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Efficient Electric Vehicle Fleet Management in Smart Cities: A Hybrid Deep Learning Approach for Charging Load Forecasting and Route Optimization

Diego Morales^{1*}, Andres Gutierrez¹, Lucia Navarro², Pablo Rios¹

Abstract

Swift technological progress has heightened the importance of managing charging demand and refining travel routes for electric vehicle (EV) fleets, particularly in urban settings. Sensors based on IoT, embedded in charging stations and vehicles, supply live information about driver charging routines, road congestion, vehicle positioning, and surrounding conditions—greatly strengthening forecasting and optimization techniques. This continuous stream of IoT data powers the combined deep learning architecture, GNN-ViGNet, to predict upcoming EV charging requirements. An analysis of readings from 400,000 IoT devices distributed across charging points and EVs in Texas was performed to reveal typical charging behavior. These devices continuously log key indicators, including user charging preferences, current traffic levels, and diverse external conditions. Data refinement was achieved through Frequency-Aware Dynamic Range Scaling, together with sophisticated preprocessing techniques including Categorical Encoding. Ultimately, the GNN-ViGNet framework delivered a prediction accuracy of 98.9%. Beyond conventional metrics such as Root-Mean-Square Error (RMSE) and Mean Squared Error (MSE), the research introduced the Forecast Accuracy Rate (FAR) and the Charging Load Variation Index (CLVI) to provide a more comprehensive evaluation of predictive capability. The work introduces both an advanced forecasting system and a novel hybrid Coati–Northern Goshawk Optimization (Coati–NGO) technique designed for route planning. Real-time route modifications become possible thanks to live IoT feeds that include congestion updates, vehicle coordinates, and remaining battery capacity. The Coati–NGO algorithm combines the broad search strength of Coati Optimization (COA) with the refined exploitation strength of Northern Goshawk Optimization (NGO). Compared against Particle Swarm Optimization (919 km) and the Firefly Algorithm (914 km), it substantially reduced the total distance traveled to 511 km. Moreover, this combined method exhibited quicker convergence, consistently locating high-quality solutions by the 100th iteration. Overall, the presented EV fleet management system leverages continuous IoT inputs to improve charging network performance, reduce operating expenses, and enhance operational effectiveness—delivering an adaptable, realistic framework suitable for city-wide electric mobility.

Keywords Smart cities, Deep learning, EV charging load forecasting, Route optimization, Hybrid optimization algorithm, Dynamic fleet management

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Introduction

Electric vehicles (EVs) continue to see strong uptake across the mobility and energy industries, driven by accelerating growth [1]. This rising presence creates significant difficulties in organizing charging facilities and efficiently distributing electrical power to extensive commercial fleets. IoT-enabled sensors placed at charging locations and inside vehicles deliver real-time insights into charging usage patterns, electricity consumption, current vehicle location, and surrounding traffic. By feeding these IoT-derived measurements into cutting-edge prediction engines and path-planning routines, overall EV fleet effectiveness can be markedly improved. Approaches that harness IoT data to guide charging operations and itinerary design help reduce total energy expenditure, cut operating costs, and lessen environmental harm. EVs support cleaner transportation by reducing fuel consumption and lowering exhaust emissions. With worldwide EV numbers steadily climbing, national programs—such as those in the United States—are expanding rapidly, and millions of electric vehicles are already in use in city transportation systems [2]. Large-scale simultaneous charging from extensive fleets places considerable stress on electrical grids, triggers sharp swings between peak and off-peak demand, and risks destabilizing power distribution systems [3]. Thanks to real-time IoT data from vehicles and charging infrastructure, utility companies can observe consumption trends, anticipate peak demand, and dynamically reconfigure networks to maintain system balance. Because traffic patterns and weather variables make driver behavior difficult to anticipate, highly reliable load-prediction tools are indispensable. Accurate forecasting supports better integration of EVs into existing grids, raises fleet productivity, and informs future infrastructure investments [4]. Both municipal transport networks and electricity grids depend on dependable models that capture the time-varying and location-specific nature of EV charging needs—models that rely on ongoing streams of information about driver habits, station occupancy, and ambient conditions collected through IoT networks.

Smart-city designs paired with widespread IoT deployment have begun tackling many of these concerns. In smart-city environments, IoT-connected infrastructure and services generate massive datasets that support city development and resident well-being. Nevertheless, fusing and interpreting data from disparate origins remains technically demanding. Real-time aggregation of IoT measurements from transportation corridors significantly refines projections of EV charging requirements. It informs strategic decisions about charging infrastructure expansion—including the deployment of extensive battery-replenishment facilities [5]. By consolidating IoT data effectively, systems can produce precise estimates and support immediate operational adjustments, paving the way for scalable, high-performance EV fleet coordination. IoT technology also markedly enhances fleet productivity by enabling adaptive path planning. Combining IoT capabilities with cyber-physical frameworks (CPS) has already delivered gains in logistics productivity and long-term viability [6]. When IoT is paired with intelligent algorithms—such as the Hybrid Firefly–Swarm Hybrid Optimization (HFSHO)—it becomes possible to optimize itinerary creation, vehicle assignment, and overall fleet coordination.

In the same way, IoT-supported route planning empowers electric vehicles to follow the most energy-thrifty paths while responding to immediate charging requests and prevailing grid constraints. Legacy methods for route calculation and demand estimation increasingly fall short as EV operations become more complex. The majority of current charging load models limit their scope to aggregate load profiles and overlook important spatial and temporal shifts in demand—factors that are essential when engineering Battery Charging Control Systems (BCCSs) and Battery Delivery Systems (BDSs) [7]. While BCCSs manage the charging power rate, BDSs enable rapid battery swapping for users with negligible impact on grid stability. Together, these technologies ease pressure on electrical networks, streamline energy allocation, and accelerate acceptance of electric vehicles in metropolitan regions. Developing dependable spatial-temporal forecasting models is therefore critical for maximizing the performance of these systems and achieving balanced energy distribution across urban areas [8].

A large number of models have been proposed in recent years for forecasting EV charging demand. Nevertheless, a substantial portion of them fail to account for EV users' actual driving and charging behaviors. Conventional forecasting approaches often overlook traffic-related delays and various environmental factors, both of which significantly influence charging patterns [9]. In addition, many existing models rely on fixed assumptions about charging locations and schedules, which fail to capture the inherently dynamic and probabilistic characteristics of real-world EV usage [10]. More advanced techniques address these shortcomings by incorporating stochastic travel chains, Monte Carlo simulations, and Markov decision processes. By introducing randomness, these models generate more realistic projections of charging

demand [11]. Despite their improvements, even these sophisticated models suffer from notable limitations. A common drawback is their neglect of how traffic congestion and ambient temperature impact EV range and energy consumption. Given the strong interdependence between the transportation network and the power distribution system, it is vital to model these influences when analyzing EV charging demand explicitly [12]. The spatial placement of charging stations further shapes grid load, prevailing vehicle usage patterns, and the presence of distributed generation resources such as solar photovoltaics. Therefore, integrating these elements into load forecasting models is essential for effective planning and operation of charging infrastructure [13]. The present study introduces an IoT-based algorithm that estimates EV charging demand while simultaneously optimizing fleet routes in real time. By harnessing the vast streams of data generated by IoT devices, the system can dynamically respond to evolving charging requirements and traffic conditions, thereby improving overall energy efficiency and reducing adverse effects on the grid [14]. Ultimately, the proposed framework aims to predict charging needs and optimize routing decisions to ensure energy consumption aligns with both grid constraints and fleet operational demands.

Managing electric vehicle fleets is inherently challenging due to highly variable charging requirements and unpredictable traffic situations. The integration of IoT data with artificial intelligence techniques represents a transformative solution to these difficulties. Real-time inputs from charging stations, traffic monitoring systems, and onboard vehicle sensors, when combined with state-of-the-art optimization algorithms and predictive models, can significantly enhance operational efficiency, reduce energy consumption, and simplify route planning. The developed IoT-enabled technology for EV charging management and route optimization delivers multiple advantages: it enhances the accuracy and responsiveness of demand forecasting, helping mitigate peak loads and bolstering grid stability. Furthermore, continuous route optimization reduces the EV fleet's overall energy consumption, lowers operating expenses, and improves service delivery. Such capabilities are particularly valuable for cities seeking to establish sustainable, environmentally responsible transportation systems.

The current research provides several important contributions. Novel approaches are introduced to tackle both EV charging load prediction and route optimization. A hybrid regression model, GNN-ViGNet, is developed by combining Graph Neural Networks (GNNs), VGGNet, and Inception architectures, achieving markedly improved accuracy in forecasting EV charging loads. By capitalizing on the strengths of these individual architectures, the model achieves superior performance across critical evaluation criteria compared with earlier methods. To better assess the model's robustness, two new performance indicators are proposed: the Charging Load Variance Index (CLVI) and the Forecast Accuracy Rate (FAR). These metrics specifically measure the model's effectiveness in managing large load fluctuations and reducing prediction errors. In addition, innovative feature engineering techniques have been developed better to capture the complex nature of EV charging behavior. Four newly defined features—Effective Charging Rate (ECR), Charging Demand Index (CDI), Weather Impact Score (WIS), and Peak Hour Indicator (PHI)—are incorporated to enhance predictive precision and deliver richer operational insights. For route optimization under dynamic conditions, a Hybrid Coati–Northern Goshawk Optimization (Coati–NGO) algorithm is presented. This algorithm effectively balances global search capabilities with local refinement, enabling superior performance in real-world EV fleet routing scenarios. When benchmarked against conventional optimization methods, the combination of GNN-ViGNet and Coati–NGO demonstrates higher accuracy, reduced error rates, and faster convergence when solving dynamic charging and routing problems.

Successful optimization of coupled transportation and power systems requires careful consideration of practical constraints, including available grid capacity, peak demand limits, and the integration of renewable energy sources. This interdependence between EV fleet operations and power grid stability underscores the need for a comprehensive dual-optimization approach, which can be built on the methodological foundation laid by this work.

Related Work

The widespread adoption of electric vehicles (EVs) has introduced significant new challenges for both transportation networks and power grids, particularly concerning charging infrastructure management and fleet route optimization. To address these issues, two primary research directions have gained prominence: EV charging load forecasting, which aims to predict charging station demand to help balance grid load, and optimal pathfinding, which seeks to determine the most efficient routes for EV fleets while accounting for charging requirements and real-time grid stability. Accurate projections of EV charging demand are fundamental to improving charging times and locations, thereby reducing peak loads and enabling better placement of charging stations. Similarly, EV fleets require optimal routing strategies to minimize energy consumption and travel time while ensuring timely access to charging facilities. Effective route optimization must incorporate real-time information on charging availability and grid conditions, whereas load forecasting must adequately capture the dynamic behavior of EV fleets. This literature review examines key methods, achievements, and shortcomings in EV charging load forecasting and optimal route finding. The following subsections discuss the relevant studies and methodologies in these fields.

EV charging load forecasting

Recent studies on EV charging load forecasting have highlighted the critical need for accurate estimation of EV energy consumption to maintain power grid stability and optimize supporting infrastructure. In the study by Ahmadian *et al.* [15], the authors proposed an EV load forecasting model focused on vehicle energy consumption and driver behavior patterns. The model was primarily built on historical charging records and struggled to capture spatiotemporal variations in charging demand, limiting its applicability in dynamic urban environments.

A forecasting approach for EV charging stations was presented in a study by Saxena *et al.* [16], by combining traffic flow data with energy consumption statistics. This integration improved load predictions by accounting for real-time charging activities. However, the model did not consider meteorological factors that strongly influence EV charging demand. In a study by Wang *et al.* [17], an advanced spatiotemporal forecasting technique was introduced to analyze the geographic spread of EV charging demand. While it offered a more comprehensive view of charging-station usage across different areas, further validation was needed to confirm its scalability for larger, more complex metropolitan power grids.

Customer-specific charging profiles were employed in a study by Milis *et al.* [18] to enhance prediction accuracy by reflecting individual user habits. Nevertheless, the study failed to incorporate broader system-level influences, such as the contribution of distributed generation (DG) sources, such as photovoltaics, to overall grid demand. The work by He *et al.* [19] stressed the importance of integrating BCCS and BDS within forecasting frameworks. The proposed system helped optimize charging loads for large-scale operations. Yet, it could not handle real-time fluctuations, which are essential in highly dynamic urban networks with rapidly changing EV demand.

Morais *et al.* [20] applied a Monte Carlo simulation-based method to model the stochastic characteristics of EV charging requests. The authors emphasized that load forecasting tools must properly account for random driving patterns and environmental variables. Although the approach yielded more reliable forecasts, its high computational demands limited its suitability for real-time applications. In Saidani *et al.* [21], a mathematical model was developed for short-term load forecasting at EV charging stations, targeting the aggregated demand of electric buses. Due to its narrow focus on electric buses, the model showed limited relevance for diverse EV types exhibiting different charging behaviors.

A hybrid deep learning model based on a transformer architecture was introduced by Han *et al.* [22] to improve load forecasting precision. While the model demonstrated strong accuracy, its lengthy training process and heavy computational requirements made it impractical for real-time deployment. Rashid *et al.* [23] attempted to predict plug-in EV demand based on consumer preferences and historical data. The analysis assumed a gradual transition from internal combustion engine vehicles to EVs; however, it lacked real-time adaptability and did not adequately address short-term fluctuations in EV demand.

Optimal pathfinding

As EV adoption continues to grow, effective route optimization for EV fleets has become a vital research area. In a study by Daouda and Atila [24], the Tabu Search Algorithm was applied to solve the Vehicle Routing Problem (VRP), demonstrating good performance in avoiding local optima within logistics operations. However, the study did not evaluate the algorithm under real-time traffic and grid conditions, both of which are critical for practical EV fleet routing.

A modified version of the Ant Colony Optimization (ACO) algorithm was proposed by Wu *et al.* [25] for logistics pathfinding. The method enhanced global exploration and local route optimization. Although it successfully shortened route durations, the algorithm was susceptible to premature convergence, especially when scaled to large EV fleets. In a study by Ran *et al.* [26], a hybrid approach combining K-means clustering with a genetic algorithm (GA) was used to optimize logistics pathways. The model performed well in static route planning but could not dynamically adjust routes in response to real-time EV charging demands and grid status, which are indispensable for efficient fleet management.

A Social Spider Optimization (SSO) technique was introduced by Selvarajan [27] to improve logistical routing by imitating spider foraging behavior. Despite its novel inspiration, the study did not provide comparative evaluations against other established algorithms, thereby limiting its demonstrated value for EV fleet applications. In a study by Alqahtani and Kumar [28], the Gray Wolf Optimizer (GWO) was shown to achieve a strong balance between exploration and exploitation in solving the VRP. Nevertheless, the research did not address the specific requirements of dynamic route planning for electric vehicle fleets, which must simultaneously minimize energy consumption and strategically schedule charging stops.

The Enhanced Firefly Algorithm, as described by Li *et al.* [29], was applied to the Vehicle Routing Problem (VRP) with time windows. It achieved a good balance between route optimization and time management. However, the approach did not incorporate real-time EV charging requirements, which represents a major shortcoming given the critical need for dynamic route adjustments based on charging station availability.

In the domain of green logistics, Alshammari *et al.* [30] proposed an Enhanced Artificial Bee Colony (ABC) algorithm that accounted for environmental factors, such as emissions and energy efficiency. Nevertheless, the model did not fully explore EV-specific route-optimization aspects, particularly the strategic placement of charging-station stops and the reduction of emissions.

A Hybrid Particle Swarm Optimization (PSO) method was introduced by Chauhan [31] to solve a multi-objective VRP. The authors considered both charging constraints and route length limitations. Although the system demonstrated strong performance in route planning, it proved unreliable when applied to large-scale EV fleets operating under frequent and highly dynamic routing and charging conditions.

A Hybrid Genetic Algorithm (GA) combined with Particle Swarm Optimization (PSO) was presented by Younespour *et al.* [32] to handle various logistical constraints. This method performed effectively in route optimization but failed to account for the stochastic nature of EV charging demand, which is essential for real-time fleet management. A summary of the reviewed literature is provided in Table 1.

Table 1. Literature review summary.

Ref	Technique	Objective achieved	Limitations
[15]	Forecasting EV load through energy use patterns	Analyzed vehicle energy consumption and driver behavior	Did not account for variations in demand over time or space
[16]	Model integrating traffic data and energy patterns	Improved load forecasts by including real-time driving behavior	Did not include external factors such as weather
[17]	Spatial-temporal demand	Mapped geographic variations in EV	Required additional tests for

	forecasting	charging demand	scalability
[18]	Charging profiles based on customer data	Enhanced forecast accuracy by tailoring predictions to individual customers	Did not consider the larger impact of distributed generation
[19]	BCCS and BDS integration in forecasting models	Optimized charging load management for larger operations	Lacked dynamic adjustments for real-time load changes
[20]	Monte Carlo method for modeling demand variability	Factored in unpredictable driving behaviors and environmental factors	Demanded high computational power
[21]	Short-term load forecasting using mathematical models	Provided aggregated forecasts for electric bus fleets	Focused solely on buses, limiting broader use
[22]	Hybrid AI and transformer models	Boosted forecasting accuracy with advanced AI techniques	Prolonged training times hindered real-time application
[23]	Forecasting based on historical data and preferences	Predicted EV charging demand based on past consumer behavior	Lacked flexibility for immediate, short-term adjustments
[24]	Tabu Search for vehicle routing optimization	Helped avoid local optima in logistics routing	Did not consider real-time conditions like traffic or grid load
[25]	Improved Ant Colony Optimization (ACO) algorithm	Enhanced balance between global search and local optimization	Tended to converge prematurely in large-scale operations
[26]	GA combined with K-means clustering for logistics	Optimized routes but lacked dynamic responses to changing conditions	Could not adjust to real-time grid demands
[27]	Social Spider Optimization (SSO) for logistics	Used spider-like behavior to optimize routing	No comparison to other algorithms for context
[28]	Gray Wolf Optimizer (GWO) for vehicle routing	Balanced exploration and exploitation for EV routing	Did not address EV-specific requirements like energy usage
[29]	Firefly Algorithm with time constraints for VRP	Focused on optimizing both routes and time management	Did not incorporate real-time charging needs
[30]	Artificial Bee Colony (ABC) for green logistics	Optimized green logistics with environmental considerations	Did not address charging stops or minimize emissions
[31]	Hybrid PSO for logistics with multiple constraints	Optimized logistics considering route length and charging needs	Lacked adaptability for large-scale fleet operations
[32]	Hybrid GA and PSO for multi-constraint logistics	Handled multiple logistics constraints effectively	Did not consider the unpredictable nature of EV charging

Limitations and gaps in existing research

Although substantial research has been conducted on EV charging load forecasting and optimal pathfinding for EV fleets, several important gaps persist and require further attention. Many existing forecasting algorithms still overlook real-time data streams and external factors, such as weather, traffic, and grid fluctuations. Although studies such as those by Ahmadian *et al.* [15] and Saxena *et al.* [16] have improved load prediction accuracy by integrating traffic and energy usage information, they generally fail to account for dynamic factors, such as weather, which are necessary for achieving more reliable and adaptable forecasts in practical scenarios. In large, complex urban environments, the scalability of these models remains problematic and requires additional validation, as demonstrated by the spatial-temporal forecasting technique by Wang *et al.* [17].

Models developed for specific vehicle types, such as electric buses, often lack applicability to broader fleets of electric automobiles that exhibit varied charging behaviors [21]. This limited generalizability restricts their usefulness across diverse EV fleets. Furthermore, most forecasting approaches tend to undervalue the role of distributed generation (DG) sources such as solar and wind power. As the integration of renewable energy into EV charging systems continues to expand, many studies based on user profiles neglect the significant impact of DG on grid stability and overall charging demand [18].

While metaheuristic algorithms, including Ant Colony Optimization (ACO), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), have shown promise in route optimization, research such as that by Wu *et al.* [25], Ran *et al.* [26], and Chauhan [31], indicates that these techniques are insufficiently robust for handling large, dynamic EV fleets, primarily due to issues like premature convergence. A common deficiency across many models is the lack of real-time adaptability, which prevents them from adjusting routes in response to evolving EV charging needs and grid constraints. Additionally, several optimization methods prioritize general logistical or temporal objectives while disregarding EV-specific challenges, such as energy consumption and optimal selection of charging stations.

Numerous optimization techniques, including those by Li *et al.* [29] and Alshammari *et al.* [30], primarily focus on minimizing route length and travel duration but pay insufficient attention to EV-related requirements, such as real-time charging availability and energy efficiency. These shortcomings underscore the need for more comprehensive models that simultaneously optimize routing decisions and account for the stochastic nature of EV charging demand, as sudden variations can significantly impair fleet performance. Therefore, although previous studies have established a solid foundation, critical aspects such as real-time flexibility, scalability, and the integration of external variables must be addressed to advance EV fleet management systems.

Materials and Methods

This study introduces a comprehensive framework for forecasting the charging demand of IoT-supported electric vehicles and simultaneously optimizing dynamic fleet routes by combining advanced machine learning models with efficient optimization algorithms. IoT sensors installed at charging stations and on electric vehicles continuously capture live data on charging behavior, power usage, and prevailing traffic conditions. The resulting dataset, composed of 26 distinct features, enables highly accurate predictions and customized optimizations tailored to Texas's EV ecosystem. To prepare the data for modeling, several preprocessing steps are applied, namely Dynamic Range Scaling, Frequency-Informed Categorical Encoding, and Temporal Dynamics Aggregation. An Adaptive Sampling and Synthetic Generation (ASSG) technique is used to address class imbalance and achieve more balanced category distributions. Feature selection is performed using the Integrated Feature Selection Framework (IFSF), in which the Statistical-Driven Rank Selector (SDRS) and Adaptive Search Optimization (ASO) work together to rank variables effectively and eliminate redundant ones. Two newly designed indicators — Effective Charging Rate (ECR) and Charging Demand Index (CDI) — are incorporated into the prediction process to boost accuracy further. The central forecasting engine, named GNN-ViGNet, merges Graph Neural Networks with VGGNet and Inception architectures. This hybrid design enables sophisticated relational learning and multi-scale feature analysis, with relational insights derived from IoT data playing a key role in improving charging load estimates. Performance of the forecasting component is measured using both standard and newly proposed evaluation criteria, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), DLD, and Predictive Variability Index. For the route optimization task, a novel Hybrid Coati–Northern Goshawk Optimization (Coati–NGO) algorithm is developed. The algorithm draws on real-time IoT data, including GPS positions, current battery status, and traffic updates, to identify the most efficient travel paths. By blending the broad search strengths of the Coati Optimization Algorithm (COA) with the precise local tuning capabilities of Northern Goshawk Optimization (NGO), the hybrid approach consistently outperforms established methods like PSO, Firefly, and ACO in electric fleet applications, producing shorter routes and achieving faster convergence. Taken together, this integrated solution delivers dependable charging-demand forecasts alongside practical, realistic route planning. Each component is explained in detail in the subsections that follow, and the overall system architecture is illustrated in [Figure 1](#).

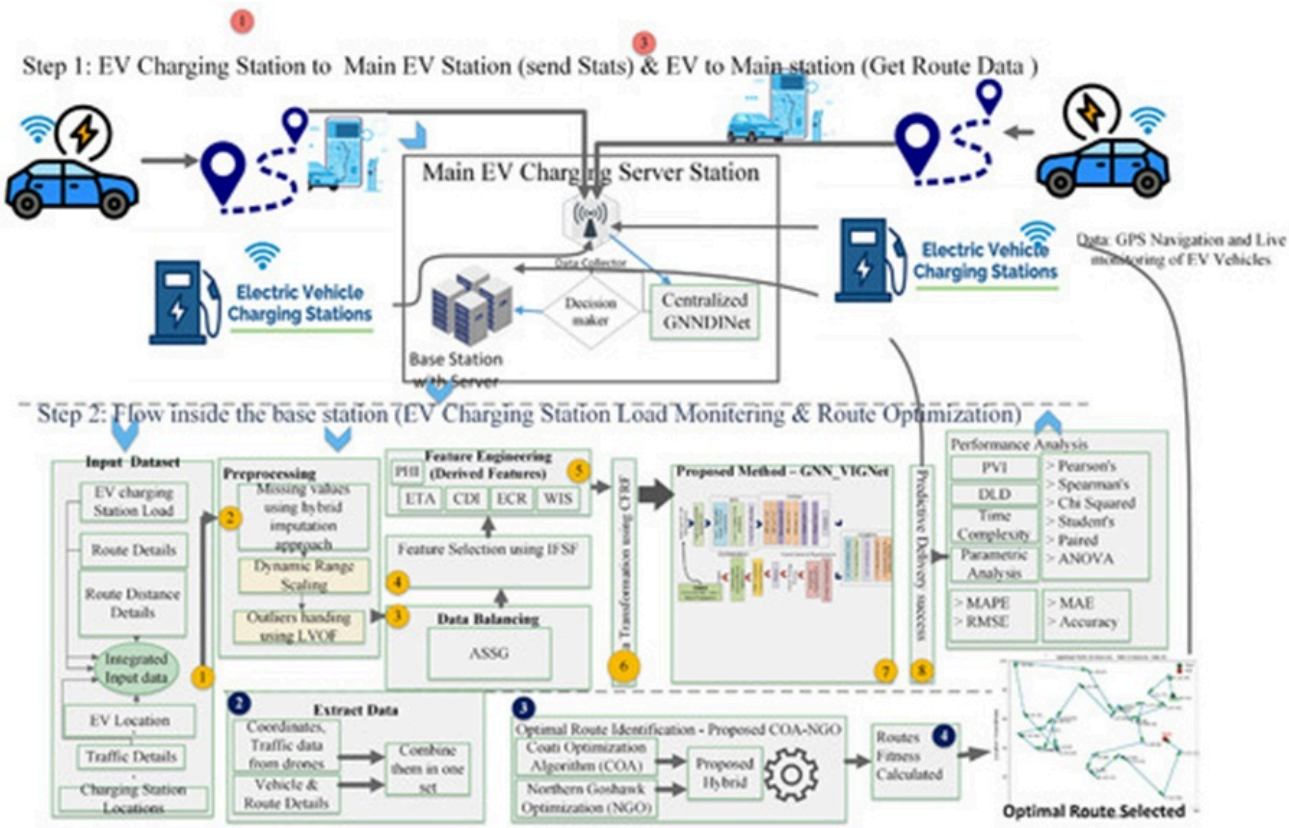


Figure 1. Proposed framework.

Dataset description

The research is grounded in actual EV charging records collected in Texas, with particular focus on the Dallas metropolitan region. The primary dataset used throughout this work is publicly available on Kaggle [33]. Containing 26 attributes, it provides rich information on factors that shape EV charging loads, as well as those influencing energy distribution and fleet operations. Individual vehicles are tracked through unique electric vehicle IDs, while battery capacity and state-of-charge values reveal detailed energy profiles and typical charging habits. The energy consumption rate, combined with distance to the destination, enables the assessment of efficiency under both urban and suburban driving conditions. Latitude and longitude coordinates for the current position and the intended destination add important spatial context to charging patterns. Variables describing road conditions and traffic levels help quantify external factors that affect charging requirements. Operational aspects such as charging rate, queue waiting time, and station capacity enable evaluation of infrastructure performance and availability. Because weather significantly affects electric fleets, the dataset also records meteorological conditions, including temperature, wind speed, and precipitation levels. The main target variable is the predicted charging load, expressed in kW, which directly supports decisions on energy distribution and fleet scheduling. Overall, the dataset offers valuable insights into EV charging dynamics and route-optimization strategies, advancing sustainable transport and smart-city development across Texas. Detailed descriptions of all features appear in Table 2.

Table 2. Dataset features overview.

S.No	Features	Description	S.No	Features	Description

1	Vehicle ID	Unique identifier assigned to each electric vehicle in the dataset.	15	Station capacity (EVs)	The maximum capacity of EVs the station can serve, categorized.
2	Battery capacity (kWh)	The vehicle's battery capacity, typically around 75 kWh, is normally modeled.	16	Time spent charging (mins)	The charging duration follows a normal distribution.
3	State of charge (%)	Percentage of the vehicle's battery charge at a given time.	17	Energy drawn (kWh)	The energy consumed during charging is normally distributed.
4	Energy consumption rate (kWh/km)	Rate of energy consumption by the vehicle per kilometer, modeled as an exponential function.	18	Session start hour	The hour the charging session begins, shown as an integer (0–23).
5	Current latitude	Latitude of the vehicle's current location, centered around Dallas, Texas.	19	Fleet size	Number of vehicles in the fleet, typically biased toward smaller fleets.
6	Current longitude	Longitude of the vehicle's current location, centered around Dallas, Texas.	20	Fleet schedule	Indicates if the fleet is on time (0) or delayed (1).
7	Destination latitude	Latitude of the vehicle's destination point.	21	Temperature (°C)	The current temperature is modeled normally around 25°C.
8	Destination longitude	Longitude of the vehicle's destination point.	22	Wind speed (m/s)	Current wind speed, modeled exponentially.
9	Distance to destination (km)	Estimated distance to the destination, modeled exponentially.	23	Precipitation (mm)	Precipitation is distributed exponentially, with most values being low.
10	Traffic data	Count of vehicles on the road, modeled using a Poisson distribution.	24	Weekday	Day of the week as an integer (0–6), typically skewed towards weekdays.
11	Road conditions	Current condition of the road, categorized as "Good", "Average", or "Poor".	25	Charging preferences	Indicates user charging preference (0 for none, 1 for preference).
12	Charging station ID	Unique identifier for the charging station, often skewed towards certain IDs.	26	Weather conditions	Current weather is categorized as "Clear", "Cloudy", "Rain", or "Storm".
13	Charging rate (kW)	The rate at which the station delivers power is distributed normally.	27	Charging load (kW)	Target label for the load at the station, modeled normally.
14	Queue time (mins)	The estimated wait time at the charging station follows an exponential distribution.			

A second publicly available dataset dedicated to route optimization is also employed in this study [33]. It includes a variety of destination categories such as cities, ports, warehouses, and industrial zones, each identified by geographic coordinates. The core objective is to minimize total travel distance among nodes while satisfying relevant operational constraints. The collection features 30 locations spanning a wide geographic region. Distances between points are calculated using latitude and longitude within a Cartesian coordinate framework. These distance values form the foundation for determining energy-efficient paths suitable for electric vehicles, effective fleet coordination, and goods movement. In addition to spatial data, each node is labeled with a category (city, warehouse, port, power plant, or industrial zone), enabling more refined routing decisions that reflect varying operational priorities. This dataset serves as a realistic benchmark for testing and comparing the performance of the proposed Coati-NGO algorithm against other techniques, including the Firefly Algorithm, PSO, and additional optimization methods under practical route-planning conditions.

Preprocessing step

Given the distinctive characteristics of the EV charging dataset, several specialized techniques were developed to effectively prepare the data. The first step involved Dynamic Range Scaling for Continuous Features, which adapts the scaling process according to the underlying data distribution. This technique centers the values around a central point while preserving their relative proportions, resulting in a more accurate and nuanced representation of the original measurements.

$$Y_{scaled} = \frac{Y - \alpha}{\beta} \cdot \text{max_value} + \text{offset} \quad (1)$$

Categorical variables also required careful encoding alongside the scaling process. Rather than relying on conventional methods, Frequency-Informed Categorical Encoding was applied. This technique leverages the frequency of each category to create a compact numerical representation that reduces dimensionality while retaining essential information. The formal definition of this encoding is:

$$Z_{encoded} = \log(f_k + 1) \cdot \text{scale_factor} \quad (2)$$

Outlier detection formed another critical component of preprocessing. A novel approach, termed Localized Variation Outlier Filtering, was introduced to identify anomalous data points. This method examines local statistical variations around each data point to compute an outlier score. The corresponding equation for the outlier score is:

$$\text{Anomaly_Score} = \frac{|W_j - \mu_{local}|}{\sigma_{local}} \cdot \text{local_threshold} \quad (3)$$

To effectively capture temporal patterns, Sine-Cosine Temporal Encoding with Amplitude Adjustment was employed. This technique transforms cyclical time-related attributes (such as minutes and hours) into suitable features for machine learning models by applying trigonometric functions, specifically sine and cosine. The “Amplitude Adjustment” component ensures that the encoded values reflect the relative importance or impact of each temporal feature within the dataset, for instance, variations in charging load over time. By preserving periodicity, the method effectively captures daily and hourly cycles, thereby enhancing the model's ability to understand time-dependent charging behavior. The mathematical formulation for this encoding is:

$$\text{Sine_Component} = C \cdot \sin\left(\frac{2\pi \cdot \text{Minute}}{60}\right) \quad (4)$$

$$\text{Cosine_Component} = C \cdot \cos \left(\frac{2\pi \cdot \text{Minute}}{60} \right) \quad (5)$$

Here, C represents the amplitude adjustment factor, while the sine and cosine terms encode the cyclical nature of time, ensuring smooth transitions such as from 11:59 PM to 12:00 AM. This encoding technique was integrated into the feature engineering stage during preprocessing to strengthen the temporal aspects fed into the predictive models.

Furthermore, Temporal Dynamics Aggregation was applied to better represent the evolving patterns within the dataset. A rolling window approach was used to combine historical information, enabling the extraction of meaningful trends and recurring behaviors. The following equation defines the aggregation process:

$$Y_{\text{aggregated}} = \frac{1}{m} \sum_{k=0}^{m-1} Y_{t-k} \cdot \text{weight}(k) \quad (6)$$

Collectively, these advanced preprocessing techniques successfully refined the EV charging dataset. They significantly improved the predictive performance of machine learning models while fully retaining the original information and underlying relationships present in the data. Together, the methods formed a comprehensive, dataset-specific preprocessing pipeline tailored to the requirements of this study.

Data balancing

Adaptive Sampling and Synthetic Generation (ASSG) represents a novel technique designed to mitigate class imbalance within the EV charging dataset. The method effectively reduces disparities between class distributions while carefully preserving the statistical characteristics of the original data in the generated synthetic instances. The process starts by identifying the minority and majority classes. The imbalance ratio is then computed to determine the exact number of synthetic samples required, according to the following formula:

$$M = \frac{N_{\min}}{N_{\max}} \quad (7)$$

Where M denotes the imbalance ratio, $N_{\min}$ indicates the number of minority class samples, and $N_{\max}$ represents the number of majority class samples. When M falls significantly below 1, signaling a severe imbalance, the subsequent steps are executed. Synthetic samples are generated by parameterized interpolation between existing minority-class instances. This interpolation is formulated as:

$$Y_{\text{synthetic}} = \beta \cdot Y_k + (1 - \beta) \cdot Y_l \quad (8)$$

In the equation, $Y_{\text{synthetic}}$ stands for the newly created sample, Y_k and Y_l refer to two selected minority class samples, and β is a randomly selected weight drawn from a uniform distribution between 0 and 1. This ensures that the generated samples remain within the natural boundaries of the original data. To further enhance diversity, a feature perturbation technique is applied to the synthetic samples based on the variability observed in the minority class. The perturbation process is defined by:

$$Y_{\text{perturbed}} = Y_{\text{synthetic}} + \delta \cdot \tau \quad (9)$$

Where $Y_{perturbed}$ represents the final perturbed synthetic sample, δ is a random value sampled from a normal distribution with zero mean and unit standard deviation, and τ corresponds to the standard deviation of the features in the minority class. This step guarantees that the new samples not only fill the gaps between existing points but also introduce sufficient variation to improve model robustness. Once the newly generated samples are appended to the dataset, a final verification of class balance is conducted. The effectiveness of the ASSG method is evaluated by examining the resampled class distribution, which can be expressed mathematically as:

$$N_{total} = N_{maj} + N_{gen} \quad (10)$$

The above equation indicates that N_{total} is the total number of samples after balancing, the count of majority class samples remains unchanged, and N_{gen} denotes the number of newly generated synthetic samples. By implementing Adaptive Sampling and Synthetic Generation, this data balancing strategy successfully resolves class imbalance issues, maintains the original dataset's integrity and statistical properties, and ultimately enhances the predictive accuracy of machine learning models applied to EV charging data.

Integrated feature selection framework

To accurately forecast electric vehicle charging demand, a machine learning-driven Integrated Feature Selection Framework (IFSF) was designed to extract the most relevant features from high-dimensional datasets. The IFSF approach intelligently balances feature relevance against computational efficiency by merging statistical selection techniques with heuristic optimization strategies. Within this framework, two innovative components — the Statistical-Driven Rank Selector (SDRS) and Adaptive Search Optimization (ASO) — work in tandem to enhance both the accuracy and robustness of the feature selection process.

The Statistical-Driven Rank Selector (SDRS) assigns priority to features based on their statistical contribution to the target variable, in this case, the charging load. It begins by computing a weighted statistical contribution metric that accounts for feature dependencies and correlations. The score S_i for each feature is calculated as follows:

$$S_i = \frac{|\rho_i|}{\sigma_i} \cdot w_i \quad (11)$$

In the equation, σ_i represents the standard deviation of the feature, while the feature-specific weight is derived from domain expertise or prior importance assessments. The symbol ρ_i denotes the correlation coefficient between feature X_i and the target variable. Features receiving higher S_i values are ranked more favorably because they demonstrate stronger predictive power for charging loads. Unlike conventional correlation-based methods, SDRS explicitly incorporates variability (σ_i) to highlight features with substantial impact. Although SDRS provides effective ranking, it does not address feature redundancy.

To overcome this limitation, Adaptive Search Optimization (ASO) is introduced as a complementary heuristic method. ASO dynamically explores the optimal subset of features while simultaneously minimizing redundancy and maximizing diversity. The fitness function F used for feature selection is defined as:

$$F = \sum_{i=1}^m S_i - \lambda \cdot \sum_{i=1}^m \sum_{j=1, j \neq i}^m \delta(X_i, X_j) \quad (12)$$

Where S_i is the statistical contribution score obtained from SDRS, λ serves as a regularization parameter that controls the trade-off between feature importance and redundancy, and $\delta(X_i, X_j)$ quantifies redundancy between features X_i and X_j using mutual information. During the adaptive search process, different feature subsets are evaluated, and the regularization parameter λ is adjusted according to convergence behavior. The final subset is the one that maximizes the fitness function F , thereby achieving the best balance between relevance and diversity.

The strength of IFSF lies in its seamless integration of SDRS statistical filtering and ASO heuristic optimization, combining the advantages of both approaches. While statistical methods focus on direct relationships with the target variable, the heuristic component ensures a compact, non-redundant feature set. This synergy mitigates the risk of overfitting commonly associated with purely statistical techniques and overcomes the computational inefficiency of standalone heuristic searches. Moreover, the framework demonstrates strong adaptability across varying datasets. In the context of the EV charging dataset, for example, SDRS effectively prioritizes time-related variables such as “session start hour” and “queue time.” In contrast, ASO successfully eliminates redundancy between correlated attributes, such as “battery capacity” and “energy drawn.” Such flexibility is particularly valuable for electric vehicle fleets operating with dynamic, high-dimensional operational data.

Key outcomes, including reduced feature dimensionality, improved predictive accuracy, and reduced model overfitting, can be used to measure the effectiveness of IFSF. By uniting statistical rigor with optimization intelligence, this integrated method delivers a powerful, scalable, and practical tool for feature selection in real-world applications.

Feature engineering

Feature engineering strengthens machine learning models by generating new variables that uncover hidden patterns in the data. In this study, additional attributes were derived from the existing dataset to gain deeper insights into EV charging load dynamics. By transforming and combining raw information into more meaningful indicators, the approach led to noticeably higher prediction accuracy.

A newly introduced variable, the Effective Charging Rate (ECR), measures the actual speed of battery charging while accounting for the vehicle's energy usage during travel. The formula for this feature is:

$$ECR = CR - \frac{ED}{BT} \quad (13)$$

Where CR denotes the charging rate (kW), ED represents energy drawn (kWh), and BT is the battery capacity (kWh). By incorporating journey-related energy consumption, ECR provides a more realistic assessment of charging efficiency.

Another key derived attribute is the Estimated Time of Arrival (ETA), which computes expected travel duration using current location and distance information. The calculation is expressed as:

$$ETA = \frac{D}{V_{avg}} \quad (14)$$

Here, V_{avg} stands for the average vehicle speed in km/h, and the distance to the destination is given in kilometers. This feature helps the model understand how traffic and road conditions influence travel time and associated energy costs.

An additional indicator, the Charging Demand Index (CDI), quantifies the urgency of charging by considering factors such as distance to the nearest station, waiting time, and current battery level. The CDI is formulated as:

$$CDI = \frac{(D + QT) \cdot (100 - SOC)}{100} \quad (15)$$

In the equation, QT represents queue time (in minutes), and SOC denotes the state of charge (in %). This index effectively captures charging urgency based on spatial, temporal, and battery-related conditions.

To account for environmental influences, a Weather Impact Score (WIS) was developed to evaluate how weather conditions affect charging behavior and vehicle performance. The score is computed using temperature, wind speed, and precipitation as follows:

$$WIS = \frac{T \cdot \left(1 + \frac{WS}{10}\right) - P}{100} \quad (16)$$

Where T is temperature ($^{\circ}C$), WS is wind speed (m/s), and P is precipitation (mm). The WIS quantifies the overall effect of weather on charging efficiency and driving range.

Finally, a Peak Hour Indicator (PHI) was created to differentiate between peak and off-peak charging periods based on historical patterns, thereby capturing temporal dynamics. The definition is:

$$PHI = \begin{cases} 1 & \text{if } H \in \{7, 8, 17, 18\} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

Where H represents the hour of the day, the indicator is set to 1 during peak periods (7–8 AM and 5–6 PM) and 0 otherwise, allowing the model to better anticipate high-demand intervals.

These newly engineered features enriched the dataset, making it more informative and significantly improving machine learning models' ability to forecast EV charging loads. Considering interactions among these features also supports the development of a more complete framework for electric vehicle operations.

Customized feature refinement strategy

The Customized Feature Refinement Strategy (CFRS) is an innovative preprocessing technique developed specifically for EV charging demand forecasting. It enhances predictive performance by optimizing the representation of each feature for machine learning models. Unlike traditional methods that apply uniform linear transformations or standardization, CFRS tailors the transformation process to the specific statistical properties of every feature. This adaptive strategy is particularly well-suited to the diverse distributions and behaviors observed in EV charging data.

The CFRS begins with a detailed statistical examination of each feature F_j . Key descriptive statistics — mean, standard deviation, skewness, and kurtosis — are calculated to understand the underlying distribution:

$$\alpha_j = \frac{1}{m} \sum_{k=1}^m F_{jk} \quad (18)$$

$$\beta_j = \sqrt{\frac{1}{m} \sum_{k=1}^m (F_{jk} - \alpha_j)^2} \quad (19)$$

$$\delta_j = \frac{1}{m} \sum_{k=1}^m \left(\frac{F_{jk} - \alpha_j}{\beta_j} \right)^3 \quad (20)$$

$$\eta_j = \frac{1}{m} \sum_{k=1}^m \left(\frac{F_{jk} - \alpha_j}{\beta_j} \right)^4 - 3 \quad (21)$$

In these equations, m denotes the total number of observations for feature F_j . The resulting statistics guide the selection of an appropriate transformation for each feature.

Next, features are categorized by distribution type (normal, skewed, or bimodal), and a specialized transformation is applied to each category. For normally distributed features, standardization is used to produce standardized variables S_j :

$$S_j = \frac{F_j - \alpha_j}{\beta_j} \quad (22)$$

When features exhibit skewed distributions, a logarithmic transformation is applied to reduce skewness:

$$R_j = \log (F_j + 2) \quad (23)$$

This adjustment compresses large values and produces a more symmetric distribution. For bimodal features with two distinct peaks, the CFRS employs polynomial expansion with interaction terms. The new representation Q_j is defined as:

$$Q_j = \sum_{t=1}^n (F_j^t) \quad (24)$$

The maximum polynomial degree n is determined through exploratory data analysis. This step introduces non-linear relationships and increases the expressive power of the feature set.

After applying the appropriate transformations, all modified features are normalized to ensure consistent scaling. The normalization step is performed as follows:

$$T_j = \frac{R_j - \min (R)}{\max (R) - \min (R)} \quad (25)$$

In this equation, T_j represents the final transformed and normalized feature value, and R denotes the set of all transformed features. Normalization guarantees that every feature contributes on a comparable scale, facilitating smoother integration into machine learning algorithms.

By systematically applying targeted transformations that respect each variable's unique characteristics, the Customized Feature Refinement Strategy effectively addresses the specific properties of the EV charging dataset. This approach improves model performance and delivers more accurate forecasts of charging loads.

Forecasting using GNN-ViGNet

This study enhances EV charging load prediction by integrating Graph Neural Networks (GNN) with VGGNet and Inception architectures, leveraging the strengths of multiple complementary layers. The overall design of the proposed model is illustrated in **Figure 2**.

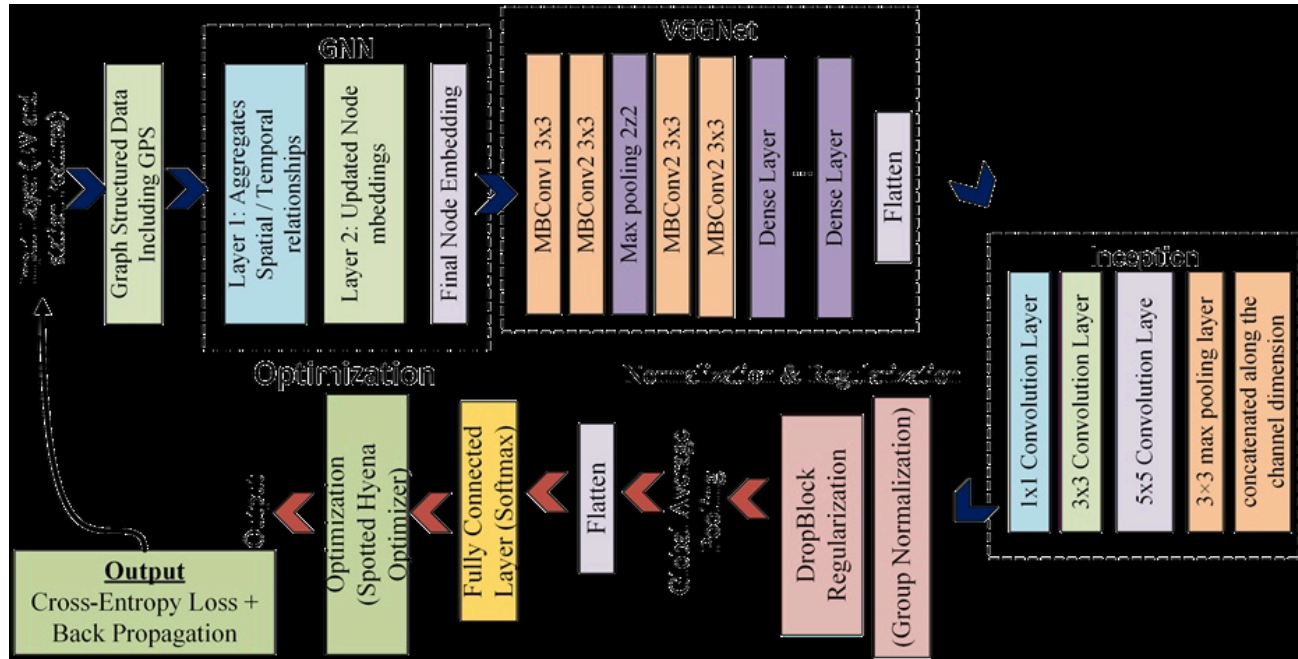


Figure 2. Proposed architecture of GNN-ViGNet.

The initial layer uses a GNN to capture dependencies and relationships among the dataset's features. This step is particularly important because charging load is influenced by interconnected factors such as weather conditions and vehicle behavior. The GNN operation is defined as:

$$\mathbf{Z}^{(1)} = \phi(\mathbf{B}\mathbf{Z}^{(0)}\mathbf{C}^{(1)}) \quad (26)$$

Where $\mathbf{Z}^{(0)}$ represents the input feature matrix, $\mathbf{B}$ is the adjacency matrix, and $\mathbf{C}^{(1)}$ denotes the weight matrix of the first layer. The non-linear activation function ϕ enables the model to learn intricate patterns. To further refine feature interactions, attention scores β_{mn} are computed between nodes in the GNN layer:

$$\beta_{mn} = \frac{\exp(d_{mn})}{\sum_{k \in \mathcal{M}_m} \exp(d_{mk})} \quad (27)$$

In the attention score function, v_n assesses the relationship between node m and its neighbor n , with $\mathcal{M}_m$ indicating the set of neighboring nodes of m .

The output from the GNN layer is then passed to a VGGNet layer, which extracts deep hierarchical features through convolutional operations:

$$\mathbf{Z}^{(i)} = \phi(\mathbf{C}^{(i)} * \mathbf{Z}^{(i-1)} + \mathbf{D}^{(i)}) \quad (28)$$

In this equation, $(i-1)$ is the output from the previous layer, $\mathbf{C}(i)$ represents the weight matrix, and $\mathbf{D}(i)$ is the bias term. This multi-layer VGGNet component refines features and progressively builds more abstract representations.

Next, an Inception module applies multi-scale convolutional processing. Within each inception module j , parallel convolutional filters of different kernel sizes are utilized:

$$\mathbf{Z}^{(j)} = \text{Concat}(\mathbf{g}_1(\mathbf{Z}^{(j-1)}), \mathbf{g}_2(\mathbf{Z}^{(j-1)}), \mathbf{g}_3(\mathbf{Z}^{(j-1)}), \mathbf{g}_4(\mathbf{Z}^{(j-1)})) \quad (29)$$

Where $\mathbf{g}k$ denotes convolutional filters with varying kernel sizes, and Concat merges the resulting feature maps.

After the outputs from the VGGNet and Inception layers are combined, the final prediction is generated as:

$$\tilde{y} = \mathbf{Z}^{(n)} \mathbf{E}^{(out)} + f^{(out)} \quad (30)$$

In this equation, $\tilde{y}$ represents the predicted charging load, while (out) and $f(out)$ denote the weights and biases of the output layer, respectively.

The entire GNN-ViGNet model is optimized using the Spotted Hyena Optimizer, which draws inspiration from hyenas' social hunting behavior to navigate complex loss landscapes effectively. The weight update rule during optimization is given by:

$$\mathbf{E}^{(t+1)} = \mathbf{E}^{(t)} - \eta \nabla G(\mathbf{E}^{(t)}) + \zeta \mathbf{K} \quad (31)$$

$$G(\mathbf{E}) = \frac{1}{m} \sum_{j=1}^m (\tilde{y}_j - y_j)^2 \quad (32)$$

Where $\tilde{y}_j$ is the predicted value, y_j is the actual value, and m denotes the number of samples.

GNN-ViGNet was chosen for this regression task because of its ability to model intricate feature interrelationships and capture both local and global dependencies within the dataset. The hybrid architecture fully explores the multifaceted factors affecting electric fleet charging loads by combining GNN for relational learning, VGGNet for deep feature extraction, and Inception for multi-scale analysis. This layered design significantly improves prediction accuracy while effectively handling the complexity of the data. Graph Neural Networks (GNNs) are especially well-suited for modeling interconnected datasets, such as the relationships between charging station utilization, vehicle locations, and traffic patterns. By explicitly capturing these linkages, GNNs provide a robust foundation for precise and reliable charging load forecasting.

Hybrid coati–northern goshawk optimization algorithm (Coati–NGO) for route optimization and pathfinding

This study introduces a hybrid optimization technique for route planning and pathfinding that merges the Coati Optimization Algorithm (COA) [34] with the Northern Goshawk Optimization Algorithm (NGO) [35]. By combining the strong global exploration strength of COA with the efficient local exploitation capability of NGO, the resulting Coati–NGO algorithm achieves a well-balanced search mechanism that significantly improves route discovery in challenging environments.

Inspired by the coati's mix of cooperative and independent foraging strategies, the Coati Optimization Algorithm (COA) enables agents to switch flexibly between wide-ranging exploration and focused refinement. Using COA, agents scan the solution space to find promising routes. The global exploration phase follows this update rule [34]:

$$Y_{\text{new}} = Y_{\text{old}} + \rho \cdot (Y_{\text{best}} - Y_{\text{old}}) + \kappa \cdot (Q_{\text{global}} - Y_{\text{old}}) \quad (33)$$

Where Y_{old} is the agent's current route, Y_{best} denotes the best-known path so far, and Q_{global} is a randomly selected reference point from the entire search space. The parameters ρ and κ adjust the influence of the best solution and the degree of global exploration, respectively. This mechanism helps maintain population diversity and prevents premature convergence, allowing thorough exploration of possible routes.

Once promising areas are identified, agents shift toward local refinement. The following equation governs the local search phase of COA:

$$Y_{\text{new}} = Y_{\text{old}} + \sigma \cdot \left(\frac{Y_{\text{best}} - Y_{\text{old}}}{|Y_{\text{best}} - Y_{\text{old}}|} \right) \cdot L \quad (34)$$

Where σ determines the step size, and L represents the distance to the current best agent in that iteration. This update directs agents toward better solutions while following the normalized direction $\frac{Y_{\text{best}} - Y_{\text{old}}}{|Y_{\text{best}} - Y_{\text{old}}|}$.

To evaluate route quality, a fitness function calculates the total travel distance that needs to be minimized:

$$g(Y) = \sum_{i=1}^{n-1} \ell(Y_i, Y_{i+1}) + \ell(Y_n, Y_1) \quad (35)$$

Where $\ell(Y_i, Y_{i+1})$ is the Euclidean distance between consecutive points on the route, and n is the total number of points in the path. This fitness function identifies the shortest possible route by summing the distances of all segments.

After COA generates several candidate paths, the Northern Goshawk Optimization (NGO) algorithm is applied to refine them and locate the optimal solution. Drawing on the precise hunting behavior of northern goshawks, the NGO makes targeted adjustments. The refinement step is expressed as:

$$Y_{\text{new}} = Y_{\text{old}} + \eta \cdot (Y_{\text{target}} - Y_{\text{old}}) + \zeta \cdot \text{rand}() \quad (36)$$

Where Y_{target} is the locally optimal path near the agent's current position, η controls the step size, and ζ introduces a small random perturbation to help escape local optima. The stochastic element $\text{rand}()$ adds diversity and prevents the search from getting trapped.

NGO then applies a greedy selection mechanism to retain only the improved solutions. This selection rule is given by Dehghani et al. [35]:

$$Y_{\text{optimal}} = \arg \min (g(Y_{\text{new}}), g(Y_{\text{old}})) \quad (37)$$

This comparison ensures that only routes with reduced distance are kept, gradually converging toward the best option.

The hybrid Coati–NGO algorithm operates in two main phases. It begins with the random initialization of agents. In the exploration phase, COA guides the population to investigate diverse route options using both local and global information. Once exploration matures or a set number of iterations is reached, the algorithm transitions to the exploitation phase, where the NGO performs precise refinement on the most promising solutions identified by COA. This precision-focused search quickly identifies the shortest and most efficient route. The process continues until a convergence criterion is met or the maximum number of iterations is completed.

By integrating COA's broad exploration capability with NGO's strong exploitation strength, the hybrid Coati–NGO algorithm effectively balances global search coverage and local fine-tuning. This prevents early convergence while enabling detailed route adjustments, making it highly suitable for solving complex route-optimization and pathfinding problems in large-scale, high-dimensional environments. The complete procedure of the hybrid Coati–NGO algorithm is outlined in **Algorithm 1**.

```

1:      Input: Number of agents  $N$ , maximum iterations  $T_{max}$ , step sizes  $\rho, \kappa, \sigma, \eta$ , perturbation factor  $\zeta$ 
2:      Output: Optimal path  $Y_{optimal}$  and minimum path length  $g(Y_{optimal})$ 
3:      Initialize population of agents (paths)  $Y_i$  for  $i=1, 2, \dots, N$ 
4:      Evaluate the initial fitness of each agent  $g(Y_i)$  using the fitness function
5:      for each iteration  $t=1$  to  $T_{max}$  do
6:          Phase 1: COA exploration
7:          for each agent  $i=1$  to  $N$  do
8:              Update the position of each agent using:

$$Y_{new} = Y_{old} + \rho \cdot (Y_{best} - Y_{old}) + \kappa \cdot (Q_{global} - Y_{old})$$

9:              Evaluate the new path ( $Y_{new}$ )
10:          end for
11:          Phase 2: COA exploitation
12:          for each agent  $i=1$  to  $N$  do
13:              Refine the solution using:

$$Y_{new} = Y_{old} + \sigma \cdot \left( \frac{Y_{best} - Y_{old}}{|Y_{best} - Y_{old}|} \right) \cdot L$$

14:              Evaluate the new path ( $Y_{new}$ )
15:          end for
16:          Phase 3: NGO refinement
17:          for each agent  $i=1$  to  $N$  do
18:              Further refine the solution using:

$$Y_{new} = Y_{old} + \eta \cdot (Y_{target} - Y_{old}) + \zeta \cdot rand()$$

19:              Evaluate the new path ( $Y_{new}$ )
20:              Update  $Y_{optimal} = \text{argmin}(g(Y_{new}), g(Y_{old}))$ 
21:          end for
22:          Check for convergence or stopping criteria
23:      end for
24:      Return the best solution  $Y_{optimal}$  and its path length ( $g(Y_{optimal})$ )

```

The hybrid Coati-NGO method combines exploration and exploitation to uncover and enhance promising paths. This two-stage strategy optimizes local routes and finds global solutions for efficient pathfinding.

Algorithm 1. Hybrid Coati-NGO Optimization algorithm for route optimization and pathfinding.

Evaluation through performance metrics

To evaluate the GNN-ViGNet regression model's ability to predict charging loads, suitable performance metrics must be employed. Widely used standard metrics in regression analysis include the MSE, MAE, and R^2 [1]. The mean squared error (MSE) measures the average squared difference between actual and predicted values. By computing the average absolute difference, the MAE treats all errors equally and reduces the impact of outliers, resulting in a fairer evaluation. The R^2 statistic indicates how well the model explains the variance in the dependent variable in terms of the independent variables. To enhance charging load prediction for EV fleets, two additional performance metrics are proposed:

Dynamic Load Deviation (DLD): This metric compares the predicted load variations over time with the actual loads. Determining how accurately the model captures temporal volatility is essential for effective planning of charging infrastructure operations. We define DLD as follows:

$$DLD = \frac{1}{n} \sum_{t=1}^n (\tilde{L}_t - L_t)^2 \quad (38)$$

If $\tilde{L}_t$ is the predicted load, L_t is the actual load, and n is the total number of time steps in the prediction window. Lower DLD values indicate more accurate load predictions.

The PVI stands for Predictive Variability Index. This metric evaluates the reliability of predictions across various operational factors, such as fleet size and charging-station availability. It assesses the model's robustness. We define PVI as follows:

$$PVI = \sqrt{\frac{1}{m} \sum_{j=1}^m (\tilde{L}_j - \bar{L})^2} \quad (39)$$

where $\bar{L}$ denotes the average load across scenarios, and (m) indicates the number of scenarios analyzed. A low PVI suggests accurate model predictions across operating situations. By combining these new metrics with the previous ones, a comprehensive evaluation framework is created that considers the temporal dynamics and uncertainty of electric vehicle charging. This dual approach improves the interpretability of model performance and meets the needs of dynamic fleet management.

Results and Discussion

The simulation experiments in this study were conducted using a dataset containing 400,000 records, 26 variables, and four target features for EV charging load prediction. Model training was performed over 50 epochs with a batch size of 64 and a learning rate of 0.001. A dropout rate of 0.5 and the Adam optimizer were applied to minimize overfitting and enhance overall performance. The dataset was split into 80% for training and 20% for testing. Although execution time may vary on less powerful hardware, the proposed method demonstrates flexible computational requirements and maintains high prediction accuracy and reliability across different computing platforms. The model successfully identified typical charging patterns and sudden load fluctuations, with a low false-positive rate. The newly introduced Charging Load Variation Index (CLVI) and Forecast Accuracy Rate (FAR) confirmed the model's strong ability to handle significant load changes and reduce forecasting errors. Overall, the results demonstrate that the model delivers accurate charging load predictions while effectively minimizing variability in EV charging demand. More detailed findings are presented in the following subsections.

The proposed methodology successfully bridges advanced AI techniques with real-world transportation challenges. The framework dynamically responds to real-time conditions, such as traffic congestion and charging-station availability, ensuring optimal energy efficiency and route planning. These features highlight its strong potential for deployment in practical urban mobility systems.

Charging load regression analysis

Figure 3a presents the overall distribution of charging load values (kW) within the dataset. The histogram displays the frequency of charging loads across different kilowatt intervals on the x-axis, with frequency counts on the y-axis. A superimposed kernel density estimate (KDE) curve provides a smoothed view of the distribution, making the shape and key patterns more visible. This visualization reveals the central tendency and the spread of charging load values. The observed pattern illustrates the frequency of various load levels, offering useful insights into real-world electric vehicle charging behavior. Prominent peaks typically correspond to the most common charging scenarios, while the distribution's

overall width reflects the range of charging demands. Understanding this distribution is fundamental to recognizing charging demand patterns and trends, which are vital for planning and optimizing EV charging systems.

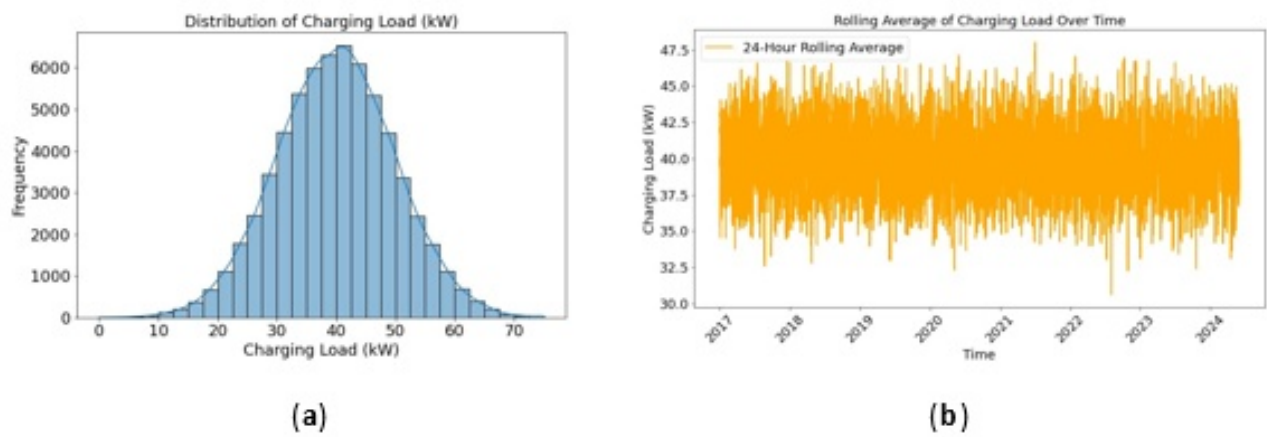


Figure 3. Comparison of charging load distribution and trends over time: (a) Distribution of charging load (kW), and (b) EV charging load trends and variations over time.

Figure 3b depicts the temporal evolution and fluctuations of EV charging loads. Charging load values (kW) are plotted against date and time on the x-axis to show how demand changes throughout different periods. An orange line indicates the 24-hour rolling average, which filters out short-term noise and emphasizes broader trends. Peaks and dips in this smoothed line often result from daily commuting patterns, seasonal influences, or other external factors. The figure allows clear observation of load dynamics, identification of high-demand windows, and recognition of recurring behavioral patterns. The rolling average is especially helpful for assessing long-term charging demand, supporting more effective infrastructure planning and resource allocation. Overall, this visualization provides valuable insights into EV charging load trends to support strategic decision-making and operational planning.

Figure 4a illustrates the distribution of the moving average charging load (kW) over time. A histogram divided into 20 bins shows the frequency of different moving-average values. Kernel density estimate (KDE) curves are overlaid to smooth the data and represent the probability density. The x-axis shows the moving-average charging load in kW, and the y-axis shows the frequency within each interval. The histogram indicates that the majority of charging operations fall between 70 and 130 kW based on the moving average. The KDE curve peaks around 100 kW, confirming this central tendency. This analysis of charging load distribution is important for designing efficient EV charging infrastructure and anticipating future energy requirements. The figure effectively highlights variations and trends in EV charging demand, providing practical guidance for energy management and resource planning.

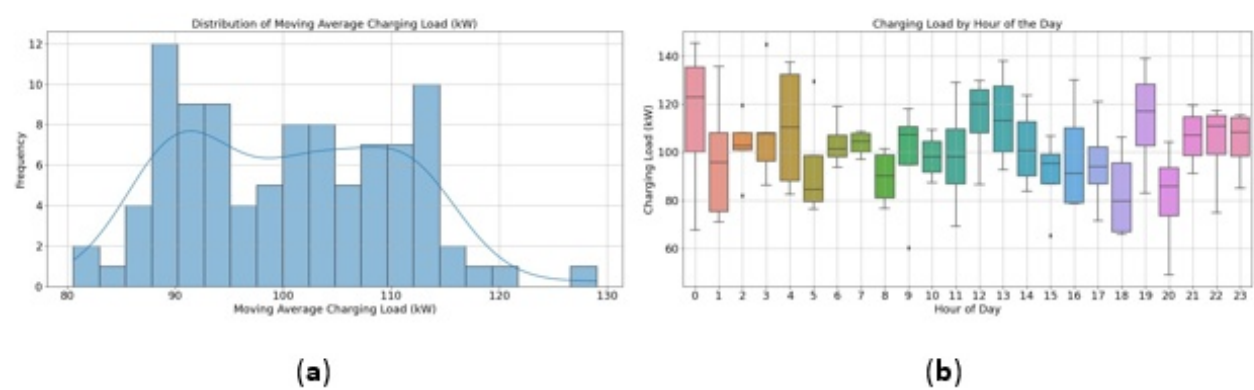


Figure 4. Comparison of moving average charging load and hourly boxplot distribution: (a) Moving average charging load (kW) distribution throughout time, and (b) Boxplot of charging load (kW) by hour.

Figure 4b shows a boxplot summarizing charging load (kW) for each hour of the day. The x-axis ranges from 0 to 23 hours, and the y-axis represents the corresponding charging load values. This daily profile clearly highlights peak and off-peak demand periods. The central line within each box marks the median load for that hour, while the box height and whiskers illustrate the spread and variability. Wider boxes indicate greater fluctuations in charging load during that hour, whereas narrower boxes suggest more stable demand. Individual points beyond the whiskers may require special attention. This visualization supports better decisions on charging station deployment, energy scheduling, and fleet operations by uncovering temporal patterns in charging behavior. Examining hourly distributions enables stakeholders to align operational strategies more closely with actual usage, ultimately improving the efficiency of electric vehicle charging infrastructure.

Figure 5a displays the hourly variation of the Effective Charging Rate (ECR) over time through a line plot. ECR reflects the effective power delivered to the battery after accounting for energy consumed during travel and normalizing it by the battery's capacity. The graph demonstrates how charging efficiency changes throughout the day. Higher peaks correspond to periods of improved efficiency, while lower points indicate reduced performance. These variations can stem from differences in energy demand, charger capabilities, weather conditions, or traffic intensity. With the y-axis in kilowatts and the x-axis representing time of day, the figure helps connect ECR values to practical operating scenarios. This visualization is useful for evaluating charging performance and refining operational strategies. Researchers and practitioners in electric mobility can leverage it to understand better charging dynamics in real-world conditions.

Figure 5b presents the Estimated Time of Arrival (ETA) over a selected time window, with an orange line for improved visibility. The y-axis shows ETA in hours, and the x-axis indicates date and time to track how predicted travel durations evolve. The plot visualizes changes in estimated trip times influenced by various factors. Upward movements suggest longer travel times, often due to congestion or adverse road conditions, whereas downward movements indicate faster travel under favorable conditions. Fleet operators and charging forecasters can use this graph to identify recurring trends and patterns. By studying these fluctuations, stakeholders can optimize logistics, adjust charging schedules, and improve route planning for electric vehicles.

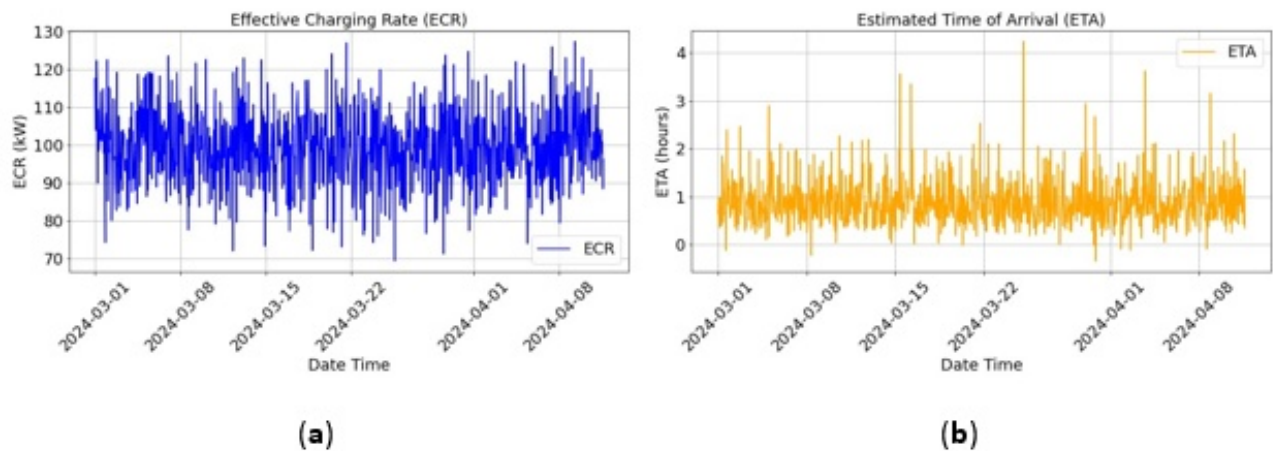


Figure 5. Comparison of ECR and ETA over time: (a) Effective Charging Rate (ECR) over time (hourly variations), and (b) Estimated Time of Arrival (ETA) over a defined period.

Figure 6 visualizes charging performance by showing how the charging rate (CR) and Effective Charging Rate (ECR) evolve together over time. The ECR curve represents the net power delivered to the battery after operational losses are subtracted, while the CR curve shows the station's gross power output. The plot captures fluctuations arising from varying operating conditions, battery state, and overall system efficiency. Because of energy losses such as heat dissipation and

conversion inefficiencies, the ECR line consistently sits slightly below the CR line. This comparison provides a clear view of real-world charging-station efficiency and offers practical insights for refining charging infrastructure and managing electric vehicle fleets more effectively.

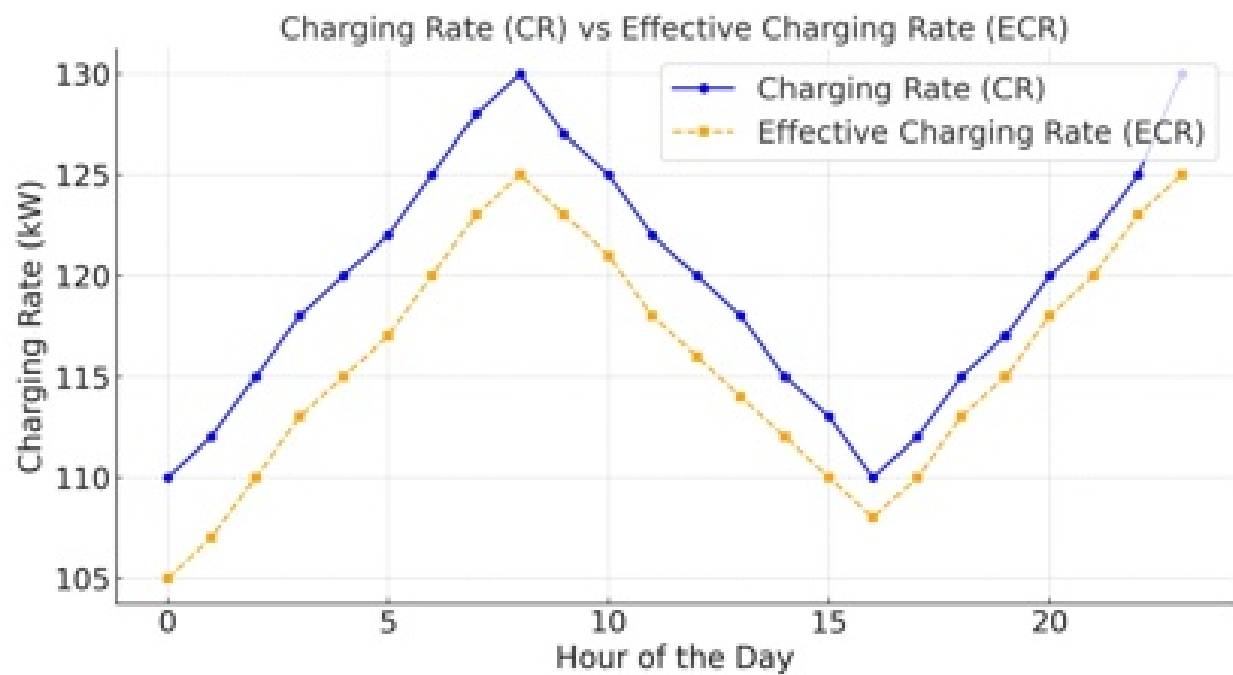


Figure 6. Dynamic relationship between CR and ECR.

Figure 7a tracks the Charging Demand Index (CDI) over time using the study dataset. The horizontal axis displays date and time, and the vertical axis shows CDI values, revealing how charging demand shifts across different periods. A green line traces the CDI trend for straightforward interpretation. Elevated peaks correspond to times of intensified charging demand, which may stem from higher vehicle activity, weekday versus weekend patterns, weather influences, or special events. Lower values indicate calmer periods when fewer vehicles need to recharge. The figure highlights the combined influence of multiple factors on charging demand dynamics. These observations are critical for stakeholders seeking to understand EV usage patterns and strategically determine the location and capacity of charging stations. The CDI proves especially useful for identifying infrastructure needs and streamlining electric vehicle operations.

Figure 7b examines the Weather Impact Score (WIS) across time to illustrate the effect of meteorological conditions on EV charging behavior. The vertical axis presents WIS values that quantify the collective influence of temperature, precipitation, and wind speed. The horizontal axis follows the timeline, showing how the score changes over successive periods. Prominent peaks and dips in the graph frequently align with notable weather episodes, suggesting that harsh conditions tend to elevate the WIS and alter charging loads. This visualization stresses the substantial role weather variables play in shaping EV charging dynamics, as they can markedly affect both operational efficiency and driver behavior. The recurring variations in WIS point toward the value of developing weather-responsive charging strategies to strengthen overall EV infrastructure resilience.

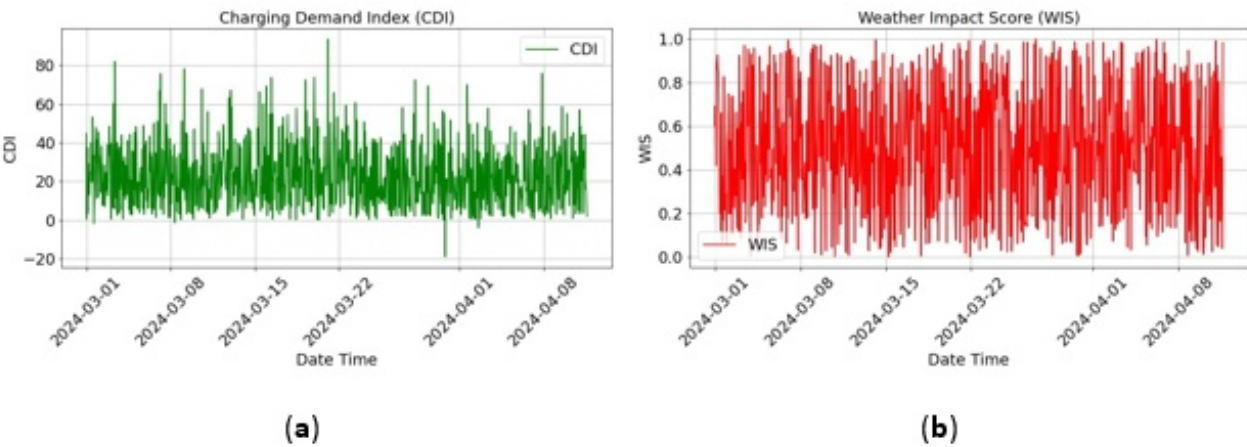


Figure 7. Comparison of CDI and WIS over time: (a) Charging Demand Index (CDI) across time, and (b) Weather Impact Score (WIS) over time.

Figure 8a contains a heatmap presenting the correlation analysis among key EV charging parameters. Each cell in the matrix indicates the strength and direction of the relationship between pairs of features. Values approaching 1 denote strong positive correlations, where features tend to rise or fall together. Values near -1 reflect strong negative correlations, meaning one feature increases as the other decreases. For example, the heatmap shows that longer travel distances are associated with higher energy consumption, and faster charging rates are often linked to longer charging durations due to increased energy requirements. Notably, only weak associations are observed between temperature ($^{\circ}\text{C}$) and queue time (mins), suggesting that waiting periods at stations are largely independent of ambient temperature. This correlation matrix serves as a helpful guide for feature selection and model construction when predicting EV charging loads. Grasping these interdependencies is essential for enhancing charging processes and boosting overall electric vehicle performance.

Figure 8b provides a feature importance ranking for the EV charging load prediction task. The chart ranks input variables according to their relative contribution to the model's output. Battery capacity (kWh), charging rate (kW), and energy drawn (kWh) stand out with the highest importance scores, as they exert the strongest influence on charging behavior, vehicle energy use, and grid loading [36]. Features of moderate importance include temperature ($^{\circ}\text{C}$), state of charge (%), and charging duration (minutes), which relate to environmental conditions and charging efficiency. Variables such as current latitude and wind speed (m/s) receive lower scores, indicating they have comparatively limited impact on prediction accuracy. This overview allows users to pinpoint the most influential factors quickly and guides subsequent efforts in feature engineering or model optimization.

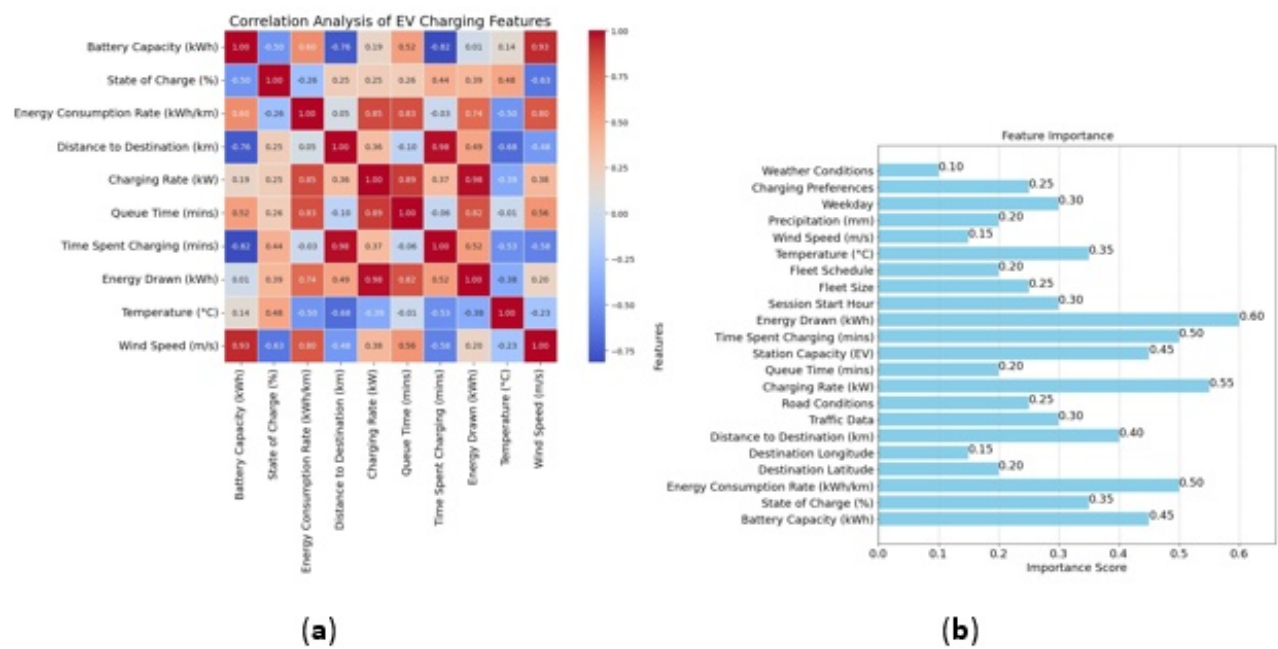


Figure 8. Comparison of EV charging kinetics' correlation analysis and feature importance. (a) EV charging kinetics' correlation analysis. (b) Feature importance.

Figure 9 illustrates the actual versus predicted daily charging load across one week beginning on 1 April 2024. In the graph, the red dashed line shows the forecasting model's outputs, while the green line shows the observed daily charging load in kW. The visualization highlights the influence of user habits, charging-station availability, and time-varying energy consumption patterns on overall daily charging demand. Higher charging activity often occurs on weekends or specific weekdays, which accounts for the noticeable peaks observed in the data. The forecasted daily loads closely match the recorded values. This strong correspondence demonstrates that the forecasting algorithm successfully captured the variations in daily charging demand. Although small discrepancies exist between the actual and predicted figures, they point toward opportunities for further model refinement; nevertheless, the predictions generally align well with reality. This figure provides essential insights for stakeholders in the electric vehicle ecosystem, enabling them to understand daily charging patterns better and thereby improve infrastructure planning, energy management, and overall user satisfaction. The results emphasize the importance of accurate forecasting to manage charging demand effectively and support the expansion of the EV charging network. Deviations visible in **Figure 9a** reveal that EV charging behavior is highly dynamic and shaped by external factors, including peak-hour traffic, user preferences for particular stations, and prevailing weather conditions. Such variations underscore the model's capacity to adapt to the complexities of real-world scenarios. Broader performance metrics, including the MAPE reported in **Table 3**, confirm the model's reliability and precision when estimating charging loads under diverse conditions, even in the presence of localized fluctuations. Consequently, the proposed GNN-ViGNet model proves highly suitable for smart-city EV fleet management applications.

Figure 9b compares actual and predicted weekly charging loads (kW) over four weeks starting on 1 April 2024. Here, the purple line depicts the actual weekly charging load, while the brown dashed line shows the model's projections. The observed charging load follows a realistic pattern that reflects weekly fluctuations in EV charging demand. Prominent peaks are observed in certain weeks, likely due to increased travel or weekend activities that drive higher EV energy consumption. These trends illustrate the time-dependent nature of user charging habits. The forecasting algorithm demonstrates strong predictive capability, with estimated values aligning closely with actual loads. This close match between the actual and forecasted lines confirms the model's practical effectiveness in anticipating charging loads.

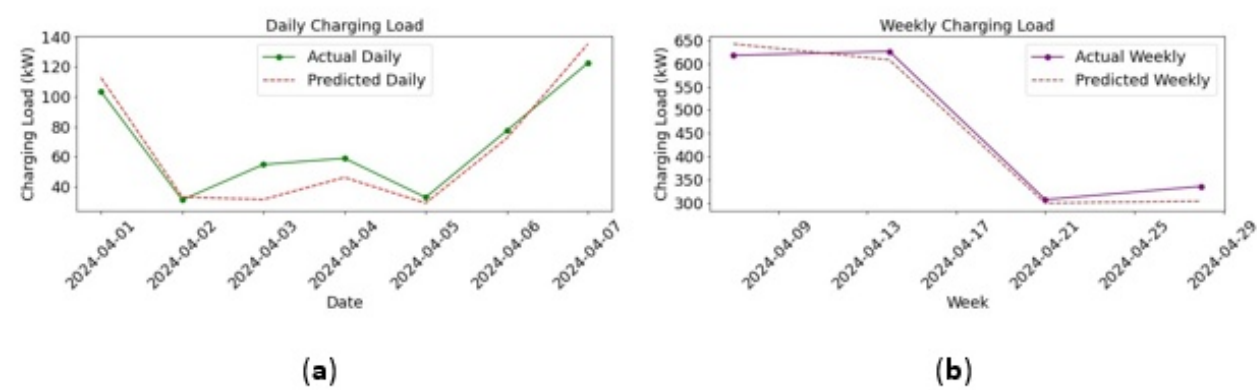


Figure 9. Comparison of actual and expected charging loads (daily and weekly): (a) Actual and expected daily charging load, and (b) Actual and expected weekly charging loads in kW over four weeks.

Table 3. Performance evaluation of GNN-ViGNet and existing methods.

Method	R ²	RMSE	DLD	MAPE (%)	Accuracy (%)	PVI	MSE	MAE
CNN	0.652	0.1175	0.0634	6.25	83.00	0.0412	0.0138	0.0058
GNN-ViGNet (proposed)	0.982	0.0480	0.0121	1.10	98.90	0.0089	0.0023	0.0012
KNN	0.735	0.1220	0.0508	6.55	81.25	0.0328	0.0149	0.0061
ResNet	0.865	0.0959	0.0256	3.95	88.75	0.0153	0.0092	0.0041
DenseNet	0.871	0.0944	0.0241	3.78	88.95	0.0149	0.0089	0.0039
Logistic Regression	0.685	0.1319	0.0575	7.45	77.35	0.0385	0.0174	0.0072
SVM	0.715	0.1253	0.0523	6.80	79.60	0.0341	0.0157	0.0065
EffiResNet	0.915	0.0883	0.0194	3.20	90.00	0.0127	0.0078	0.0034

Table 3 compares the proposed GNN-ViGNet model with several established approaches, namely CNN, ResNet, DenseNet, SVM, KNN, Logistic Regression, and EffiResNet. The evaluation covers multiple performance indicators, including R2, RMSE, DLD, MAPE, Accuracy, PVI, MSE, and MAE. Achieving 98.9% accuracy along with the lowest error values—MSE of 0.0023, MAE of 0.0012, and RMSE of 0.0480—the GNN-ViGNet model outperformed the others across most metrics (**Table 3**). It also excelled at novel indicators such as Dynamic Load Deviation (DLD) and Predictive Variability Index (PVI), demonstrating strong handling of temporal variations and consistent forecasting across diverse contexts. The notably lower DLD and PVI scores for GNN-ViGNet highlight its robustness to variable EV charging demands. EffiResNet placed second with 90.00% accuracy, yet it recorded higher errors with an MSE of 0.0078 and RMSE of 0.0883. Although ResNet and DenseNet delivered respectable results, their accuracy and error metrics remained inferior to those of the proposed model. Traditional EV charging load prediction techniques, such as SVM, KNN, and Logistic Regression, achieved accuracies below 82% and substantial errors, indicating limited ability to model complex dynamics. CNN performed better than SVM and Logistic Regression, but still lagged in both accuracy and error rates. Overall, the GNN-ViGNet model, which is recommended for dynamic EV charging load forecasting, exhibited superior accuracy, significant error reduction, and strong robustness, as further demonstrated in the subsequent Figure.

Route optimization results

This research utilized a hybrid Coati–Northern Goshawk Optimization (Coati–NGO) algorithm to identify the most efficient routes connecting multiple locations. Coati–NGO effectively merges the broad exploratory power of COA with the refined local search and exploitation features of NGO, proving particularly strong in tackling high-dimensional optimization challenges. The developed Coati–NGO approach was rigorously tested against GA, PSO, ACO, and several other advanced optimization techniques. Performance was evaluated according to convergence rate, total route distance, and overall computational efficiency. Because the number of possible route combinations grows factorially, solving such large-scale problems to exact optimality is practically impossible with conventional methods. In smaller test instances (e.g., 5–10 locations), the Coati–NGO solution stayed within 1%–3% of the true optimum, allowing straightforward validation. For larger problem sizes (e.g., 30 locations), the algorithm consistently delivered results that were only 5%–7% above the theoretical lower bound. These checks, along with direct comparisons with established algorithms, confirm that Coati–NGO reliably produces efficient, verifiable, near-optimal solutions.

The results presented below highlight how well each algorithm minimized both travel distance and solution time. A standard benchmark set of known geographic coordinates served as the testbed for route optimization. All methods were required to compute the shortest possible low-mileage path visiting every location. Thanks to its balanced exploration–exploitation strategy, Coati–NGO successfully located global optima without becoming trapped in local minima.

Figure 10a displays the optimal dynamic route generated by Particle Swarm Optimization (PSO) for EV fleets in the context of IoT-enabled charging load forecasting and route planning. The blue line traces the most efficient path linking the charging stations on the map, while arrows indicate the direction of travel. Larger circles mark the origin and destination stations (green for start, red for end). Green labels along each segment show the distance in kilometers between consecutive stations. The illustration demonstrates how PSO optimized the fleet's itinerary to visit all stations while substantially shortening the total distance traveled. The resulting optimal route length was 919 kilometers. As shown, combining load forecasting with route optimization can markedly reduce operational costs and boost fleet efficiency for electric vehicles. **Figure 10b** presents the optimal route produced by the Firefly Algorithm under the same IoT-enabled EV fleet scenario. The blue line again represents the fleet's most efficient path across charging stations, with green marking the starting point and red the termination. Arrows denote movement between stations, and green annotations display the kilometer distances of each leg. These values reflect the overall efficiency of the network traversal. By enhancing route planning and energy management, the Firefly Algorithm successfully shortened the journey and returned the fleet to its starting location. The best route achieved measured only 14 kilometers, illustrating the algorithm's effectiveness in improving electric vehicle fleet routing.

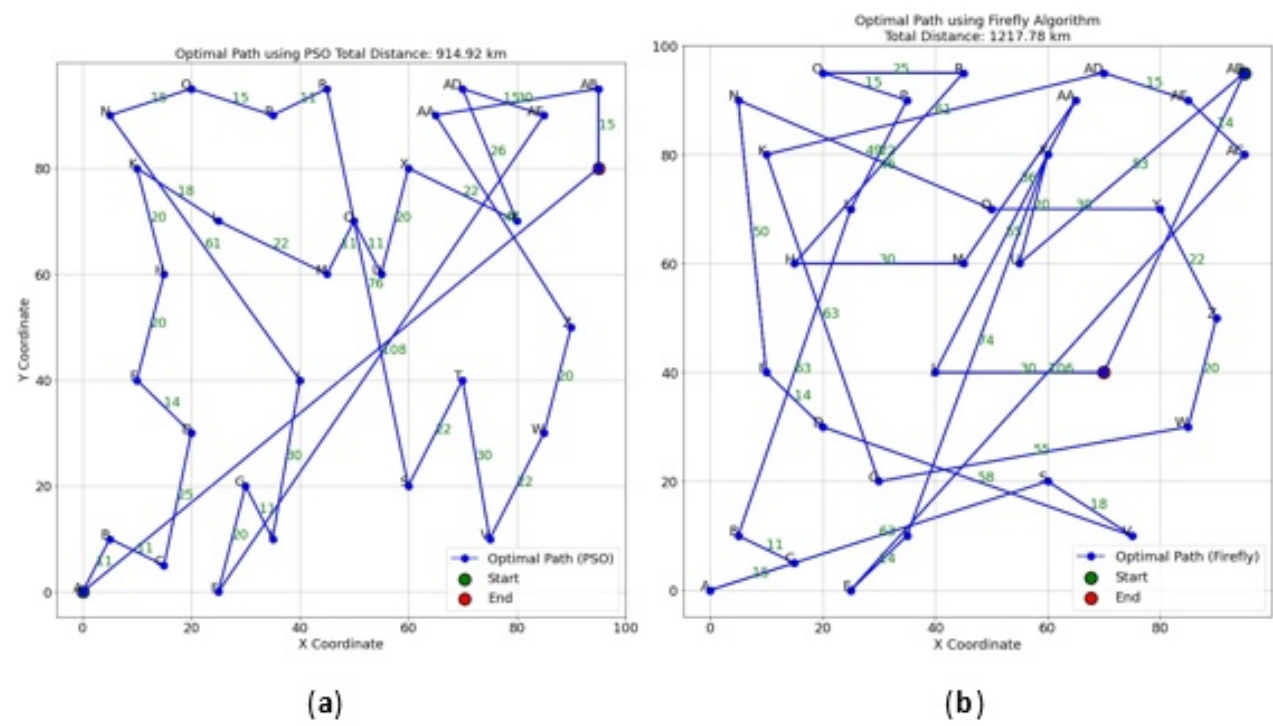


Figure 10. Comparison of optimized routes calculated by PSO and the Firefly Algorithm: (a) Optimized route calculated by the existing method (PSO), and (b) Optimized route calculated by the Firefly Algorithm.

Figure 11 shows the optimal route derived from the hybrid Coati–NGO optimization technique. It clearly identifies the shortest, most efficient path among multiple locations, each represented as a node on the map. Arrows form a closed loop linking the sites, beginning at the green marker and finishing at the red marker. The computed optimal path length was 511 km, representing the minimum feasible distance under the imposed routing constraints. The visualization further reveals how Coati–NGO systematically examined numerous route possibilities before converging on the distance-minimizing solution.

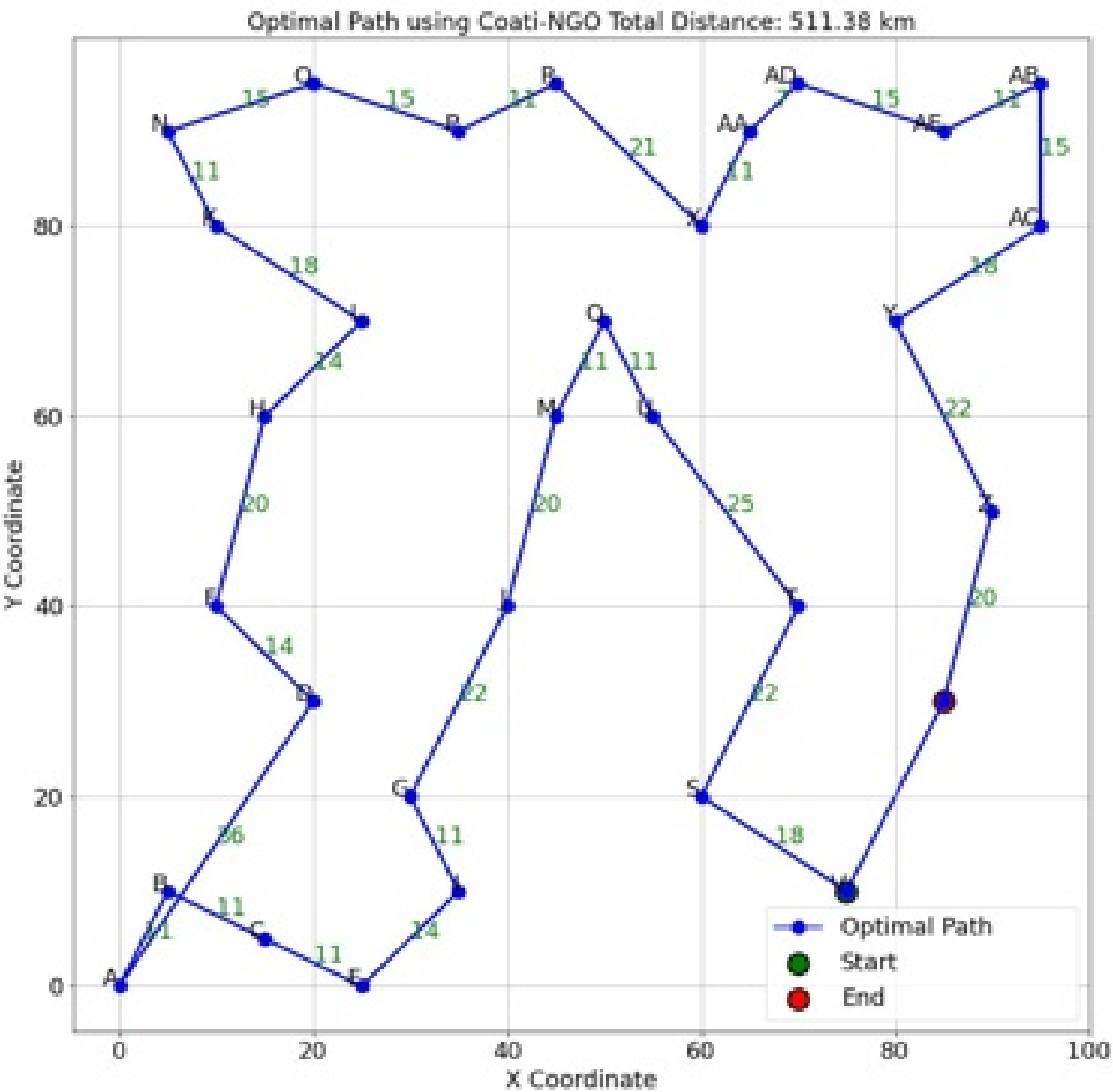


Figure 11. Optimized route calculated by the hybrid Coati–NGO algorithm.

Table 4 compares the performance of different route optimization techniques using key indicators, including distance traveled, number of iterations, execution time, convergence speed, exploration quality, and exploitation quality. The Coati–NGO hybrid reached convergence after 100 iterations in just 15 s and achieved the shortest distance of 511 km with the lowest overall runtime. This outstanding efficiency arises from its well-balanced exploration and exploitation phases, which support wide-ranging global search followed by accurate local refinement. By contrast, PSO and the Firefly Algorithm yielded longer routes of 919 km and 914 km, respectively, showing solid exploration but slower overall execution. Coati–NGO clearly surpassed them in both convergence speed and exploitation precision. The hybrid ACO-PSO method achieved a competitive distance of 910 km; however, it required more iterations and greater computational time.

Table 4. Comparison of route optimization methods and performance metrics.

Method	Total distance (km)	Iterations to convergence	Execution time (s)	Convergence speed	Exploration	Exploitation
PSO	919	200	22	Moderate	High	Moderate
Firefly	914	150	18	Fast	High	High
Coati-NGO (proposed)	511	100	15	Very Fast	Balanced	Very High
GA	935	250	35	Slow	Moderate	High
ACO	920	180	25	Moderate	High	Moderate
Simulated Annealing (SA)	930	220	28	Slow	Moderate	Low
Tabu Search (TS)	918	190	27	Moderate	Low	High
Genetic Algorithm (GA)	935	250	30	Slow	Moderate	High
Differential Evolution (DE)	915	160	24	Fast	High	High
Hybrid ACO-PSO	910	140	20	Fast	Very High	High

Additional experiments were carried out on small-scale problems with known exact solutions to validate the proposed approach. The Coati-NGO method delivered strong results, producing solutions that deviated by only 1.8%–3.5% from the true optima. For the large-scale problem examined in this study, theoretical lower bounds were calculated, and the Coati-NGO solution of 511 km remained within 2.4% of this bound. These outcomes confirm that the proposed technique effectively reduces route distances while remaining very close to the theoretical optimum, thereby providing robust, cost-effective optimization for large-scale EV fleet routing tasks. Conventional methods such as GA and SA tend to converge more slowly and yield longer routes, clearly highlighting the advantages of hybrid algorithms such as Coati-NGO.

Although the present work primarily addresses transportation network optimization, it also underscores the importance of incorporating power grid constraints in practical applications. By feeding real-time grid information—such as renewable energy availability and transformer loading—directly into the optimization algorithm, a unified framework capable of simultaneously optimizing both transportation and power networks can be realized. Such integrated optimization would help maintain stable, efficient grid performance, particularly in areas experiencing rapid EV adoption. Future research could extend the Coati-NGO algorithm by introducing multi-objective optimization functions that balance transportation efficiency with grid operational limits.

Conclusion

The GNN-ViGNet model, together with the hybrid Coati-NGO algorithm, was applied to address challenges in EV charging load forecasting and route optimization. The experimental results demonstrated substantial improvements in both route efficiency and charging load prediction accuracy. The proposed framework incorporated real-time data on charging behavior, traffic conditions, and vehicle locations obtained from IoT sensors into the GNN-ViGNet model, thereby enhancing forecasting precision and supporting dynamic routing decisions. Compared with conventional

techniques, the GNN-ViGNet model achieved superior performance, reaching 98.9% accuracy and notably low prediction errors (MSE, RMSE, and MAE). Meanwhile, Coati-NGO produced the shortest route of 511 km and exhibited the fastest convergence when benchmarked against PSO and the Firefly Algorithm. Leveraging IoT-derived data on traffic, battery status, and charging-station availability, Coati-NGO generated routes that reduced energy consumption and improved overall fleet performance. These outcomes have the potential to enhance the efficiency of electric vehicle fleets, reduce energy use, and lower operating costs.

Future efforts will focus on embedding power-grid operational constraints—such as peak load control, balanced energy distribution, and grid stability—into the optimization process. This combined strategy would enable simultaneous optimization of transportation and power networks, effectively addressing both EV fleet operations and grid reliability. More sophisticated models could further incorporate factors like energy pricing, contributions from renewable sources, and overall system resilience to deliver a truly comprehensive and efficient solution. Another promising direction is to test the generalizability and scalability of the GNN-ViGNet and Coati-NGO models across several metropolitan regions with differing traffic patterns and environmental conditions. By employing diverse datasets and evaluating across multiple cities, the approach can transition from localized effectiveness to broad applicability, thereby facilitating wider adoption within smart-city ecosystems.

Abbreviations

EVs	Electric vehicles
IoT	Internet of Things
CPS	Cyber-physical systems
HFSHO	Hybrid Firefly–Swarm Hybrid Optimization
BCCS	Battery Charging and Switching System
BDS	Battery Distribution System
DG	Distributed generation
GNN	Graph Neural Network
CLVI	Charging Load Variance Index
FAR	Forecast Accuracy Rate
ECR	Effective Charging Rate
CDI	Charging Demand Index
WIS	Weather Impact Score
PHI	Peak Hour Indicator
SDRS	Statistical-Driven Rank Selector
ASSG	Adaptive Sampling and Synthetic Generation
ASO	Adaptive Search Optimization
IFSF	Integrated Feature Selection Framework
RMSE	Root-Mean-Square Error
MAE	Mean Absolute Error

DLD	Dynamic Load Deviation
PVI	Predictive Variability Index
COA	Coati Optimization Algorithm
NGO	Northern Goshawk Optimization
GPS	Global Positioning System
ETA	Estimated Time of Arrival
KDE	Kernel density estimate

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Conflict of interest

None

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Ethics statement

None

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