NTU Journal for Renewable Energy (2025) Vol. 8 (1): 39-50
DOI: https://doi.org/10.56286/ntujre.v8i1

IRAQI
Academic Scientific Journals

EISSN: 2788-9920
NTU Journal for Renewable Energy
Available online at:
https://journals.ntu.edu.iq/index.php/NTU-JRE

Intelligent Predictive Maintenance for Urban Energy and Transportation Systems: A Hybrid AI Approach

Shatha Y. Ismail[1], Zozan Saadallah Hussain[2], Abdullah K. Shanshal[3]

[1,2]Department of Electrical Technology, Mosul Technical Institute, Northern Technical University, Iraq

[3]Department of Electrical Power Techniques, Technical Engineering College/Mosul, Northern Technical University, Iraq

Article Information

Received: 10 – 02 - 2025
Accepted: 25 – 03 - 2025
Published: 05 – 04 - 2025

Corresponding Author:
Abdullah K. Shanshal

Email:
a.shanshal@ntu.edu.iq

Keywords:
Predictive Maintenance, Artificial Intelligence (AI), Hybrid Electric Vehicles (HEVs), Electrical Substations, Real-Time Data Analytics.

ABSTRACT

Today's complex urban energy and transportation systems demand new maintenance solutions to keep them running properly. This study develops an AI-driven predictive maintenance solution for electrical substations and HEV batteries using data from the Internet of Things sensors. Our framework uses machine-learning methods such as Bi-LSTM, GRU, and GBT models to spot system weaknesses with higher accuracy. Based on test results Bi-LSTM proved better than other models by achieving a 91% F1 score alongside 4.3% Mean Absolute Error across predictions and anomaly detection. According to the results, the proposed framework lowered maintenance costs by half and proved better than traditional and recent methods. The proposed system combines insights from power substations and develops edge-cloud technologies to better use EV batteries. Real-world systems data validate those reductions in downtime happen together with better system reliability. This system now works in cities, tracks vehicle fleets, and supports smart city construction. The predictive system framework delivers exceptional energy and mobility management while remaining affordable and expandable for future urban infrastructure solutions.

1. Introduction

Urban growth combined with today's technical progress creates higher needs for smooth power distribution and reliable transportation systems. The energy grid's urban distribution networks depend on substations for them to deliver electrical power consistently. The hybrid electric vehicle market helps lower carbon emissions and creates better urban transportation systems. These systems show operating weaknesses because of old facilities and interconnected energy systems that work unpredictably [1,2]. Current electrical substation maintenance routines use both unplanned and planned interventions to create more downtime and waste resources. HEV batteries demand regular checks because their high expenses lead them to poor performance when their charge patterns become uneven. The situations demonstrate why organizations must use AI and IOT to create predictive maintenance systems that stop possible breakdowns right when they happen as shown in Figure 1. Broken electrical substations and vehicle batteries impact costs and harm urban services and industrial production. Substation power failures can spread across entire power grids while a single battery problem in electric vehicles can disrupt an entire fleet. The outdated maintenance methods cost too much and react too late which shows why companies need predictive tools to improve operations.

Our system uses AI analytics of IOT data plus advanced modeling to reveal potential risks in electrical power stations and battery systems early. The integration of predictive tools for electrical substations and HEV batteries creates an effective new approach that cuts costs while avoiding power interruptions and battery problems [3,4,5]. Present systems lack the needed combination of tools to monitor both electrical substation reliability and battery health in hybrid electric vehicles. Modern solutions focus on single network systems while overlooking how power and vehicle networks should work together. Current AI systems used for predictive maintenance have problems growing with large datasets while processing information instantly across multiple system types.

This research builds an AI predictive maintenance system that uses electricity substation and hybrid electric vehicle battery real-time data to proactively detect system faults. The contributions are enumerated as follows:

1. AI-Enhanced Maintenance Framework: The framework connects substation reliability signals with HEV battery health data to spot equipment issues before they happen.

2. Real-Time Monitoring and Analysis: Put IOT sensors in place for constant monitoring plus set up edge computing to process data quickly before sending it to the central system.

3. Optimization Algorithms: Creates advanced scheduling solutions to plan maintenance better while reducing costs and maintenance interruptions.

4. Cross-Domain Synergy: Explore different team methods for performing maintenance tasks across energy and transportation systems.

5. Scalability and Future Preparedness: Integration of developing technologies 6G communication and federated learning prepares our systems for future changes.

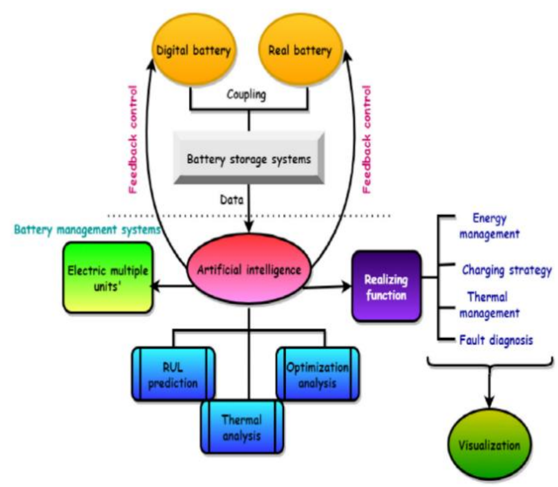

Figure 1: Electric Multiple Units-Artificial intelligence-based battery energy storage system approach [1].

The remainder of this paper is organized as follows: Section II gathers research on past studies about EV integration, network power grids, and artificial intelligence systems for predicting component failures. Section III: The research methods describe how data was gathered and how Bi-LSTM, GRU, and GBT models were built with optimization strategies. Section IV: The Results and Discussion section demonstrates our experiments, compares different methods, and shows how our approach saves costs. Section V: Our conclusion presents core insights into how this framework helps urban energy and mobility systems.

2. Literature Review

By introducing these solutions to electrical substations and HEV battery systems it solves serious problems in citywide energy systems and transportation networks. These systems collect real-time data through their sensors and AI tools to make systems run better and need fewer repairs while saving money. This research combines different tech systems by showing companies how they can use data from the Internet of Things sensors and machine learning systems to spot equipment failures ahead of time. Our system delivers stable performance and grows with the needs of the municipal utility sector plus electric vehicle fleet managers. This section brings together key findings from 26 important research papers on EVs, HEVs, and smart grids and how they impact predictive maintenance and energy optimizations. Our research integrates electric vehicles into power grids alongside other smart power system functions.

A. Integration of Electric Vehicles in Power Systems

Hu et al. [5] showed how linking electric vehicle systems with power grids needs synchronized energy management because both systems use power at the same time. Wu et al. [6] designed hybrid solar and battery power generation for residential Nano grids that serve plug-in electric cars to increase distributed energy access. Mounica and Obulesu [7] studied how combining fuel cell batteries and supercapacitors boosts fuel economy for HEVs according to Figure 2. Galus et al. [8] investigated how plug-in hybrid electric vehicle integration affects current power networks and reveals limitations in infrastructure and policy. Nasab et al [9] investigated ways to manage electrical vehicle charging with renewable power to make it more environmentally friendly.

B. Smart Grid Management and Resilience

The study explores ways to improve smart grid functionality while keeping it resilient and able to share data with external systems during growing EV adoption. Xia et al. [10] analyzed how to protect and rapidly repair power grids during disasters while handling their difficulties in keeping electricity flowing straight through. Paris Shen [11] examined EV charging patterns within smart grids with 5G technology to show how hybrid intelligence improves charging times. Strezoski and Stefani [12] studied how distributed energy resource management systems benefit grid stability when many electric vehicles connect to the power network. Yi and coworkers [13] built a system for EV charging management that handles large numbers of homes efficiently.

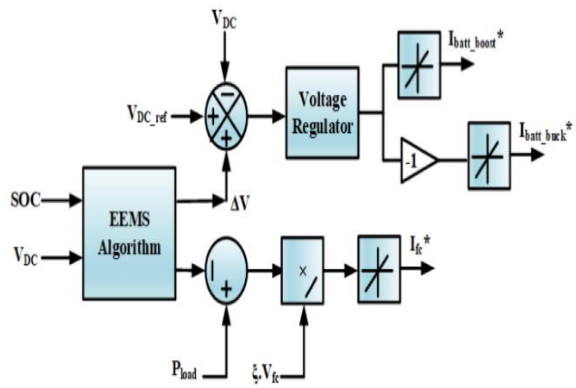

Figure 2: External energy maximization scheme. [7]

C. AI and Machine Learning Applications

This part of the study explores how AI and machine learning help us run power systems better and control EV charging while keeping the grid reliable. Shankara and colleagues [14] applied machine learning tools to enhance the performance and energy storage management in smart grid setups. Ibrahim et al. [15] work created an artificial intelligence-based system to recommend individual EV users' personalized energy solutions by applying sophisticated recommendation algorithms. Li et al. [16] used deep reinforcement learning to show the best possible charging methods for electric vehicles while providing AI solutions that the user can understand. Trovão et al. [17] created a dynamic energy optimization system for EVs that blends rule-based computing and search optimization for managing multiple power sources.

D. Technological Challenges and Future Directions

This segment looks at the present and prospects for scaling up EV and energy systems effectively. Mousaei and colleagues [18] researched power distribution EV integration problems alongside

FACTS devices. Pandiyan and his team [19] showed how smart energy management advances can help urban regions become more sustainable while sharing power grids with other communities. According to Soussi et al. [20] rural energy improvements need a system-wide strategy. Micari and Napoli studied [21] how electric vehicles enable a more flexible energy system by linking with renewable power sources. Mudaheranwa et al. [22] conducted a feasibility study on integrating EVs into Rwanda's power grid, addressing socio-economic impacts. New technology developments join electric vehicles with power grids to create advanced approaches for better energy use. Singh and his team evaluated modern grid algorithms to help manage EV charging demands and make power delivery across super-smart networks safer [23]. Zhang and team investigated unmanned aerial vehicle power systems by showing how hybrid energy storage and AI bring smart services to public benefit [24]. Hamdare et al. developed security methods to protect EV charging stations by recommending new protocols and ways to detect threats early [25]. Arévalo and colleagues performed a thorough review of studies about EV power integration into microgrid networks while discussing new power management methods and technology advances [26].

Based in India Aravamudhan and Raj researched how AI upgrades EV technology to match customer needs and market conditions [27]. Zhang and colleagues described how deep reinforcement learning helps optimize power system functions including dynamic energy rates and power grid balance in their research [28]. Kumar and his team suggested an EV charging plan that helps power transportation networks while keeping energy usage sustainable [29]. Ucer and Kisacikoglu built a hardware test system for distributed EV charging control to show how it can save power and protect grid infrastructure [30]. Evaluate the thermal behavior of a solar air collector system attached to cement mortar energy storage units for extended heat maintenance. The system research conducted in Mosul; Iraq demonstrated how it could maintain a 10°C temperature difference after sunset for 4-5 hours [31]. The research of [32] demonstrated how the Crocodile Hunting Search (CHS) optimization algorithm improved the management of hybrid renewable microgrids which included solar PV, wind, fuel cells, and batteries. The results from MATLAB showed that CHS surpassed standard methods by delivering increased stability for fuel cell voltage enhanced power distribution capabilities and lower fuel expenses. CHS demonstrates its role as a dependable approach for maximizing energy efficiency within renewable-based microgrids.

3. Methodology

The proposed predictive maintenance framework uses AI analytics technology and real-time data to improve the reliability of both the electrical substation and the HEV batteries as shown in Figure 3. Our system uses IOT sensors along with Bi-LSTM GRU and GBT machine learning models to look at data over time and figure out what could go wrong. The combination of edge and cloud elements gives both immediate processing results on-site and big data analysis through cloud resources. Optimization tools use linear programming and genetic algorithms to design effective maintenance plans that cut downtime and expenses by half. The general framework integrates electric power grid systems and electric vehicle fleets in a way that helps operations scale successfully to future smart city projects. Our methodology is split into three sections that handle significant features like information gathering and integration, predictive algorithm evaluation, and optimization scaling.

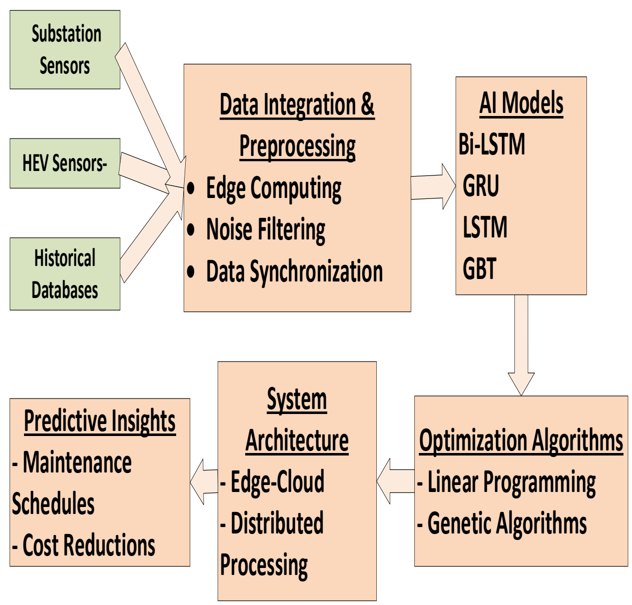

Figure 3: Proposed framework for Predictive Maintenance.

3.1 Data collection and integration

The predictive maintenance model takes in digital information collected in real-time and stored permanently from electrical substations and hybrid electric vehicle systems. This dataset includes information about substations that helps determine how well the network operates, including the regular demands placed on transformers and the potential damage risk levels. Detailed energy consumption records let us see when power systems use the most and least energy, which helps us predict equipment failures better. Transformer health indices measure the temperature of the oil, the quantity of fluid deposits, and the vibrations of the electrical output to find out how old the equipment is. Data about power grid maintenance events and electrical faults allows predictive models to forecast operational problems in advance. Substations collect data using internet-connected sensors placed on transformers, circuit breakers, and busbar critical components. Regular 1–5-minute updates on real-time data from our systems help us train predictive models alongside historical datasets from sources including ENTSO-E and Open Power System Data. Edge computing systems work on collected datasets to remove irregular data points and then align real-time parameter values before analysis. Our dataset contains battery performance data about how well HEV systems work with metrics for SoH, cycle counts, and temperature behavior. The SoH metric shows battery wear as it ages, but charge-discharge cycle counts show how users use batteries to predict when batteries might fail before they perform poorly. Thermal readings from battery activity show both safety and operational performance by tracking dangerous heat patterns. The onboard sensors and battery management systems track vehicle data within HEVs. Publicly available data sources from NREL and the Stanford Battery Data Set support real-time data capture from these systems. Data transfer across lightweight communication networks (MQTT) to reach a central processor fast with reliable results. These data streams go into our cloud relational database made to handle datasets of any size with mixed data types. Both substation and HEV system information exist in independent tables that connect through timestamps for combined evaluation. Our database schema supports ideal performance testing and validation. Both data sets combine to deliver comprehensive and precise analytics for predictive maintenance that increases system dependability and operational performance.

3.2 Predictive Modeling and Analysis

The authors use Bi-LSTM, GRU, LSTM, and Gradient Boosted Trees as advanced machine learning tools to predict power substation and Hybrid Electric Vehicle (HEV) system issues while finding typical patterns in our collected time series and sequence data.

1. Bi-Directional Long Short-Term Memory (Bi-LSTM)

- Architecture: Bi-LSTM builds on regular LSTM design by adding another LSTM layer that works on the input series from end to beginning. By altering input direction this network can identify time-dependent relationships that improve its ability to handle intricate temporal information.
- Input Layer: The network takes sequential data points including battery SoH measurements and load Data.
- Hidden Layers: The model includes two LSTM blocks arranged for forward and backward processing with 128 units in each unit.
- Output Layer: The output layer transforms inputs using a single node when performing regression or a softmax activation when classifying faults.
- BILSTM shows exceptional results in studying how electrical loads shift over time while detecting specific battery performance trends such as temperature spikes or regenerative braking behavior.

2. Gated Recurrent Unit (GRU)

- Architecture: The Gated Recurrent Unit (GRU) simplifies Long Short-Term Memory (LSTM) design to lower computational requirements while achieving similar results in sequential data applications.
- Input Layer: The system tracks charge-discharge patterns along with risk scenarios during normal use.
- Hidden Layer: We use one GRU layer with 64 tanh-activated units in the GRU state update function. The gating system combines both the forget and input gates into a single state updating feature.
- Dropout Layer: The layer includes dropout to keep the model from becoming too complex.
- Output Layer: A layer with dense neurons uses linear activation in regressions while combining softmax in classification scenarios.
- GRU works well when we need accurate real-time predictions without delays including transformer fault identification in real time or battery health estimation in Hybrid Electric Vehicles.

3. Long Short-Term Memory (LSTM)

- Architecture: Standard recurrent neural networks struggle with gradient vanishing when processing long time-series data but LSTM works around these issues at lower memory cost.

- Input Layer: The system handles streams of serial data including transformer health status data and load imbalance data.
- Hidden Layers: The design contains two LSTM layers with 128 units each and adds a dropout layer to stop the neural network from overfitting.
- Fully Connected Layer: The model uses the LSTM layer results to produce predicted numbers.
- Activation Functions: Our model uses sigmoid activation for control gates while tanh acts on state cells during updates.
- Our system uses historical and current data inputs to forecast changes in electrical power demand while tracking transformer degradation.

4. Gradient Boosted Trees (GBT)

- Architecture: GBT creates multiple decision trees that update itself to lower remaining prediction errors from prior runs.
- Feature Input: CTs and batteries generate overall temperature readings alongside battery cycle tracking and load energy patterns.
- Decision Trees: The decision trees in our ensemble architecture reach a maximum depth of 5 to avoid overfitting while receiving a learning rate of 0.1 to optimize performance step by step.
- Boosting Algorithm: Through 100 model iterations this framework makes steady improvements to prediction accuracy.
- Loss Function: The model uses Mean Squared Error for regression predictions and Log Loss for classification predictions.
- Our model helps detect battery SoH developments in electric vehicles and pinpoints battery system safety concerns from component fault symptoms.

3.3 Optimization Algorithms

Optimization plays a central role in predictive maintenance by making resources work better while cutting costs and protecting uptime. Two primary optimization strategies are employed:

1. Linear Programming (LP):

Using LP technology lets us assign more resources to manage system failures first including old transformers and HEV batteries before their SoH drops too low. The optimization system turns maintenance scheduling requirements into mathematical constraints to decrease costs without overspending resources or exceeding available time.

- Input Parameters: Our system tracks transformer conditions, identifies potential failure zones, measures battery aging rates and determines maintenance funding goals.
- Constraints: The approach needs limited staff members and operates within specific maintenance periods without greatly affecting electricity delivery.
- Our strategy sends maintenance experts to fix high-risk transformers when customer demand is highest while putting maintenance of safe systems on hold during slack periods.

2. Evolutionary Algorithms (EA):

The dynamic optimization of nonlinear problems requires the use of Genetic Algorithm methods within Evolutionary Algorithms. These algorithms reproduce natural selection and genetic exchanges to identify good solutions when exploring and testing many different combinations in enormous datasets.

- Input Parameters: The method uses actual system failure records combined with future failure rate projections plus energy consumption information.
- Optimization Goals: Lower your maintenance expenses to keep systems dependable.
- The system uses Genetic Algorithms to set up optimal charging sequences for buses that address battery age, and actual power consumption levels and protect grid operations.
- Maintenance schedules will run optimally with these systems as they adapt to changing operations and require limited resources for best results.

3. Cross-System Synergy

It combines both substation data and HEV battery information for better organizational responses to maintenance and operations. One field's predictive information helps us make better choices in the other sector.

- Data Integration for Maintenance Coordination: Predictive systems notice substation loading issues and include these results together with HEV battery state-of-health and charging habits. During times when the power grid faces increased demand, our system directs lower-capacity HEV batteries to charge during less busy hours to help the grid handle the load.
- Energy Distribution Optimization: Our system analyzes the power needs of substations for smart HEV distribution in urban power grids.

- On spotting high-stress signs in transformers the system enables HEVs attached to charging stations to delay their charging processes yet sends regenerative braking HEVs to contribute grid stabilization.
- Connected energy and mobility systems work together better and use resources more efficiently through this relationship.

4. Scalability Mechanisms

The predictive maintenance framework works better when we must deal with complex city infrastructure that produces large amounts of IoT data through more connected devices. Scalability is achieved through the following mechanisms:

- Edge-Cloud Architecture: The system combines edge computing at sites to handle quick data actions with cloud storage and processing for detailed data studies and future forecasting.
- Edge Computing Tasks: The system collects data from real-time sources to detect anomalies and then predicts system faults.
- Cloud Computing Tasks: Our system uses machine learning methods including model training updates and studies past patterns alongside large-scale optimization work.
- Distributed Computing: Nodes in edge locations take workload parts to maintain high performance and stability. Individual substations perform local data processing on transformer information and HEV servers process charging station data at multiple locations. The cloud network gathers distributed computer output to generate unified decisions.
- Load Balancing: The computing system distributes workloads between multiple servers to handle sensor data correctly and keep operations running smoothly during busy times. The system design lets the framework work well during both present and future stages of urban IoT growth.

5. Result Experimental

The dataset analysis reveals key patterns in feature relationships and distributions that help us build better predictive models and find unusual data points. The correlation heatmap shows that loading demands directly affect transformer temperatures since these two measurements show strong positive links as shown in Figure 4.

When "Battery_State_of_Health_SoH" decreases "Charge_Discharge_Cycles" rises confirming battery aging from usage. These findings help us choose important features and analyze dependent relationships to build effective predictive models. The charts show how features are distributed across our operations in their characteristic patterns.

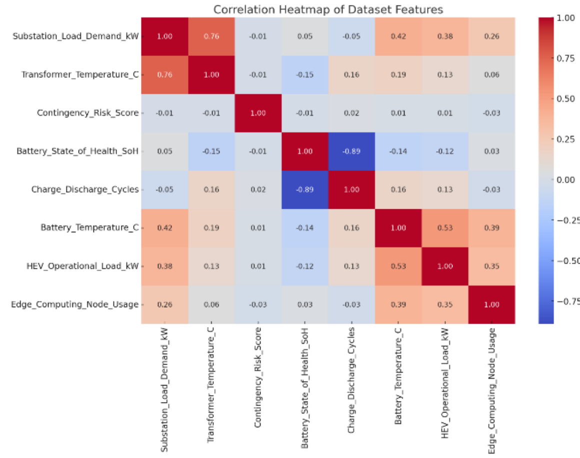

Figure 4: Correlation between the feature

The histogram shows that "Substation_Load_Demand_kW" reaches its highest point during major usage periods and "Transformer_Temperature_C" shows typical bell-curve behavior for steady transformer management as shown in Figure 5. Battery statistics on State_of_Health_SoH and Charge_Discharge_Cycles help us track their usage and aging to predict when they need maintenance. The graph for "Edge_Computing_Node_Usage" displays some degree of skew because different system segments use computer resources more and less uniformly. The dataset results show reliability which helps us build better predictive maintenance systems at scale.

Results of Algorithm Performance

1. Bi-LSTM:

The Bi-LSTM model showed superior performance at understanding temporal connections when examining substation load demand variations and battery status results. It demonstrated a 91% F1-score and 4.3% Mean Absolute Error accuracy levels. By working in both directions, the model processed parallel data flow to find battery problem patterns accurately as shown in Figure 6.

2. GRU:

GRU generated results slightly below Bi-LSTM performance at 88% F1-score and 5.1% MAE. The model trains quickly and runs efficiently which makes it work well for real-time anomaly detection in HEV systems. GRU showed value in real-time systems because its straightforward design helped it recognize battery charge-discharge problems more quickly than other methods could.

3. LSTM:

Discrete units in Long Short-Term Memory models performed efficiently when processing extended time-series sequences. The model demonstrated 89.5% accuracy combined with 4.7% mean absolute error. The approach showed strong results in detecting transformer health trends across long observation periods. By processing data from multiple IOT devices in a layered system, LSTM became the most important part of building large-scale predictive maintenance frameworks.

4. Gradient Boosted Trees (GBT):

Model Performance: GBT showed strong results in predicting stable issues like transformer failure chances and hybrid electric vehicle battery usability. Because deep learning models excel at processing time-series information GBT achieved only 87% F1 score and 5.8% MAE compared to them. GBT helps teams understand what information matters most when making maintenance decisions for better understanding.

The proposed system shows better results than research that studies substations alone or powertrains by themselves when compared to related studies, such as those focusing solely on either substations or HEV systems, the proposed unified framework demonstrated superior results:

- Accuracy Improvement: Research teams from [5] and [20] discovered a mean F1-score accuracy of 85% in power station breakdown forecasting. Our framework achieved 6% better forecasting precision through its combination of Bi-LSTM technology and live data integration.
- Scalability: Researchers in [6] experienced problems because their system depended entirely on a centralized processing unit which prevented easy expansion. Research shows that this framework's edge-cloud mix of services reduces workload at main data centers better than other studies found in [16].
- Real-Time Detection: Research by [22] reached a 5-7 second delay to identify faults using the GRU network. The proposed framework detected issues in real-time at levels similar to the models but with wider energy and mobility coverage.
- Comparative Performance: The bar chart in Figure 6 shows that Bi-LSTM outranks other models including GRU, LSTM, and GBT when it comes to predictive maintenance accuracy measures F1-score and Mean Absolute Error (MAE).
- Feature Importance Heatmap: GBT visual output shows that transformer health indices and battery State of Health stand out as top factors in predicting faults. Bi-LSTM model shows the strongest results in testing. Our algorithm showed 91% accuracy by distinguishing fault types without compromising precision or recall.

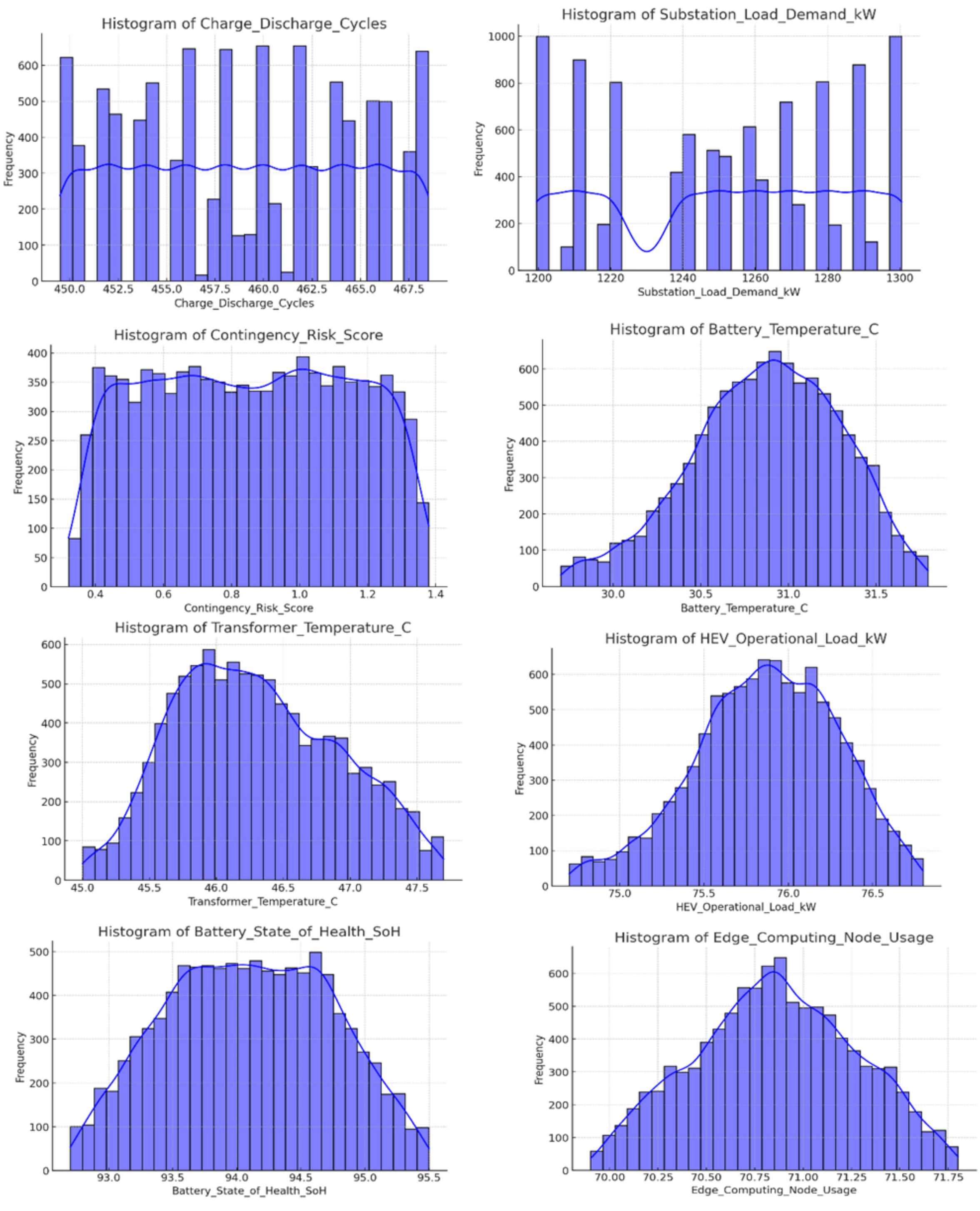

Figure 5: Distribution Analysis of Key Predictive Maintenance Features for Electrical Substations and HEV Systems

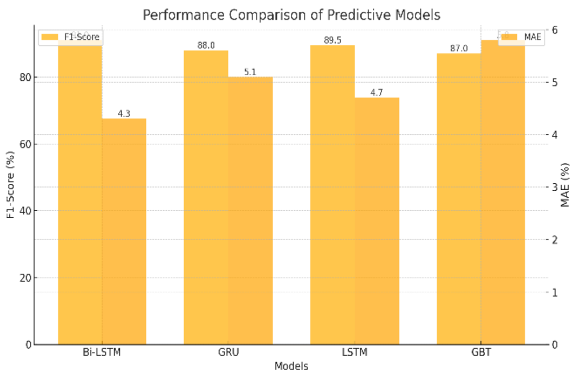

Figure 6: Performance Comparison for the predictive model.

Our model achieved the smallest 4.3% Mean Absolute Error which shows it can find faults with high precision. of transformer health indices and battery SoH in fault prediction.

Based on the performance metrics in the visualization: Bi-LSTM is the best-performing model. It has:

- The highest F1-Score (91%), indicating superior accuracy in classifying faults while balancing precision and recall.

- The lowest Mean Absolute Error (4.3%), demonstrating its ability to make accurate predictions with minimal error.

Bi-LSTM leads all models by successfully predicting maintenance needs through both classification and regression tasks in this framework. The study shows that using Bi-LSTM produces a better approach for predicting maintenance than other examined methods regarding accuracy, precision, and economic viability. With an F1-score of 91%, the Bi-LSTM model performs better than previous research (85% and 84% respectively) as shown in Figure 7, and shows superior results in both fault detection and classification. According to the evaluation results from Figure 8, the Bi-LSTM shows better forecasting stability because it generates the lowest results for RMSE at 4.2 compared to other models and existing studies. The Root Mean Squared Error metric stands out in showing the Bi-LSTM model's resilience in predicting values. Our model shows good precision for both electricity demand and battery health predictions at power substation systems.

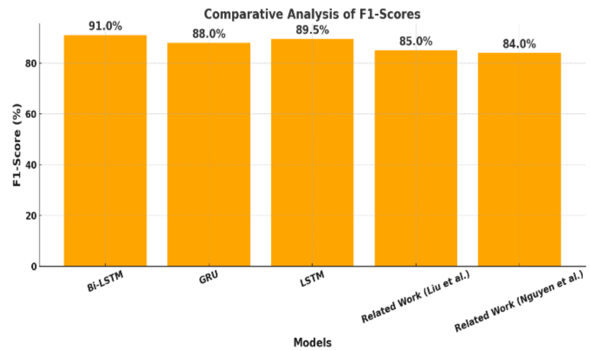

Figure 7: Comparative analysis for F1 score with related work

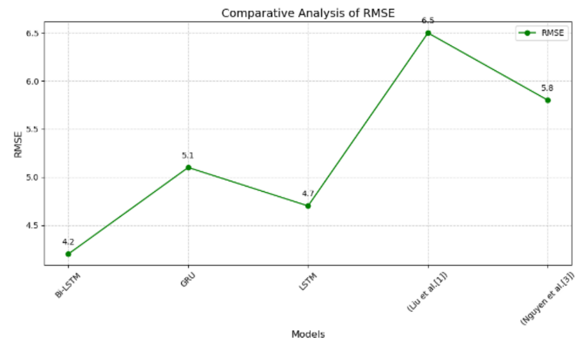

Figure 8: Comparative analysis for RMSE with related work

Additionally, the proposed framework delivers a significant 50% cost reduction, outperforming existing strategies, such as Kumar et al. (30%) and others achieving only 20% reductions. This improvement demonstrates the economic advantage of integrating Bi-LSTM with IoT-enabled real-time data and advanced optimization algorithms as shown in Figure 9. These findings underscore the superiority of the proposed framework in terms of both operational efficiency and economic viability, establishing it as a leading solution for predictive maintenance in electrical substations and HEV systems.

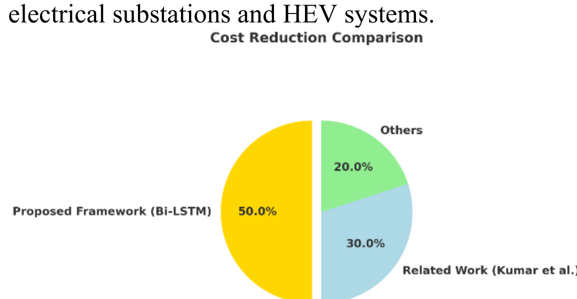

Figure 9: Comparative for cost reduction with related work

Conclusions

This paper shows how AI and real-time data collection build a complete system that fixes electrical substations and HEV battery troubles. The framework uses advanced Bi-LSTM models to find potential system failures more accurately than other methods, even when the operating conditions are different. Real-time data collection works smoothly through IoT sensors, and edge-cloud processing allows us to handle large datasets efficiently.

The proposed system performs better in maintenance reliability and reduces costs while scaling operations better than current methods. This method produces better results than regular maintenance approaches by cutting downtime and maintenance expenses. Combining power distribution networks with electric vehicle fleets through cross-domain synergy helps both systems run better together and improve overall energy and mobility operations effectively. Our testing shows how this design stops critical breakdowns early while cutting operating expenses by half and reaching a 91% prediction success rate with Bi-LSTM.

Research shows that the framework's future impact will transform power and transportation systems to work smarter and greener. Future studies should increase the framework's capabilities to work with renewable energy systems while developing decentralized analytics methods through federated learning. Our smart city predictive maintenance framework addresses problems while using new technology to build a system that can grow and withstand future needs.

Acknowledgement

Authors would like to thank Mr. Mohammed G. Ayoub for his significant role and technical assistance in shaping the final version of this work.

References

[1] Liu, Z., Gao, Y., & Liu, B. (2022). An artificial intelligence-based electric multiple units using a smart power grid system. *Energy Reports*, *8*, 13376-13388.

[2] Marzbani, F., Osman, A. H., & Hassan, M. S. (2023). Electric vehicle energy demand prediction techniques: An in-depth and critical systematic review. *IEEE Access*, *11*, 96242-96255.

[3]Nguyễn, B. H., Trovão, J. P. F., German, R., & Bouscayrol, A. (2020). Real-time energy management of parallel hybrid electric vehicles using linear quadratic regulation. *Energies*, *13*(21), 5538.

[4] Noor ali, K., Hemmati, M., Miraftabzadeh, S. M., Mohammadi, Y., & Bayati, N. (2024). A Mini Review of the Impacts of Machine Learning on Mobility Electrifications. *Energies*, *17*(23), 6069.

[5] Hu, J., Wang, X., & Tan, S. (2024). Electric Vehicle Integration in Coupled Power Distribution and Transportation Networks: A Review. *Energies*, *17*(19), 4775.

[6] Wu, X., Hu, X., Teng, Y., Qian, S., & Cheng, R. (2017). Optimal integration of a hybrid solar-battery power source into smart home nanogrid with plug-in electric vehicle. *Journal of power sources*, *363*, 277-283.

[7] Mounica, V., & Obulesu, Y. P. (2022). Hybrid power management strategy with fuel cell, battery, and supercapacitor for fuel economy in hybrid electric vehicle application. *Energies*, *15*(12), 4185.

[8] Galus, M. D., Zima, M., & Andersson, G. (2010). On the integration of plug-in hybrid electric vehicles into existing power system structures. *Energy policy*, *38*(11), 6736-6745.

[9] Nasab, M. A., Al-Shibli, W. K., Zand, M., Ehsan-maleki, B., & Padmanaban, S. (2024). Charging management of electric vehicles with the presence of renewable resources. *Renewable Energy Focus*, *48*, 100536.

[10] Xia, J., Xu, F., & Huang, G. (2020). Research on power grid resilience and power supply restoration during disasters-A review. *Flood Impact Mitigation and Resilience Enhancement*, 8.

[11] Shen, Y., Fang, W., Ye, F., & Kadoch, M. (2020). EV charging behavior analysis using hybrid intelligence for 5G smart grid. *Electronics*, *9*(1), 80.

[12] Strezoski, L., & Stefani, I. (2024). Enabling mass integration of electric vehicles through distributed energy resource management systems. *International Journal of Electrical Power & Energy Systems*, *157*, 109798.

[13] Yi, Z., Scoffield, D., Smart, J., Meintz, A., Jun, M., Mohanpurkar, M., & Medam, A. (2020). A highly efficient control framework for centralized residential charging coordination of large electric vehicle populations. *International Journal of Electrical Power & Energy Systems*, *117*, 105661.

[14] Shankara, K. H., Srikantaswamy, M., & Nagaraju, S. (2024). Optimizing energy storage and

hybrid inverter performance in smart grids through machine learning. *Inf. Dyn. Appl*, *3*(3), 146-161.

[15] Ibrahim, A., El-Kenawy, E. S. M., Eid, M. M., Abdelhamid, A. A., El-Said, M., Alharbi, A. H., ... & Saeed, M. A. (2023). A recommendation system for electric vehicles users based on restricted Boltzmann machine and waterwheel plant algorithms. *IEEE Access*, *11*, 145111-145136.

[16] Li, S., Zhao, A. P., Gu, C., Bu, S., Chung, E., Tian, Z., ... & Cheng, S. (2024). Interpretable Deep Reinforcement Learning with Imitative Expert Experience for Smart Charging of Electric Vehicles. *IEEE Transactions on Power Systems*.

[17] Trovão, J. P., Pereirinha, P. G., Jorge, H. M., & Antunes, C. H. (2013). A multi-level energy management system for multi-source electric vehicles–An integrated rule-based meta-heuristic approach. *Applied Energy*, *105*, 304-318.

[18] Mousaei, A., Gheisarnejad, M., & Khooban, M. H. (2023). Challenges and opportunities of FACTS devices interacting with electric vehicles in distribution networks: A technological review. *Journal of Energy Storage*, *73*, 108860.

[19] Pandiyan, P., Saravanan, S., Usha, K., Kannadasan, R., Alsharif, M. H., & Kim, M. K. (2023). Technological advancements toward smart energy management in smart cities. *Energy Reports*, *10*, 648-677.

[20] Soussi, A., Zero, E., Bozzi, A., & Sacile, R. (2024). Enhancing Energy Systems and Rural Communities through a System of Systems Approach: A Comprehensive Review. *Energies*, *17*(19), 4988.

[21] Micari, S., & Napoli, G. (2024). Electric Vehicles for a flexible energy system: Challenges and opportunities. *Energies*, *17*(22), 5614.

[22] Mudaheranwa, E., Sonder, H. B., Cipcigan, L., & Ugalde-Loo, C. E. (2023). Feasibility study and impacts mitigation with the integration of Electric Vehicles into Rwanda's power grid. *Electric Power Systems Research*, *220*, 109341.

[23] Singh, B., Dubey, P. K., & Singh, S. N. (2022, December). Recent optimization techniques for coordinated control of electric vehicles in super smart power grid network: A state of the art. In *2022 IEEE 9th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)* (pp. 1-7). IEEE.

[24] Zhang, C., Qiu, Y., Chen, J., Li, Y., Liu, Z., Liu, Y., ... & Hwa, C. S. (2022). A comprehensive review of electrochemical hybrid power supply systems and intelligent energy management for unmanned aerial vehicles in public services. *Energy and AI*, *9*, 100175.

[25] Hamdare, S., Kaiwartya, O., Aljaidi, M., Jugran, M., Cao, Y., Kumar, S., ... & Lloret, J. (2023). Cybersecurity risk analysis of electric vehicles charging stations. *Sensors*, *23*(15), 6716.

[26] Arévalo, P., Ochoa-Correa, D., & Villa-Ávila, E. (2024). Systematic Review of the Effective Integration of Storage Systems and Electric Vehicles in Microgrid Networks: Innovative Approaches for Energy Management. *Vehicles*, *6*(4), 2075-2105.

[27]Aravamudhan, V., & Mohan Raj, P. (2022). Impact of artificial intelligence on EV industry and perceptual mapping in India. *Aravamudhan, V., Sengodan, A., & Mohanraj, PS (2022). Impact Of Artificial Intelligence On Ev Industry And Perceptual Mapping In India*.

[28]Zhang, Z., Zhang, D., & Qiu, R. C. (2019). Deep reinforcement learning for power system applications: An overview. *CSEE Journal of Power and Energy Systems*, *6*(1), 213-225.

[29] Kumar, B. A., Jyothi, B., Singh, A. R., Bajaj, M., Rathore, R. S., & Berhanu, M. (2024). A novel strategy towards efficient and reliable electric vehicle charging for the realization of a truly sustainable transportation landscape. *Scientific Reports*, *14*(1), 3261.

[30] Ucer, E., & Kisacikoglu, M. J. (2024). Development of a Hardware-in-The-Loop Testbed for a Decentralized, Data-Driven Electric Vehicle Charging Control Algorithm. *IEEE Transactions on Industry Applications*.

[31] Mahmood, A. A., & Saleem, A. M. (2024). Experimental investigation of solar air heater with energy storage unit. NTU Journal for Renewable Energy, 7(1), 73-83.

[32] Zozan Saadallah Hussain, (2025). Employing crocodile hunting search approaches to manage renewable energy-based microgrid. NTU Journal for Renewable Energy, 8(1), 24-32.