International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

Prediction-Based Smart EV Charging Management for Distribution Transformer verload Prevention Using MATLAB/Simulink

Gaurav Shirish Abhang[1], Prof. Ms Alfiya A. Mahat[2]

[1]*PG Scholar, Department of Eletrical Engineering (Electrical Power System), MSS's College of Engineering and Technology, Nagewadi, Jalna, Maharashtra, India*

[2]*Assistant Professor, Department of Electrical Engineering, MSS's College of Engineering and Technology, Nagewadi, Jalna, Maharashtra, India*

(Affiliated to Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, - 431004

gauravabhang2002@gmail.com alfiya704@gmail.com

ABSTRACT

The rapid growth of electric vehicle (EV) adoption has significantly increased electricity demand within power distribution networks, creating new operational challenges for distribution transformers during peak charging periods. Uncoordinated charging of multiple EVs can result in transformer overloading, increased power losses, voltage instability, and accelerated equipment aging, thereby affecting the reliability and efficiency of the electrical distribution system. Consequently, the development of intelligent charging management strategies has become essential for ensuring reliable grid operation while supporting the increasing penetration of electric vehicles. This paper proposes a prediction-based smart EV charging management framework for preventing distribution transformer overloading using MATLAB and Simulink. Initially, a realistic EV charging dataset is generated by considering practical charging parameters such as arrival time, battery capacity, initial state of charge (SOC), desired SOC, charging power, and charging duration. Historical charging demand is then analysed to develop an hourly charging profile, which is utilized to forecast future charging demand through a moving-average-based prediction approach. The predicted demand is continuously compared with the transformer's rated capacity to identify potential overload conditions before they occur.

1. INTRODUCTION

The global transition towards sustainable transportation has accelerated the adoption of electric vehicles (EVs) due to increasing environmental concerns, rapid depletion of fossil fuel reserves, and stringent government regulations aimed at reducing greenhouse gas emissions. Unlike conventional internal combustion engine vehicles, electric vehicles provide higher energy efficiency, lower operating costs, and zero tailpipe emissions, making them an essential component of future sustainable transportation systems.

Governments and utility companies worldwide are actively promoting EV adoption through financial incentives, charging infrastructure development, and supportive energy policies. As a result, the number of electric vehicles connected to distribution networks is increasing rapidly, creating new challenges for existing electrical power systems.

ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

Traditional approaches to mitigating transformer overloading primarily involve upgrading distribution infrastructure, installing higher-capacity transformers, or constructing additional charging facilities. Although these solutions improve network capacity, they require considerable capital investment, extended implementation periods, and complex planning procedures. Alternatively, intelligent charging management techniques have emerged as an economical and practical solution capable of optimizing EV charging schedules without requiring extensive infrastructure modifications. Recent research has explored optimization algorithms, artificial intelligence, fuzzy logic, reinforcement learning, and machine learning techniques for coordinated EV charging. While these methods often achieve satisfactory performance, they generally require extensive computational resources, large training datasets, and sophisticated implementation frameworks, limiting their applicability for small-scale utilities and developing regions.

2. LITERATURE REVIEW

The rapid expansion of electric vehicle (EV) adoption has significantly influenced the operation of modern power distribution systems. Although EVs contribute to reducing greenhouse gas emissions and dependence on fossil fuels, the increasing penetration of charging infrastructure has introduced considerable challenges related to transformer overloading, voltage regulation, power quality degradation, and peak load management. Consequently, numerous researchers have proposed various smart charging strategies, demand forecasting techniques, and optimization algorithms to improve the reliability and efficiency of power distribution networks.

Several researchers have investigated coordinated EV charging methods to minimize the adverse impacts of simultaneous charging on distribution transformers. Traditional charging strategies primarily focus on time-based scheduling, where charging activities are shifted from peak demand periods to off-peak hours. Although these approaches reduce transformer loading to a certain extent, they often ignore real-time charging demand variations and transformer operating conditions, thereby limiting their effectiveness in practical distribution networks.

With the advancement of computational intelligence, machine learning (ML) and artificial intelligence (AI) techniques have gained significant attention for EV charging demand prediction and charging optimization. Algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), Deep Learning (DL), and Reinforcement Learning (RL) have demonstrated promising prediction accuracy by learning charging patterns from historical datasets. These methods are capable of forecasting charging demand under varying operating conditions and improving charging coordination. However, their implementation generally requires extensive historical datasets, complex parameter tuning, high computational resources, and longer training times, which may restrict their practical deployment in small-scale distribution systems and developing regions.

3. PROBLEM STATEMENT

The rapid increase in the adoption of electric vehicles has introduced significant operational challenges for existing electrical power distribution systems. Distribution transformers, which were originally designed to supply conventional residential and commercial loads, are now required to accommodate the additional

charging demand of a rapidly growing EV population. Since a majority of EV users tend to charge their vehicles during evening hours after returning from work, a large number of charging events occur simultaneously, producing a substantial increase in peak electricity demand. This uncoordinated charging behavior often results in transformer overloading, excessive thermal stress, voltage fluctuations, increased power losses, and accelerated insulation ageing, ultimately reducing transformer service life and compromising the reliability of the distribution network.

Conventional approaches adopted by utility companies for mitigating transformer overloading primarily involve infrastructure expansion through transformer replacement, feeder reinforcement, or installation of additional charging stations. Although these methods effectively increase network capacity, they require considerable financial investment, long implementation periods, and extensive modifications to the existing distribution infrastructure. Alternatively, advanced optimization and machine learning techniques have been proposed for coordinated EV charging. However, these methods generally require high computational capability, extensive historical datasets, complex optimization algorithms, and continuous communication between charging stations and utility operators, making them difficult to implement in practical distribution systems, particularly in developing countries and small-scale utility networks.

Another major challenge associated with uncontrolled EV charging is the inability of conventional charging systems to anticipate future charging demand. Most existing charging strategies operate in a reactive manner by responding only after transformer loading exceeds its permissible operating limit. Such delayed control actions may still expose transformers to temporary overload conditions, resulting in undesirable thermal stress and deterioration of equipment reliability. Therefore, an intelligent charging framework capable of predicting charging demand before overload occurs is essential for ensuring reliable and efficient operation of future smart distribution systems.

4. RESEARCH OBJECTIVE

The primary objective of this research is to develop a Prediction-Based Smart EV Charging Management System capable of preventing distribution transformer overloading while ensuring efficient utilization of the available electrical infrastructure. The proposed framework integrates charging demand prediction, transformer loading assessment, and intelligent charging control to improve the operational reliability of power distribution systems under increasing electric vehicle penetration.

5. PROPOSED MEHODOLOGY

The proposed Prediction-Based Smart EV Charging Management Framework is developed to prevent distribution transformer overloading caused by the simultaneous charging of multiple electric vehicles. The framework combines EV charging demand prediction, transformer loading assessment, and intelligent charging control into a unified decision-making system. Unlike conventional charging strategies that react only after transformer overloading occurs, the proposed methodology predicts future charging demand using historical charging data and proactively regulates EV charging to maintain transformer loading within safe operating limits.

The proposed framework consists of six major functional modules that operate sequentially to achieve intelligent EV charging management:

ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

- EV Dataset Generation
- Charging demand Analysis
- Load prediction
- Transformer Loading Assessment
- Smart Charging Controller
- Performance Evaluation

Initially, a realistic EV charging dataset is generated considering practical charging parameters such as vehicle arrival time, battery capacity, initial state of charge (SOC), target SOC, charging power, and charging duration. The generated dataset is subsequently analysed to obtain the hourly charging demand profile. Historical charging demand is then utilized to estimate future charging demand using a moving-average prediction technique.

In the proposed architecture, each functional module performs a specific task while exchanging information with the subsequent module, thereby forming an integrated and sequential decision-making framework. The EV dataset generation module serves as the input layer by creating realistic charging scenarios based on practical vehicle charging characteristics.

The proposed system consists of five major functional modules that operate sequentially to achieve intelligent EV charging management. The first module generates a realistic EV charging dataset by considering parameters such as EV arrival time, battery capacity, initial state of charge (SOC), target SOC, and charging power. Using this dataset, the second module calculates the hourly charging demand, which represents the total charging load on the distribution transformer over a 24-hour period. The third module employs a moving-average forecasting technique to predict future charging demand based on historical load data, enabling the system to anticipate upcoming charging requirements.

A realistic EV charging dataset was generated by considering variations in vehicle arrival time, battery capacity, initial state of charge (SOC), target SOC, charging power, and charging duration. The arrival time of electric vehicles was modelled to represent practical daily charging behaviour, where most charging requests occur during evening hours after commuters return from work. This dataset serves as the input for hourly charging demand calculation and subsequent load forecasting.

The complete framework is implemented in MATLAB and Simulink, where all modules are integrated into a unified simulation environment. Dashboard displays, scopes, and monitoring blocks provide real-time visualization of charging demand, transformer loading, and controller actions. The modular architecture offers flexibility, scalability, and ease of future enhancement through the integration of advanced forecasting algorithms, renewable energy sources, battery energy storage systems, and Vehicle-to-Grid (V2G) technologies.

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research

ISSN (Online): 3139 – 2687

(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

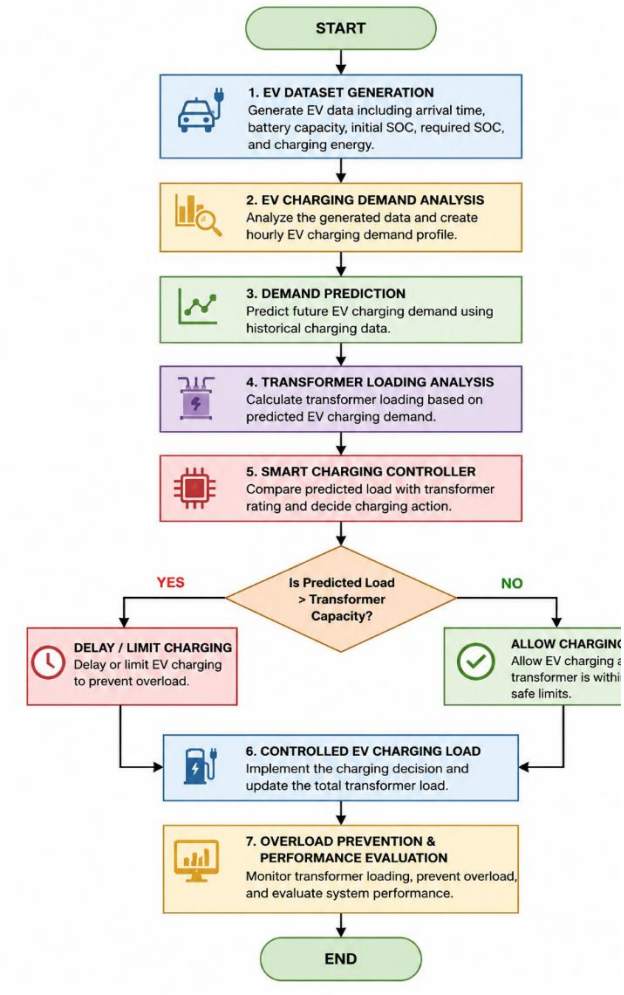


Fig 1. Overall Methodology Flowchart

Fig. 2 illustrates the distribution of EV arrival times over a 24-hour period. It can be observed that relatively few vehicles arrive during late-night and early-morning hours, whereas the number of arrivals increases gradually during the afternoon and reaches its maximum between 17:00 and 22:00 hours. This trend closely reflects real-world charging behaviour, where residential charging demand is concentrated during evening hours. The generated arrival pattern provides a realistic basis for evaluating the proposed charging demand prediction and smart charging control strategy.

Vehicle arrival times are randomly distributed throughout the day to simulate realistic charging behaviour observed in residential and commercial charging stations. Battery capacities are assigned within a practical range of modern electric vehicles, while initial and desired SOC values are generated within realistic operating limits. Based on these parameters, the charging energy requirement and charging duration for each vehicle are calculated. The generated dataset provides the basis for estimating hourly charging demand and evaluating transformer loading under different charging scenarios.

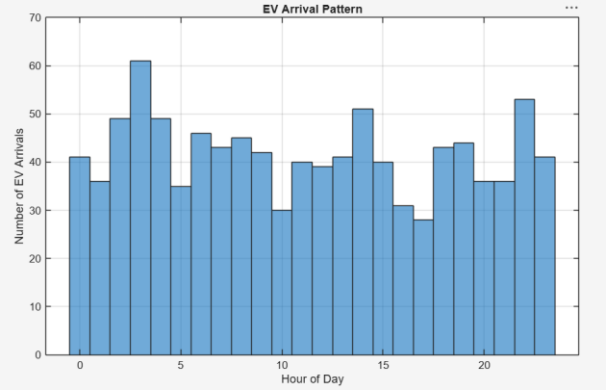


Fig 2. EV Arrival Pattern

The charging dataset is analysed to determine the aggregate charging demand created by all connected electric vehicles. The charging load of each vehicle is assigned to its corresponding charging interval, and the total charging demand for each hour is calculated by summing the charging power of all simultaneously connected vehicles. The resulting hourly charging demand profile represents the temporal variation of EV charging demand over a complete 24-hour period. This profile provides valuable information regarding peak charging periods, average charging demand, and transformer loading characteristics. The generated load profile also serves as the input for the prediction algorithm used in the subsequent stage of the proposed framework.

The EV charging demand analysis module is responsible for evaluating the aggregate

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

charging requirement of all electric vehicles over a 24-hour period. Using the generated EV charging dataset, the charging demand of individual vehicles is grouped according to their respective arrival times, and the total charging power required during each hourly interval is calculated. This process provides a comprehensive understanding of the temporal distribution of charging demand and helps identify periods of high and low electricity consumption. The hourly charging demand profile reflects the cumulative charging behavior of the connected EVs and serves as a realistic representation of daily charging patterns observed in residential and commercial charging environments.

The generated charging demand profile is subsequently utilized to identify peak charging hours, during which simultaneous charging of multiple electric vehicles may result in excessive transformer loading. By analysing the variation in hourly demand, the proposed framework establishes the baseline operating conditions of the distribution transformer before implementing the prediction and smart charging algorithms. Furthermore, the hourly demand profile serves as the primary input for the load forecasting module, enabling the system to estimate future charging requirements and proactively regulate charging activities. Consequently, EV charging demand analysis plays a crucial role in improving transformer utilization, reducing overload risk, and enhancing the overall reliability of the distribution network.

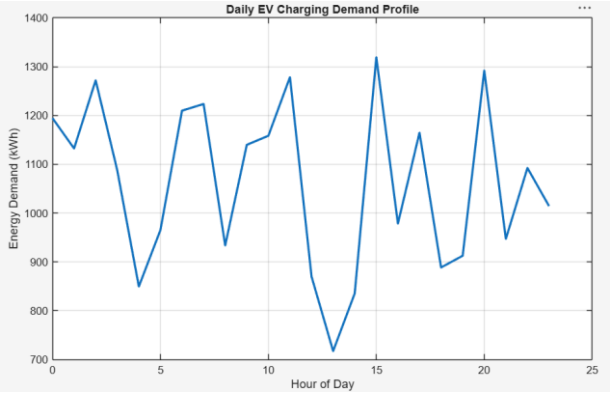


Fig 3. Daily EV Charging Demand

Accurate prediction of future charging demand is essential for proactive charging management. Instead of reacting after transformer overloading occurs, the proposed framework estimates future charging demand using historical charging information. A moving-average prediction technique is employed due to its computational simplicity and suitability for short-term load forecasting. The predicted charging demand for each hour is obtained by averaging the charging demand observed during the previous three time intervals. This approach effectively smoothens random fluctuations in charging demand while preserving the overall charging trend. The predicted charging demand enables the controller to estimate future transformer loading before actual charging takes place. Consequently, charging decisions can be made proactively, thereby minimizing the probability of transformer overloading during peak charging periods.

Although advanced forecasting techniques such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest (RF), and Deep Learning models can provide higher prediction accuracy, they generally require extensive historical datasets, significant computational resources, and complex model training procedures. In contrast, the moving-average prediction method employed in the

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research

ISSN (Online): 3139 – 2687

(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

proposed framework offers an efficient balance between prediction accuracy and implementation simplicity. Consequently, the proposed forecasting approach is particularly suitable for academic research, prototype development, and practical deployment in distribution systems where computational efficiency and ease of implementation are essential.

The predicted hourly charging demand was continuously monitored by the proposed smart charging controller. Whenever the predicted demand exceeded the transformer's rated capacity, charging requests were intelligently delayed until sufficient transformer capacity became available. As a result, the controller successfully maintained the transformer loading within the permissible operating limit throughout the simulation period. The maximum transformer loading under the proposed smart charging strategy remained at 100 kW, completely eliminating transformer overload.

Furthermore, comparative analysis between uncontrolled and controlled charging scenarios demonstrates that the proposed framework effectively reduces peak transformer loading while ensuring reliable charging management. The integration of demand prediction with intelligent charging control enables proactive decision-making, thereby improving transformer utilization, enhancing grid reliability, and supporting large-scale EV integration. The MATLAB and Simulink results validate the practicality and effectiveness of the proposed methodology for smart distribution networks.

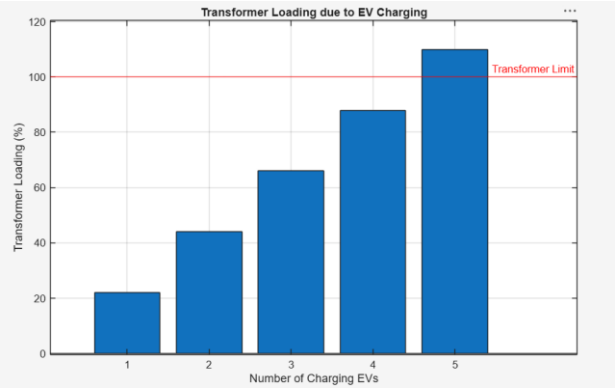


Fig 4. Transformer Loading

Simulation results indicate that uncontrolled EV charging causes a significant increase in transformer loading due to simultaneous charging during peak demand periods. The maximum transformer loading under uncontrolled charging reached 1319.37 kW, which is considerably higher than the transformer rated capacity of 100 kW, indicating severe overload conditions. Such excessive loading can reduce transformer lifespan, increase thermal stress, and negatively affect the reliability of the distribution network.

6. CONCLUSION

The increasing penetration of electric vehicles has introduced significant challenges for existing power distribution systems, particularly in terms of transformer overloading caused by uncontrolled charging. This paper presented a Prediction-Based Smart EV Charging Management Framework for preventing distribution transformer overload using MATLAB and Simulink. A realistic EV charging dataset was generated, and a moving-average forecasting technique was employed to predict future charging demand. Based on the predicted demand, a smart charging controller was developed to regulate EV charging according to the available transformer capacity.

Simulation results demonstrated that uncontrolled EV charging resulted in transformer loading of 1319.37 kW, significantly exceeding the transformer rating of 100 kW. In contrast, the proposed smart charging strategy successfully maintained transformer loading within the permissible operating limit by intelligently delaying charging requests whenever overload conditions were anticipated. The comparative analysis confirmed the effectiveness of the proposed framework in reducing transformer loading, preventing overload, and improving the operational reliability of the distribution network.

7. FUTURE WORK

The proposed prediction-based smart EV charging management framework can be further enhanced by integrating advanced machine learning and deep learning algorithms for more accurate charging demand forecasting. Although the current work employs a moving-average prediction technique due to its simplicity and computational efficiency, future studies may incorporate algorithms such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, Random Forest Regression, or Extreme Gradient Boosting (XGBoost). These intelligent forecasting models can capture complex charging patterns, seasonal variations, and consumer behavior more effectively, thereby improving prediction accuracy and enabling more efficient charging decisions.

Another promising extension of this research is the integration of renewable energy resources and Battery Energy Storage Systems (BESS) within the EV charging infrastructure. By coordinating EV charging with locally generated solar photovoltaic (PV) or wind energy, the dependence on the utility grid can be significantly reduced while improving the utilization of clean energy sources. In addition, battery storage can be employed to supply power during peak demand periods and store excess renewable energy during off-peak hours, thereby minimizing transformer loading and enhancing overall energy efficiency.

8. LIMITATIONS

Although the proposed prediction-based smart EV charging management framework effectively demonstrates transformer overload prevention through intelligent charging control, it has certain limitations. The charging demand prediction is based on a three-hour moving-average forecasting technique, which is computationally simple but may not accurately capture highly dynamic or irregular EV charging patterns under varying user behaviors and seasonal conditions. More sophisticated forecasting models could improve prediction accuracy in real-world application.

Furthermore, the proposed framework has been validated using MATLAB and Simulink simulations with a generated EV charging dataset. Although the dataset represents realistic charging scenarios, the system has not been validated using real-time charging station data or large-scale field experiments. Practical implementation may involve additional challenges such as communication delays, measurement uncertainties, and variations in user charging preferences that are not considered in the current study.

9. REFERENCES

[1] M. Yilmaz and P. T. Krein, "Review of battery charger topologies, charging power levels, and infrastructure for plug-in electric and hybrid vehicles," *IEEE Transactions on Power Electronics*, vol. 28, no. 5, pp. 2151–2169, May 2013.

ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

[2] International Energy Agency (IEA), *Global EV Outlook 2024*, Paris, France: IEA Publications, 2024.

[3] S. Deilami, A. S. Masoum, P. S. Moses, and M. A. S. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," *IEEE Transactions on Smart Grid*, vol. 2, no. 3, pp. 456–467, Sept. 2011.

[4] W. Kempton and J. Tomic, "Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy," *Journal of Power Sources*, vol. 144, no. 1, pp. 280–294, 2005.

[5] M. Muratori, "Impact of uncoordinated plug-in electric vehicle charging on residential power demand," *Nature Energy*, vol. 3, no. 3, pp. 193–201, 2018.

[6] H. Turker, S. Bacha, D. Chatroux, and A. Hably, "Low-voltage transformer loss-of-life assessments for a high penetration of plug-in hybrid electric vehicles," *IEEE Transactions on Power Delivery*, vol. 27, no. 3, pp. 1323–1331, Jul. 2012.

[7] Y. He, B. Venkatesh, and L. Guan, "Optimal scheduling for charging and discharging of electric vehicles," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1095–1105, Sept. 2012.

[8] N. Liu, Q. Chen, X. Lu, J. Liu, and J. Zhang, "A charging strategy for electric vehicles considering user satisfaction and transformer loading," *Applied Energy*, vol. 194, pp. 255–263, 2017.

[9] M. E. Khodayar, M. Shahidehpour, and L. Wu, "Enhancing the dispatchability of variable wind generation by coordinated operation of plug-in electric vehicles," *IEEE Transactions on Sustainable Energy*, vol. 3, no. 4, pp. 794–801, Oct. 2012.

[10] A. Dubey and S. Santoso, "Electric vehicle charging on residential distribution systems: Impacts and mitigations," *IEEE Access*, vol. 3, pp. 1871–1893, 2015.

[11] S. Shao, M. Pipattanasomporn, and S. Rahman, "Demand response as a load shaping tool in an intelligent grid," *IEEE Transactions on Smart Grid*, vol. 2, no. 4, pp. 624–631, Dec. 2011.

[12] Y. Zheng, Z. Luo, and D. J. Hill, "Optimal coordinated charging strategy for electric vehicles considering transformer capacity," *Electric Power Systems Research*, vol. 189, 2020.

[13] J. Hu, J. You, H. Lind, and J. Østergaard, "Coordinated charging of electric vehicles for congestion prevention in distribution systems," *IEEE Transactions on Smart Grid*, vol. 5, no. 2, pp. 703–711, Mar. 2014.

[14] X. Wang, P. Wang, and D. Wang, "Electric vehicle charging scheduling based on load forecasting in smart grids," *IEEE Access*, vol. 8, pp. 169012–169024, 2020.

[15] M. Mwasilu, J. J. Justo, E. K. Kim, T. D. Do, and J. W. Jung, "Electric vehicles and smart grid interaction: A review on vehicle-to-grid and renewable energy sources integration," *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 501–516, 2014.

International Journal Of Innovative Trends In Multi Disciplinary Scientific Research

ISSN (Online): 3139 – 2687

(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

Prediction-Based Smart EV Charging Management for Distribution Transformer Overload Prevention Using MATLAB/Simulink.

Name: **Gaurav Shirish Abhang**

Author1



Mr. Gaurav Shirish Abhang is pursuing M.TECH degree in stream of Electrical Power System from Mss's college of Engineering and technology, Jalna, DR BATU University, Lonere. He has completed his B.E in the stream of Electrical Engineering from CSMSS Chh. Shahu College Of Engineering, Chh. Sambhajinagar, DR BATU University.

Email Id: gauravabhang2002@gmail.com

Author2



Prof.Miss Alfiya A. Mahat received M.Tech in Electronics engineering from Savitribai Phule women's College of engineering. She is currently working as Assistant Professor in Department of Electrical Engineering & Technology at MSS's College of Engineering and Technology,Jalna.

Email Id: alfiya704@gmail.com

ACKNOWLEDGMENT

I am greatly indebted forever to my guide Alfiya Mahat and HOD K .Chandra Obula Reddy and to all teaching and non teaching staff who supported me directly and indirectly to complete my work. I am sincerely thankful to my Principal Dr. S.K. Biradar for their continued encouragement and active interest in my progress throughout the work I am grateful to be an M.Tech Electrical Power System student at Matsyodari Shikshan Sansthas College of Engineering and Technology, Jalna, Maharashtra.