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Demand Forecasting for Electric Vehicle Charging Infrastructure in Nashik: A Predictive Analytics Approach

Govinda Heda[1]
Research Scholar,
Shri Venkateshwara University.
Gajraula, Amroha, (Uttar Pradesh), India.

Prof. (Dr.) V. B. Singh[2]
Professor & Research Supervisor,
Shri Venkateshwara University.
Gajraula, Amroha, (Uttar Pradesh), India.

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Abstract: ***The rapid urbanization of Indian cities and the nationwide push towards electric mobility have created an urgent need for localized, data-driven strategies to support electric vehicle (EV) infrastructure. This research focuses on developing a comprehensive predictive analytics framework tailored to forecast EV charging Demand in Nashik, Maharashtra—a tier-2 Indian city witnessing accelerating EV adoption due to increasing environmental awareness, policy incentives, and improved vehicle availability.***

To achieve this objective, we leverage a robust multivariate time-series dataset incorporating various influential parameters such as real-time EV charging station logs, historical weather data (temperature, humidity, precipitation), traffic flow metrics (vehicle count and congestion levels), and socio-demographic indicators (population density, income levels, and EV ownership rates). These variables are collected at high granularity to enable precise day-ahead forecasting at 15-minute intervals, essential for dynamic energy distribution and optimal station management.

We employ traditional statistical and modern deep learning techniques for model development. Specifically, the Autoregressive Integrated Moving Average (ARIMA) model is a benchmark due to its effectiveness in linear time-series forecasting. In contrast, the Long Short-Term Memory (LSTM) neural network, a variant of recurrent neural networks (RNN), captures nonlinear and temporal dependencies inherent in high-frequency charging data. The modeling is implemented in IBM SPSS Statistics for data preprocessing, variable selection, and preliminary regression analysis, while the LSTM model is trained using Python with TensorFlow/Keras libraries.

Model performance is evaluated using standard error metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The LSTM model achieves superior accuracy, with an MAE of 2.51%, RMSE of 3.12%, and MAPE of 3.45%, outperforming the ARIMA model across all benchmarks. This demonstrates the LSTM's capacity to handle complex, nonlinear interactions among multiple variables and make more accurate short-term forecasts.

An SHAP (SHapley Additive exPlanations) analysis was conducted to understand each predictor's relative influence. The analysis reveals that temperature accounts for approximately 30% of the model's predictive power, followed by the day of the week (25%) and traffic volume (20%). These findings are further validated through multivariate regression and hypothesis testing. The results confirm the statistical significance of the identified predictors, with p-values less than 0.01, indicating a strong and non-random association with charging Demand.

This study yields practical and policy-relevant outcomes. Accurate demand forecasting allows for more effective charging station placement, helps determine the number of connectors and battery swapping stations required at each location, and supports grid-level load balancing. For energy utilities and city planners, these insights can be used to reduce peak load issues, manage real-time electricity distribution, and align infrastructure development with demand trends.

Importantly, this research addresses a critical knowledge gap: the absence of localized EV demand forecasting models for mid-sized Indian cities. Unlike metropolitan-focused studies, our approach is scalable and context-sensitive, offering a blueprint for implementing predictive analytics frameworks in similar urban settings across India. The methodology and findings are expected to contribute meaningfully to India's broader agenda of achieving sustainable and equitable electric mobility through intelligent, anticipatory infrastructure planning.

Keywords: Diversity Management Practices, Higher Education Institutions, etc.

I. INTRODUCTION

1.1 Background of the Study

The global transportation sector is undergoing a significant transformation with the advent and rapid growth of electric vehicles (EVs). Electric mobility is increasingly recognized as a strategic lever for reducing greenhouse gas emissions, improving urban air quality, and decreasing dependence on fossil fuels (International Energy Agency [IEA], 2023). As the world's third-largest emitter of carbon dioxide, India has committed to ambitious climate targets under the Paris Agreement, and electric vehicles are a cornerstone of this transition (Ministry of Power, 2022). The Indian government's Faster Adoption and Manufacturing of Hybrid and Electric Vehicles (FAME) scheme and various state-level EV policies have catalyzed growth in EV registrations, particularly in urban and semi-urban areas (NITI Aayog, 2021).

Despite this growth, the deployment of charging infrastructure lags, especially in mid-sized cities such as Nashik. Unlike metro cities that attract concentrated investment and policy focus, tier-2 cities often face infrastructural bottlenecks, inconsistent demand forecasting, and unplanned installations, resulting in underutilization of resources and user inconvenience (Ghosh & Ghosh, 2020). Nashik, a rapidly urbanizing city in Maharashtra, exemplifies these challenges. While the adoption of EVs in Nashik is on the rise, data-driven strategies to anticipate Demand and guide the placement of charging stations remain underdeveloped.

1.2 Problem Statement

The lack of precise, real-time forecasting tools and localized demand analysis impedes the efficient rollout of EV infrastructure in cities like Nashik. Traditional planning approaches often rely on static demographic data and ignore the dynamic nature of electricity demand, temporal travel behavior, and environmental variables such as weather and traffic congestion (Zhang et al., 2022). Without accurate demand forecasting models, policymakers and utility providers face difficulties optimizing the number, location, and capacity of EV charging stations, leading to poor service quality, range anxiety, and slow user adoption.

1.3 Significance of the Study

This study addresses the research and policy gap by developing a **predictive analytics framework** that uses real-time multivariate data to forecast EV charging Demand at fine temporal granularity (15-minute intervals). This research aims to provide city authorities, energy utilities, and private charging providers with actionable insights using advanced machine learning techniques such as **Long Short-Term Memory (LSTM)** and classical time-series models like **ARIMA**. The study enhances the forecast's predictive power and contextual relevance by integrating diverse data sources such as charging station usage logs, traffic flow data, weather patterns, and socio-demographic variables (Li et al., 2021).

The implications are broad and multi-stakeholder. Accurate demand forecasts will support energy load balancing for utility companies (Ruan et al., 2019), improve service planning for charging station operators (Yilmaz & Krein, 2013), and guide local governments in achieving sustainability goals and reducing urban air pollution (Bharti & Agarwal, 2020). Furthermore, the study contributes to the academic literature by developing a hybrid forecasting model validated through statistical methods such as SHAP analysis and hypothesis testing.

1.4 Research Objectives

The core objectives of this study are as follows:

1. To develop a data-driven forecasting model for predicting EV charging Demand in Nashik using machine learning and statistical methods.
2. To identify the key influencing factors such as temperature, day of the week, and traffic volume that contribute significantly to charging behavior.
3. To validate the model using error metrics such as MAE, RMSE, and MAPE and evaluate feature importance using SHAP analysis.
4. To conduct hypothesis testing to determine the statistical significance of selected predictors.
5. To provide recommendations for the optimal placement and capacity planning of EV charging stations in Nashik.

1.5 Research Questions

The following questions guide the research:

1. What are the significant factors influencing Nashik's Demand for EV charging infrastructure?
2. How effectively can multivariate time-series forecasting models predict short-term charging Demand?
3. Which model—ARIMA or LSTM—offers better performance for demand forecasting in this context?
4. How can the insights derived from forecasting models be used for infrastructure optimization?

1.6 Scope of the Study

This study focuses on Nashik, a tier-2 city in India, as a representative case for mid-sized urban centers undergoing EV transition. The forecasting is done at 15-minute intervals for day-ahead predictions to support dynamic grid and infrastructure planning. The dataset integrates historical charging logs, weather variables, traffic data, and user demographics, making the approach comprehensive and scalable.

1.7 Structure of the Paper

This paper is structured into five chapters. Chapter 1 introduces the research background, objectives, and scope. Chapter 2 reviews the existing literature on EV demand forecasting and predictive analytics. Chapter 3 outlines the methodology, including data sources, model architecture, and validation strategies. Chapter 4 presents the results and analysis, and Chapter 5 concludes with key findings, policy implications, and recommendations for future research.

II. Literature Review

2.1 Introduction

The transition to electric mobility has led to a burgeoning interest in developing robust and scalable EV charging infrastructure. A key component of this development is accurately forecasting Demand for charging services. Demand forecasting allows for optimal planning, efficient allocation of resources, and better integration of EVs into the power grid. This chapter comprehensively reviews existing literature on electric vehicle (EV) demand forecasting, charging infrastructure planning, and the application of predictive analytics models in the context of transportation and energy systems. It further explores various modeling approaches, data sources, and contextual studies shaping current understanding. Finally, the chapter highlights research gaps and positions the present study within the existing body of knowledge.

2.2 Electric Vehicle Growth and Infrastructure Challenges

EV adoption has surged globally due to declining battery prices, government incentives, and increasing environmental awareness. The International Energy Agency (IEA, 2023) reported that global EV sales exceeded 10 million in 2022, with projections indicating a 35% share of total vehicle sales by 2030. However, the expansion of EV infrastructure has not kept pace with this growth. Research by Ghosh and Ghosh (2020) highlights that inadequate and poorly planned charging infrastructure remains a critical barrier to EV adoption, especially in developing countries.

In India, government initiatives such as FAME I & II (Faster Adoption and Manufacturing of Electric Vehicles) and state EV policies have facilitated EV uptake (NITI Aayog, 2021). However, studies (Bharti & Agarwal, 2020) indicate that infrastructure planning often lacks data-driven forecasting models, resulting in misallocating charging stations and limited accessibility in non-metro areas.

2.3 Importance of Demand Forecasting for EV Infrastructure

Demand forecasting is essential for balancing the load on electrical grids, optimizing investment in infrastructure, and improving user experience. As per Li et al. (2021), accurate forecasting helps avoid under- and over-provisioning of charging stations. It enables dynamic pricing, demand-side management, and integration with renewable energy sources.

Several studies (Zhang et al., 2022; Ruan et al., 2019) argue that traditional forecasting approaches based on static demographic or historical averages are inadequate due to EV charging patterns' temporal and spatial variability. These patterns are influenced by numerous dynamic factors, including weather, traffic congestion, vehicle type, user behavior, and socioeconomic status (Yilmaz & Krein, 2013).

2.4 Types of Forecasting Models

2.4.1 Statistical Models

Classical statistical methods such as Auto-Regressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Exponential Smoothing have been widely used in energy demand forecasting. For example, in a study by Chandra and Aggarwal (2020), SARIMA models were employed to forecast daily electricity demand in Delhi. While effective for short-term predictions in stable environments, these models often fail to capture nonlinear dependencies and complex patterns in multi-source EV data.

2.4.2 Machine Learning Models

Machine learning (ML) models offer a powerful alternative by learning complex nonlinear relationships in large datasets. Techniques such as Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting Machines (GBM), and Deep Neural Networks (DNN) have shown improved accuracy in electricity and mobility-related forecasts (Zhang et al., 2022).

Long Short-Term Memory (LSTM) networks, a variant of Recurrent Neural Networks (RNN), are particularly suitable for time-series forecasting. Studies such as Li et al. (2021) and Xu et al. (2020) demonstrated that LSTM models outperform ARIMA and traditional ML models in predicting EV demand, thanks to their ability to retain long-term temporal dependencies.

2.5 Data Sources for EV Demand Forecasting

Robust forecasting models rely on diverse and high-quality data. Key data sources identified in the literature include:

- **Charging Station Logs**: Contain timestamps, kWh usage, duration, and user ID. These are critical for understanding temporal usage patterns (Li et al., 2021).
- **Weather Data**: Variables like temperature, humidity, and rainfall significantly influence charging Demand, especially for shared EV fleets (Zhang et al., 2022).
- **Traffic Flow Data**: Real-time or historical data on traffic volumes and congestion levels help model vehicle movement and potential charging needs (Ghosh & Ghosh, 2020).
- **Socio-Demographic Factors**: Income level, urban density, vehicle ownership, and electricity tariffs are important context variables (Bharti & Agarwal, 2020).

Combining these sources enhances the forecasting accuracy and allows for more granular predictions.

2.6 Feature Engineering and Model Evaluation

Practical feature engineering transforms raw data into meaningful inputs for forecasting models. Techniques such as time lagging, normalization, principal component analysis (PCA), and feature selection via mutual information or correlation matrices are commonly used (Ruan et al., 2019).

Model performance is usually evaluated using error metrics such as:

- **Mean Absolute Error (MAE)**
- **Root Mean Square Error (RMSE)**
- **Mean Absolute Percentage Error (MAPE)**

Recent studies also use SHAP (SHapley Additive exPlanations) to interpret model outputs and understand the importance of features. For instance, in Xu et al. (2020), SHAP analysis revealed that temperature and day-of-week were dominant factors influencing charging Demand.

2.7 Hypothesis-Driven Forecasting Studies

Some research adopts a hypothesis-driven approach to validate the influence of independent variables. For example, in a study by Park et al. (2019), the hypothesis that temperature significantly affects EV charging Demand was confirmed using t-tests and ANOVA. Similar approaches are advocated by Bhatti et al. (2021) in the context of urban transport electrification.

2.8 Forecasting in the Indian Context

Indian studies are limited but growing. Singh and Garg (2021) developed a demand forecasting model for Delhi using SVR and found that traffic congestion and pricing policies significantly influenced Demand. Ramesh et al. (2022) proposed a hybrid ARIMA-ANN model for Bengaluru, achieving an RMSE of 4.85% in day-ahead predictions.

However, most studies focus on large metropolitan cities. Mid-sized cities like Nashik, which face unique infrastructural and behavioral dynamics, remain under-researched. This study aims to fill that gap.

2.9 Gaps in Existing Literature

Despite extensive work in the field, several gaps persist:

- **Geographical Bias**: Most models are developed for developed countries or large Indian cities.
- **Lack of Real-Time Data**: Many studies rely on static datasets without real-time integration.
- **Underutilization of Hybrid Models**: Few studies combine statistical and deep learning models.
- **Interpretability Issues**: While LSTM offers high accuracy, model interpretability remains low without techniques like SHAP.
- **Lack of Policy Integration**: There is limited focus on translating technical results into actionable policy insights.

2.10 Summary

This chapter reviewed the key strands of literature related to EV demand forecasting, highlighting advances in statistical and machine learning methods. It emphasized the need for localized, real-time, and interpretable models that can aid mid-sized cities like Nashik in planning EV infrastructure. The next chapter will describe the methodology used in this study, including model selection, data collection, feature engineering, and hypothesis testing.

III. Research Methodology

3.1 Introduction

This chapter presents the detailed methodology employed to examine and forecast electric vehicle (EV) charging demand in Nashik, India. The research aims to construct a predictive analytics framework integrating both machine learning and statistical models, with an emphasis on data accuracy, reliability, and applicability in mid-sized urban Indian contexts. The research adopts a mixed-methods approach—quantitative analysis through statistical modeling and machine learning and qualitative insights through stakeholder interviews—to develop a comprehensive understanding of EV charging patterns. The study duration spans from April 2023 to March 2025, encompassing significant seasonal variations and urban transportation trends.

3.2 Research Design

The research follows a **descriptive and predictive research design** that is appropriate for identifying existing patterns in EV charging behavior and projecting future demand. The primary objective is to forecast EV charging requirements at 15-minute intervals using advanced analytical tools. The design also incorporates validation methods, model comparison, and interpretability mechanisms such as SHAP analysis and statistical hypothesis testing.

3.3 Data Collection

Data was collected from a variety of sources, including:

- **EV Charging Records**: Collected from the Nashik Municipal Smart City EV charging infrastructure network across 27 public charging stations.
- **Traffic Flow Data**: Obtained from Maharashtra State Transport Department and Google Mobility Reports.
- **Weather Data**: Retrieved from the Indian Meteorological Department (IMD), including temperature, humidity, and rainfall.
- **Socio-Demographic Data**: Census 2011 and projected demographic data from the Nashik Urban Development Corporation (NUDC).
- **Time Span**: Data covers **April 2023 to March 2025**, ensuring comprehensive seasonal and event-based trend capturing.

3.4 Sampling Technique

Purposive sampling was employed to select EV charging stations based on their geographic diversity, volume of usage, and proximity to key transport hubs. From the total of 27 stations, 15 high-traffic stations were selected for modeling, covering over 80% of total charging activity.

3.5 Variables

Dependent Variable:

- Charging Demand (kWh) per 15-minute interval.

Independent Variables:

- Temperature (°C)
- Day of the Week
- Traffic Flow (vehicle count)
- Time of Day (categorical: morning, afternoon, evening, night)
- Rainfall (mm)
- Socioeconomic Index (clustered from census data)

3.6 Tools and Software Used

1. **IBM SPSS Statistics v28**: For descriptive statistics, correlation analysis, regression testing, and hypothesis testing.
2. **Python (TensorFlow & Keras)**: For LSTM model development.
3. **R Software**: For ARIMA modeling and AIC/BIC comparisons.
4. **SHAP (SHapley Additive ExPlanations)**: This is for model interpretability and feature importance.
5. **MS Excel**: For raw data preprocessing and visualization.

3.7 Model Development Process

3.7.1 Data Preprocessing

- Missing data imputation using the k-NN algorithm in SPSS.
- Standardization using Z-scores for variables with significant variance.
- One-hot encoding for categorical variables like "Day of the Week."

3.7.2 Feature Engineering

- Lag variables were created to capture temporal dependencies in Demand.
- Rolling averages and exponential smoothing were applied for noise reduction.

3.7.3 Model Training

- LSTM neural networks were trained on 80% of the dataset, with 20% reserved for testing.
- ARIMA models optimized using auto.arima() function in R.

3.7.4 Model Evaluation Metrics

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Mean Absolute Percentage Error (MAPE)

3.8 Hypothesis Development

Null Hypothesis (H_0): Weather, traffic, and socio-demographic variables do not significantly affect EV charging Demand.

Alternative Hypothesis (H_1): Weather, traffic, and socio-demographic variables significantly affect EV charging Demand.

3.9 Hypothesis Testing

- Linear regression was conducted using SPSS with the dependent variable as charging Demand.
- ANOVA was used to test the overall significance of the regression model.
- P-values were computed for each predictor.
- A confidence level of 95% was used ($\alpha = 0.05$).

Results:

- Temperature ($p = 0.000$)
- Day of Week ($p = 0.001$)
- Traffic Flow ($p = 0.002$)

All values < 0.01, leading to **rejection of the null hypothesis.**

3.10 Validation Techniques

- **K-fold cross-validation** (k=10) was used for model robustness.
- **Residual analysis was** performed for ARIMA and LSTM.
- **Out-of-sample testing** on data from January 2025 to March 2025.

3.11 Ethical Considerations

- Data anonymization for individual-level records.
- All institutional data is accessed with formal permissions.
- GDPR and Indian Data Protection guidelines followed.

3.12 Limitations of the Study

- There is some missing data during the monsoon season (July–August 2023).
- Model performance may be reduced with abrupt changes in technology or EV adoption policies.

3.13 Summary

This chapter has laid out a detailed methodological framework for forecasting EV charging Demand in Nashik using a combination of machine learning and statistical techniques. The inclusion of SHAP analysis, SPSS-based hypothesis testing, and a comprehensive variable set ensures reliability and interpretability. The study's approach is replicable and scalable, capable of supporting policy and infrastructure planning for mid-sized Indian cities facing rapid EV adoption.

IV. DATA ANALYSIS AND RESULTS

4.1 Introduction

This chapter presents a comprehensive analysis of the collected data and the results of various statistical and machine learning models employed to forecast electric vehicle (EV) charging Demand in Nashik. The period under consideration spans from April 2023 to March 2025, and the objective is to identify the key factors influencing EV charging patterns and to evaluate the accuracy and interpretability of forecasting models. Tools used include IBM SPSS for statistical analysis, R for ARIMA modeling, Python (TensorFlow) for LSTM, and SHAP analysis for feature importance.

4.2 Descriptive Statistics

Descriptive statistics for key variables were computed using SPSS to understand the central tendencies and dispersions in the dataset.

Variable	Mean	Standard Deviation	Min	Max
Charging Demand (kWh)	34.2	9.87	10.1	67.9
Temperature (°C)	28.4	4.1	19.0	38.7
Traffic Volume	1160	245	580	1680
Rainfall (mm)	2.4	3.8	0	22.6

4.3 Correlation Matrix

The Pearson correlation coefficients among independent variables and charging Demand are as follows:

Variable	Charging Demand
Temperature	0.54
Traffic Volume	0.49
Rainfall	-0.21
Day of the Week	0.35

This shows a moderately strong positive correlation between charging Demand and both temperature and traffic volume.

4.4 Regression Analysis

A multiple linear regression model was developed in SPSS to identify the predictors of EV charging demand.

Regression Equation:

Charging Demand = 5.72 + 0.81(Temperature) + 0.0031(Traffic Volume) + 1.27(Day of the Week dummy) - 0.18(Rainfall)

Model Summary:

- R-squared: 0.65
- Adjusted R-squared: 0.63
- F-statistic: 36.42 ($p < 0.001$)

Coefficient Significance:

- Temperature: $p = 0.000$
- Traffic Volume: $p = 0.001$
- Day of Week: $p = 0.002$
- Rainfall: $p = 0.054$ (not statistically significant at 5% level)

4.5 ARIMA Model Results

Using R software, the best ARIMA model was auto-selected as ARIMA(2,1,2).

Performance Metrics (Test Set):

- MAE: 3.94
- RMSE: 4.62
- MAPE: 5.76%

Interpretation: While ARIMA captured seasonality, it underperformed on shorter-term patterns, such as weekend vs. weekday fluctuations.

4.6 LSTM Model Results

The LSTM model was trained in Python using TensorFlow. The dataset was split 80:20 for training and testing.

Performance Metrics (Test Set):

- MAE: 2.51
- RMSE: 3.12
- MAPE: 3.45%

Training Epochs: 150

Activation Function: ReLU

Optimizer: Adam

Interpretation: LSTM outperformed ARIMA due to its ability to capture nonlinear and temporal dependencies in data.

4.7 Feature Importance: SHAP Analysis

SHAP analysis was used to interpret the LSTM model. Feature contribution to the prediction was quantified:

Feature	SHAP Value Contribution
Temperature	30%
Day of the Week	25%
Traffic Volume	20%
Rainfall	10%
Time of Day	15%

Interpretation: Temperature and day of the week were the most influential features in demand prediction, aligning with regression findings.

4.8 Hypothesis Testing (Revisited)

As outlined in Chapter 3, hypothesis testing was conducted using SPSS.

Null Hypothesis (H_0): Independent variables have no significant impact on charging Demand.

Alternative Hypothesis (H_1): Independent variables significantly impact charging Demand.

Conclusion: Since p-values for temperature, day of week, and traffic volume are < 0.01, the null hypothesis is rejected, confirming statistical significance.

4.9 Cross-Validation

The LSTM model was validated using 10-fold cross-validation.

Fold	MAPE (%)
1	3.42
2	3.39
3	3.51
...	...
10	3.44
Average	**3.45**

The model maintained high accuracy across all folds, suggesting robustness.

4.10 Model Comparison Summary

Model	MAE	RMSE	MAPE	Best Performer
ARIMA	3.94	4.62	5.76%	No
LSTM	2.51	3.12	3.45%	Yes

4.11 Implications of Findings

1. **Infrastructure Planning**: High Demand predicted during weekday evenings and summer months suggests where and when to prioritize capacity upgrades.
2. **Policy Development**: Peak traffic hours align with demand surges; staggered charging incentives can reduce grid load.
3. **Environmental Impact**: Rainfall had a minor effect, suggesting EV usage in Nashik remains resilient to seasonal variations.

4.12 Summary

This chapter provided a detailed statistical and predictive analysis of EV charging Demand in Nashik. Both regression and machine learning models validated the significance of key variables. The LSTM model demonstrated superior predictive performance and interpretability via SHAP analysis. The results serve as a foundation for data-driven infrastructure and policy planning.

V. Discussion and Recommendations

5.1 Discussion of Key Findings

This study explores the use of predictive analytics to forecast electric vehicle (EV) charging Demand in Nashik, India, utilizing machine learning models (Long Short-Term Memory, LSTM) and traditional statistical models (ARIMA). The goal was to create a robust predictive framework that can provide reliable forecasts for EV charging stations, with the specific intention of assisting in infrastructure planning and capacity management in a rapidly growing city.

5.1.1 Performance of Predictive Models

The analysis shows that the LSTM model outperforms ARIMA in terms of accuracy across various evaluation metrics. The LSTM model achieved a **Mean Absolute Error (MAE)** of 2.51%, **Root Mean Squared Error (RMSE)** of 3.12%, and **Mean Absolute Percentage Error (MAPE)** of 3.45%. These values indicate a relatively low error in the predictions, validating the effectiveness of LSTM in capturing complex, nonlinear patterns inherent in the time-series data, such as seasonal variations, traffic patterns, and other external influences. In contrast, ARIMA performed less optimally, with higher error values across all metrics (MAE: 4.76%, RMSE: 5.24%, MAPE: 6.02%).

The results suggest that LSTM's ability to capture long-term dependencies in time-series data gives it an edge over ARIMA, especially in a context like EV charging demand forecasting where historical patterns are influenced by a variety of dynamic factors, including time of day, weather, and traffic flow. ARIMA, which is based on linear relationships, struggles to model such complexity as effectively as LSTM.

5.1.2 Key Factors Influencing EV Charging Demand

Several key predictors were identified in this study, and their contributions to the forecasting model were validated through SHAP (SHapley Additive exPlanations) analysis. The most significant predictors were:

- **Temperature**: This factor contributed 30% to the model's prediction, highlighting the importance of weather patterns in influencing consumer behavior and charging Demand. Warmer temperatures may lead to higher EV use, as users may prefer to travel in better weather conditions, and the efficiency of charging stations may vary with temperature.
- **Day of the Week**: Contributing 25% to the model, this factor reflects the variability in charging Demand based on weekdays and weekends. EV charging Demand tends to increase on weekdays due to commuting needs but can also peak on weekends due to leisure travel or longer trips.
- **Traffic Volume**: With a 20% contribution, traffic flow has a direct impact on EV charging demand. More vehicles on the road lead to more opportunities for EV users to charge their cars, particularly in urban environments like Nashik, where congestion is common.
- **Time of Day**: Charging Demand shows a clear time-based pattern, with peaks during working hours (morning and evening) and lower Demand during off-hours. This is common in many transportation-related services and underscores the importance of time-based demand forecasting.

The significant predictors were confirmed using regression modeling, which highlighted the correlations between these variables and charging Demand. Hypothesis testing further confirmed the statistical significance of these factors ($p < 0.01$), ensuring the reliability of the model.

5.2 Implications of the Study

5.2.1 EV Infrastructure Planning

The results of this study have profound implications for EV infrastructure planning in Nashik. By predicting Demand at 15-minute intervals, the model allows urban planners to anticipate better peak demand times and locations, which is crucial for the optimal placement and sizing of EV charging stations. In particular, charging stations can be strategically located in areas with high traffic volumes and near key business districts, where Demand is expected to be the highest.

The identification of temperature, traffic volume, and time of day as key demand drivers also provides actionable insights for infrastructure developers. For example, charging stations may be located in areas where temperature fluctuations and traffic congestion are most significant, ensuring that the infrastructure can accommodate peak demand during the hottest or busiest times.

5.2.2 Grid Management and Energy Distribution

With the expected growth of EV adoption, especially in urban areas like Nashik, there will be increasing pressure on the electricity grid. Efficient grid management is essential to avoid overloading and to ensure that power is available for both residential and commercial needs, including EV charging. The predictive model developed in this study can provide valuable information for grid operators, allowing them to anticipate charging Demand and adjust energy distribution accordingly.

For instance, by forecasting the Demand during peak hours, energy providers can optimize power usage, reduce waste, and prevent blackouts. Demand-side management strategies, such as incentivizing off-peak charging, can also be implemented based on the forecasted charging patterns. For example, users could be encouraged to charge their vehicles during off-peak hours when grid demand is low.

5.2.3 Policy and Regulatory Recommendations

This study provides evidence-based recommendations for policymakers in Nashik and other Indian cities experiencing growing EV adoption. Governments and regulatory bodies can use the findings to promote sustainable EV infrastructure development, ensuring charging stations are placed in areas with the highest Demand.

The research also provides insights into the incentives that could encourage EV adoption. By understanding the factors that drive EV charging Demand, policymakers can design targeted policies such as tax incentives for individuals to switch to EVs, subsidies for charging station development, and public-private partnerships for expanding EV infrastructure.

Moreover, the government could use this study's findings to set benchmarks for energy usage and carbon emissions, which aligns with India's goal of reducing its carbon footprint and promoting clean energy. Policymakers can also ensure that EV charging is integrated with renewable energy sources, such as solar or wind, to reduce the environmental impact of EV infrastructure further.

5.3 Limitations of the Study

While the study provides valuable insights into the forecasting of EV charging Demand in Nashik, it also has several limitations that should be considered:

1. **Data Availability**: The study relied on multivariate time-series data from publicly available sources, including traffic data, weather patterns, and charging station usage records. While this data was sufficient for model development, the lack of granular data on individual charging behaviors (e.g., duration of charging, types of EVs used, charging frequency) may limit the model's predictive power in certain situations.
2. **External Variables**: Other external factors, such as economic conditions, government policies, and technological advancements in EVs or charging infrastructure, were not incorporated into the model. These factors could significantly impact EV charging demand and should be considered in future research.
3. **Generalizability**: Although the study focuses on Nashik, the findings may not be directly applicable to other cities with different traffic patterns, weather conditions, and infrastructure. Future research could extend the model to other cities in India, particularly those with rapidly growing EV adoption rates.
4. **Model Limitations**: While the LSTM model performed well in this study, it may still be prone to overfitting or may require further tuning to handle specific conditions in Nashik. Additionally, ARIMA's lower performance highlights the limitations of traditional statistical methods in handling complex, nonlinear time-series data.

5.4 Future Research Directions

Building upon the current study, several avenues for future research can be explored:

1. **Integration of More Complex Models**: Future research could explore the use of hybrid models, combining machine learning algorithms like LSTM with traditional statistical techniques or other machine learning methods (e.g., Random Forest, XGBoost). This could improve the model's accuracy by leveraging the strengths of multiple approaches.
2. **Incorporating Real-Time Data**: The model could be expanded to incorporate real-time data streams from traffic sensors, weather stations, and EV charging stations. This would allow for more accurate and dynamic forecasting, especially during unexpected events (e.g., extreme weather, special events).

3. **Demand-Side Management and Energy Optimization**: Future studies could explore the application of this model for demand-side management strategies, helping grid operators to optimize energy distribution in real time. Research could also explore using renewable energy sources for EV charging stations, improving the environmental sustainability of EV infrastructure.

4. **Impact of Government Policies**: As EV adoption continues to increase in India, understanding how government incentives and policies influence charging Demand could be another valuable avenue for research. This could help in shaping future regulatory frameworks that support sustainable transportation.

5. **Cross-City Comparisons**: A broader study comparing EV charging Demand across multiple cities in India would be invaluable. This could identify key regional differences and provide a comprehensive understanding of the national EV landscape.

VI. Conclusion

This research has contributed significantly to understanding EV charging demand forecasting in Nashik, India, using a data-driven approach. The LSTM model proved highly effective in forecasting EV charging Demand at 15-minute intervals, outperforming the ARIMA model. The study identified temperature, traffic volume, and the day of the week as the key factors influencing charging Demand, and these findings were validated through statistical and SHAP analysis.

The results of this study offer practical insights for EV infrastructure planning, grid management, and policymaking in Nashik and other similar cities. By leveraging predictive analytics, urban planners and policymakers can make data-informed decisions, optimizing charging station placement, capacity planning, and energy distribution. This research lays a foundation for future studies and provides a scalable model for other cities in India and beyond as they work towards achieving their sustainability goals.

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