Context-aware parking occupancy forecasting is a critical component of such systems as it provides real-time information on parking availability, making it easier for drivers to find parking spaces without circling the block or driving long distances. This, in turn, reduces fuel consumption, emissions, and traffic congestion, making the city more livable and sustainable.

Context-aware parking occupancy forecasting in urban environments is an essential tool for a sustainable smart parking system. This paper explores the concept of context-aware parking occupancy forecasting, the technologies used, and its benefits for smart parking systems' sustainability.

Context-aware parking occupancy forecasting is the process of using real-time data, machine learning techniques, and predictive analytics to forecast the availability of parking spaces. Parking occupancy forecasting involves predicting the number of vacant parking spaces in a given parking lot or a city's area. This prediction helps drivers plan their trips and avoids congested areas. Context-aware parking occupancy forecasting takes into account various contextual factors, such as weather, events, and time of day, to make more accurate predictions. By incorporating contextual factors, the parking occupancy forecasting system can provide real-time parking availability information to drivers, which can reduce traffic congestion and carbon emissions.

The primary objective of context-aware parking occupancy forecasting is to provide drivers with real-time information about available parking spaces, allowing them to make informed decisions about where to park. This information can be delivered to drivers through various means, such as mobile applications or electronic signage. By providing drivers with this information, the congestion caused by drivers searching for a parking space can be significantly reduced. This, in turn, reduces the time spent by drivers on the road, leading to a reduction in air pollution and greenhouse gas emissions.

Context-aware parking occupancy forecasting can also benefit parking operators by providing them with real-time information on parking occupancy. This can help parking operators to manage their parking resources more efficiently, leading to increased revenue and reduced operating costs. Parking operators can also use this information to optimize their parking operations, such as adjusting parking rates based on parking demand. The data collected are then processed using machine learning algorithms to forecast parking occupancy. The accuracy of the parking occupancy prediction depends on the quality and quantity of data collected, the selection of appropriate machine learning algorithms, and the integration of context-aware features. Context-aware features include weather conditions, time of day, and events happening in the surrounding area, which can impact parking occupancy.

Context-aware parking occupancy forecasting is an innovative solution that utilizes real-time data from various sources to provide accurate predictions of parking availability in urban environments. This method takes into account various factors such as weather conditions, time of day, events, and traffic congestion to provide accurate parking occupancy forecasts. Context-aware parking occupancy forecasting uses machine learning algorithms that analyze data from various sources, including parking sensors, weather forecasts, traffic data, and events calendars. This method can also take into account historical parking data to provide accurate predictions of future parking occupancy.

4 Contextual Factors for Parking Occupancy Forecasting

Different contexts parking information that influences parking occupancy, technology used and the source of that contextual information explained in the following sub sections.

4.1 Contextual factors influence parking occupancy forecasting

Parking occupancy is significantly influenced by various contextual factors, requiring data-driven forecasting models for accurate forecasting.

- **Weather conditions :** Adverse weather (e.g., heavy rain, snowstorms) deters individuals from venturing out, while mild weather (e.g., sunny or cloudy days) encourages outdoor activities. Consequently, parking demand exhibits a positive correlation with favorable weather conditions.
- **Local Events:** Events such as sports games, concerts, festivals, and conventions significantly impact parking occupancy. During events, more people visit the area, leading to high parking demand. Therefore, it is crucial

to consider events while predicting parking occupancy. Large-scale events (e.g., sports games, concerts, festivals) attract substantial crowds, increasing parking demand significantly. Incorporating event schedules and anticipated attendance is crucial for accurate occupancy forecasting.

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- **Time of Day:** Parking demand fluctuates throughout the day, peaking during rush hour and lunchtime. Conversely, off-peak hours (e.g., early mornings, late nights) experience lower demand.

4.2 Data Sources for Contextual Factors

Accurate forecasting models require diverse datasets, including:

- **Weather Data:** Temperature, precipitation, wind speed, and humidity data sourced from meteorological agencies or weather forecasts.
- **Event Data:** Information on upcoming events (date, time, location, expected attendance) obtained from organizers, social media, or online calendars.
- **Traffic Data:** Real-time traffic flow (vehicle count, speed, direction) collected from traffic cameras, sensors, and GPS devices.
- **Parking Data:** Occupancy status of parking spots (vacant/occupied, location, timestamp) gathered from sensors, cameras, or manual surveys.

Effective data processing techniques are essential for analyzing these diverse datasets and generating accurate parking occupancy predictions.

4.3 Technologies used in Context-Aware Parking Occupancy Forecasting

Context-aware parking occupancy forecasting requires a combination of technologies to collect, process, and analyze data. The technologies used in context-aware parking occupancy forecasting include:

- Sensors: Sensors are devices that detect changes in the environment, such as the presence of a vehicle. In a smart parking system, sensors are installed in parking spaces to detect whether the space is occupied or vacant.
- Wireless Communication Networks: Wireless communication networks are used to transmit data from sensors to a central database. The data is then analyzed to determine the occupancy status of parking spaces.
- Data Analytics: Data analytics is the process of analyzing and interpreting large datasets to extract meaningful insights. In the context of parking occupancy forecasting, data analytics is used to process the data collected from sensors and wireless communication networks to predict the availability of parking spaces.

– Machine Learning: Machine learning is a subset of artificial intelligence that involves training algorithms to learn from data. In the context of parking occupancy forecasting, machine learning algorithms are used to analyze historical parking data to predict future occupancy levels.

Context-aware parking occupancy forecasting is not merely a technological advancement, it is a fundamental pillar of sustain able smart parking systems, offering a multitude of benefits for both drivers and cities. By intelligently predicting parking availability based on real-time contextual factors, these systems hold the potential to revolutionize urban mobility and enhance overall quality of life. This technology directly tackles the pervasive issue of traffic congestion by guiding drivers directly to available parking spaces, eliminating the need for time-consuming and fuel-wasting searches. This targeted approach maximizes parking efficiency, ensuring optimal utilization of existing parking infrastructure. The positive ripple effects extend beyond parking itself, contributing to a significant reduction in carbon emissions and improved air quality in urban environments. Furthermore, by providing drivers with accurate, real-time information and potentially even suggesting alternative transportation options, these systems cultivate a seamless and stress-free parking experience. This enhanced user experience translates to increased satisfaction and encourages the use of public transportation, further bolstering sustainable urban development. Beyond individual benefits, context-aware forecasting enables cost savings for municipalities and businesses by optimizing parking space utilization and mitigating the need for costly expansions.

5 Challenges and limitations

Despite its evident potential, context-aware parking occupancy forecasting faces notable challenges and limitations hindering widespread adoption and optimal performance. A primary concern revolves around the financial investment required for implementation. Deploying a comprehensive system necessitates significant capital expenditure on sensors, sophisticated machine learning algorithms, and robust data storage infrastructure, potentially posing a barrier for municipalities and organizations with limited resources. Furthermore, the collection and storage of extensive parking occupancy data, particularly if tracking individual vehicles, raise valid privacy concerns. Addressing these concerns transparently and ethically, ensuring user trust and regulatory compliance, is paramount for successful implementation. Beyond cost and privacy, ensuring the accuracy and reliability of forecasting is critical. The system's effectiveness hinges on the quality and timeliness of the data it processes. Sensor malfunctions, unforeseen events, or inaccurate algorithms can compromise data integrity, leading to unreliable predictions and user frustration. Guaranteeing data accuracy through robust quality control measures and continuously updating algorithms are ongoing challenges.

The integration of recent models like LSTM and ARIMA into context-aware systems is still in its infancy, despite their potential to enhance predictive capabilities. Current research highlights several key areas where these models can be further developed. Context-aware recommender systems (CARS) face challenges in incorporating user context effectively, often leading to increased sparsity and dimensionality issues [22]. Traditional models like ARIMA do not inherently account for contextual variables, limiting their applicability in dynamic environments [23]. Newer approaches, such as Deep Context-Based Factorization Machines, leverage deep learning to better model non-linear interactions among user, item, and contextual dimensions, outperforming traditional models [22]. Context-aware machine learning has shown significant improvements in applications like intelligent transportation systems, where contextual data enhances traffic prediction and decision-making capabilities [26]. While these advancements are promising, the field still requires more comprehensive frameworks and methodologies to fully exploit the potential of LSTM and ARIMA in context-aware systems.

6 Techniques and Models for Context-Aware Parking Occupancy Forecasting

6.1 Techniques

Context-aware parking prediction techniques leverage contextual information, including road conditions, parking garage status, expected driving duration [4], and historical data [5], to predict parking availability. Machine learning algorithms, such as self-organizing maps [6] and artificial neural networks [4], effectively classify sensor data for context-aware predictions. Additionally, adversarial domain adaptation, utilizing few-shot learning, shows promise in predicting parking occupancy in areas with limited sensor data [7].

6.2 Forecasting Models

Various models have been explored for context-aware parking occupancy forecasting, including:

Computer Vision with Location Awareness: This approach utilizes computer vision techniques coupled with location data to predict parking availability [9].

Comparative Study of Prediction Methods: This research focuses on comparing the effectiveness of different prediction methods based on parking type and location [10].

Short-Term Holiday Prediction: This model specifically addresses the challenges of predicting parking availability during holidays [11].

LSTM and ARIMA for Curbside Parking: This study applies Long-Short Term Memory (LSTM) and Autoregressive Integrated Moving Average (ARIMA) methods to parking data collected from curbside sensors [12].

Contextual Prediction Using Parking Sensor Data (PSD): This model leverages real-time PSD to provide contextual predictions of parking spot availability [5].

Common models used for context-aware parking prediction including: Long Short-Term Memory (LSTM) models, Multiple Linear Regression models, Vector Regressive models, Wavelet Neural Networks. These models can be enhanced by incorporating weather influence features [13, 5, 14, 25].

6.3 Algorithms

Context-aware parking algorithms utilize various approaches to optimize parking predictions and resource allocation:

Route Comparison: This algorithm analyzes routes of different drivers to identify relationships and predict parking patterns [14].

Map-Based Prediction: This approach stores maps of designated areas and compares paths to estimate available parking slots [2].

Optimization Algorithms: These algorithms determine the best parking strategy based on real-time conditions and driver preferences [18].

Dynamic Parking Assistance: These algorithms provide real-time assistance to drivers, guiding them to available parking spots dynamically [19, 2].

Context-aware parking prediction algorithms often leverage historical parking data, weather information, and location information to predict future parking occupancy rates [13, 2, 25].

6.4 Optimizations and Services

Optimizing context-aware parking occupancy involves developing systems that dynamically assign and manage parking slots in real time [2]. This can be achieved through context-awareness, enabling efficient parking slot allocation [2].

Deep learning methods can be employed to predict future parking occupancy rates based on historical data, weather, and location information [13]. This empowers car owners with short-term and long-term parking predictions, reducing search times and promoting eco-friendly driving habits [13].

Context-aware parking services aim to enhance the driver experience:

Parking Availability Assistance: Providing real-time information to drivers about free parking slots [14].

Dynamic Parking Guidance: Offering turn-by-turn navigation to guide drivers to available parking spaces [2].

Parking Reservation Systems: Enabling drivers to conveniently locate and reserve parking spaces in advance [17].

By integrating these techniques, models, algorithms, and optimizations, context-aware parking occupancy forecasting can contribute to the development of sustainable and efficient smart parking systems in urban environments.

7 Methodology and Early Experiments

7.1 Methodology

Our research adopts a comprehensive methodology for context-aware parking occupancy forecasting, encompassing the following steps (see Figure 1):

1. **Data Collection:** The first step in developing a parking occupancy forecasting model is collecting primary data, specifically historical parking occupancy records. These datasets capture past usage patterns across different locations and times, forming the foundation for model development. Alongside this, secondary data or contextual information is crucial for improving predictive accuracy.
   Contextual factors such as weather conditions, the type of day (weekday vs. weekend), and special events or holidays can significantly affect parking demand. For example, inclement weather might reduce parking demand, while holidays or major events can lead to higher occupancy. Understanding these patterns helps refine forecasts.
   Moreover, parking turnover—the rate at which spaces are filled and vacated—provides insight into the dynamic nature of parking use. High turnover indicates that spaces become available more frequently, affecting overall occupancy trends.
   Incorporating additional secondary data, such as traffic flow, event schedules, or demographic insights, further enhances the model's depth. By integrating these diverse datasets, we can build a more comprehensive and accurate parking occupancy forecasting model, contributing to better urban mobility and parking management strategies.
2. **Data Preprocessing:**Cleaning, transforming, and preparing the collected data for model training and evaluation are crucial steps in ensuring the reliability and accuracy of the forecasting model. The raw data collected from various sources often contain inconsistencies, missing values, and inaccuracies that must be addressed before analysis.
   Data Cleaning: The first stage involves identifying and rectifying errors within the dataset. This may include removing duplicates, correcting erroneous entries, and dealing with missing data points. For instance, if historical parking occupancy records are incomplete due to sensor malfunctions or data collection issues, appropriate techniques such as imputation can be applied to estimate missing values based on existing data patterns. Additionally, outlier detection methods may be employed to identify anomalies that could skew the results, ensuring that only valid and relevant data contribute to the model's training process.
   Data Transformation: Once the data is cleaned, it needs to be transformed into a suitable format for modeling. This process may involve normalizing or standardizing numerical features to bring them onto a common scale, which is essential for algorithms sensitive to the scale of input data, such as neural networks. Categorical variables, such as day names or weather types,

may require encoding into numerical formats through techniques like one-hot encoding or label encoding. This ensures that the model can interpret these features effectively during training.

Feature Engineering: In addition to cleaning and transforming, feature engineering plays a vital role in preparing the data. This involves creating new variables that can provide additional insights to the model. For example, generating features such as lagged occupancy rates (previous day's occupancy) or rolling averages can capture temporal patterns that enhance the model's predictive capabilities.

Data Splitting: Finally, the prepared dataset is typically divided into training, validation, and test sets. The training set is used to build the model, while the validation set helps fine-tune the model's hyperparameters and assess its performance during development. The test set, kept separate from the training and validation processes, is used to evaluate the model's generalization ability on unseen data, ensuring that the performance metrics are indicative of its effectiveness in real-world scenarios.

By meticulously cleaning, transforming, and preparing the collected data, we lay a solid foundation for model training and evaluation. This thorough preprocessing not only enhances the model's ability to learn from the data but also ensures that the predictions made are both reliable and actionable in the context of parking occupancy forecasting.

3. **Model Development:** We selected and developed forecasting models based on their well-established performance in previous studies and their suitability for the specific characteristics of our data. Models such as Long Short-Term Memory (LSTM), Autoregressive Integrated Moving Average (ARIMA), and hybrid approaches were chosen. LSTM was selected for its proven ability to capture complex temporal dependencies in sequential data, while ARIMA was chosen for its effectiveness in modeling and forecasting seasonal trends. The combination of these models allows for a more comprehensive approach, leveraging both the strengths of deep learning for handling long-term dependencies and traditional statistical methods for capturing seasonal patterns.
4. **Integrating Contextual Information:** To enhance prediction accuracy, we incorporated relevant contextual variables into the model. Specifically, we utilized weather conditions, day name (e.g., Monday, Tuesday), day type (e.g., weekday or weekend), and parking turnover—an indicator of how frequently parking spots are occupied and vacated—to assess the relative busyness of different parking locations. These exogenous factors were integrated with historical data and included as input variables in the Recurrent Neural Network-Long Short-Term Memory (RNN-LSTM) model. The integration was achieved by mapping these factors to the corresponding date and time of the historical parking data, ensuring their alignment with the temporal information fed into the model illustrates in Figure 3.
5. **Model Selection and Evaluation:** Evaluating different model configurations and selecting the best-performing one was conducted using a set of predefined metrics, which are commonly used in forecasting accuracy assess-

ments. The evaluation metrics include Root Mean Square Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), among others.

RMSE (Root Mean Square Error): RMSE measures the square root of the average of the squared differences between predicted and actual values. It gives higher weight to larger errors and is particularly useful when large errors are undesirable. The formula is:

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

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of observations.

MSE (Mean Squared Error): MSE is the average of the squared differences between predicted and actual values. It is a common metric for measuring prediction accuracy in regression models. The formula is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

MAE (Mean Absolute Error): MAE represents the average of the absolute differences between predicted and actual values, offering a straightforward measure of forecast accuracy. Unlike RMSE and MSE, it treats all errors equally, without emphasizing larger ones. The formula is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

MAPE (Mean Absolute Percentage Error): MAPE expresses the forecast error as a percentage, making it useful for comparing forecast accuracy across different scales. The formula is:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100$$

Each model was evaluated based on these metrics, allowing us to compare their accuracy in predicting parking occupancy. RMSE was particularly useful in identifying models with large errors, while MSE provided a general measure of overall prediction error. MAE offered a more balanced view of overall prediction performance, and MAPE provided insight into the relative accuracy of the models, particularly when comparing different parking locations with varying occupancy rates. The best-performing model was selected based on its performance across these metrics, ensuring a robust and reliable forecasting capability.

6. **Monitoring and Updating Models:**Continuously monitoring model performance is essential for ensuring the reliability and effectiveness of the parking occupancy forecasting system over time. As urban environments evolve and user behaviors change, the underlying patterns in parking occupancy may also shift. To maintain optimal performance, it is crucial to implement a robust framework for performance monitoring that includes regular evaluations of the model against predefined metrics such as RMSE, MAE, and MAPE. This allows for the early detection of any degradation in predictive accuracy, which can occur due to factors such as changes in traffic patterns, seasonal variations, or shifts in local events that influence parking demand.

   When performance issues are identified, retraining or updating the model becomes necessary to adapt to these changing patterns. This process involves collecting new data that reflects the current state of parking occupancy and integrating it into the existing dataset. By doing so, the model can learn from recent trends and adjust its predictions accordingly. Techniques such as incremental learning or online learning can be employed to update the model efficiently without the need for complete retraining from scratch, thus saving computational resources and time.

   Furthermore, our previous work [24] emphasizes the importance of developing a continuous forecasting mechanism that incorporates feedback loops for model enhancement. This mechanism enables the system to dynamically adjust its parameters and features based on the latest data inputs, thereby improving its adaptability to real-world conditions. Such a proactive approach not only enhances the accuracy of predictions but also increases the overall resilience of the forecasting system, ensuring that it remains relevant and effective in the face of evolving urban dynamics.

   By establishing a continuous monitoring and retraining strategy, we can significantly enhance the longevity and effectiveness of the parking occupancy forecasting model, ultimately contributing to better urban mobility solutions and more efficient use of parking resources.

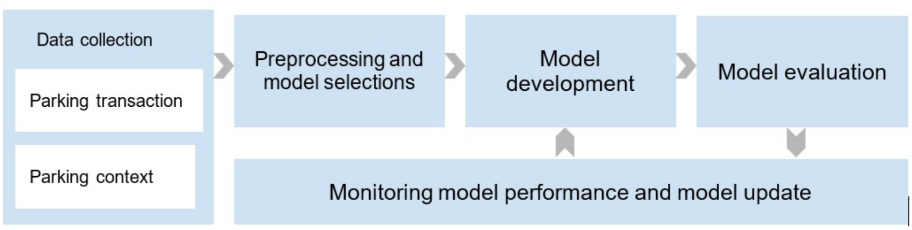

Fig. 1. Methodology for Context-Aware Parking Occupancy Forecasting

7.2 Early Experiments

Initial experiments focused on analyzing parking dynamics across different road segments (Figure 2) and assessing the impact of integrating contextual information (Figure 3). Figure 2 highlights the diverse occupancy patterns, with some segments exhibiting higher volatility than others, posing challenges for accurate prediction.

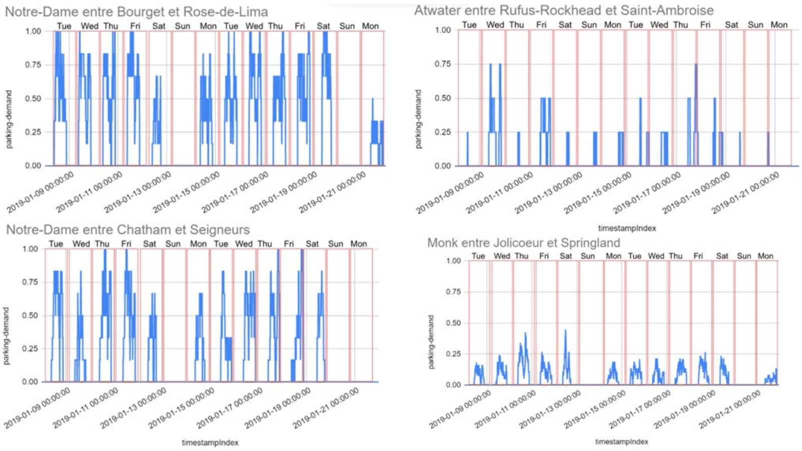

Fig. 2. Parking Occupancy Dynamics Across Road Segments

Table 1 and Figure 4 present the results of incorporating context-aware information. The findings demonstrate a notable improvement in model performance across various evaluation metrics. Adding contextual features, such as parking contact information, significantly enhances prediction accuracy.

Table 1. Model Performance Comparison with Context Information

Parameters	RMSE	MSE	MAE	MAPE
Uni-variate	11.75	137.96	4.08	62.24
Multi-variate	0.20	0.0344	0.0996	61.0977
Exogenous factor	0.20	0.1073	0.0396	66.0892
Augmented data	0.18	0.0306	0.0814	50.3652
Mul+Exo+Aug	**0.18**	**0.0388**	**0.0306**	**48.47**

In this study, we compared the performance of our proposed context-aware Long Short-Term Memory (LSTM) model against baseline models, focusing on various evaluation metrics: RMSE, MSE, MAE, and MAPE. The results indicate a marked improvement in predictive accuracy when contextual data was incorporated. Specifically, the multi-variate model achieved an RMSE of 0.20 and a MAE

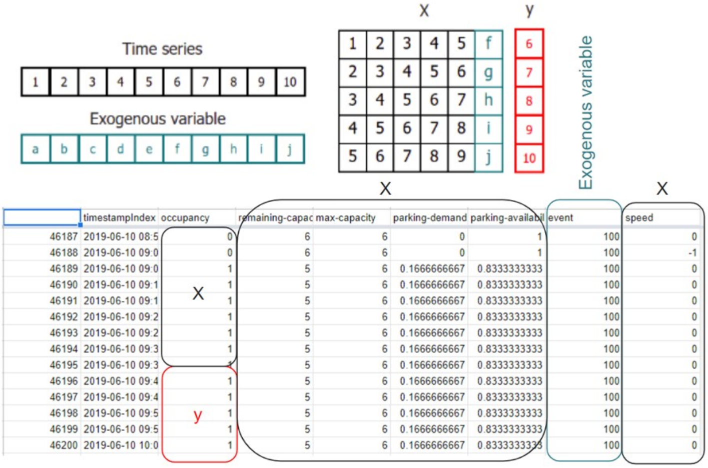

Fig. 3. Incorporating Context Information for Model Enhancement

of 0.0996, demonstrating significant enhancements over the uni-variate model, which had an RMSE of 11.75 and a MAE of 4.08. Furthermore, when exogenous factors were included, the model maintained an RMSE of 0.20, indicating consistent performance while effectively accounting for external influences. The integration of augmented data further refined the predictions, yielding an RMSE of 0.18 and a MAE of 0.0814. Notably, the combined model utilizing multiple variables, exogenous factors, and augmented data (denoted as Mul+Exo+Aug) achieved an RMSE of 0.18 and a MAE of 0.0306, representing a substantial improvement in predictive capability compared to traditional approaches. This improvement illustrates the efficacy of the LSTM model in leveraging contextual data to enhance forecasting accuracy, underscoring its potential as a robust solution for parking occupancy forecasting in urban environments. When contrasted with baseline models from the literature, our proposed LSTM model demonstrates a clear advantage, providing a pathway toward more effective and sustainable smart parking systems.

The preliminary results from our experiments demonstrate a notable improvement in the performance of the parking occupancy forecasting model. Specifically, the model without the incorporation of exogenous factors showed an average improvement of 13.14% in predictive accuracy, which is already significant. However, when relevant exogenous factors such as weather conditions, day type, and parking turnover were integrated into the model, an additional improvement of 3.27% was observed. This enhancement highlights the critical role that contextual awareness plays in refining forecasting accuracy, underscoring the value of using external factors to improve model predictions.

These early findings strongly suggest that context-aware forecasting models offer a substantial advantage over traditional approaches, providing more accurate and reliable parking occupancy predictions. By incorporating real-time

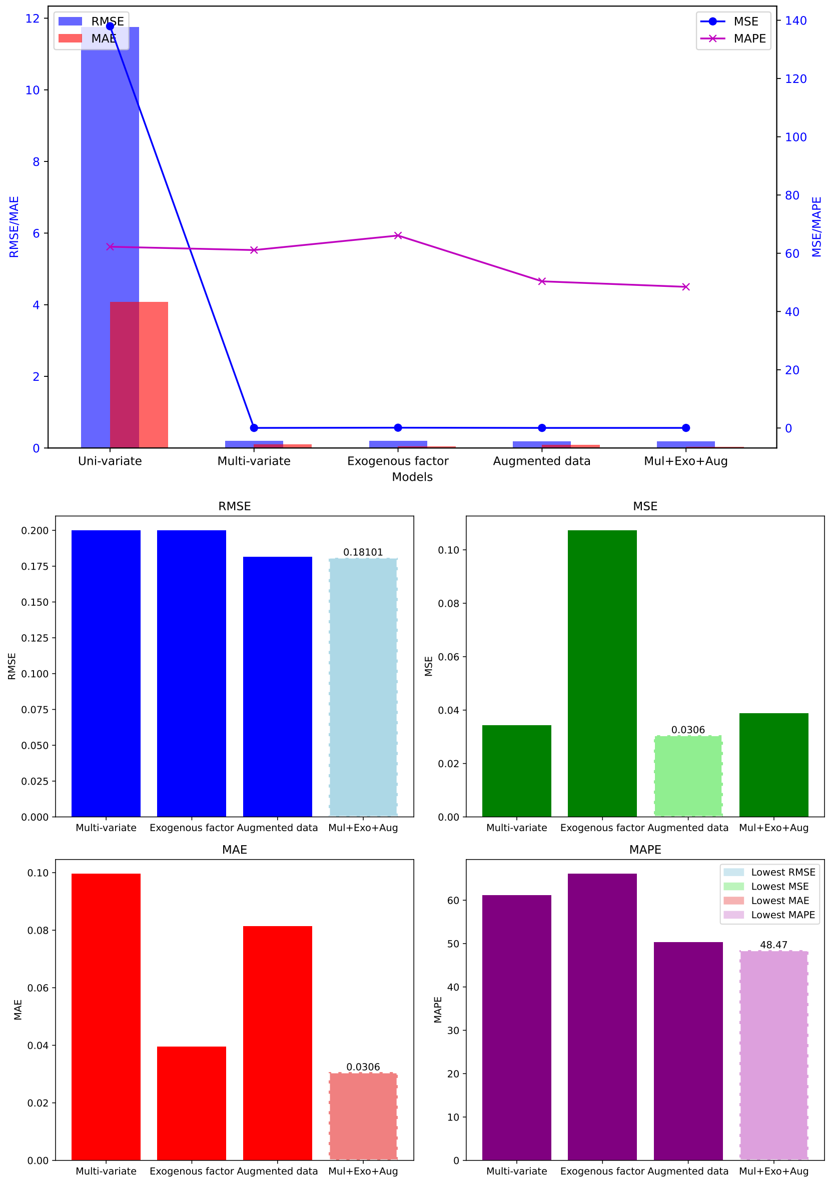

Fig. 4. Impact of Context Information on Model Performance

external data, the proposed system is better equipped to handle the dynamic nature of urban environments, where parking demand is influenced by a variety of situational factors. The improvement in performance indicates that context-aware models are a promising direction for future smart city applications, where efficient parking management is crucial for reducing congestion, emissions, and driver frustration.

Despite these positive results, there are several challenges that must be addressed for successful real-world implementation. The scalability of the proposed system is clear, as it can be adapted to different urban settings and various types of parking environments. However, issues related to data privacy arise, particularly in the collection and use of sensitive real-time data such as vehicle tracking or personal driving habits. To mitigate these concerns, it is essential to implement robust privacy measures, such as anonymizing data, employing encryption techniques, and ensuring compliance with privacy regulations. Additionally, developing transparent data usage policies will be critical in gaining public trust and securing the widespread adoption of such systems.

The cost of implementation remains another significant concern. Deploying the necessary infrastructure, including sensors, communication networks, and data processing capabilities, requires substantial investment. To address this issue, exploring cost-effective deployment strategies is crucial. For example, leveraging existing urban infrastructure, utilizing low-cost sensor technologies, and collaborating with local businesses for funding or data sharing can help reduce implementation costs. Furthermore, our published work [24] discusses an updated model designed to preserve model performance over time, while our research [25] on spatiotemporal clustering for continuous parking occupancy forecasting provides insights on minimizing costs associated with model training and hyperparameter tuning at the city level.

Finally, while the preliminary results demonstrate the effectiveness of context-aware parking occupancy forecasting, further research is needed to address the practical challenges of deployment, particularly in terms of privacy and cost. Nonetheless, these findings provide a strong foundation for future work and signal the potential for context-aware models to revolutionize urban parking management systems.

8 Conclusion and future directions

Context-aware parking occupancy forecasting is an essential component of sustainable smart parking systems in urban environments. By providing real-time information on parking availability, it reduces traffic congestion, emissions, and energy use. This method offers accurate predictions of parking availability, helping drivers plan their trips and choose the most convenient parking spots, thereby reducing traffic congestion in areas with limited parking spaces. In addition, context-aware forecasting can lower air pollution and carbon emissions by minimizing the time drivers spend searching for parking spaces, which also improves overall quality of life by reducing noise pollution and traffic congestion.

Our early experiments demonstrate that context-aware models significantly outperform traditional approaches in parking occupancy forecasting, indicating a promising direction for future smart city applications. Future work will focus on experimenting with more parking lots and types, as well as distinguishing between different parking categories (e.g., near offices, restaurants, or housing), to enhance the research and develop more explainable models.

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