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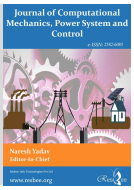

Optimized the Allocation of Electric Vehicle Charging Stations and Distributed Generation in Microgrids with The Incorporation of Gaussian Mixture Models

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Abstract: Electric vehicles (EVs) are essential to reaching the UN Sustainable Development Goals for 2030 because they reduce emissions and improve air quality. They also play a pivotal role in decarbonizing the transport sector, which accounts for nearly one-quarter of global CO2 emissions. In order to encourage the shift to sustainable transportation, Electric Vehicle Charging Stations, or EVCSs, must be placed strategically across cities. However, problems, including increasing power losses, deteriorating voltage profiles, and voltage instability, have arisen in microgrids. These technical challenges become more severe with the growing penetration of renewable energy resources and variable EV charging demands. Thus, to overcome these obstacles, the model clustered the intricate, spatiotemporal charging patterns of EVs and proposed a novel Gaussian Mixture Model (GMM) to optimize the distribution of EVs and Distributed Generation (DG) at the same time due to the stochastic behaviors of renewable energy sources and EV uncertainties. Furthermore, it may facilitate enhanced grid stability and resource efficiency. The goal of this energy storage system allocation model is to maximize voltage stability, minimize power losses, and have the benefit of improving voltage profiles by solving an optimization issue with multiple objectives. This multi-objective optimization is handled using advanced algorithms that consider both technical constraints and economic efficiency. To investigate the proposed approach, the IEEE 33-bus test system is examined. Simulation results show that the proposed model outperforms existing analytical techniques by 1.45% in accuracy and has a suitable execution time.

Keywords: Electric Vehicles; Distributed Generation; Smart Grids; Electric Vehicle Charging Stations; Gaussian Mixture Models; Wind Turbine; Photovoltaic.

Nomenclature

Abbreviation	Description
EVs	Electric Vehicles
PVs	Photovoltaics
WTs	Wind Turbines
SGs	Smart Grids
'EVCSs	Electric Vehicle Charging Stations
GMMs	Gaussian Mixture Models
DG	Distributed Generation
PE	Protection Equipment
CS	Charging Station
MCS	Monte Carlo simulation
RDGs	Renewable Distributed Generations
RERs	Renewable Energy Resources
EENS	Expected Energy Not Supplied

1. Introduction

EVs are becoming more and more popular because of their numerous economic and environmental advantages [1]. They contribute significantly to global carbon neutrality efforts by reducing tailpipe emissions and dependence on petroleum-based fuels. Similarly, EVs have promise for addressing both the issue of climate change and the potential limitation of fossil resources. Although it is predicted that the demand for EVs will rise over the coming years, several issues, such as the cost of batteries, the availability of CS infrastructure, and gasoline prices, will continue to limit this desire [2]. However, only when there is a sufficient number of users in the network, the investors be willing to invest money in electronic

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infrastructure. Therefore, establishing a balanced ecosystem between demand, investment, and infrastructure growth is essential for sustainable EV market expansion. As environmental pollution issues and the fossil fuel crisis get more attention, more and more uses for DG and EVs are being proposed [3]. Further, government and business support are being provided for the construction of EVCSs, and the infrastructure is also required for EVs [4]. While the power system was functioning under the circumstances, the large-scale DG and EVCS integration faced a number of problems, including rising power losses and voltage sags. Such challenges necessitate innovative optimization approaches that can ensure grid stability while accommodating fluctuating EV charging demands. Thus, the planning issue of DG and EVCS allocation in a reasonable manner is receiving a lot of attention shown in the outcomes of the model.

Launching EV charging services requires thorough analysis of both operational charging demands allocation and tactical charging infrastructure planning from the standpoint of total operating expenses [5]. Strategic decision-making at this level requires balancing technical performance with economic sustainability to achieve optimal deployment. However, the demand allocation is impacted by the charging staff's travel distance, which is determined by the charging station's location and vice versa. Additionally, charging time is inevitable because of the low charging capabilities [6]. The increasing heterogeneity of EV battery capacities and charging technologies adds further complexity to this planning process. These present difficulties of an organization obtaining effective planning and encourage us to investigate the linked optimization problem of valet charging service allocation and EV charging position. The location of charging stations and the quantity of charging demands at each node that needs to be allocated to each station are thus optimized simultaneously. This dual optimization framework ensures equitable service distribution while reducing congestion at high-demand nodes. The average charging waiting time is calculated by modelling the charging system as a queuing system [7]. The whole cost is kept to a minimum, including the development of charging stations and the launch of EV charging services (i.e., road service for charging staff, round-trip time, and waiting time for charging).

In general, the studies regarding DG and EVCS combined the preparation and implementation of active management strategies [8]. The model proposes a bi-level planning concept of a combined EVCS and DG system that considers the active management strategy of the distribution network. Similarly, MCS is used to initially determine the daily characteristic curve of EV charging load, and then the overall charging load is designated in the area [9]. The K-means++ clustering approach is used to produce both DG and conventional load situations. A two-layer model of joint coordination planning incorporating DG and EVCS is developed in [10]. The interaction between the upper and lower levels ensures that operational constraints are respected while achieving broader economic and environmental goals. The lower level of planning suggests three active management strategies to maximize power flow in typical conditions, whereas the higher level specifies the objectives of social and environmental welfare, power loss cost, and investment cost. To optimize power flow in any typical situation, the lower-level active management proposes three active management techniques. Improved GMM solves the overall issue and is validated on the IEEE-33 node and PG & E-69 node test systems.

This paper allocates the DGs and EVCSs in microgrids to increase voltage stability, lower power losses, and improve grid dependability. The integration of GMM-based clustering with optimization algorithms enhances both accuracy and computational efficiency. In this model, the GMMs are used in microgrid optimization for more effective DG sizing and placement, EVCS allocation, and scheduling. The organization of the paper are given below, Section 2 represents the survey of the different optimization methods used in the proposed model. Section 3 shows the proposed method, which allocates the EVCSs and DGs in the microgrids. Section 4 signifies the result and discussion with the proposed technique for the EVCSs and DGs allocation in the microgrids. The conclusion of the work is condensed in Section 5.

2. Literature Survey

2.1 Related Work

In 2024, Yaghoubi-Nia et al. [11] proposed a novel clustering-based technique to optimize the simultaneous distribution of DGs and EVs while keeping the benefit of the stochastic and uncertain behaviors of renewable DGs and EVs. Their research aimed to address the inherent randomness of EV charging demand and renewable energy generation, which often challenge the stability of modern microgrids. In this model, the most significant developments of the technique were the use of clustering to create a novel stochastic model for EVs. The proposed strategy could handle the execution time issues with Monte Carlo simulation-based methods that deal with smart grid stochastic behaviors. However, another key contribution of the model was the proposed clustering-based approach, which optimized the distribution of EVCSs, DGs, and protection equipment while preserving dependability. Similarly, the introduced method was examined

using the IEEE 33-bus test system. While its execution time was suitable, simulation findings showed that an accuracy improvement of 1.45% could be achieved when compared to currently available analytical ones.

In 2024, Guindi et al. [12] addressed the multi-objective optimization problem of optimal allocation and sizing of RDGs and EVCSs to enhance distribution systems' voltage profiles and reduce power losses. The study focused on balancing technical performance indicators, such as voltage regulation and power efficiency, with economic considerations in infrastructure planning. Similarly, the RDGs and EVCSs were placed on the different buses of the system as part of the study's constraints. The optimal locations and sizes of the RDGs, as well as the optimal placements of the EVCSs, were simultaneously determined using the particle swarm optimization technique and the cuckoo search algorithm. Using IEEE 33 radial and meshed distribution system simulations, the efficacy of the proposed techniques was shown and simultaneously demonstrated their capacity to find the best configurations for combining RDG.

In 2023, Asaad et al. [13] proposed an optimal planning approach for the allocation of hybrid RERs and controllable charging stations for EVs in multi-microgrids. Their model integrated renewable energy management with EV charging control to minimize system imbalances and economic losses. The charging method in the proposed technique decreased the voltage variation, energy not delivered, and total cost to 26.03%, 49.57%, and 70.45%, respectively, while improving power quality and overall system cost. The simulation results were compared with those derived from various optimization techniques to validate the effectiveness of the proposed methodology. While expanding the capacity of the charging stations, the projected simultaneous allocation strategy for EVCSs and RERs might decrease the operational expenses for both types of stations.

In 2023, Zainab et al. [14] proposed a new framework for EVCS and DG planning. This framework aimed to ensure resilient energy management under both normal and islanded operating conditions. For both islanded and grid-connected scenarios, the planned approach effectively generated a single solution for the joint planning of DGs and EVCSs. A fresh two-stage planning problem formulation was used for the challenge. While the second step of planning finds the best islands for the islanded microgrid scenario, the first stage establishes the locations and sizes of the DGs using the locations of EVCSs in the grid-connected scenario. Four test cases were used to verify the proposed framework's implementation on the IEEE 33-bus system. The outcomes confirmed, however, that the proposed approach was effective and that both grid-connected and islanded microgrids could effectively use the sizes and placements of DGs and EVCSs.

In 2022, Ali et al. [15] demonstrated the optimal planning of microgrids using an optimization method to precisely identify the ideal locations and dimensions of wind and solar energy units in microgrids with the use of EVs. Their approach highlighted the interdependence between renewable generation profiles and EV charging behaviors in decentralized grids. 2) This proposed technique considered the DSTATCOM operation capacity of photovoltaic and wind energy units, 3) various branch and node constraints in the microgrid, 4) generation profile variability among wind and photovoltaic energy units, and 5) total load demand. The solution for this intricate planning model was based on a bi-level metaheuristic. However, the EV decision factors and renewable energy sources were optimized by the inner-level and outer-level functions. Similarly, optimizing grid power and voltage variations were sub-objectives. The final results showed the demonstration of the proposed approach, which controlled the EVs and scheduled the renewable energy sources to create autonomous microgrids.

2.2 Problem Statement

This section displays the benefits and the limitations of the existing approaches for the allocation of EVCSs and DGs in the microgrids. While several models demonstrate remarkable optimization efficiency, the complexity of integrating stochastic renewable sources and uncertain EV charging patterns remains a significant challenge. In Paper [11], the proposed model had the benefits of improved dependability, lower system costs, higher EV customer satisfaction, and greater integration of renewable energy of the concept presented. Though this model also had the disadvantage that the performance of many traditional and meta-heuristic clustering techniques might not be integrated by this approach. Likewise, Paper [12] offered the advantages of power losses reduction and distribution systems' voltage profiles enhancement. However, drawbacks include the requirement of sophisticated control systems, the difficulty of optimizing many objectives, and the expensive initial setup costs, respectively. These constraints may limit deployment feasibility in developing regions with restricted capital resources. Also, Paper [13] had better power quality and total system cost, but it had some major drawbacks, including the intricacy of multi-objective modelling, the costly initial infrastructure investment, and the possible intermittent nature of renewable sources. Alternatively, the high upfront expenditures and complicated coordination for DGs and EVCS are among the issues faced by the concept in Paper [14], which offers benefits including lower losses, enhanced grid stability, and incorporation of renewables. Lastly, improvements in energy resilience, cost-

effectiveness, and decreased dependency on fossil fuels are derived from Paper [15]. Nevertheless, it still had drawbacks, such as high initial investment costs, the difficulty of integrating unstable renewable sources, and possible power quality problems.

3. Proposed Methodology

This work proposed a GMM to optimize the distribution of DG and EVCS in the SG. The core objective of this model is to develop an intelligent clustering mechanism that can accurately capture the stochastic variations in renewable energy and EV charging demand. In this model, the two-input sources are used, such as solar PV supply and wind turbine supply, to provide the SG with a more dependable and steady power source. The DGs, EVCSs, and protective equipment are positioned and sized according to the model's reliability optimization approach for microgrid and use a GMM to improve system dependability. This optimisation framework incorporates probabilistic data derived from renewable generation and load profiles to identify optimal sizing and allocation schemes. By limiting the solution space and reducing the possibility of convergence to less-than-ideal solutions, the GMM assists in the optimization process and enhances power systems. According to the best possible distribution of DGs, EVCSs, and safety equipment, the proposed GMM-based reliability optimization of the SGs is carried out in this model. Fig. 1 shows the typical representation of the EVCS and DG allocation in the SG.

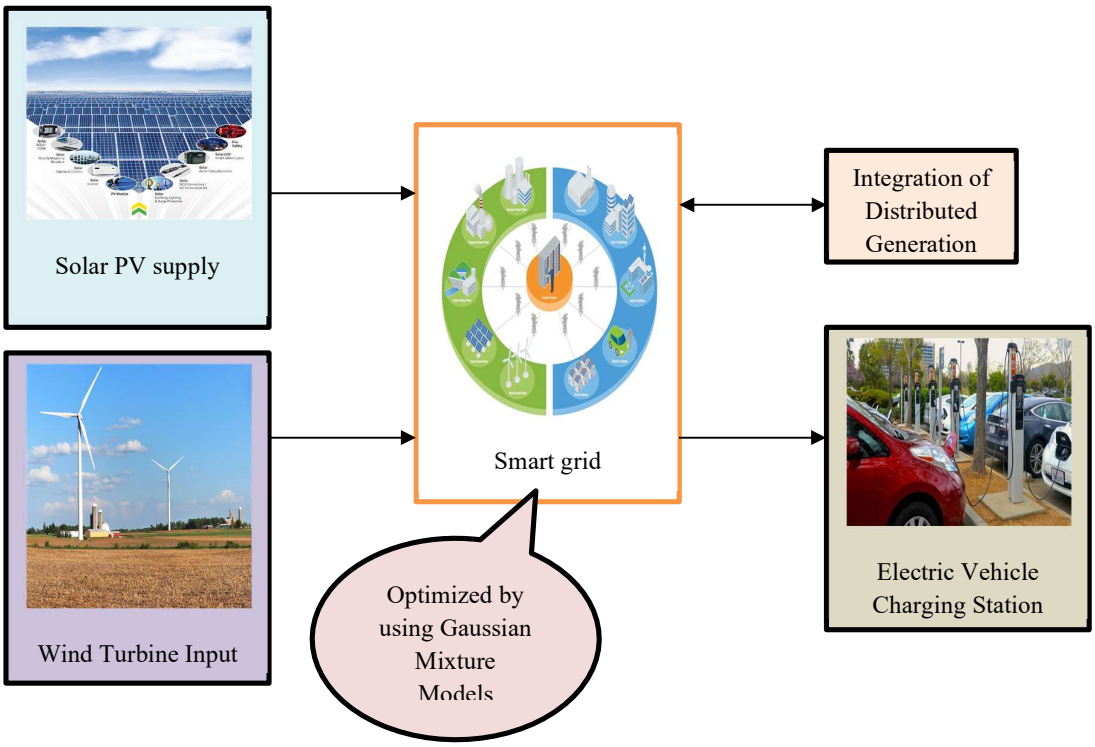


Fig. 1. *Typical representation of the EVCS and DG allocation in the SG*

Primarily, it is important to differentiate the system state based on the subsystems' availability and unavailability. This classification helps in modelling component reliability, system redundancy, and operational risk under different fault conditions. However, the PV and WT scenarios are created with a MCS. Further, situation lessening is used for both WTs and PVs. With the MCS, the EVCS load situations are simulated. In order to model the EVCSs, the stochastic behaviors of EV owners are simulated. The load on the EVCSs is determined by the scenario reduction. The PV, WT, and EVCS clusters are integrated to improve the system condition. The updated system state and the proposed approach can be used to assess the system reliability based on clusters of stochastic elements. DG and EVCS sizing and protective equipment placement are optimized based on a reliability-oriented goal. The optimization objective function minimizes system losses, enhances voltage profiles, and ensures maximum energy utilization from renewable sources. This technique helps to identify the ideal locations and sizes for DGs and EVCSs to eliminate reliability challenges, lower costs, and improve system performance by using the GMM to manage complex data distributions.

3.1 Proposed GMM-Based Reliability Evaluation Based on the Upgraded System State

In general, the components of the SG are not optimal and may not be operational. Due to this inherent uncertainty, system reliability must be assessed considering both functional and failed conditions of each component. The two-state reliability model is therefore among the most used methods for SG's reliability modelling components.

Equation (1) illustrates the correct approach to compute the EENS.

$$EENS = \sum_{i'=1}^{I'} \sum_{t=1}^{T} \left[\mathrm{P}_{i'} \times \mathrm{P}_{t} \times LC_{i',t} \right] \tag{1}$$

The probability calculation for various improved system states is expressed mathematically in Equation (2). The probability of changing system states is distinguished by the accessibility and inaccessibility of various components. Here, accessibility refers to the operational readiness of DGs, EVCSs, and renewable subsystems, while inaccessibility represents component downtime due to failures or maintenance. A likelihood of different clusters of uncertain sub-systems is presented in this model.

$$\mathrm{P}(USS_{i'}) = \prod_{e=1}^{E} \left(B_e^{(s_{e,i'})} H_e^{(1-s_{e,i'})} \right) \times \mathrm{P}_{j}^{PVC} \times \mathrm{P}_{j'}^{WTC} \times \mathrm{P}_{j''}^{EVC} \tag{2}$$

Equation (3) implies that the power balance requirement must be satisfied at every time step. In fact, the loads, losses, and charging loads of EVCSs should be less than the available power from the DGs and the upstream substations.

$$\mathrm{P}_{t,i'}^{G} + \mathrm{P}_{t,i'}^{MainSub} \geq \mathrm{P}_{t,i'}^{Load} + \mathrm{P}_{t,i'}^{Loss} + \mathrm{P}_{t,i'}^{EV} \tag{3}$$

This ensures energy equilibrium and prevents overloading within the distribution system, maintaining operational stability even under fluctuating generation and demand conditions.

Equation (4) should be used to calculate the load curtailment at any time step with respect to a specific improved system condition.

$$LC_{t,i'} = Max\left\{0, P_{t,i'}^{Load} + P_{t,i'}^{Loss} + P_{t,i'}^{EV} - P_{t,i'}^{G} - P_{t,i'}^{MainSub}\right\} \tag{4}$$

In the above equation, the PVs, WTs, and EVCSs raise the overall number of system states within the model under discussion. Multiplying the number of clusters for PVs, WTs, and EVCSs, as shown by Equation (5), by the number of basic system states, as indicated in [6] of Equation (2), yields the number of upgraded system states.

$$M_{USS}^{i} = 2^{E} \times M_{WTC} \times M_{WTC} \times M_{EVC} \tag{5}$$

This approach effectively captures the combined stochastic interactions among distributed energy resources, resulting in a comprehensive representation of the smart grid's reliability profile.

3.1.1 Gaussian Mixture Models for the Optimization of the Proposed Model

A popular method for representing multimodal probability density functions in this proposed model is the GMM [16]. The GMM is particularly suited for systems characterized by multiple operational modes or uncertainty sources, such as varying renewable generation and diverse EV charging behaviors. Let's use m samples to $Y = [y_1, y_2, ..., y_n]$ represent the dataset, with m features present in each sample x. These characteristics line up with the modal frequency ordering. In most situations, the multidimensional data's probability density function x can be accurately captured by combining multiple Gaussian distributions $q(y)$.

$$q(y) = \sum_{k=1}^{K} \mu_k \mathrm{M}\left(y \mid \rho_k, D_k\right) \tag{6}$$

The quantity of Gaussian distributions included in the model is shown by K the following variables:, $\mathrm{M}\left(y \mid \rho_k, D_k\right)$ representing the likelihood density function of the k-th Gaussian component, and ρ_k is the mean vector, the covariance matrix of the k-th Gaussian component is D_k, and the mixture's k-th coefficient, which satisfies the demand that $\sum_{k=1}^{K} \mu_k = 1$ and $\mu_k > 0$. The $\mathrm{M}\left(Y \mid \rho_k, D_k\right)$ expression has a particular expression is denoted as follows:

$$M\left(y \mid \rho_k, D_k\right) = \frac{1}{(2\pi)^{\frac{n}{2}} \left|D_k\right|^{\frac{1}{2}}} \exp\left[-\frac{1}{2} (y \mid -\rho_k)^T D_k^{-1} (y - \rho_k) \right] \tag{7}$$

These parameters collectively define the model's shape and scale, allowing for probabilistic inference on system reliability patterns under various operational conditions.

Let $\Xi = \{\mu_k, \rho_k, D_k\}_{k=1}^{K}$ denote the GMM's parameters. Because of the iterative convergence of the Expectation-Maximization (EM) approach to the maximum likelihood approximation, it is commonly used for estimation of Ξ. The method involves performing the expectation step (E-step) and the maximization

step (M-step) in reverse. During these steps, posterior probabilities and parameter updates are alternated until the log-likelihood function converges, ensuring stability in model estimation. The posterior probabilities are calculated in the E-step using the following formula:

$$q_{ik}(y_i \mid \Theta) = \frac{\mu_k \mathrm{M}(y_i \mid \rho_k, D_k)}{\sum_{j=1}^{K} \mu_j \mathrm{M}(y_i \mid \rho_j, D_j)} \tag{8}$$

The parameter set Ξ is updated in the M-step using the posterior probability in the manner described below:

$$\mu_k = \frac{1}{m} \sum_{i=1}^{n} Q_{ik}(y_i \mid \Xi) \tag{9}$$

$$\rho_k = \frac{\sum_{i=1}^{n} \left[Q_{ik}(y_i \mid \Xi) y_i \right]}{\sum_{i=1}^{n} \left[Q_{ik}(y_i \mid \Xi) \right]} \tag{10}$$

$$D_k = \frac{\sum_{i=1}^{n} \left[Q_{ik}(y_i \mid \Xi)(y_i - \rho_k)(y_i - \rho_k)^T \right]}{\sum_{i=1}^{n} \left[Q_{ik}(y_i \mid \Xi) \right]} \tag{11}$$

Through these iterative updates, the model refines its internal structure to better represent the stochastic relationships among the distributed components of the smart grid.

The log-likelihood function, as shown by Equation (12), $H(Y \mid \Xi)$ is iteratively evaluated until it finds a local maximum value.

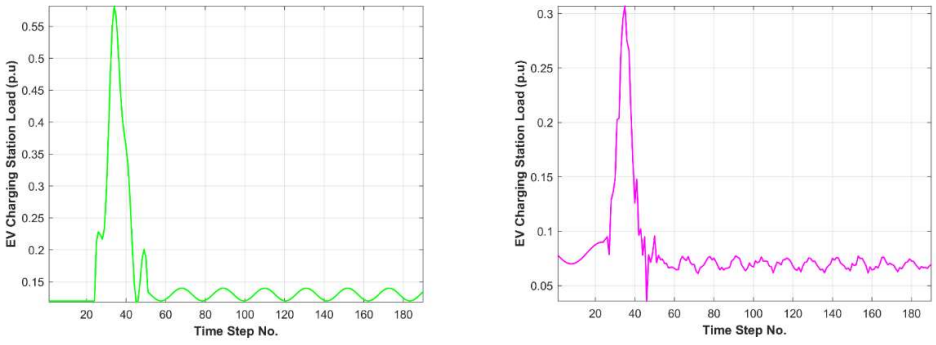
$$H(Y \mid \Xi) = \ln \prod_{i=1}^{n} q(y_i) = \sum_{i=1}^{n} \ln \left\{ \sum_{k=1}^{K} \mu_k \mathrm{M}\left(y \mid \rho_k, D_k \right) \right\} \tag{12}$$

The parameters of a GMM with a fixed number of Gaussian components are frequently estimated using the system reliability enhancement. However, the initial parameter values Θ have a significant impact on its efficacy. Changes in these starting values can result in inconsistent GMMs for damage feature datasets, compromising the damage detection method's stability. To overcome this limitation, careful initialization using methods such as K-means clustering or hierarchical partitioning can be employed, ensuring reproducible and stable convergence.

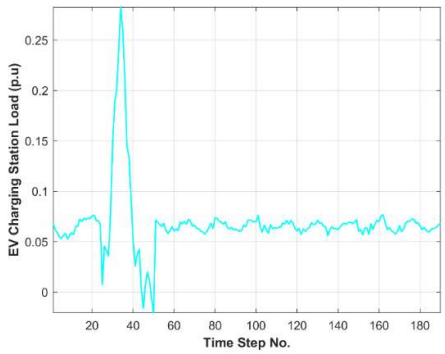
4. Result and Discussion

For the purpose of assessing the effectiveness of the GMM-based model, MATLAB 2021b was used to produce data from the Simulink model. The simulation included dynamic modeling of the microgrid components, incorporating both renewable generation variability and stochastic EV charging loads. To confirm the accuracy of the proposed approach for distributing the EVCS and DG in microgrids, several clusters were also created for the sample's testing. The EVCS cost for every cluster in simulated scenarios is determined in this model using the K-means algorithm. This cost evaluation allows for the identification of economically optimal station locations while considering user demand patterns. The WT and PV output generation is also calculated using simulated scenarios and K-means.

The IEEE 33-bus test system is assessed based on the optimal placement of PE; moreover, the positioning and dimensions of the EVCSs and DGs. This standard test system provides a well-established benchmark for evaluating voltage stability, power losses, and overall system reliability. It is used for the purpose of investigating the claimed advantages of the clustering-based approach used for allocating the EVCS and DG in microgrids.



(a) (b)



(c)

Fig. 2. *Clusters for the EVCS load, applying the K-means to simulated scenarios. (a) Cluster 1 (b) Cluster 2 (c) Cluster 3*

Fig. 2 shows the results of the clustering. To figure out how many clusters are optimal, sensitivity studies are employed. Sensitivity analysis helps determine the minimum number of clusters required to accurately represent stochastic variations without unnecessary computational burden. Three clusters produce sufficiently exact findings. For the EVCS loads, clusters 1, 2, and 3 have respective probabilities of 31%, 40.1%, and 28.9%. These probabilities indicate the relative frequency of typical EV charging demand patterns and inform the allocation of resources accordingly. Ten thousand scenarios have been created using MCS to get prepared for the PV and WT units' stochastic patterns. Similar to EVCS load clustering, PV and WT scenarios have been modelled using the K-means algorithm.

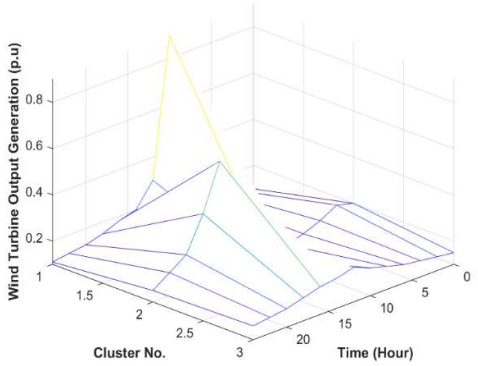


Fig. 3. *Clusters for the WT output creation using simulated scenarios and K-means.*

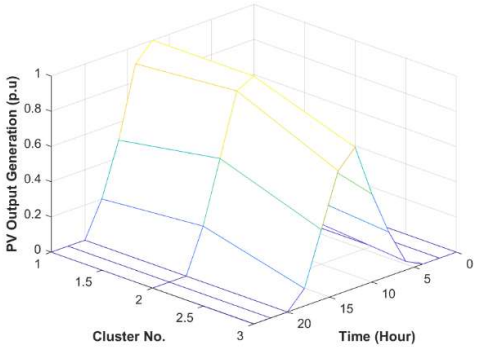


Fig. 4. *PV output generating clusters using K-means in simulated situations*

Fig. 3 displays the results of the WT output generating scenarios' grouping. Similarly, investigating the optimum number of clusters for WT output creation may be assisted by the sensitivity analysis. Choosing the correct number of clusters balances model accuracy and computational efficiency, ensuring that rare but critical scenarios are not overlooked. Three clusters have been found to produce findings that are sufficiently exact. Clusters 1, 2, and 3 have respective probabilities of 59.74%, 5.15%, and 35.12% for the creation of WT output. Fig. 4 displays the outcomes of clustering the PV output production scenarios.

Based on sensitivity analyses, the ideal number of clusters for PV output generation has been determined. Three clusters have been found to produce sufficient, accurate results. For the PV output generation, Clusters 1, 2, and 3 have respective probabilities of 41.27%, 25.62%, and 33.12%. These clusters reflect daily and seasonal variations in solar generation and help in scheduling DGs and EVCS loads more efficiently.

When the DGs are allocated optimally, the system may help the loads and customers during both grid-connected and islanded modes; similarly, while the system is operating normally or one of SG's sections fails. The simultaneous optimization of DG and EVCS placement ensures that critical loads are served even during contingencies, improving energy security and system resilience. Thus, the system's reliability is increased while the PE and DG allocations are optimized simultaneously.

Table 1. *Proposed reliability calculations' optimization findings cluster the stochastic parameter possibilities*

Results		**Values**
Optimized OF (kWh/year)		25.232
Optimized allocation of PVs	Bus No.	17
	Capacity(kW)	575
	Bus No.	23
	Capacity(kW)	155
	Bus No.	20
	Capacity(kW)	250
	Bus No.	32
	Capacity(kW)	625
Optimized allocations of WTs	Bus No.	14
	Capacity(kW)	675
	Bus No.	31
	Capacity(kW)	725
	Bus No.	19
	Capacity(kW)	300
	Bus No.	11
	Capacity(kW)	110
Optimized allocation of non-renewable DGs	Bus No.	17
	Capacity(kW)	750
	Bus No.	31
	Capacity(kW)	675
	Bus No.	21
	Capacity(kW)	230
	Bus No.	9
	Capacity(kW)	150
Optimized allocation of EVCSs	Bus No.	3
	Capacity (Number of EVs)	750
	Bus No.	8
	Capacity (Number of EVs)	500
	Bus No.	29
	Capacity (Number of EVs)	250
Optimized the location of the PE	Distribution Line	1
	Distribution Line	8
	Distribution Line	14
	Distribution Line	20
	Distribution Line	23

The proposed reliability calculations' optimization findings cluster the stochastic parameter possibilities are presented in Table 1. These clusters summarize the most probable operational states of EVCS loads, DG outputs, and stochastic system behaviors, providing a structured framework for optimization. According to test results, Segment 1 at Bus No. 3 has been chosen as the optimized allocation of EVCSs with the maximum capacity (750 EVs). The grid and other DGs can supply the EVCSs, which should be connected to upstream segments as they are significant load locations. The remaining optimized allocation of EVCSs, which have capacities of 500 and 250 EVs, have been allocated to Segments 2 (at Bus No. 8) and 3 (at Bus No. 29), respectively. In the islanded mode, DGs can supply the EVCSs, just like they would for other conventional loads. This demonstrates the flexibility of the proposed method in maintaining reliability under both grid-connected and islanded operation scenarios. Therefore, the best possible distribution of PE, DGs, and EVCSs can increase system reliability.

5. Conclusion

In this study, GMMs were used to optimize the distribution of EVCS and DG in microgrids to improve voltage profiles, lower power losses, and increase grid dependability despite operational uncertainties. By integrating stochastic modeling of renewable generation and EV charging demand, the GMM-based method provided a data-driven framework for reliable microgrid planning. This model provided more reliable planning and deployment by efficiently clustering and modelling the stochastic behaviors of renewable DGs and EV charging loads. However, the DGs and EVCS were positioned and sized optimally with the help of the proposed GMMs, which could optimize the allocation of EV arrival times and energy consumption. This optimization ensures that both peak and off-peak charging demands are managed efficiently, reducing operational stress on the microgrid. The proposed model provided a precise optimization that allowed for improving the EVCS and DG integration. Similarly, the proposed model had the advantages of boosting the stability, lowering the power losses and minimizing the voltage variations to improve the overall performance of the microgrid. Moreover, the GMM-based proposed approach was accurate and sufficiently quick. Thus, the benefits of the proposed approach allowed for more precise modelling of their dependencies and uncertainties than traditional approaches. The future scope will concentrate on improving the grid efficiency, stability, and dependability by employing advanced algorithms to model complex, stochastic renewable DG production and EV charging demand. Further research could explore the integration of machine learning-based predictive models with GMMs to enhance short-term forecasting of load and generation variability. The expansion of strong optimization frameworks that integrate technical and economic objectives to assist sustainable urban energy systems is a key area for future research.

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.

Reference

[1] Yaghoubi-Nia, Mohammad-Reza, Hamed Hashemi-Dezaki, and Abolfazl Halvaei Niasar. "Optimal stochastic scenario-based allocation of smart grids' renewable and non-renewable distributed generation units and protective devices." Sustainable Energy Technologies and Assessments 44 (2021): 101033.

[2] Bilal, Mohd, Muhammad Rizwan, Ibrahim Alsaidan, and Fahad M. Almasoudi. "AI-based approach for optimal placement of EVCS and DG with reliability analysis." IEEE Access 9 (2021): 154204-154224.

[3] Abdelaziz, M. A., A. A. Ali, R. A. Swief, and Rasha Elazab. "A reliable optimal electric Vehicle charging stations allocation." Ain Shams Engineering Journal 15, no. 7 (2024): 102763.

[4] Alharbi, Talal, Ahmed Abdalrahman, Mostafa H. Mostafa, and Loay Alkhalifa. "Joint Optimization of EV Charging and Renewable Distributed Energy with Storage Systems Under Uncertainty." IEEE Access (2025).

[5] Zhou, Siyu, Yang Han, Karar Mahmoud, Mohamed MF Darwish, Matti Lehtonen, Ping Yang, and Amr S. Zalhaf. "A novel unified planning model for distributed generation and electric vehicle charging station considering multi-uncertainties and battery degradation." Applied Energy 348 (2023): 121566.

[6] Hariri, Ali-Mohammad, Maryam A. Hejazi, and Hamed Hashemi-Dezaki. "Reliability optimization of smart grid based on optimal allocation of protective devices, distributed energy resources, and electric vehicle/plug-in hybrid electric vehicle charging stations." Journal of power sources 436 (2019): 226824.

[7] Woo, Hyeon, Yongju Son, Jintae Cho, and Sungyun Choi. "Stochastic second-order conic programming for optimal sizing of distributed generator units and electric vehicle charging stations." Sustainability 14, no. 9 (2022): 4964.

[8] Sadhukhan, Arindam, S. Sivasubramani, and Md Samar Ahmad. "Optimal placement of electric vehicle charging stations in a distribution network." In 2019 8th International Conference on Power Systems (ICPS), pp. 1-6. IEEE, 2019.

[9] Huang, Wei, Keying Luo, Yikang Li, Haiqiao Liu, and Jihong Qiang. "Multi-objective planning of community microgrid based on electric vehicles' orderly charging/discharging strategy." Journal of Energy Storage 114 (2025): 115623.

[10] Rene, Ebunle Akupan, Willy Stephen Tounsi Fokui, and Paule Kevin Nembou Kouonchie. "Optimal allocation of plug-in electric vehicle charging stations in the distribution network with distributed generation." *Green Energy and Intelligent Transportation* 2, no. 3 (2023): 100094.

[11] Yaghoubi-Nia, Mohammad-Reza, Hamed Hashemi-Dezaki, and Abolfazl Halvaei Niasar. "Optimized allocation of microgrids' distributed generations and electric vehicle charging stations considering system uncertainties by clustering algorithms." *IET Renewable Power Generation* 18, no. 11 (2024): 1798-1818.

[12] Guindi, Marina, and Rashad M. Kamel. "Optimal location and sizing of renewable distributed generations and electric vehicle charging stations." *Renewable Energy* 235 (2024): 121272.

[13] Asaad, Ali, Abdelfatah Ali, Karar Mahmoud, Mostafa F. Shaaban, Matti Lehtonen, Ahmed M. Kassem, and Mohamed Ebeed. "Multi-objective optimal planning of EV charging stations and renewable energy resources for smart microgrids." *Energy Science & Engineering* 11, no. 3 (2023): 1202-1218.

[14] Zainab, Fasiha, Komal Naz, Khawaja Khalid Mehmood, Syed Basit Ali Bukhari, Abdul Wadood, Hassan Abdullah Khalid, and Herie Park. "An optimal joint planning of DGs and electric vehicle charging stations in grid-connected and islanded microgrids." *IET Renewable Power Generation* 17, no. 7 (2023): 1623-1634.

[15] Ali, Abdelfatah, Karar Mahmoud, and Matti Lehtonen. "Optimal planning of inverter-based renewable energy sources towards autonomous microgrids accommodating electric vehicle charging stations." *IET Generation, Transmission & Distribution* 16, no. 2 (2022): 219-232.

[16] Pei, Xue-Yang, Hai-Bin Huang, and Peng Cao. "An Improved Gaussian Mixture Model-Based Data Normalization Method for Removing Environmental Effects on Damage Detection of Structures." Buildings 15, no. 3 (2025): 359.