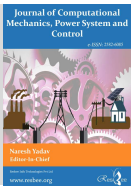
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Artificial Neural Network-Driven Dynamic Capacity Expansion for Optimizing EV Charging Infrastructure

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Abstract: The demand for dependable efficient and effective Electric Vehicle Charging Station (EVCS) infrastructure is rising as a result of the growing popularity and quantity of EVs worldwide. This increasing demand necessitates intelligent energy management strategies capable of addressing fluctuations in charging loads and renewable energy availability. Moreover, there have been significant developments in advanced energy research that have greatly increased EV feasibility. This study proposes an Artificial Neural Network-Driven Dynamic Capacity Expansion (ANN-DCE) approach for EV charging stations. The proposed framework integrates predictive analytics with dynamic infrastructure planning to improve operational flexibility and energy utilization efficiency. The ANN model's performance is estimated using Root Mean Squared Error (RMSE). The proposed capacity expansion plan focuses on enhancing the energy of Battery Energy Storage Systems (BESS) wind and solar energy installations and microturbines. Charging time for EVs waiting for recharging is also considered. Furthermore, the optimization framework minimizes user waiting time and improves the quality of service at charging stations during peak demand periods. The proposed ANN-DCE model demonstrates strong, reliable, sustainable and cost-efficient strategy for balancing energy demand, renewable integration and infrastructure expansion and an accurate evaluation of the capacity expansion problem in the ANN. Simulation outcomes indicate that the proposed method effectively adapts to varying load conditions and supports long-term scalability of EVCS infrastructure. Subsequently, the resulting energy demand exhibits a significant increase during the evening hours, with the highest peak reaching approximately 110 kWh at 18 hours and another high value of 105 kWh at 20 hours.

Keywords: Electric Vehicles, Dynamic Capacity Expansion, Battery Energy Storage Systems, Artificial Neural Network

Nomenclature

Abbreviation	Description
EV	Electrical Vehicles
EVCS	Electric Vehicle Charging Station
SRO	Stochastic Robust Optimization
ANN	Artificial Neural Network
PV	Photovoltaic
SOP	State Of Power
ADNO	Active Distribution Network Operator
BESS	Battery Energy Storage System
EVA	Electric Vehicle Aggregator
MILP	Mixed Integer Linear Programming
DCE	Dynamic capacitor expansion
CG	Constraint Generation
AIS	Alternating Iteration Strategy
MCS	Mobile Charging Station
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
ADN	Active Distribution Network
RMSE	Root Mean Square Error
SPV	Solar Photovoltaic
WPS	Wind Power System

1. Introduction

Due to their low emissions and affordability, EVs have become a significant approach to the growing worldwide climate change and energy concerns. The transition from conventional fossil-fuel-based transportation to electric mobility is considered an essential step toward achieving global sustainability

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and carbon neutrality goals. However, the number of EVs rises significantly as a result of their broad adoption. [1] [2] Similarly, plug-in electric vehicles are praised for their high performance, low operating costs, cheap maintenance and lower exhaust emissions (zero for battery EVs and plug-in hybrid EVs running in all-electric mode). Indeed, a significant turning point for widespread acceptance was reached recently when EV sales in the US topped 5% of all new passenger car sales. [3] [4][5] Thus, the load produced in the charging station can lessen the unequal distribution of distributed energy and effectively encourage the use of renewable energy [6]. The integration of renewable energy sources within charging infrastructure also contributes to reducing greenhouse gas emissions and improving overall energy efficiency. The complementary advantages of multiple resources can be used to improve the power quality, which is conducive to ensuring the stability and reliability of the distribution network system [7].

The charging behavior of EVs is affected not only by the capacity and stability of the power grid [8] but also by traffic flow and congestion within the transportation network [9][10]. Variations in charging demand during peak traffic hours can create additional stress on the power grid and increase waiting times at charging stations. Therefore, when planning the expansion of EV charging stations, it is essential to consider the operational characteristics of both the power grid and the transportation network, along with the inherent uncertainty in EV charging demand [11][12]. To accommodate this, the capacities of existing generating units may be increased, or new generation technologies may be installed. Generation expansion planning is typically formulated as an optimization problem, which can be represented using linear or nonlinear models [13]. Advanced optimization approaches can further assist in balancing energy supply, minimizing operational costs and maximizing renewable energy utilization. This optimization determines the location, technology type, size, operation schedule and installation timing of new generation systems while simultaneously optimizing the objective function, which encompasses investment costs, maintenance and operational costs, reliability and environmental impacts [14][15].

EVCS serve as the backbone of the EV industry. Efficient, convenient and cost effective EVCS not only enhance consumer willingness to adopt electric vehicles but also drive overall industry growth [16][17][18]. As a critical preliminary step in EVCS development, site selection plays a pivotal role throughout the station's life cycle, significantly influencing service quality and operational efficiency [19][20]. Improper placement or insufficient capacity planning may lead to congestion, energy imbalance and reduced user satisfaction. However, EVCS development faces challenges such as high upfront and ongoing costs, inconsistent charging standards, unreliable grid infrastructure and range anxiety. To address these issues, a novel model, ANN-DCE for Optimizing EV Charging Infrastructure, has been proposed to optimize grid efficiency and meet the growing demand for EV charging. This methodology introduces an ANN-DCE method for EV charging stations, designed to address growing energy demands and optimize grid infrastructure through intelligent planning. The proposed approach leverages the predictive capability of artificial neural networks to support efficient decision-making for infrastructure expansion and energy allocation. The proposed ANN-DCE approach enhances BESS, microturbines and renewable energy namely wind and solar energy, while considering EV charging waiting time, efficient, reliable and sustainable energy management. Performance evaluation using RMSE demonstrates that ANN-DCE outperforms existing methods by reducing short-term planning costs achieving capacity expansion in the long term and attributing the expansion costs to wind energy confirming its cost-effectiveness and scalability. This paper is organized as follows: literature review is given in Section 2, the proposed method is described in Section 3, results are presented in Section 4 and conclusions are drawn in Section 5.

2. Literature Survey

2.1 Related Work

In 2025, Dong et al. [21] introduced a stochastic scheduling optimization framework for the integrated PV-BESS-EVCS system. The study focused on improving the coordination between renewable energy generation, battery storage systems and EV charging demand under uncertain operating conditions. The approach utilizes a hybrid modeling technique to account for the multi-source uncertainties in PV generation, along with a piecewise linear formulation to describe the dynamic SOP limits of BESS. Its performance was verified using representative commercial-area scenarios, demonstrating that, compared to deterministic optimization, the suggested approach improved operational profits by 0.41%, while lowering equivalent carbon emissions by 0.61% and reducing power curtailment by 3.05%.The findings highlight the importance of incorporating uncertainty-aware scheduling mechanisms in future EVCS energy management systems.

In 2025, H. Ameer et al. [22] proposed a linear programming approach that integrates key factors such as seasonal utility grid tariffs, station capacity, consumer charging costs, traffic flow, demand density and coverage radius. The proposed framework emphasizes strategic charging station placement and

operational planning to improve user accessibility and energy efficiency. The approach was assessed using simulation experiments based on the road network of Hefei, resulting in a 35% improvement in EVCS coverage and a 5% decrease in user charging costs compared with current placements and pricing schemes. By integrating urban data analysis with optimization methods, the method efficiently determines suitable locations for charging stations and offers an innovative framework for EV infrastructure planning, contributing to both urban development and broader sustainability objectives. Despite these improvements, the absence of adaptive real-time pricing mechanisms limits the system's responsiveness to rapidly changing charging demands.

In 2024, X. J. Dong et al. [23] introduced a simultaneous capacity configuration and scheduling optimization model for PV/BESS integrated EV charging stations, combining hybrid modeling for PV power prediction with an optimal scheduling strategy for charging piles. The study aimed to improve both the operational efficiency and economic feasibility of integrated charging infrastructure systems. To reduce computational complexity, The model was restructured as a MILP formulation using the Big-M technique. Its validity was demonstrated through a representative commercial-area case study, where it achieved a 15.67% improvement in economic performance and a 37.14% reduction in carbon emissions compared to a fully grid-dependent system. In addition, the combination of PV hybrid modeling with optimized charging schedules led to more efficient capacity planning and notable improvements in overall system performance, underscoring the model's potential for the optimal design and operation of PV/BESS-combined EVCS. However, the effectiveness of the framework largely depends on accurate estimation of uncertain operational variables and environmental conditions.

In 2025, Q. Meng et al. [24] proposed a dynamic pricing mechanism that models the interaction between Active Distribution Network Operators (ADNOs) and Electric Vehicle Aggregators (EVAs) to enhance the management of active distribution networks. The framework introduces intelligent coordination between network operators and charging participants to achieve efficient energy distribution and renewable energy utilization. The framework implements a multi-mode pricing scheme that categorizes EV charging into emergency, scheduled, and real-time modes, enabling improved network performance in terms of load balancing, renewable energy utilization, and loss reduction. To manage uncertainties in renewable energy generation, a multi-stage SRO approach is incorporated within a bi-level framework, enhancing both economic efficiency and system reliability. The suggested approach delivered substantial improvements, including an 18% decrease in ADN load variability, a 30.02% reduction in renewable energy curtailment costs, and a 10.84% decline in network loss expenses. By applying a bisection technique alongside the Column-and-Constraint Generation Alternating Iteration Strategy (C&CG-AIS), the model demonstrated high computational efficiency, achieving a total cost of 3502.28 CNY and reducing iteration time by 92.29%. Its effectiveness was further verified on a modified IEEE 33-bus system, where it showed enhanced network reliability and better utilization of renewable energy compared to traditional approaches. Nevertheless, the reliance on predefined uncertainty distributions and limited consideration of regional charging behavior reduces its adaptability in diverse real-world scenarios.

In 2024, H. Li et al. [25] proposed a novel method to optimize the operation of Mobile Charging Stations (MCS) for economic efficiency. The research concentrated on improving charging accessibility and operational flexibility through intelligent scheduling of mobile charging resources. The study developed a variant of a MILP approach aimed at maximizing MCS operators' profits while considering user centric factors, scheduling EV charging, including clustering, meeting user demand, establishing temporary charging locations, dispatching MCS units for charging and discharging. As the problem scale increases, solving the MILP model becomes computationally inefficient. To address this, an improved genetic algorithm was introduced for large-scale instances of the model. The performance and validity of the suggested algorithm were evaluated using Solomon's benchmarking instance data, complemented by sensitivity analyses to provide managerial insights into MCS operations. Although the proposed method improves operational flexibility, the deterministic optimization structure and increasing operational expenses remain significant limitations for large-scale deployment.

Table 1. *Methodologies and challenges of optimization in EV charging and energy management*

Author	Methodology	Advantage	Disadvantage
Dong et al [21] (2025)	Stochastic scheduling optimization framework	Improve operational profits, decreasing carbon emission equivalents and reducing power curtailment	Internal and external uncertainties
H Ameer et al [22] (2025)	Linear programming+ DBSCAN	Transforming charging stations into profitable and eco-friendly energy systems	Lack of progress in real-time pricing algorithm design
XJ Dong et al [23] (2024)	scheduling optimization model	Improved economic benefits and reduce carbon emissions	Effects of variability in both internal and external factors and the need for accurate characterization of key internal variables
Q Meng et al [24] (2025)	Bi-level four-stage optimization Method	Minimizing ADN load variability and decreasing curtailment costs of renewable energy, modified IEEE 33-bus system and reduction in iteration time	Reliance on assumed distributions of uncertain parameters and incorporating regional EVA characteristics
H Li et al [25] (2024)	Genetic algorithm	Provides flexibility and convenience, Reduces user issues, Benchmarking and sensitivity analysis	Deterministic optimization problem and high operating costs

2.2 Problem Statement

The methodologies and challenges of optimization in EV charging and energy management can be summarized in table 1: [21] presents a stochastic scheduling optimization method that enhances operational profits, lowers carbon emissions and reduces power curtailment, though it is limited by internal and external uncertainties. In [22], a linear programming approach with DBSCAN transforms charging stations into profitable and eco-friendly energy hubs, but lacks real-time pricing algorithm development. Similarly, [23] proposes a scheduling optimization model that improves economic benefits and reduces emissions. However, it is restricted by uncertainties and the absence of accurate modeling of key parameters. In [24], a bi-level, four stage optimization method effectively reduces ADN load fluctuations, curtailment costs and iteration time in a modified IEEE 33-bus system. However, it depends on prior knowledge of uncertainties and omits regional EVA characteristics. Lastly, [25] employs a genetic algorithm, offering flexibility, convenience and validation, but faces limitations from deterministic optimization and high operating costs.

3. Proposed Methodology

3.1 EV Charging Station-Connected Microgrid with Diverse Energy Sources

A microgrid uses capacity resources and the utility grid to meet load demands. The integration of distributed renewable energy resources within a microgrid enables flexible and sustainable power management for EV charging applications. Expanding capacity resources is necessary since a microgrid with this capacity will not be able to fulfill the demand as load demand rises in the coming years. In order to determine the operation, technology, time and capacity of the additional resources that might be installed into a microgrid, a plan to increase the capacity resources is carried out on the microgrid, as shown in Fig. 1. The proposed expansion planning framework evaluates both renewable and conventional energy resources to ensure reliable and continuous energy supply under varying load conditions. This expansion plan will take both technical and financial factors into account to meet the growing demand. This study uses ESD, wind, micro gas turbines and solar as resources to derive the capacity expansion model. Capacity additions to meet rising demand are calculated based on yearly load growth trends. The proposed framework dynamically adjusts infrastructure expansion decisions according to future energy consumption forecasts and charging requirements.

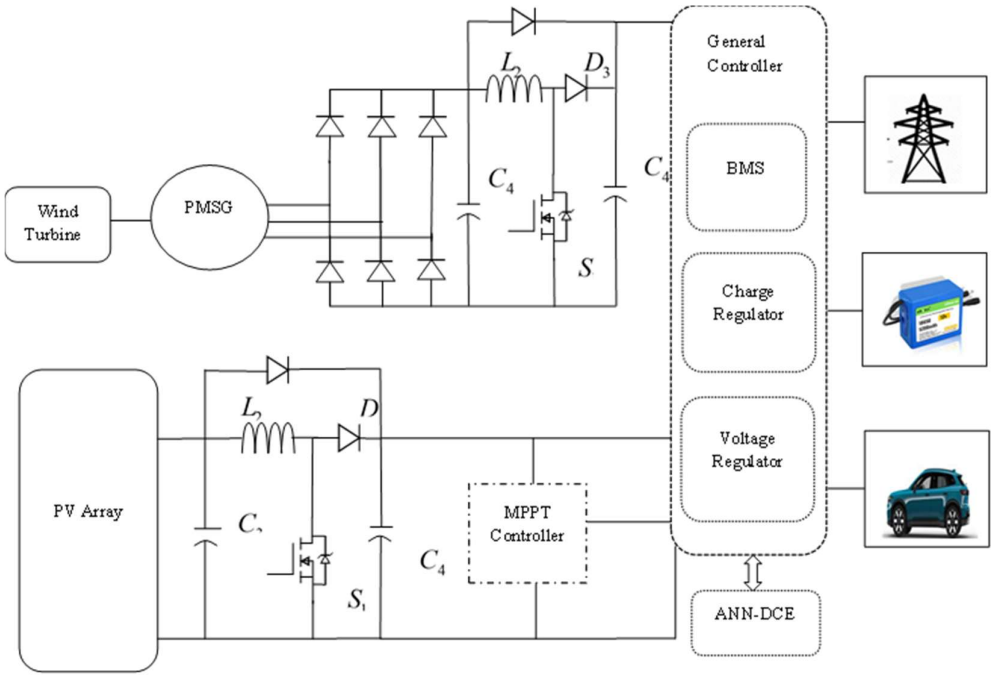


Fig. 1. *EV Charging Station-Connected Microgrid with Diverse Energy Sources Architecture*

3.1.1 MPPT controller

The MPPT strategy incorporated in the proposed system is designed to excerpt the highest possible energy from the solar panel under varying environmental conditions. Efficient MPPT control is essential for maximizing solar energy utilization and improving the overall efficiency of the EV charging microgrid. Its primary objective is to optimize the PV output so that maximum power is obtained for a given level of solar irradiance and temperature. To achieve this, the Perturb and Observe (P&O) method is implemented for MPPT control [26]. The converter duty cycle is used to regulate the voltage. The algorithm incrementally adjusts the duty cycle increasing it until the operating point reaches the MPP. Once this point is exceeded, the algorithm reverses direction causing the system to oscillate around the MPP. A smaller step size in the adjustment leads to more stable and efficient operation.

3.1.2 BMS

Battery management system (BMS) [27] integration involves defining the specifications, features and functions required to effectively monitor, regulate and maintain battery performance. The BMS plays a vital role in ensuring safe and reliable operation of battery storage systems used in EV charging infrastructure. These requirements are essential across a wide range of with user electronics, applications, EV and RES. A well-designed BMS is essential for optimizing ensuring safe operation, battery efficiency and extending the overall lifespan of the battery system.

3.1.3 Charge Controller

Numerous approaches to EV charging management focused on centralized control [28] strategies. Centralized charging management enables coordinated control of charging operations to optimize energy usage and reduce stress on the power grid. In such systems, all relevant data such as the status of electric vehicles, user preferences, electricity prices and grid constraints are gathered and processed at a central point. Based on this information, a central entity, such as an aggregator or system operator determines the charging schedule and control actions. While this method can achieve highly efficient use of available resources, it depends heavily on a well-developed and reliable communication infrastructure.

3.1.4 Voltage Controller

Coordinating EV chargers with other Volt/Var control devices can support effective voltage regulation in distribution feeders. Voltage regulation is essential for maintaining power quality and preventing instability within the charging network. Maintaining proper voltage levels is essential for grid stability and reliable operation. This coordinated approach can also help minimize power losses and the inclusion of RES within the grid network.

3.2 Modeling the investment cost of solar, wind, microturbine and ESS

The capital and operational costs of the solar power system, microturbine, inverter, wind energy system and ESS are shown. Accurate modeling of investment and operational costs is essential for evaluating the economic feasibility of EVCS capacity expansion. $\left(C_{\cos t}^{pv}\right)$ is the capital cost of the SPV system given as

$$C_{\cos t}^{pv} = \sum_{y \in Y} (NI_{pv}^{y} \times P_{pv} \times R_{pv} \times N_{eq} \times N_{p1}) \tag{1}$$

Where P_{pv}, R_{pv} and NI_{pv}^{y} expressed the newly installed cost of the solar system, SPV system. The yearly equivalent expense $N_{eq} = D \times (1+D)^{L} / (1+D)^{L} - 1$, the present value $N_{p1} = N_f / (1+D)^{L}$ and N_f D and L correspond to the discount rate of net cash flow and the asset lifespan, respectively. The index of years is denoted as y and Y is denoted as the set of years. The maintenance and operational costs of the SPV system are given as

$$C_{op}^{pv} = \sum_{y \in Y} \left(PV_{a}^{y} \times P_{pv} \times O_{pv} \times N_{p1} \times 365 \right) \tag{2}$$

where O_{pv} and PV_{a}^{y} represent the percentage of SP presented per year and the annual operational expense of the solar system. The capital expense of the WPS $\left(C_{\cos t}^{wp}\right)$ is given as

$$C_{\cos t}^{wp} = \sum_{y \in Y} \left(NI_{wp}^{y} \times P_{wp} \times R_{wp} \times N_{eq} \times N_{p1} \right) \tag{3}$$

Where NI_{wp}^{y} denoted the newly installed rated WPS (kW), P_{wp} is represented the cost of the wind system ($/kW) and R_{wp} denoted the wind power in each year (%). The maintenance and operational cost of the WPS $\left(C_{op}^{wp}\right)$ is denoted as

$$C_{op}^{MT} = \sum_{y \in Y} \left(MT_{p}^{y} \times O_{MT} \times N_{p1} \times 365 \right) \tag{4}$$

where O_{wp} and WT_{a}^{y} represent the annual availability of SP (%) and the operating expenses of the solar system ($/year). The capital expenses of the WPS $\left(C_{\cos t}^{MT}\right)$ is denoted as

$$C_{\cos t}^{MT} = \sum_{y \in Y} \left(NI_{MT}^{y} \times P_{MT} \times R_{MT} \times N_{eq} \times N_{p1} \right) \tag{5}$$

Where R_{MT} NI_{MT}^{y} and P_{MT} expressed, respectively, the newly installed price of the microturbine ($/kW), the microturbine each year (%) and the energy produced using microturbine. The maintenance and operational cost of the WPS $\left(C_{op}^{MT}\right)$ is denoted as

$$C_{op}^{MT} = \sum_{y \in Y} \left(MT_{p}^{y} \times O_{MT} \times N_{p1} \times 365 \right) \tag{6}$$

Where O_{MT} denotes the operational expenses of microturbine and MT_{P}^{Y} denotes the power produced by microturbine (kw). ESS is used for the investment cost of converters $\left(C_{con}^{inv}\right)$ is resolved as

$$C_{con}^{inv} = \sum_{y \in Y} \left(NC_{con}^{y} \times P_{con} \times R_{con} \times N_{eq} \times N_{p1} \right) \tag{7}$$

where NC_{con}^{y} denotes the amount of new ESS installations added each year, R_{con} represents the cost of the ESS converter and P_{con} denotes the converter's rated power, respectively. The operation and maintenance expenses associated with the ESS converter are expressed as

$$C_{op}^{con} = \sum_{y \in Y} \left(NCT_{con}^{y} \times P_{con} \times O_{con} \times N_{p1} \times 365 \right) \tag{8}$$

where NCT_{con}^{Y} is the available converter power in a given year and O_{con} is denoted as the yearly operating expenses of the converter system (in $/year). ESS is used for the investment cost of converters $\left(C_{inv}^{ESS}\right)$ is given as

$$C_{con}^{inv} = \sum_{y \in Y} \left(NC_{con}^{y} \times P_{con} \times R_{con} \times N_{eq} \times N_{p1} \right) \tag{9}$$

Where P_{ESS} denotes the rated power of the converter for ESS, R_{ESS} is the price of the converter for ESS and NCT_{ESS}^{y} the amount of new ESS installations added each year. The maintenance and operational expenses of the ESS converter is expressed as

$$C_{op}^{ESS} = \sum_{y \in Y} \left(NCT_{ESS}^{y} \times P_{ESS} \times O_{ESS} \times N_{eq} \times 365 \right) \tag{10}$$

Where O_{ESS} denotes the annual operational cost associated with the ESS capacity (in $/year) and NCT_{ESS}^{y} is the available ESS capacity each year (in %). Based on these parameters, the objective function (F) for EVCS expansion can be formulated as follows

$$Min(F) = C_{cost}^{pv} + C_{op}^{pv} + C_{cost}^{wp} + C_{op}^{wp} + C_{cost}^{MT} + C_{op}^{MT} + C_{con}^{inv} + C_{op}^{con} + C_{inv}^{ESS} + C_{op}^{ESS} + C_{in}^{L} \tag{11}$$

3.3 Modelling of PMSG

In a salient-pole permanent magnet synchronous generator (PMSG) [29], the stator inductances vary with the rotor position, which complicates the voltage equations and control design. PMSG systems are widely utilized in renewable energy applications because of their high efficiency, compact structure and reliable performance. A reference frame transformation is applied so that the inductances no longer depend on the rotor position. Specifically, a synchronous reference frame is chosen such that the d-axis aligns with the rotor magnetic flux. In this frame, the voltage equations are expressed in the synchronous reference frame, as given in equations (12)-(16).

$$V_{sd} = R_s i_{sd} + d\Phi_{sd} / dt - \omega_e \Phi_{sq} \tag{12}$$

$$V_{sq} = R_s i_{sq} + d\Phi_{sq} / dt - \omega_e \Phi_{sd} \tag{13}$$

$$\Phi_{sd} = L_d i_{sd} + \Phi_m \tag{14}$$

$$\Phi_{sq} = L_q i_{sq} \tag{15}$$

$$\omega_e = p\omega_m \tag{16}$$

Where $i_{sd}, i_{sq}, \Phi_{sd}, \Phi_{sq}, V_{sd}, V_{sq}$ denotes the d and q-axis components of the stator current, flux and voltage, L_d *and* L_q represents the d and q-axis inductance, R_s denotes the stator resistance, p represents the total number of pole pair, Φ_m denotes the magnetic flux produced by the permanent magnet, ω_m represents the mechanical rotational speed of the drivetrain and ω_e denotes the angular speed in electrical terms. These mathematical formulations enable accurate dynamic analysis and control of the PMSG within the renewable energy-based EV charging system.

3.4 ANN Modeling

ANNs are a widely recognized AI technique inspired by the human brain, offering flexibility for applications such as power electronic control systems. ANN models are capable of learning complex nonlinear relationships between input and output variables, making them suitable for energy forecasting and optimization problems. The Multilayer Perceptron (MLP), illustrated in Fig. 2, is the most commonly used type of ANN and consists of fully connected layers ANN. The Output Layer (OL), Hidden Layer (HIL) and Input Layer (INL). Raw data is delivered to the INL, where each neuron stands for a feature. With neuron counts determined by task difficulty, HIL carry out calculations by using nonlinear transformations on weighted input signals. Using a single neuron can be used for binary classification tasks, while multiple neurons are employed for multiclass issues, the OL produces predictions.

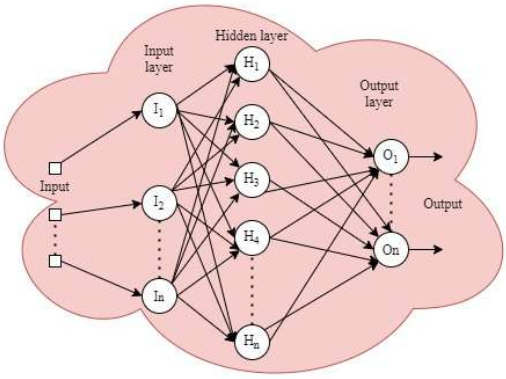


Fig. 2. *ANN architecture*

The training process has a significant impact on an ANN's performance. To reduce prediction mistakes, training modifies the weights of neurons across layers illustrate in Fig. 2. Supervised and unsupervised learning, which are further divided into gradient search and metaheuristic techniques, are common strategies. Backpropagation (BP), a conventional gradient based technique for MLPs, often suffers from slow convergence, poor initial weight selection and a tendency to get trapped in local minima. Metaheuristic methods, however, randomly initialize control variables and can achieve global optimization without previous existing information, facilitating optimal ANN and weights, design and biases. The aim of supervised learning is to minimize the gap between predicted outputs and the actual target values. In the proposed model, ANN training is utilized to predict energy demand patterns and support intelligent capacity expansion planning for EV charging infrastructure.

In an MLP network, each neuron integrates a summation step followed by an activation function, with neurons across layers linked through weighted connections. The summation function, as defined in Equation (17), calculates the weighted sum of inputs along with the inclusion of a bias term.

Whereas, bias B_k and the number of input neurons are represented as n ,while w_{ik} denotes the weight connecting input neuron L_i to the neuron k

$$A_k = \sum_{i=1}^{n} w_{ik} L_i + B_k \tag{17}$$

In equation (18), a nonlinear sigmoid activation function can be expressed as

$$F(z) = \frac{1}{1+e^{-z}} \tag{18}$$

Hence, k is the neuron output can be expressed as

$$X_k = F_k\left(\sum_{i=1}^{n} w_{ik} L_i + B_k\right) \tag{19}$$

4. Result and Discussion

To evaluate the performance of the ANN-based DCE for the EV charging infrastructure model, data were generated from a Simulink model using MATLAB 2021b. The simulation environment was developed to analyze the effectiveness of the proposed ANN-DCE framework under varying load demand and renewable energy conditions. This section presents a comparative analysis of the proposed ANN-DCE method against three existing advanced techniques. Performance evaluation focuses on prediction accuracy, cost efficiency, energy management capability and infrastructure scalability. The discussion also includes an assessment of the neuron count on RMSE, load growth, the analysis of charging requirement for EV arrival and fuel price trends for the proposed model.

Fig. 3 shows that by using RMSE, the training error was estimated, which illustrates the error progression during training. RMSE is adopted as the primary performance metric because it effectively measures prediction accuracy and training stability of the ANN model. The resulting datasets were then applied to the ANN. Throughout the training, the RMSE of each neuron of the hidden layer varied. In this training from 2 to 10, we assessed the performance of neurons. From the 6th neuron that a minimal RMSE value was obtained, while the RMSE increased from the 6th to 10th neuron and decreased tediously from the 2nd to 6th neurons (Fig. 2). Thus, the 6th neuron provided an accurate valuation of the capacity extension problem. As the outcome, a 6-neuron ANN, with 60-fold iterated, was used in this training. The results indicate that selecting an optimal neuron configuration significantly improves prediction accuracy and avoids unnecessary computational complexity.

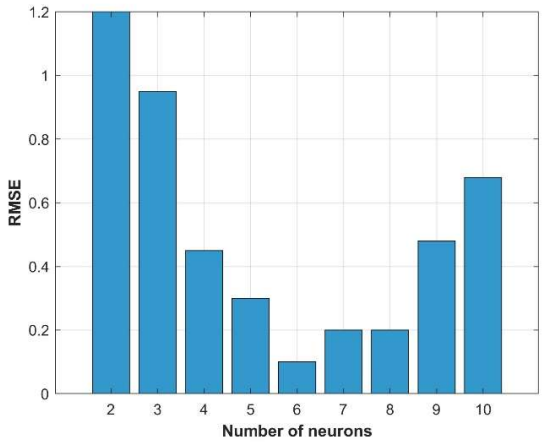


Fig. 3. *Impact of Neuron Count on RMSE for Capacity Expansion Testing*

The growth of the fuel cost and load over this span of years is shown in Fig. 4. The analysis demonstrates the increasing energy requirements associated with the rapid expansion of EV charging infrastructure over time. The load shows a steady increase from 107% to about 125%, whereas the fuel cost extended from 101% to 106% over the five years. Both parameters exhibit an upward trend, the energy demand and associated cost growth increase during the planning period.

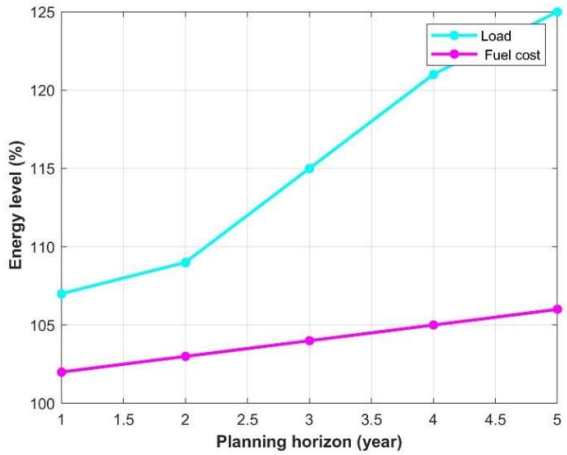


Fig. 4. *Projected changes in electricity demand and fuel costs over the planning period.*

Fig. 5 illustrates the variation of energy consumption over time. The hourly demand profile provides insights into EV charging behavior and peak load distribution within the charging network. The energy demand shows a significant rise during the evening hours, with the highest peak reaching approximately 110 kWh at 18 hours and another high value of 105 kWh at 20 hours. Between these peaks, the energy level low value of around 45 kWh at 19 hours, indicating a short period of reduced consumption. During the early hours at 17 hours and later at 21 hours, the energy levels remain low, near 10 kWh. This figure shows that the peak energy demand occurs between 18 and 20 hours.

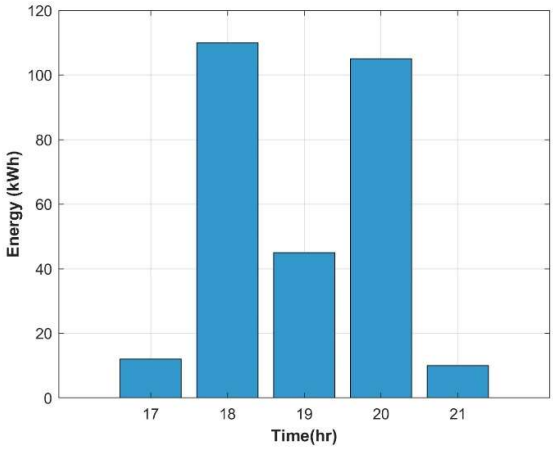


Fig. 5 *EV Arrival at Hour 20 with 10 kW Charging Requirement*

Table 2. *Yearly Investment Required for Energy Resource Expansion*

Cost component	Solar energy	Wind energy	Microturbine	BEES Capacitor	BEES energy	Total Cost/Year
Annual expansion cost ($/year)	1480.2	2348.232	8875.323	6642.03	965.23	20311.02

Table 2 illustrate the total annual expansion cost for the renewable power system is 20,311.02. The investment analysis provides a detailed understanding of the economic contribution of each energy resource within the proposed microgrid architecture. Between the components, the Microturbine has the highest cost at 8,875.32 per year and the BEES Capacitor at 6,642.03. Wind Power contributes 2,348.23, whereas Solar Power at 1,480.20 annually. The BEES Power component has the lowest cost of 965.23 per year. The table 1indicate that the microturbines require the largest investment solar and wind power remain cost-effective options for sustainable energy expansion. Overall, combining these technologies provides a balanced approach to renewable energy and cost efficiency. The results demonstrate that integrating multiple energy resources enhances operational flexibility while supporting sustainable and reliable EV charging infrastructure development.

Table 3. *EVCS Power Contribution to the Microgrid Over a Day Within a Five-Year Horizon*

S. No	Hours	1	5	6	7	11	12	15	17	20	22	23
1	Year-1	110	0	0	0	0	22.23	0	0	105	88	107
2	Year-2	0	43.023	29.235	0	0	18.236	25.26	0	0	95	770
3	Year-3	22.32	0	14.235	38.235	0	19.26	23.26	0	12.32	0	0
4	Year-4	27	109.25	25.236	19.235	30.263	0	27.023	39.2363	67.263	0	63
5	Year-5	56.03	75.236	0	0	16.236	0	0	0	90.263	55	0

Table 3 illustrates the power injected into the microgrid by EVCS over the five-year planning horizon. Power injection varies across different hours, with the highest peaks during specific periods such as hours 1, 5, 20, 22 and 23. Typically, when energy prices are high, power is injected into the microgrid. This behavior indicates that the proposed ANN-DCE framework can effectively coordinate charging and energy distribution strategies to maximize economic and operational efficiency.

Table 4. *Expansion Plan for Various Capacity Resources with and Without Uncertainty*

S.No	Condition	Solar	Wind	Microturbine	Power of energy	Capacity of BESS
1	Without uncertainty	-	205	_	-	70
2	With certainty	25	240	60	75	220

The expansion with and without uncertainty is shown in Table 4. Considering uncertainty in energy demand and renewable generation requires higher reserve capacity to maintain reliable system operation. When uncertainty is considered, higher capacities of solar, wind, microturbine and BESS are required to ensure reliability. Similarly, for the model without uncertainty the microgrid requires a reduced number of resources and lower capacity.

5. Conclusion

The proposed ANN-DCE approach offers an effective method for EVCS infrastructure whereas integrating the RES and energy storage systems. The proposed framework successfully addresses the growing challenges associated with EV charging demand, renewable energy integration and microgrid capacity expansion. By employing ANN modeling, the method optimally coordinates BESS, microturbines and renewable sources namely wind and solar power, ensuring a reliable and adaptive energy supply. The ANN-based prediction mechanism improves decision-making capability by accurately forecasting energy demand and supporting intelligent resource allocation. Charging time for EVs was specifically considered, enhancing operational efficiency. Comparative evaluations with three advanced methods demonstrate that ANN-DCE reduces short-term planning costs while achieving a significant expansion in long-term capacity, highlighting its effectiveness in both short term and future planning scenarios. Wind energy stands as the major contributor, accounting for the expansion cost, highlighting the importance of renewable integration. Overall, ANN-DCE offers a robust, data driven and cost-efficient approach for dynamic capacity planning, supporting sustainable energy adoption, efficient grid utilization and scalable EV charging infrastructure development. The proposed methodology therefore contributes to the advancement of intelligent and environmentally sustainable EV charging infrastructure for next-generation smart grids. Future work can enhance the ANN-DCE approach through real-time adaptive learning, V2G integration and hybrid AI models to improve scalability, forecasting and sustainable operation.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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