# Hybrid Knowledge Graph and Deep Reinforcement Learning Model for Intelligent Anomaly Detection in EV Charging Behavior

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2026 International Conference on Innovations in Computational Intelligence (ICICI) | 979-8-3315-4616-8/26/$31.00 ©2026 IEEE | DOI: 10.1109/ICICI68867.2026.11564864

***Abstract* – Electric vehicle production, charging infrastructure, and Electric Vehicle Supply Equipment have all grown in response to the fast adoption of EVs spurred by government subsidies and clean energy requirements. It is now crucial to monitor and detect abnormalities in EV charging behaviour to maintain secure and efficient operations, especially as EVSEs interact with cloud platforms, payment systems, and battery management units. To improve anomaly detection capabilities, this work uses StandardScaler to normalise charging session data and an MTM-based approach to extract critical behavioural aspects. An RL-based model is utilised to detect anomalous relational patterns in EV charging procedures; the challenge is presented as a reasoning assignment across huge KG. The system is able to effectively distinguish between conventional and abnormal charging behaviours thanks to a bespoke incentive algorithm that maximises accuracy, detection efficiency, and path diversity. By achieving a high detection accuracy of 96.38%, the suggested KG-RL model seems to be successful in finding anomalies in EV charging networks, according to experimental evaluation. Future improvements in predictive maintenance, fraud prevention, and safe EV charging ecosystems can be facilitated by this method, which showcases the potential of intelligent KG-RL frameworks in assuring dependable EVSE management.**

***Keywords*— Electric Vehicle Charging Stations (EVCSs), Information Technologies (ITs), Operational Technologies (OTs), cyber physical power system (CPPS), knowledge graphs (KGs).**

## I. Introduction

The growth of the EV market has garnered significant interest from governments, automakers, and energy companies. EV are thought to be a practical solution to the growing pollution of the environment and the depletion of fossil fuels. EV charging facilities have proliferated in tandem with the development of EVs. On the other hand, power grid safety and optimal dispatching are threatened by the unpredictable, intermittent, and volatile nature of the load. In order to increase the popularity of EV, rationalize the building of charging stations, and improve prediction precision for optimal dispatching, it is necessary to establish a scientific and realistic short-term load forecasting model for EV charging stations. Focusing studies on load predictions for EV charging stations is thus highly significant[1]. The advancement of distributed energy resources, such as EVs, distributed photovoltaics and others, has recently attracted social attention as a means to lessen the impact of pollution, energy crises, and climate change. As the number of distributed energy resources on the load side continues to rise, more and more people are shifting from being traditional power consumers to prosumers, or people that can generate their own electricity[2]. As mentioned, the worldwide trend towards a society with sustainable renewable energy depends on prosumers' active involvement at the end user energy side. Typical prosumers on the grid include commercial buildings with solar PV panels and EV charging stations. The building energy management system can optimize the energy use of these structures under the incentives of electricity pricing. Electricity cost savings, load levelling, and consumption of distributed power are thus promising areas for commercial building energy management.

The importance of predicting EV charging demands in power system management has grown in tandem with the booming EV market. While centralized EV charging has many benefits, it also has the potential to significantly increase grid load and strain the power system. An imbalance between the supply and demand for power can cause instability in the system or power outages if these load changes are not correctly predicted. Conversely, efficient energy scheduling and management are two outcomes of reliable demand forecasting that contribute to the grid's capacity to incorporate renewable energy sources[3]. Nevertheless, there are still a lot of obstacles to overcome, even though EV charging load prediction technology are constantly improving[4]. There are notable spatiotemporal features to EV charging loads. While daily, seasonal, and holiday variations affect charging loads in the time dimension, charging demand varies by region in the spatial dimension, with notable distinctions between urban and suburban areas as well as between commercial and non-commercial areas. Large-scale EV deployment poses significant hurdles for regulators, power providers, and urban planners despite the fact that it promises a great deal of sustainability[5]. The hardest of them is predicting charging demand accurately given varied charging patterns and user behavior. When compared to the consistent use of fuel, the duration and frequency of electric car charging sessions might vary greatly over time, thereby putting sporadic strain on local power networks. Inadequate or unregulated forecasting has the potential to lead to infrastructure overinvestment, operational bottlenecks, and grid overload.

In this work, EV charging anomaly detection is formulated as a sequential decision-making problem over a knowledge graph. Each charging event is represented as a node with associated features, and relationships capture temporal and behavioral dependencies. An anomaly is defined as any significant deviation from normal charging patterns, including irregular energy consumption, abnormal charging duration, or unexpected temporal behavior. The objective is to enable the RL agent to identify such deviations by exploring relational paths within the graph.

The following section provides an overview of relevant research on detecting anomalies in electric vehicle charging behaviour. In Section 3, the KG-RL approach that our team intend to use is detailed. In Section 4, they display the outcomes of our experiments. Section 5 concludes our discussion.

## II. LITERATURE SURVEY

In this study, a technique based on load power flow is suggested to coordinate EV charging in order to minimize Transformer loss. A comparable method based on smart charging points is offered to flatten the load profile. Moreover, decentralized solutions may be employed in addition to centralized controller-based demand response strategies[6]. A distributed charging control approach that takes into account battery charging costs, ageing, and distribution Transformer energy loss is proposed by the authors. To lower peak load, the authors suggest a smart home energy management system that regulates EV charging schedules. Transformer overloading mitigation strategies based on active demand response could leave the end user uncertain about the charging pace and duration. The capacity of RL, a branch of machine learning, to acquire optimum decision policies by direct interaction with dynamic environments has garnered considerable interest as a crucial strategy for adaptive control[7]. RL is different from conventional methods in that it optimizes for cumulative rewards over the long term rather than requiring explicit modelling of system behavior. Use of this approach has been fruitful in a wide variety of settings impacted by complicated and unpredictable dynamics, including demand response, robotic navigation, building energy management, and traffic control. It seems that RL is especially useful in the EVCS sector because it can adjust to uncertainties like fluctuating electricity costs, unpredictable user behavior, and intermittent renewable generation. Because of its proficiency in managing complicated, multi-agent systems, it is also well-suited for control of EVCS, where a great deal of interdependent decision-making must occur in real time. A CNN was used to disaggregate the total power information and solve the non-intrusive load monitoring problem in the study. This methodology outperforms the proposed solutions in terms of energy disaggregation performance while taking less time[8]. By creating a load sample library for various types of loads, the study greatly increased the accuracy of the non-intrusive load monitoring algorithm. Nevertheless, EV were not considered in these analyses. In addition, the suggested load decomposition techniques are limited to disaggregating load data from residential buildings or residences.

Studies on EV load forecasting have fallen into one of two groups: one that stresses the use of deep learning and machine algorithms, and the other that uses more traditional statistical time series methods. A time series is a way to forecast a variable's future worth by looking at its historical data. A common statistical time series model used for load forecasting is ARIMA[9]. In order to predict the daily charging demand of EV parking lots, they utilized ARIMA. Due to the charging data's intrinsic sequential nature, traditional load forecasting methods, such as basic ANNs and statistical models, are likely to encounter difficulties[10]. On the other hand, recent developments in deep learning, particularly with LSTM networks, offer better prediction capabilities. LSTMs are built to selectively recall or discard material over time, preserving both short-term and long-term dependencies in sequential data. Speech recognition, predicting financial model specifications, and, most recently, analysis of energy systems is just a few of the numerous areas that have proven their worthwhile usage for time-series forecasting.

Recent studies have explored machine learning and deep learning approaches for EV charging prediction and anomaly detection, including LSTM-based forecasting, CNN-based load analysis, and reinforcement learning for energy management. However, most existing works focus on prediction accuracy or optimization strategies, with limited attention to relational reasoning and anomaly detection in complex interconnected systems. In particular, the integration of Knowledge Graphs with Reinforcement Learning for capturing relational dependencies and sequential decision-making remains underexplored. This research addresses this gap by proposing a hybrid KG–RL framework for intelligent anomaly detection in EV charging behavior.

There are three ways in which individuals contribute:

- ✓ When it comes to learning relational pathways in knowledge graphs, humans are the first to consider RL approaches;
- ✓ To improve control and flexibility in pathfinding, our learning method employs a complicated reward function that simultaneously measures efficiency, accuracy, and route diversity;
- ✓ By surpassing KG-RL embedding approaches in two tasks, researchers demonstrate that our method is capable of handling large-scale knowledge graphs.

## III. PROPOSED SYSTEM

In light of the anticipated energy consumption from EV batteries, this motivates organisations to establish numerous charging infrastructures. The majority of charging infrastructures use a CSMS for remote control of a network of interconnected charging behaviours. More functionality and intelligence can be added to the system through the use of IT and OT in these infrastructures. For example, EMSs can monitor charging profiles from external entities, enable online reservations, and accept payments through bank entities.

Hourly readings of 200 buildings' power meters taken over the course of a year make up our big training dataset[11]. There is an annotation that states whether a datapoint in the meter readings represents normal consumption (0) or abnormal usage (1). Your job is to use this training dataset to train your anomaly detection models, and then use those models to forecast whether a meter reading in the test dataset (which contains data from 206 more buildings) is abnormal (1) or normal (0).

The LEAD dataset was utilized as a proxy dataset for anomaly detection due to its high-resolution time-series energy consumption data with labeled anomalies. In our study, building-level energy patterns are used to approximate EV charging behavior, as both exhibit similar temporal variations, peak demand fluctuations, and anomalous patterns such as irregular spikes and drops. To improve clarity, we have revised the manuscript to explicitly state that this dataset is used for methodological validation and that the proposed KG–RL framework is generalizable to real-world EV charging datasets. Additionally, we have included a detailed description of typical EV charging datasets, including their sources, number of sessions, features (such as charging duration, energy consumption, timestamps, and station IDs), time span, and labeling approaches based on statistical thresholds and domain rules.

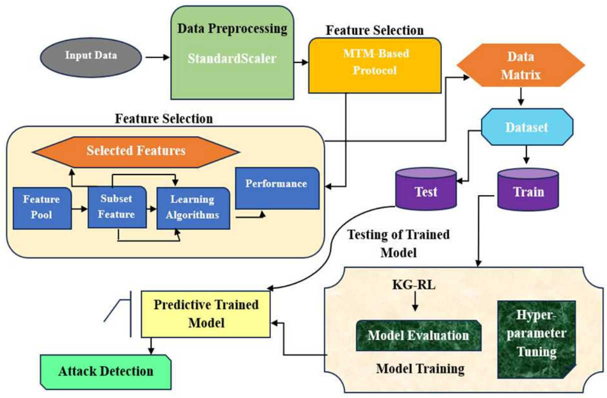


Fig. 1. Block Diagram Of Proposed Method

The suggested KG-RL is shown in Figure 1 as a flow diagram. Including both common disruptions and instances of cyberattacks, researchers will detail a methodical methodology to building the dataset and a suggested robust collection of feature vectors in the sections that follow[12]. In addition, the article delves into the topic of the suggested KG-RL extracted feature, feature selection through the wrapper technique, and training of the KG-RL model.

### *A. Data Preprocessing:*

The input data is preprocessed and the adaptive classification model is initialised in the second phase of the suggested system. This method makes sure the data is consistent and ready to be processed and that the classifier can handle real-time, dynamic network traffic[13]. The input features are standardised using the StandardScaler $S_{scaler}$. This scaler ensures that all features contribute equally to the model's learning process by transforming each feature in the input vector $c'$ to have zero mean and unit variance. Equation (1) defines the transformation.

$$c' = H_{scaler}(c) = \frac{c - \sigma}{\mu} \quad (1)$$

where $\mu$ is the feature's standard deviation and $\sigma$ is its mean throughout the dataset. In order to keep feature scaling inconsistencies from affecting the classifier's performance, the system normalises the data.

### *B. Feature Selection:*

In order to determine if an instruction is normal, the MTM-based protocol feature model follows and analyses the instruction frame of a historical protocol message, comparing it with the rules in the rule set[14]. The essential component of the message space's abnormal state diagram is the exception detection rule set generating module. It is an integral part of the model's data flow. According to equation (2), the Markov time-varying model can be used to represent the anomaly state diagram in the message space.

$$N = (H, h_0, E, R, K, Z, G) \quad (2)$$

where $H = \{h_0, h_1, \ldots, h_m\}$ is a non-empty set of states that defines the processes that the security protocol message goes through when conducting a non-abnormality investigation.

$H_0$: Initially, the non-abnormality analysis method is described in the initial state.

$K$: A group of statements that manipulate variables. It lays out the steps of the non-abnormality analysis process and the decisions that need to be made at each one.

$Z$: A collection of instructions that manipulates a variable. In order to set an assertion, it specifies which variables must be changed, for example, an execution counter plus one or zero.

$G$: During a non-abnormality study, a non-empty transition set is used to explain the state transition of a Markov time-varying model. It lays down the circumstances and outcomes of the transfer.

$$G = H \times E \times R \times K \rightarrow H \times E \times Z; \forall g_r \epsilon G, g_r = (h_{start}, r, k, z, h_{end}) \quad (3)$$

where the beginning and ending states of the transition $g_r$ are denoted by $h_{start}$ and $h_{end}$, respectively. The input primitive of the transformation $g_r$ is denoted by $r \epsilon R$. When the transition $g_r$ is executed, the predicate conditional expression denoted by $k \epsilon K$ must be satisfied. Equation (3) shows that when the transition $g_r$ is done, the action denoted by an $z \epsilon Z$ must be accomplished.

### *C. Model Training:*

The relation set might be rather extensive, which is a major barrier for KG reasoning in reality. The RL agent typically faces hundreds, if not thousands, of potential actions for a typical KG. A ten-policy network's output layer is, hence, quite dimensional. The relation graph is complex and the action space is huge, therefore the RL model will have poor convergence properties if trained directly by trial and error, as is usual of RL techniques. The agents have been trained for a long time, yet they still haven't found anything useful[15]. In order to address this issue, they begin our training with a supervised policy that takes inspiration from AlphaGo's imitation learning pipeline. Nearly 250 possible legal moves are presented to the player at each step of the Go game. Training the agent to select actions directly from the initial action space might be challenging. Using expert moves, AlphaGo trains a supervised policy network. Our supervised policy is taught via a BFS, which stands for randomised breadth-first search.

*1) Supervised Policy Learning:*

Our supervised policy learning process uses a subset of the positive samples for each relation. A two-side BFS is performed for every affirmative sample $(v_{source}, v_{target})$ in order to discover the same correct pathways between the entities. Using the Monte-Carlo Policy Gradient, they optimise the parameters $J$ for every path $k$ that has a succession of relations $i_1 \to i_2 \to \cdots \to i_m$. This maximises the expected cumulative reward is shown in equation $(4) - (5)$.

$$Q(\theta) = V_{z\sim\pi(z\backslash h;\theta)}\left(\sum\nolimits_{g} I_{h_g,z_g}\right) \quad (4)$$

$$= \sum_{g}\sum\nolimits_{z\epsilon Z} \pi(z\backslash h_g;\theta) I_{h_g,z_g} \quad (5)$$

where the expected grand prize for one episode is denoted by $Q(\theta)$. Each successful episode stage is rewarded with a $+1$ in supervised learning. Equation $(6) - (7)$ shows the approximated gradient used to update the policy network by adding the paths revealed by the BFS.

$$\nabla_\theta Q(\theta) = \sum_{g}\sum\nolimits_{z\epsilon Z} \pi(z\backslash h_g;\theta)\nabla_\theta log\, \pi(z\backslash h_g;\theta) \quad (6)$$

$$\approx \nabla_\theta \sum_{g} \log \pi(z = i_g\backslash h_g;\theta) \quad (7)$$

where the path $k$ includes $i_g$.

One search algorithm that favours short pathways is the vanilla BFS, though. The agent has a harder time finding longer paths that may be useful when they plug in these biassed paths. It is our intention for the pathways to be guided solely by the specified reward functions. A simple method involving adding random mechanisms to the BFS is used to prevent biassed search. Picking an intermediate node $v_{inter}$ at random and then performing two BFS between $(v_{source}, v_{inter})$ and $(v_{inter}, v_{target})$ allows us to avoid directly searching the path between $(v_{source}, v_{target})$. The agent is trained using the concatenated pathways. The agent can avoid wasting a lot of time trying to figure out what didn't work thanks to supervised learning. They teach the agent to seek out good routes using the experience it has gained.

*2) Retraining with Rewards:*

The supervised policy network is retrained using reward functions to discover the reasoning paths regulated by the reward functions. Each relation is considered to have its own episode when reasoning with a single entity pair. The agent's reasoning path begins at the source node $(v_{source})$ and continues through a relation chosen in accordance with the stochastic policy $\pi(z\backslash h)$ a probability distribution over all relations. A new entity could emerge from this relational relationship, or it could remain unchanged. Negative incentives will be handed to the agent as a result of these unsuccessful steps. The agent will remain in its current state following these unsuccessful actions. The agent will not become stuck due to accidentally repeating steps because it is pursuing a stochastic policy. With an upper bound max$_$ $length$, they restrict the episode length to enhance the training efficiency.

| **Algorithm 1: Algorithm for KG-RL** |
|---|
| Restore parameters $\theta$ from supervised policy; |
| **For** $episode \leftarrow 1toN$ **do** |
| Initialize state vector $h_g \leftarrow h_0$ |
| Initialize episode length $steps \leftarrow 0$ |
| **While** $num\_steps < \max\_length$ **do** |
| Randomly sample action $z\sim\pi(z\backslash h;\theta)$ |
| Observe reward $I_g$, next states $h_{g+1}$ |
| $if\ the\ step\ fails$ |
| **If** $I_g = 1$**then** |
| $Save < h_g, z > to\ N_{neg}$ |
| **If** $success\ or\ steps = \max\_length$ |
| **Then** |
| Break |
| $Increment\ num\_steps$ |
| $Penalize\ Failed\ Steps$ |
| Update $\theta$ using |
| $t \propto \nabla_\theta N_{neg} \log \pi(z = i_g\backslash h_g;\theta)\,(-1)$ |
| If $success$ then |
| $I_{total} \leftarrow \rho_1 i_{GLOBAL} + \rho_2 i_{EFFICIENCY} + \rho_2 i_{DIVERSITY}$ |
| Update $\theta$ using |
| $t \propto \nabla_\theta \log \pi(z = i_g\backslash h_g;\theta) I_{total}$ |

There will be no more episodes unless the agent reaches the target entity in the allotted time. The policy network is modified after each episode using the gradient provided in equation (8).

$$\nabla_\theta Q(\theta) = \nabla_\theta \sum_{g} \log \pi(z = i_g\backslash h_g;\theta)\, I_{total} \quad (8)$$

where the defined reward functions are linearly combined to form $I_{total}$. Algorithm 1 shows the KG-RL process in detail. The Adam Optimiser with $O_2$ regularisation is used to update $\theta$ in practice.

## IV. Result and Discussion

Infrastructural issues are multiplying in response to the burgeoning EV market. One difficulty is that it necessitates the extensive construction of EV charging stations, which need to be capable of delivering massive amounts of power on demand. This can put a lot of strain on the charging infrastructure's electrical and electronic parts, which can reduce their reliability and increase the expenses of operation and maintenance. In order to aid with the condition monitoring and predictive maintenance of the power converters used in EV charging stations, this research presents a data-driven approach for anomaly identification that is human-interpretable.

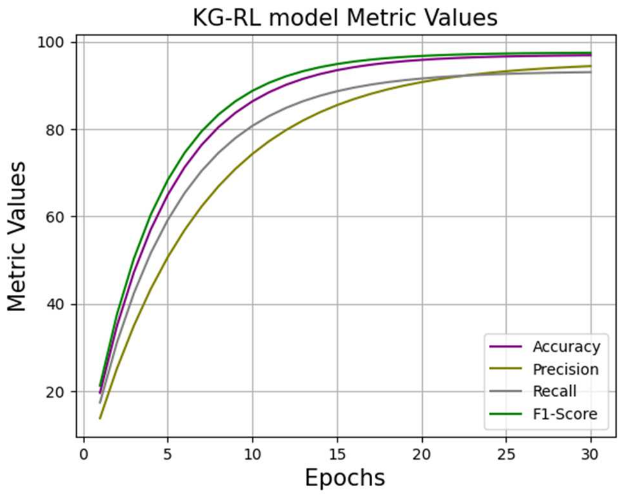


Fig. 2. KG-RL Model Metric Values

Figure 2 shows how well the KG-RL model did throughout 30 epochs. It shows that Accuracy, Precision, Recall, and F1-Score all steadily increased and came near to 100%. This shows that learning is quite effective and that the capacity to detect things becomes better with each training iteration.

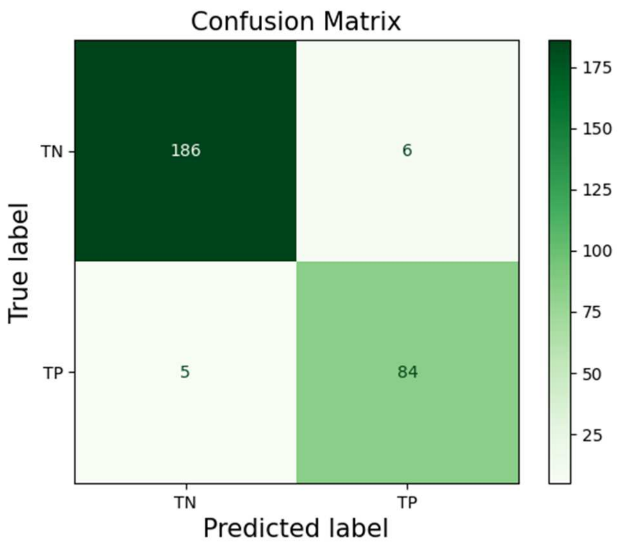


Fig. 3. Confusion Matrix

Figure 3 illustrates a confusion matrix that shows how well the model works. It shows that the model is accurate with very few misclassifications: 186 true negatives, 84 true positives, 6 erroneous positives, and 5 false negatives.

TABLE I. PERFORMANCE COMPARISON

| Models | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|
| **KG-RL** | **96.38** | **94.82** | **92.62** | **96.89** |
| **KG** | 83.45 | 81.79 | 79.52 | 83.72 |
| **RL** | 94.12 | 92.48 | 90.69 | 94.89 |
| **DQN** | 87.24 | 85.86 | 83.72 | 87.74 |

The performance of the proposed KG-RL approach is compared to that of RL, DQN, and KG in Table 1. When compared to competing models, our suggested KG-RL model outperforms them all with a 96.38% accuracy, 94.82% precision, 92.62% recall, and a 96.89% F1-Score.

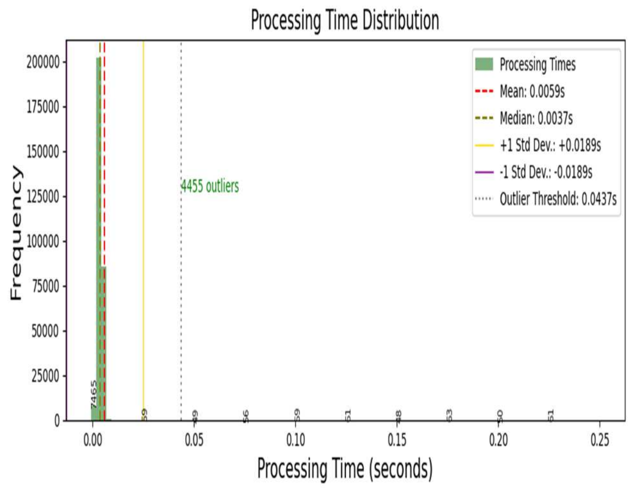


Fig. 4. Processing Time Distribution

Figure 4 shows the distribution of processing times, which shows that the system is quite efficient with a median of 0.0030 s and an average of 0.0037 s. With just 3492 cases going over the specified outlier threshold of 0.0192 s, most examples are processed inside this range.

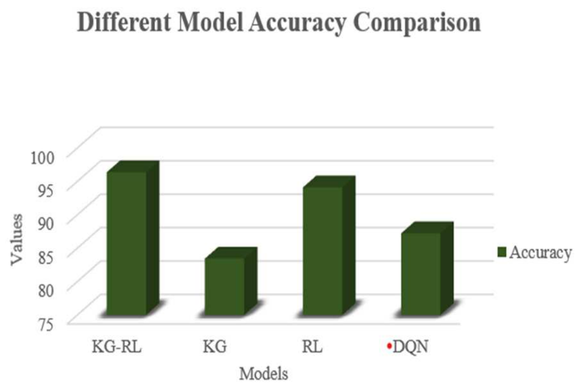


Fig. 5. Different Model Accuracy Comparison

Figure 5 displays a comparison of the accuracy of four different models, including KG-RL, KG, RL, and DQN. With an accuracy of 96.38%, our suggested model outperforms the competition.

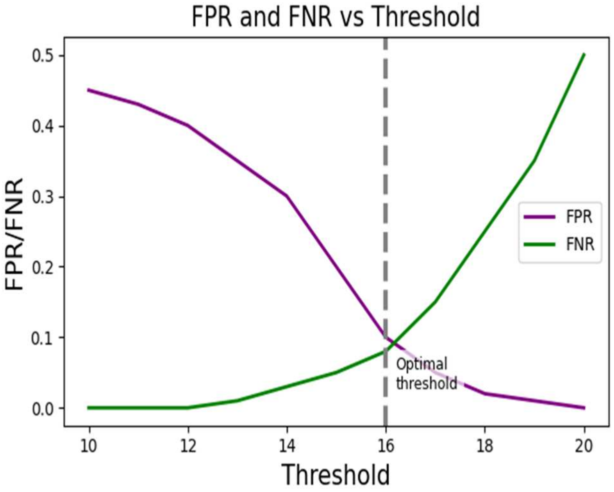


Fig. 6. FPR and FNR vs Threshold

The effect of changing the threshold parameter on the performance of the KG-RL model is shown in Figure 6. The optimal threshold in this case is 16.1, however increasing the threshold has raised the FPR and decreasing it has raised the FNR.

The computational complexity of the proposed model depends on the size of the knowledge graph and the action space of the RL agent. As the number of nodes and relationships increases, the search space grows significantly. However, the use of supervised pretraining and optimized policy learning improves convergence efficiency. While training may be computationally intensive, the inference phase is relatively lightweight, making the model suitable for near real-time deployment in EV charging systems.

## V. Conclusion

Congestion at charging stations has become a key issue due to the surge in EV adoption, demanding improvements to the EVCI to facilitate fast and secure charging. The integration of digital communication with physical charging systems makes EVCI a CPPS. This makes it susceptible to cyberattacks, which can lead to unauthorised data access, energy theft, and financial discrepancies. For example, the EVCI operator could end up paying too much for consumed energy, or EV owners could end up paying too much for power that wasn't actually used. The acquired data from charging sessions is normalised using StandardScaler, and important behavioural aspects are retrieved using an MTM-based procedure in order to identify such EV charging behaviour anomalies. This study presents a new paradigm for KG driven by RL, in which RL agents are taught to intelligently travel relational paths in order to detect abnormal charging behaviours. This method maximises accuracy, efficiency, and path diversity through a tailored reward mechanism, unlike classic random-walk-based pathfinding. It also allows for controlled and adaptive reasoning. An impressive 96.38% accuracy was attained by the suggested KG-RL anomaly detection framework, proving its efficacy in spotting fraudulent and unusual behaviours in EV charging environments.

## References

[1] Y. Li, Y. Huang, and M. Zhang, "Short-term load forecasting for electric vehicle charging station based on niche immunity lion algorithm and convolutional neural network," *Energies*, vol. 11, no. 5, 2018, doi: 10.3390/en11051253.

[2] H. Zhou *et al.*, "LSTM-based Energy Management for Electric Vehicle Charging in Commercial-building Prosumers," *J. Mod. Power Syst. Clean Energy*, vol. 9, no. 5, pp. 1205–1216, 2021, doi: 10.35833/MPCE.2020.000501.

[3] R. Shang and Y. Ma, "Electric Vehicle Charging Load Forecasting Based on K-Means++-GRU-KSVR," *World Electr. Veh. J.*, vol. 15, no. 12, 2024, doi: 10.3390/wevj15120582.

[4] K. B. N. K. Reddy, G. Abhishek, M. Muthaiah, V. Nagendra, and B. Thanooja, "Optimizing Energy Management for Hybrid Renewable Energy Electric Vehicle Charging Stations Using Convolutional LSTM Models," *3rd Int. Conf. Integr. Circuits Commun. Syst. ICICACS 2025*, pp. 1–6, 2025, doi: 10.1109/ICICACS65178.2025.10968573.

[5] C. Xie, "Predicting Electric Vehicle Charging Behavior: Integrating Clustering Analysis and LSTM Networks," *Predict. Electr. Veh. Charg. Behav. Integr. Clust. Anal. LSTM Networks*, no. 2720477, pp. 1–30, 2025.

[6] A. Jain and M. Karimi-Ghartemani, "Mitigating Adverse Impacts of Increased Electric Vehicle Charging on Distribution Transformers," *Energies*, vol. 15, no. 23, 2022, doi: 10.3390/en15239023.

[7] P. Michailidis and I. Michailidis, "Reinforcement Learning for Electric Vehicle Charging Management: Theory and Applications," *Energies*, pp. 1–50, 2025.

[8] Y. Yin, B. Xu, Y. Zhong, T. Bao, and P. Wang, "A Non-Intrusive Load Monitoring Model for Electric Vehicles Based on Multi-Kernel Conventional Neural Network," *World Electr. Veh. J.*, vol. 14, no. 2, pp. 1–13, 2023, doi: 10.3390/wevj14020051.

[9] S. Koohfar, W. Woldemariam, and A. Kumar, "Prediction of Electric Vehicles Charging Demand: A Transformer-Based Deep Learning Approach," *Sustain.*, vol. 15, no. 3, 2023, doi: 10.3390/su15032105.

[10] K. A. Sharada, A. Kathiravan, P. Mannam, D. Akila, B. Suresh Kumar, and V. V. Godase, "Advanced Neural Network Models for Optimal Energy Management in Microgrids with Integrated Electric Vehicles," *Proc. 5th Int. Conf. Trends Mater. Sci. Inven. Mater. ICTMIM 2025*, pp. 1869–1874, 2025, doi: 10.1109/ICTMIM65579.2025.10988248.

[11] "Large-scale Energy Anomaly Detection (LEAD) | Kaggle." Accessed: Oct. 17, 2025. [Online]. Available: https://www.kaggle.com/competitions/energy-anomaly-detection/data

[12] A. Hussain, A. Yadav, and G. Ravikumar, "Anomaly Detection Using Bi-Directional Long Short-Term Memory Networks for Cyber-Physical Electric Vehicle Charging Stations," *IEEE Trans. Ind. Cyber-Physical Syst.*, vol. 2, pp. 508–518, 2024, doi: 10.1109/ticps.2024.3437349.

[13] F. Makhmudov, D. Kilichev, U. Giyosov, and F. Akhmedov, "Online Machine Learning for Intrusion Detection in Electric Vehicle Charging Systems," *Mathematics*, vol. 13, no. 5, pp. 1–28, 2025, doi: 10.3390/math13050712.

[14] Q. Li, S. Meng, S. Wang, J. Zhang, and J. Hou, "CAD: Command-Level Anomaly Detection for Vehicle-Road Collaborative Charging Network," *IEEE Access*, vol. 7, pp. 34910–34924, 2019, doi: 10.1109/ACCESS.2019.2904047.

[15] W. Xiong, T. Hoang, and W. Y. Wang, "DeepPath: A reinforcement learning method for knowledge graph reasoning," *EMNLP 2017 - Conf. Empir. Methods Nat. Lang. Process. Proc.*, pp. 564–573, 2017, doi: 10.18653/v1/d17-1060.