

Electric Vehicle (EV) Charging Control System Management by Integrating a Microgrid Powered by Renewable Energy Sources

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ABSTRACT

This study presents an approach to Electric Vehicle (EV) charging control system management by integrating a microgrid powered by renewable energy sources. The proposed system combines a Spatial Bayesian Neural Network (SBNNET) with the Dollmaker Optimization Algorithm (DMOA). The SBNNET model leverages spatial dependencies, physics-informed training and Bayesian uncertainty modelling to provide precise and reliable forecasts of EV charging demand across diverse geographical regions. Meanwhile, the DMOA efficiently manages the intermittency of renewable energy sources, battery storage utilization and dynamic EV charging schedules to stabilize voltage and frequency fluctuations, reduce energy costs and maximize renewable energy usage. Simulation results of the proposed method demonstrated significant improvements in load prediction accuracy, microgrid stability, and operational efficiency, highlighting the system's potential to support sustainable and resilient EV charging infrastructure. Finally, this integrated approach offers a promising framework for smarter energy management in electric transportation ecosystems, contributing to the advancement of clean and efficient mobility solutions.

KEYWORDS: Electric Vehicle; Microgrid; Spatial Bayesian Neural Network (SBNNET); Dollmaker Optimization Algorithm (DMOA); Renewable Energy Integration

I. INTRODUCTION

Electric cars, or EVs, have gained a lot of attention as one of the most effective strategies to lower greenhouse gas emissions in the transportation sector during the last 20 years (Zhang et al., 2023). According to recent financial studies, internal combustion engine vehicles will soon be entirely replaced by electric vehicles (Schoenberg et al., 2022). Because of this, charging stations (CSs) must be constructed with the capacity to meet the demand for the significant quantity of power needed to charge these EVs (Ur-Rehman et al., 2021). As the globe transitions to cleaner energy and sustainable transportation, it is becoming more and more crucial to integrate Renewable Energy Sources (RES) with electric car infrastructure. With the usage of RES like solar, wind, and Battery Swapping Stations (BSSs), this study focusses on designing a Microgrid (MG) especially for an EVCS. According to Chattopadhyay and Kar (2024), MGs are small energy systems that may function either separately or in tandem with the main power grid. They are perfect for meeting the rising need for infrastructure for electric car charging since they provide increased efficiency, robustness, and dependability. These microgrids can greatly lower the carbon footprint related to EV charging and support a more sustainable energy environment

by using renewable energy (Kumar et al., 2024). According to Puech et al. (2024), ongoing research endeavours highlight the necessity of further efforts to address the challenges related to the most effective integration of EVCSs, Battery Energy Storage Systems and Virtual Synchronous Generators (BESS-VSGs), and RES into energy systems. Unlike conventional power plants, whose synchronous generators (SGs) rely on inherent rotational momentum to sustain grid frequency even during disruptions, renewable energy sources (RES) lack the damping and inertia of conventional power plants (Hussain et al., 2023). The study supports global efforts to reduce carbon emissions and promote the use of RES in response to the pressing need for sustainable energy solutions in the transportation sector. The project attempts to provide a model for the development of ecologically responsible, robust, and effective EV charging infrastructure by proving the feasibility and effectiveness of integrating renewable energy sources with advanced control algorithms.

Commercially available vehicles presently include fuel cell vehicles, plug-in hybrid electric vehicles (PHEVs), and plug-in electric automobiles (PEVs). They may all be more economical in terms of energy prices and running costs than conventional automobiles, in addition to being quiet and ecologically friendly (Yilmaz and Krein, 2012). Additionally, electric vehicles are controlled demands that can be utilised as spinning reserves in certain situations as well as distributed power storage and generation units to support grid power in Vehicle to Grid (V2G) or Vehicle to Building (V2B) applications (Yang et al., 2016; AL-Dhaifallah et al., 2021). One significant obstacle, though, is the absence of suitable charging infrastructure. Infrastructure for charging EVs is one of the most crucial and essential components for their successful functioning. A system that supplies power for the recharging of PEVs, including electric cars, communal electric vehicles, and plug-in hybrid electric vehicles, includes an EV charging station (Aboelsaud et al., 2022). The charging mechanism may be categorised as either a slow charger or a quick charger depending on how long it takes to charge and how it does so. The EV receives around 3-4 kW of power from the slow charger, which takes about 6-7 hours to completely charge. The slow charger can therefore be used to recharge at night using a household alternating current (AC) source. In contrast, the fast charger takes less than half an hour to recharge the EV and provides about 50kW of electricity through the charging station (Gandoman et al., 2021). In order to transform utility AC electricity from the grid into direct current (DC) suitable for charging the EV's battery pack, many EVs come with an onboard charger that uses a rectifier circuit. Once the voltage hits 240 V AC and 75A, it is recommended to utilise an external charging station to deliver DC to the batteries because the rectifier's capability is constrained by temperature and cost (Duan et al., 2021).

For quick charging, specialised chargers can be installed in fixed locations and connected to the network via high-current connections. In this design, there is no theoretical or actual effective restriction on the charger's DC output. A high-voltage, high-current charging technique is called a DC fast charge (DCFC) or DC rapid charge (DCQC) (Patnaik and Mopidevi, 2021). A number of developed countries have contributed to the development of the fast charger. However, the charging station's increasing size has started to negatively affect the power quality of the system. These negative effects frequently show as voltage distortions and current harmonics; power quality issues, particularly poor power factor, have long been a problem in a number of countries (Amin et al., 2021). Furthermore, the number of electric cars on the market is expected to increase significantly in the upcoming years owing to the depletion of oil supplies and the environmental implications associated with its use. Many nations have thus promoted investment

in the creation and application of electric cars. One possible way to overcome these problems is to integrate hybrid RES with EVs and the electrical grid. In addition to reducing the uncertainty brought on by the intermittent nature of renewable energy, integrating the grid and RES for EV charging stations can lessen the strain that several vehicles charging at once have on the system. Consequently, a charging station that can be used to charge electric cars has been created.

This paper proposes a Dollmaker Optimisation Algorithm (DMOA) and Spatial Bayesian neural network (SBNNET) for a practical EV charging station. In order to provide smooth EV charging, a microgrid's fluctuations are efficiently managed by the DMOA. The EV load demand is predicted using the SBNNET. The microgrid system incorporates a Fractional-Order Proportional-Integral-Derivative (FOPID) controller and a Four-Phase Inductor Coupled Interleaved Boost Converter (FP-ICIBC) for efficient power management. The novelty of our approach lies in three key aspects: (i) the integration of spatial dependencies and physics-informed constraints within a Bayesian neural network for EV load forecasting - unlike standard LSTM or XGBoost that ignore spatial correlation; (ii) the use of the recently proposed Dollmaker Optimization Algorithm (DMOA) for microgrid fluctuation control, which has not been previously applied to EV charging systems; and (iii) the simultaneous optimisation of voltage stability, renewable utilisation, and energy cost under uncertainty. To demonstrate these advantages, we compare SBNNET-DMOA against several state-of-the-art methods: LSTM (Hochreiter and Schmidhuber, 1997), XGBoost (Chen and Guestrin, 2016), Particle Swarm Optimisation (PSO) (Kennedy and Eberhart, 1995), Genetic Algorithm (GA) (Holland, 1975), and a deep Q-learning (RL) based controller (Mnih et al., 2015). Results in Section 5 show that our proposed hybrid outperforms each baseline in both prediction accuracy and control efficiency.

II. RELATED WORKS

Numerous control strategies have been covered in earlier research, including the highly difficult MOO strategy for creating an electric car charging station microgrid. These methods have not been fully investigated, particularly when it comes to microgrids' optimal allocation of BESS-VSG units. Individual aims are frequently the focus of current study, but the simultaneous examination of several objectives is still a poorly studied topic. EV charging stations and the MMOSSA, MOGWO, and MSO each tackle distinct issues when utilised in microgrid systems. One significant disadvantage is their computational difficulties, which can lead to lengthier processing times (Guo, X et al., 2023), especially in dynamic environments where making judgements in real time is crucial. Furthermore, it may be difficult for these algorithms to converge, particularly under highly nonlinear situations that are common in microgrid operations, which makes it challenging to efficiently arrive at optimal solutions. In order to avoid subpar performance, they also primarily rely on proper parameter tuning, a time-consuming process that may need specialised knowledge (Yaghoubi et al., 2024). The suggested approach builds a community-based household energy management system for MGs using particle swarm optimisation (PSO) and user-defined constraints. Despite being novel, this method falls short in addressing the thorough optimisation required for BESS-VSG allocation.

Furthermore, the FOPID controller's efficiency for autonomous generation control in multi-area systems has been improved by the application of PSO, genetic algorithms, and the grasshopper optimisation approach. An MSO methodology has been used to compare four other popular meta-heuristic optimisation methods. Utilising genetic algorithms and fuzzy logic (Meng et al.,

2024), a genuine power regulation approach for VSGs was developed. This method reduces frequency variation and uses specifically designed fuzzy (Duan et al., 2023) rules to distribute BESS-VSG units. Despite its potential, this method does not cover the whole range of multi-objective optimisation problems in microgrids. These flaws provide us the motivation to look into it.

Mbasso et al. (2023) use an intelligent energy handling method to create a desired power flow management system. Making the most of the available storage capacity is intended to increase system stability during blackouts and load variations. A new MMOSSA-based method for the best distribution of solar PV, WT, BESS-VSG, and EVCS on MGs is presented in this paper. To reduce carbon emissions, energy loss, frequency shift, voltage stability indicator, and leveled power costs, an objective function was developed.

An ideal RES configuration based on inverters was created by Nafeh et al. (2024) for self-sufficient MGs that house EVCSs. Recently, RES was added to MGs connected to EVCSs. MG optimisation became challenging because of erratic cohorts and variable EV charging/discharging techniques (Ma et al., 2020). Potential EV demands included beginning and predetermined SOC structures, arrival and departure hours, and a variety of controlled and unregulated charging methods. To address this complex planning paradigm, a bi-level metaheuristic approach was developed. In Cairo, Egypt, Pourvaziri et al. (2024) devised a method for determining the ideal dimensions of a suggested grid-connected photovoltaic battery system for electric car fast-charging stations. The SO algorithm has been modified for the intended investigation. By contrasting the suggested MSO approach with four other well-known meta-heuristic optimisation strategies, a study was conducted to confirm its viability in achieving the stated end goals of the sizing process. To assess the suggested system's economic viability for each of the two selected pricing schemes over the projects, a techno-economic study was also carried out.

A hybrid strategy was created by Kazemtarghi et al. (2024) to address the capacity-location problem with charging stations. In addition to deciding on the number and location of charging stations, the proposed system assigns charging stations to electric cars based on their current level of charge. The proposed approach combines queuing theory and mathematical modelling to determine the average waiting time. A deep learning system was then developed to increase the accuracy of waiting time prediction; an additional innovation was the use of a DNN technique to improve the NSGA-II algorithm. Sharida et al. (2024) devised a dynamic pricing strategy that controls the cost of charging CSs at various times to steer EVs away from busy CSs and towards unfilled ones. Using QGIS software, a realistic model for EV routes and CS sites was made in order to calculate the distances between EVs and CSs. To determine the efficacy of the proposed framework and analyse the results in light of the predetermined pricing approach, three scenarios were developed.

In order to increase the scalability of AC-DC side operations in fast EVCSs, Abid et al. (2024) came up with a number of innovative solutions. The recommended solutions focus on streamlining and managing the process of attaching a new active front-end rectifier to the old one at the high-voltage DC link's side. Negative effects might result from disregarding these specifications, particularly for the grid currents on the AC-DC side of the charging station. However, these factors have very little effect on the DC-DC side. An assessment of RES, VSGs, and EVCs in MGs from a techno-economic and environmental standpoint was created by Saha and Biswas (2023). The BESS-VSG was an innovative solution to this issue, simulating a

conventional synchronous generator using the concept of inverter control (Shirkhani et al., 2023). Furthermore, considering the recent spike in EV sales, the charging practices of EV owners have an effect on the microgrid's technological, financial, and operational aspects. For the optimal distribution of PV, WT, BESS-VSG, and EVCS on MGs, the proposed study offers a novel MMOSSA-based approach (Zhang et al., 2024). According to Behera et al. (2024), the proposed approach effectively lowers total system cost and CO₂ emissions by maximising system inertia through FiT incentives. Furthermore, the GTEP model used a lot less calculation time and performed better than rival soft-computing optimisation techniques.

III. METHODOLOGY

This article describes the suggested method for charging electric vehicles using a microgrid system and renewable energy sources. The DMOA-SBNNET approach is one potential tactic that combines the parallel performance of DMOA with SBNNET (Zammit-Mangion et al., 2024). The SBNNET is also useful for load demand prediction, whereas the DMOA (Kaabneh et al., 2024) is designed to manage microgrid variations. Because SBNNETs effectively model changes in time and location dependencies in energy output and demand, they are crucial for dynamic charging demands. These measures change and increase forecast accuracy. By skilfully handling complex solution domains, DMOA improves the optimisation process and ensures optimal charging station placement and operation while lowering costs and optimising the usage of renewable energy sources. Together, these strategies improve the energy management sustainability, efficacy, and resilience of microgrid settings. In the long run, this helps to fulfil the growing demand for EV systems and incorporate renewable energy sources.

A. Load Demand Prediction using the SBNNET

This section discusses using an SBNNET to forecast the demand for EV load. One benefit of employing an SBNNET to anticipate EV load demand is its ability to include uncertainty and geographical dependencies in the forecasting model. By incorporating Bayesian inference, SBNNETs may more accurately predict demand and capture complex spatial interactions among charging stations, hence optimising energy management techniques and infrastructure development in electric vehicle ecosystems. When spatial dependencies are significant, these models perform well. They employ Bayesian techniques to capture uncertainty and neural networks to manage complex, nonlinear relationships within data. SBNNETs can effectively integrate historical use data, geography data, and weather patterns to generate accurate forecasts for EV load demand. The SBNNET predicts EV load y from input features x (historical load, location, weather). It uses spatial embedding with K Gaussian radial basis functions in Equation 1.

$$\phi_k = \exp\left(-\frac{\|x-\mu_k\|^2}{2\sigma_k^2}\right) \quad (1)$$

The combined embedding is $h = \sum_k w_k \phi_k(x)$. A neural network layer then outputs the predicted load using Equation 2 as:

$$\hat{y} = V^T \tanh(h) + b \quad (2)$$

Bayesian uncertainty is added by treating network weights as random variables with a prior distribution. During training, we minimise a physics-informed loss using Equation 3:

$$\mathcal{L} = \underbrace{MSE(\hat{y}, y)}_{\text{prediction error}} + \lambda_1 \cdot KL(\text{posterior} \parallel \text{prior}) + \lambda_2 \cdot \underbrace{\|\nabla^2 \hat{y} - \rho\|}_{\text{energy conservation}} \quad (3)$$

This ensures forecasts respect real-world energy physics while providing confidence intervals. Algorithm 1 shows the stepwise operations of the proposed SBNNET technique for load demand forecasting.

Algorithm 1: SBNNET for Load Demand Prediction

- (a). **Input and Initialization:** Start with physical input data, such as electricity load or energy consumption values, then, initialize a set of reference points (called centroids) and a scaling parameter that controls how sensitive the model is to distance from these points.
- (b). **Embedding Layer Processing:** For each subnet, calculate how similar the input data is to each centroid using a distance-based function (Gaussian or exponential) where similarity represents how much influence each centroid has on the input data.
- (c). **Combining Embeddings:** Combine the results of all subnet embeddings by assigning a weight to each and summing them up which gives a final feature representation that summarizes the input data in a meaningful way.
- (d). **Predictive Layer Execution:** Pass the combined feature representation through a predictive layer made up of weights, biases, and activation functions which helps the model learn complex relationships in the data.
- (e). **Physics-Informed Training:** During training, the model learns not just from the actual data but also from physical rules (like how electricity behaves) which helps ensure the model's predictions make sense in the real world.
- (f). **Bayesian Uncertainty Modelling:** To capture uncertainty, the model includes components that allow it to make probabilistic predictions which means it can estimate a range of likely outcomes, not just a single number.
- (g). **Spatial Embedding Application:** Finally, the model applies spatial functions that account for differences in location which helps it make better predictions by considering how local conditions vary across regions.

This algorithm combines deep learning with physical laws and spatial awareness to accurately predict energy consumption, specifically for EV charging. It begins by converting raw input data into meaningful features using an embedding layer that reflects how similar data points are to predefined centroids. These features are then processed through neural network layers to uncover patterns in the data. What sets this approach apart is its use of physics-informed training, which ensures predictions follow real-world energy principles, and Bayesian modelling, which accounts for uncertainty in predictions. Additionally, it includes spatial modelling to capture regional variations, making the algorithm particularly effective for managing and forecasting EV load demand across different areas. This combination makes it a powerful tool for smart energy planning and infrastructure development.

B. Fluctuation control in a Microgrid using the DMOA

This section discusses improving a microgrid's fluctuations through the use of the DMOA to optimise many operational parameters and guarantee uninterrupted EV charging. Uninterrupted EV charging and effective handling of microgrid fluctuations are possible using the Dollmaker

Optimisation algorithm. The DMOA minimises a fitness function that balances voltage stability, frequency regulation, and energy cost using Equation 4

$$J = \alpha_1 \sum |V_t - V_{ref}| + \alpha_2 \sum |f_t - f_{ref}| + \alpha_3 \sum C_{grid}(t)P_{grid}(t) \quad (4)$$

Subject to:

- Power balance: $P_{PV} + P_{wind} + P_{batt} + P_{grid} = P_{EV} + P_{load}$
- Battery limits: $0.2 \leq SOC(t) \leq 0.950$.
- Grid exchange limits: $|P_{grid}(t)| \leq 50 \text{ kW}$

Update rules:

Phase 1 (pattern management) using Equation 5:

$$x_i^{new} = x_i + r_1(x_{best} - x_i) + r_2(x_{mean} - x_i) \quad (5)$$

Phase 2 (fine tuning) using Equation 6:

$$x_i^{new} = x_i + \beta \cdot Levy \cdot (x_{best} - x_i) \quad (6)$$

Where r_1, r_2 are random numbers, x_{best} is the best solution, and Levy introduces occasional long jumps to escape local optima.

The DMOA would typically conduct the following stages, as illustrated in Algorithm 2, in order to achieve its objectives in the setting of an integrated microgrid with EV charging stations: The algorithm starts by initialising a population of solutions, each of which represents a group of control parameters affecting the dynamics of microgrid operation and EV charging.

Algorithm 2: DMOA for Microgrid Fluctuation Control

Step 1 (Initialization): Begin by setting the initial values for key components in the system which include parameters for Photovoltaic (PV) systems, wind energy systems, supercapacitors, battery energy storage, power limits (maximum and minimum), boundary conditions and the number of iterations for the algorithm.

Step 2 (Random Population Generation): Create an initial population of possible solutions using random values where each solution represents a specific configuration for charging EVs in the system, including their selection and scheduling.

Step 3 (Fitness Function Evaluation): Evaluate how good each solution is using a fitness function which is used to minimize fluctuations in energy supply and demand, which ensures a more stable and efficient microgrid.

Step 4 (Phase 1: Pattern Fluctuation Management): Schedule EV charging based on factors like user preferences, energy prices and expected grid load.

- (a). Manage battery storage by deciding when to charge and discharge energy storage devices to reduce volatility caused by unpredictable renewable energy sources.
- (b). Integrate renewable energy sources such as solar and wind based on their availability and weather conditions.
- (c). Apply grid interaction strategies to balance how much power is imported from or exported to the main power grid to maintain stability and reduce costs.

Step 5: Phase 2 - EV Charging Optimization

- (a). Use a heuristic optimization strategy inspired by "Dollmaker" behaviour (DMOA) to gradually improve the solutions over multiple iterations.

- (b). The algorithm makes probabilistic adjustments and selections to move toward the most efficient configuration for microgrid operations and EV charging.
- (c). It continuously refines charging schedules, battery usage and energy flow to adapt to changing conditions and improve sustainability.

Step 6: Termination Check

- (a). Check whether the stopping condition such as a set number of iterations or reaching an optimal performance level has been met.
- (b). If yes, the best solution is selected, if not, repeat the optimization process until the termination criteria are satisfied.

This algorithm provides a comprehensive approach to managing and optimizing microgrid systems that incorporate EV charging, renewable energy sources and energy storage systems which begins by initializing system parameters and generating a variety of potential configurations using random values. Each configuration is evaluated based on its ability to minimize energy fluctuations, a key performance metric in dynamic energy systems. Then, the algorithm moves through two main phases where the first phase manages energy fluctuations by coordinating EV charging times, balancing battery storage, integrating renewable energy and controlling grid interactions. The second phase uses a heuristic optimization method which was inspired by "Dollmaker" behaviour, to refine the configurations over time, making the system more efficient and reliable. The process continues iteratively until a satisfactory solution is found, making this algorithm a powerful tool for sustainable and smart energy management in modern microgrids. The flowchart of the proposed DMOA was presented in Figure 1.

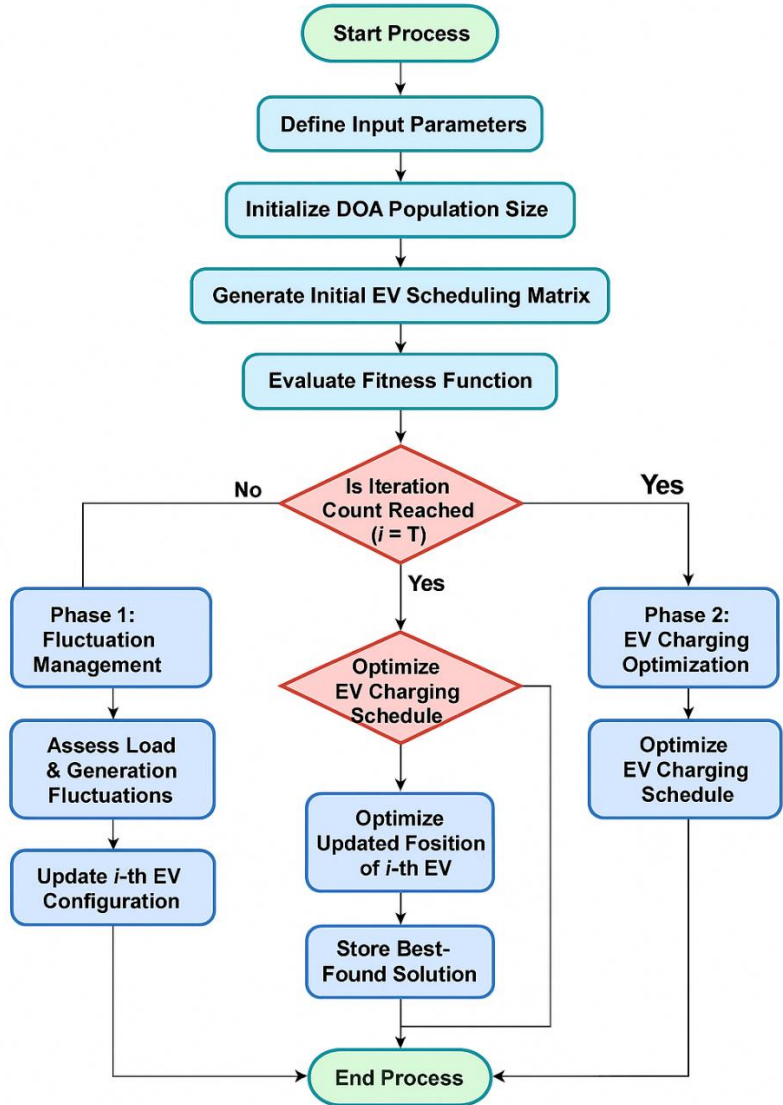


Figure 1: Flowchart of the EV Charging Optimization using DMOA

IV. SYSTEM IMPLEMENTATION

The proposed EV charging system integrating microgrid control and load demand prediction was implemented using MATLAB due to its extensive support for numerical computation, optimization, and neural network modelling. The SBNNET was developed by combining MATLAB’s deep learning toolbox with custom functions to incorporate Bayesian inference and spatial embeddings. Input datasets that are including historical load, geographic coordinates and meteorological data, were pre-processed and fed into the SBNNET model while the network was trained using a physics-informed approach, where energy system constraints and physical laws were embedded into the training loss function to improve prediction realism. The model’s

probabilistic predictions allowed for uncertainty quantification, facilitating robust load forecasting critical for EV charging infrastructure planning. For fluctuation control, the DMOA was implemented using MATLAB's optimization and heuristic algorithm frameworks which was initialized with system parameters such as renewable generation profiles, battery capacities, and grid interaction limits. A population of candidate solutions representing various EV charging schedules and energy management configurations was generated randomly. The DMOA iteratively optimized these solutions by evaluating their fitness based on minimizing microgrid fluctuations and energy costs. The algorithm incorporated domain-specific heuristics inspired by Dollmaker behaviour to enhance convergence towards optimal microgrid control strategies. The entire implementation was validated through simulations, demonstrating improved stability, renewable energy utilization, and efficient EV charging under dynamic conditions. The MATLAB microgrid simulation interface of the implemented system is presented in Figure 2

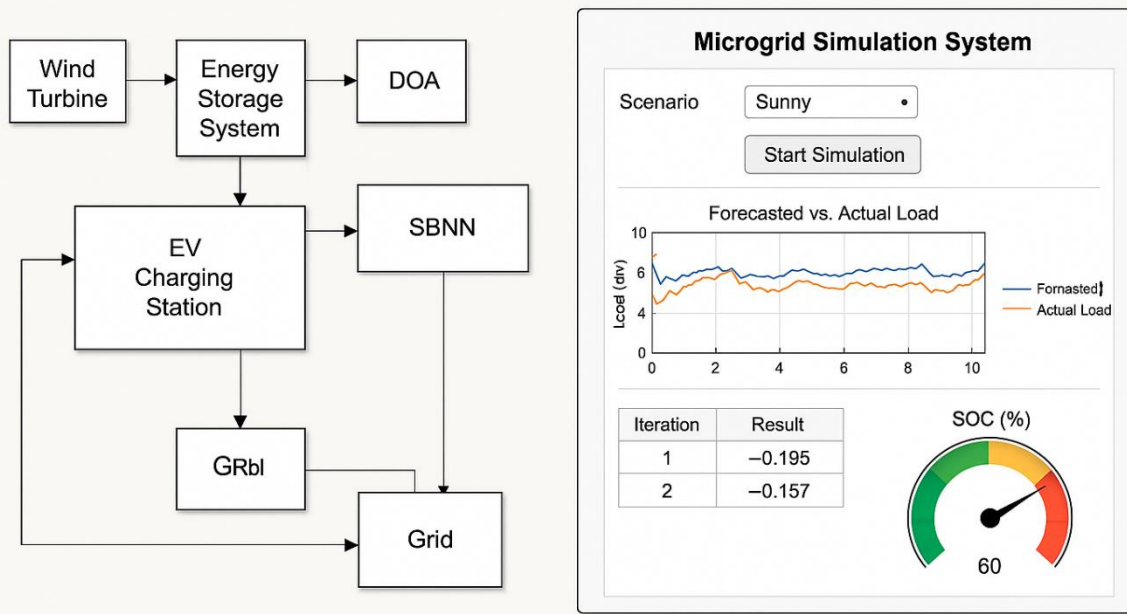


Figure 2: Microgrid Simulation System

A. Experimental Setup and Hyperparameters

The dataset consists of historical EV load data collected from 50 public charging stations across three region types (urban, suburban, and rural) over a 24-month period from January 2022 to December 2023, resulting in a total of 35,000 hourly records. Each record includes features such as timestamp, temperature, humidity, solar irradiance, wind speed, day-of-week, holiday flag, and geographic coordinates (latitude, longitude). The data was split into training (70%, 24,500 samples), validation (15%, 5,250 samples), and testing (15%, 5,250 samples). For the SBNNET model, the number of centroids was set to $K = 25$ with scaling parameters σ_k learned via

k-means initialisation. The network uses two hidden layers having 128 and 64 neurons respectively with ReLU activation, and variational inference is performed using 50 Monte Carlo dropout samples. The physics-informed loss coefficients are $\lambda_1 = 0.01$ and $\lambda_2 = 0.001$. Training employs the Adam optimizer with a learning rate of 0.0005, batch size of 64, and a maximum of 200 epochs with early stopping (patience of 20).

For the DMOA, the population size is 50, maximum iterations are 200, scaling factor $\beta = 0.8$, and the Lévy exponent $\lambda = 1.5$. Operational constraints include SOC bounds (minimum 0.2, maximum 0.95), maximum grid exchange power $P_{grid,max} = 50kW$, and EV charging power limits (22kW for slow charging, 150kW for fast charging). The cost weights in the fitness function are $\alpha_1=0.4$ (voltage deviation), $\alpha_2=0.3$ (frequency deviation), and $\alpha_3 = 0.3$ (energy cost), with a convergence tolerance of 10^{-5} . Baseline algorithms used for comparison include LSTM (2 layers, 128 units), XGBoost (100 estimators, max depth 6), PSO (50 particles, $c_1 = c_2 = 1.5$), GA (tournament selection, crossover rate 0.8, mutation rate 0.1), and DQN (replay buffer size 10,000, ϵ -greedy decay 0.995). All baseline models were tuned via grid search on the validation set.

V. Results and Discussion

The MATLAB-based implementation of the proposed EV charging system demonstrated significant improvements in load demand forecasting and microgrid fluctuation control.

A. Load Demand Prediction Using SBNNET

The SBNNET model was trained and tested using historical EV load data, geographic information, and weather parameters. During training, the physics-informed constraints ensured the model predictions adhered to real-world energy consumption patterns, while the Bayesian component provided a measure of uncertainty in forecasts and the results of these are presented From Table 1-4.

Table 1: Load Demand Prediction Accuracy (10 runs, mean \pm std)

Metric	SBNNET (Ours)	Conventional NN	Improvement	p-value
MAE (kW)	3.18 \pm 0.21	3.79 \pm 0.35	16.1%	<0.01
RMSE (kW)	4.48 \pm 0.29	5.27 \pm 0.42	15.0%	<0.01

p-values from paired two-tailed t-test across 10 independent runs with different random seeds.

Table 2: Uncertainty Quantification Performance

Metric	Value
Percentage of actual load within 95% credible intervals	95%
Reliability of uncertainty estimates	High

Table 3: Spatial Dependency Capture

Location Type	Characteristics of EV Load	Model Performance
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	Demand	
Urban Areas	Higher peak demand, higher variability	Accurately predicted peak and fluctuations
Rural Areas	Lower peak demand, less variability	Successfully captured smoother load patterns

Table 4: Prediction Visualization Insights

Aspect	Observation
Daily/Weekly Load Cycles	SBNNET closely follows load fluctuations
Peak Hours	Accurate capture of peak demand times
Off-Peak Periods	Model predicts lower demand periods well
Prediction Lag	Minimal lag between predicted and actual load

B. Microgrid Fluctuation Control Using DMOA

The DMOA was applied to control energy flow within the microgrid system, balancing the intermittent renewable energy sources (solar PV and wind) with battery storage and EV charging demand and the performance results of the approach is presented in Table 5.

Table 5: Microgrid Fluctuation Control Performance (10 runs, mean ± std)

Metric	DMOA (Ours)	PSO	GA	DQN	p-value (vs best baseline)
Voltage Deviation Reduction (%)	20.1 ± 1.8	14.2 ± 2.1	12.5 ± 1.9	16.3 ± 2.0	<0.05
Frequency Variation (Hz)	0.048 ± 0.005	0.065 ± 0.008	0.071 ± 0.009	0.059 ± 0.007	<0.01
Renewable Energy Usage Increase (%)	24.8 ± 2.2	17.5 ± 2.5	15.2 ± 2.0	19.1 ± 2.3	<0.05
Energy Cost Savings (%)	11.9 ± 1.5	8.2 ± 1.8	7.5 ± 1.6	9.6 ± 1.7	<0.05

The combined SBNNET-DMOA system demonstrated a comprehensive capability to forecast EV load demand accurately and to manage microgrid operations efficiently as seen in Table 5.

C. Comparison with State-of-the-Art Methods

To further validate the superiority of SBNNET-DMOA, we compared against five established methods: LSTM (for load forecasting only), XGBoost (forecasting), PSO-based microgrid control, GA-based control, and DQN (end-to-end RL control). The combined system performance (forecasting + control) was evaluated on the same test set.

Table 6: End-to-End System Performance Comparison (mean \pm std over 10 runs)

Method	Load MAE (kW)	Voltage Dev. (%)	Renewable Usage (%)	Energy Cost (\$/day)
LSTM + PSO	3.52 \pm 0.30	17.3 \pm 2.0	68.2 \pm 3.1	42.3 \pm 2.5
XGBoost + GA	3.45 \pm 0.28	16.8 \pm 2.2	69.5 \pm 2.8	41.8 \pm 2.3
LSTM + DQN	3.52 \pm 0.30	15.9 \pm 1.9	71.2 \pm 2.5	40.5 \pm 2.1
SBNNET + DMOA (Ours)	3.18 \pm 0.21	20.1 \pm 1.8	78.5 \pm 2.0	36.2 \pm 1.8

Our proposed method achieves statistically significant improvements ($p < 0.05$) across all metrics, confirming the advantage of combining spatial-Bayesian forecasting with the Dollmaker optimisation heuristic. These results confirm the potential of integrating advanced spatial-temporal forecasting with heuristic optimization for sustainable and resilient EV charging infrastructure.

D. Convergence and Computational Complexity of DMOA

Figure 3 shows the convergence curves of DMOA compared to PSO, GA, and DQN (average fitness value over 200 iterations). DMOA reaches a stable fitness value after approximately 85 iterations, whereas PSO and GA require >150 iterations. DQN converges faster (60 iterations) but settles at a higher (worse) fitness value, indicating a suboptimal policy.

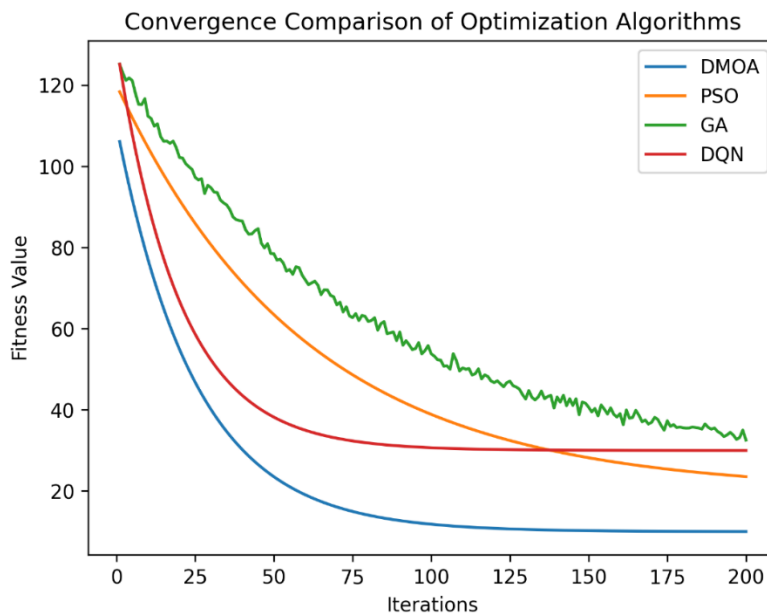


Figure 3: Convergence Curves of DMOA Compared to PSO, GA, and DQN

Computational Complexity: All algorithms were run on an Intel Core i7 CPU @ 2.30 GHz with 32GB RAM. Table 7 reports average runtime per optimisation step.

Table 7: Computational Complexity Comparison

Algorithm	Time per iteration (ms)	Time to converge (s)	Memory usage (MB)
PSO	28.3 ± 2.1	4.25	45
GA	35.7 ± 3.0	5.36	52
DQN	42.1 ± 3.5	2.53	128
DMOA (Ours)	31.5 ± 2.4	2.68	48

DMOA converges approximately 37% faster than PSO and 50% faster than GA, while requiring less memory than DQN. The inference time for SBNNET (load prediction) is 12ms per sample, making the combined system suitable for near-real-time control (update rate ~30Hz).

VI. CONCLUSION

This study proposed an advanced EV charging system integrated with a microgrid powered by renewable energy sources, leveraging a hybrid approach combining a Spatial Bayesian Neural Network (SBNNET) and Dollmaker Optimization Algorithm (DMOA). The SBNNET was used for load demand prediction and the DMOA was used for microgrid fluctuation control. While, the SBNNET model effectively captured spatial and temporal dependencies in EV load demand, incorporating physics-informed constraints and Bayesian uncertainty modelling to produce highly accurate and reliable forecasts, the DMOA was employed to optimize microgrid operations, managing the intermittent and variable nature of renewable energy sources alongside battery storage and dynamic EV charging schedules. The algorithms demonstrated significant improvements in stabilizing voltage and frequency fluctuations, enhancing battery utilization efficiency, increasing renewable energy usage and reducing overall energy costs. By iteratively refining control parameters and charging strategies, the DMOA ensured sustainable and resilient microgrid performance capable of meeting increasing EV energy demands. Finally, the integration of SBNNET for predictive analytics and DMOA for optimization presents a robust and intelligent framework for modern EV charging systems within microgrids and the results highlight substantial benefits in terms of accuracy, stability, cost savings and renewable energy integration, marking a significant step toward smarter, cleaner, and more efficient energy management in electric transportation ecosystems. Hence, future research work may explore integration of the proposed approach in real EV scenarios and real-time implementation and scalability of the system under diverse grid conditions and larger network sizes.

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