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Strategy for EV Charging Station Placement Using a Bootstrapping-Based Probabilistic Power Flow

Estrategia para la ubicación de estaciones de carga de EVs utilizando un flujo de carga probabilístico basado en *bootstrapping*

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ABSTRACT

This work proposes a technique for placing electric vehicle charging stations using a bootstrapping-based probabilistic power flow. The methodology employs maximum likelihood estimation to model uncertainties in EV charging demand and establish robust confidence intervals for key system metrics. This approach was implemented in the Matpower simulation software within the IEEE-14 bus system, modeling the probabilistic load profile of 4500 EVs while considering 4000 realizations to obtain a wide spectrum of operation scenarios. The main results identified bus 9 as the optimal location for EV charging infrastructure, obtaining minimal active power losses (26.5 ± 0.5 MW) and a maximum efficiency of 92.87 ± 0.08%. The strategic placement of charging stations is closely linked to the lowest active power losses, offering optimal efficiency. However, beyond an optimal placement, this paper aims to increase the robustness of modern grids, overcoming drawbacks related to the integration of electromobility infrastructure. The selection of the most representative features, combined with uncertainty analysis, contributes to an improved decision-making, emphasizing the need for supporting sustainable mobility.

Keywords: Bootstrap method, charging stations, electric vehicles, decision-making, energy efficiency, probabilistic power flow, probability density function, uncertainty

RESUMEN

Este trabajo propone una técnica para ubicar estaciones de carga de vehículos eléctricos mediante un flujo de potencia probabilístico basado en *bootstrapping*. La metodología emplea la estimación de máxima verosimilitud para modelar las incertidumbres en la demanda de carga de vehículos eléctricos y establecer intervalos de confianza robustos para los principales indicadores del sistema. Este enfoque se implementó en el *software* de simulación Matpower dentro del sistema de 14 nodos del IEEE, modelando el perfil de carga probabilístico de 4500 vehículos eléctricos y considerando 4000 realizaciones para obtener un amplio espectro de escenarios de operación. Los principales resultados identificaron el bus 9 como la ubicación óptima para la infraestructura de carga de vehículos eléctricos, obteniendo pérdidas activas mínimas (26.5 ± 0.5 MW) y una eficiencia máxima de 92.87 ± 0.08 %. La ubicación estratégica de las estaciones de carga está estrechamente vinculada con las menores pérdidas de potencia activa, ofreciendo una eficiencia óptima. No obstante, más allá de una ubicación óptima, este artículo buscó incrementar la robustez de las redes modernas, superando las limitaciones relacionadas con la integración de infraestructura de electromovilidad. La selección de las características más representativas, combinada con el análisis de incertidumbre, contribuye a una mejor toma de decisiones, subrayando la necesidad de apoyar la movilidad sostenible.

Palabras clave: método *bootstrap*, estaciones de carga, vehículos eléctricos, toma de decisiones, eficiencia energética, flujo de carga probabilístico, función de densidad de probabilidad, incertidumbre

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Introduction

Contemporary electrical networks are changing quickly due to the addition of renewable energy sources, the expanding electrification of the demand, and the increasing complexity of operations. This has made it increasingly challenging to model and analyze these systems. Therefore, uncertainty, unpredictability, and probabilistic behavior must be incorporated into planning and operational frameworks as fundamental elements rather than as supplementary upgrades.

Modern power systems require complex cyber-physical networks where information and energy are combined. These layers integrate conventional generation with variable distributed energy resources (DERs), introducing stochasticity and potential grid disturbances, helping intelligent transmission and distribution systems, and

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actively engaging end-users through advanced information technologies [1]. As a result, conventional deterministic planning and operational approaches are no longer enough to increase resilience. The accurate and precise modeling of power flow equations is a fundamental tool for analyzing system states that now explicitly account for these inherent uncertainties, in order to ensure robust socioeconomic development. The fundamental aspect of conducting this explicit study requires solving nonlinear equations obtained through numerical methods, where the steady-state voltages and angles are employed. The main disadvantage is the need for complete information regarding the inputs to the power flow problem. Therefore, we propose considering the parameters and inputs as random variables. Hence, advanced methodologies are required to quantify the impact of the approach on system states and performance.

Power system analysis and planning employs two distinct approaches: the deterministic (DPF) and the probabilistic (PPF) power flow. The DPF uses fixed parameters for steady-state studies like load flow and economic dispatch, providing precise results. In contrast, the PPF handles uncertainties in demand and renewable generation through methods like Monte Carlo simulation (MCS) [2], evaluating system reliability and risk. While DPF offers precision, PPF reveals behaviors under uncertainty, guiding efficient decision-making [3]. Both techniques are applicable across various operational and planning timescales, enhancing system efficiency, reliability, and performance [4].

When using this probabilistic and statistical approach, it is of paramount importance to derive robust performance guarantees from limited and uncertain information, reducing the computational burden and assumptions about physics-informed modeling. This is relevant in assessing the uncertainty in stability claims provided by standard techniques. The high penetration of DERs induces uncertainty in state variables, which must be quantified for steady-state stability analysis. Different methods and techniques based on analytical and computational approaches have been tested while computing and analyzing uncertainty during power system operation [5].

The integration of electric vehicles (EV) further compounds these challenges. EVs represent not only significant stochastic loads but also a potential fleet of distributed energy storage devices, enabling bidirectional grid-to-vehicle (G2V) and vehicle-to-grid (V2G) power flows. The randomness of these flows|in terms of arrival times, charging rates, and battery state of charge (SoC)|induces significant variations in power flow profiles, challenges voltage regulation, and impacts the overall system stability [6], [7]. Efficient analysis techniques are therefore needed to establish data-driven metrics for measuring robustness against load variations [8], as well as to provide insights into system reliability and risk assessment through statistical distributions [9]. Strategically locating EV charging stations is thus imperative for seamless integration, requiring the adaptation of existing systems to accommodate the growing demand based on infrastructure capacity, grid stability, and user convenience principles [10], [11], [12].

Several methods have been proposed to address uncertainty in the power flow equations. While classical deterministic calculations remain prevalent, PPF models and stochastic optimization are suitable tools. [13], [14]. Most recent improvements include optimization methods for EV charging station placement using metaheuristic algorithms and Monte Carlo-based multi-objective methods [15], [16]. However, there remains a research gap in developing a unified probabilistic framework that explicitly accounts for joint uncertainty propagation from both generation and demand profiles. Consequently, this work focuses on the need to certificate the reliable, efficient, and secure operation of power systems under significant uncertainty, as contemporary approaches often face scalability challenges, limited assumptions, or poor adaptation to changing conditions, which constrain practical implementation.

This paper builds upon this background by utilizing the IEEE-14 bus system as a foundational framework to comprehensively refine charging station locations. It addresses an EV charging station placement method aimed at enhancing steady-state grid stability, focusing on the challenges associated with the increasing demand for electric mobility. This study introduces a methodology that encompasses data analysis, normalization, and PPF, as well as the application of the bootstrapping technique. Charging station modeling and realistic simulations contribute to a robust understanding of optimal placement. The results, presented for a base case and representative scenarios, provide practical knowledge for planning EV infrastructure, bridging the gap between theoretical analyses and practical applications.

Compared to other related studies, our research focuses on strategic charging station placement at the fundamental frequency. We employ maximum likelihood estimation (MLE) to determine expected values, thereby improving our understanding of system behavior under uncertainties. This probabilistic approach uses a probability density function (PDF) to capture diverse scenarios related to power system uncertainties, enabling more informed decision-making and planning [17]. To adopt less conservative assumptions, we utilize a Bayesian framework with approximated Bayesian computation in order to estimate input uncertainty priors, reducing classical complexity and providing uncertainty estimates for power flow state variables [18].

Our approach stands out for its integration of a bootstrapped-based PPF, considering MLE to manage uncertainty and derive confidence intervals. In comparison with the DPF, which does not consider uncertainties, and the conventional PPF by means of Monte Carlo simulation, which is computationally expensive, this method exhibits an efficient and statistically robust analysis. In contrast to Bayesian frameworks that require prior assumptions, this approach remains simple while preserving accuracy, enabling better decision-making for EV charging station placement.

The specific contributions of this work include a novel joint probabilistic estimation method that represents dependency, which allows computing the uncertainty propagation of electric generation and demand profiles; an efficient computational methodology leveraging bootstrapping and MLE to overcome the scalability limitations of prior studies; and a comprehensive validation via a realistic case study that translates into practical, actionable insights for real-world system operation and planning.

The subsequent sections of this paper are organized as follows. The Methodology describes the methods and materials used, including data analysis, data normalization, the PPF, bootstrapping techniques, and the modeling of charging stations. In the Results section, we present the most revealing findings of this study. Additionally, the Discussion engages in an exchange of ideas regarding the results obtained. Finally, in the Conclusion section, we propose potential improvements for future work.

Methodology

The proposed method involves finding underlying patterns within a dataset that contains samples of the demand for EV charging stations. Firstly, the set of candidate load buses (PQ buses) is defined to place the charging stations. In this case, low-voltage buses are selected (*i.e.*, 33 kV buses). Secondly, the charging station demand is modeled, considering its probabilistic nature by defining different demand scenarios. The results of the power flows of each demand scenario are also obtained through the PPF. Using the bootstrapping technique, the uncertainty of the variables of interest in the different demand scenarios is quantified. Finally, based on the results, the method yields the most robust bus to plug in the charging stations. A flowchart is presented in Fig. 1 for the deep understanding and visualization of the method.

Data analysis

Our goal was to develop a data-driven approach to determine a robust bus for strategically locating EV charging stations within a power system while ensuring adequate losses and efficiency levels. Once the test system had been selected|in this case, the 14-bus IEEE system|, a deterministic power flow was executed based on the Newton-Raphson solution method, using the Matpower simulation software [19]. A constant power model was considered for the static loads of the system [20].

Data normalization

Data normalization and per-unit (p.u.) are two widely used techniques for managing and comparing electrical quantities. Data normalization is a general pre-processing method that transforms variables into a specific scale, often between 0 and 1. These quantities correspond to their minimum and maximum values, respectively [21]. This method is particularly effective for algorithms involving neural networks, clustering, and classification, as it ensures that variables with different units contribute equally to the analysis. This linear transformation converts feature values in their original, real-world units into dimensionless values within the specified range [22].

On the other hand, the per-unit system is specific to electrical power systems. This conversion allows engineers to focus on relative values. It expresses electrical features as fractions or multiples of defined base values, where the apparent power and voltage are commonly used, thereby simplifying numerical calculations and analyses [23].

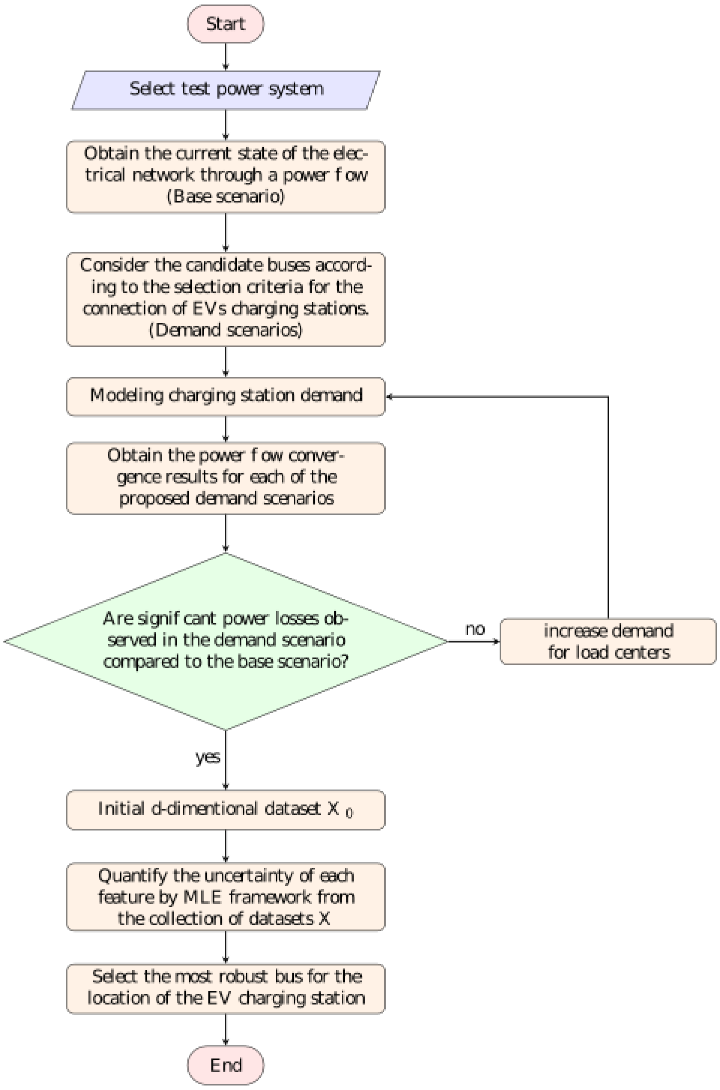

Figure 1. Methodology flowchart
Source: Authors

Probabilistic power flow (PPF)

The PPF is a robust technique used in modern power systems for evaluating the uncertainties and variability of locally available energy resources| it is similar to bootstrapping in statistics, which provides a deep analysis of scenarios. This approach considers the stochastic behavior of the demand, generation, and faults [24]. Unlike the traditional DPF, which relies on fixed parameters, PPF relaxes this condition by modeling system states as random variables in order to capture real-world applications. The original dataset, denoted as $\boldsymbol{X}_0$, with d input variables (features) and n samples, is used for incorporating random realizations, preserving the original statistical properties, providing a detailed description of the output variables (targets), and enhancing decision-making processes regarding planning and operation.

The bootstrapping technique

The bootstrapping technique applies to both parametric and non-parametric distributions, requiring minimal assumptions regarding the underlying population distribution. Its fundamental objective is to estimate the distribution of a chosen feature. This flexibility is helpful in unknown or intricate distribution scenarios, allowing data scientists to make inferences without relying on strict parametric models [25]. This procedure involves the following iterative steps: firstly, each realization is created by randomly selecting data points from the original d-dimensional dataset $\boldsymbol{X}_0$ with replacements; subsequently, the features are obtained in each realization, which belongs to the set collection of sampled datasets $\mathcal{X} = \{\boldsymbol{X}_1, ..., \boldsymbol{X}_{nb}\}$ | the process is repeated numerous times, often thousands, denoted as nb, to yield PDFs; finally, the resulting plots are employed to provide a visual representation of the variability in the estimated statistic.

Charging station modeling

In this subsection, a model for the overall charging demand of EVs is introduced, particularly that of plug-in hybrid EVs (PHEVs), following the proposals of [6] and [7]. This approach establishes a unified model for PHEV charging demand, utilizing queuing theory to depict the behavior of multiple PHEVs. The energy consumption required to charge a PHEV is formulated by means a probabilistic model. This ensures the inclusion of key factors influencing PHEV charging behavior, including battery capacity, operating status, daily driving range, and other relevant considerations. The operating status parameter, k_{EV}, is defined as follows:

$$k_{\mathrm{EV}} = \frac{E_{\mathrm{Bat}}}{E_{\mathrm{Eng}} + E_{\mathrm{Bat}}},$$

where E_{Eng} represents the overall energy supplied to the vehicle engine and electric drive controller within a specific timeframe, as E_{Bat} is the energy provided by the onboard battery to the electric drive controller. In the case of a charge-sustaining EV, where the battery provides no energy, $k_{\mathrm{EV}} = 0$. Conversely, for a zero-emissions electric vehicle (ZEV) exclusively powered by the battery, $k_{\mathrm{EV}} = 1$. In the context of a PHEV, the specific value is between 0 and 1. Another factor characterizing a PHEV is its overall battery capacity, denoted as C_{Bat}. The control strategy of a PHEV is assumed to regulate k_{EV}, which represents its operating status based on its C_{Bat} [6] and [7]. Therefore, it can be inferred that k_{EV} and C_{Bat} are interrelated and can be represented as a bivariate normal distribution:

$$\begin{bmatrix} k_{\mathrm{EV}} \\ C_{\mathrm{Bat}} \end{bmatrix} = \begin{bmatrix} \mu_{k_{\mathrm{EV}}} \\ \mu_{C_{\mathrm{Bat}}} \end{bmatrix} + \boldsymbol{L} \begin{bmatrix} N_1 \\ N_2 \end{bmatrix},$$

where $\mu_{k_{\mathrm{EV}}}$ and $\mu_{C_{\mathrm{Bat}}}$ are the means of k_{EV} and C_{Bat}, respectively. $\boldsymbol{L}$ stands for the Cholesky decomposition of their covariance matrix $\boldsymbol{\Sigma}$, expressed as $\boldsymbol{\Sigma} = \boldsymbol{L}\boldsymbol{L}^T$. N_1 and N_2 represent two independent standard normal variables.

PHEV performance is assessed through the energy consumption per mile driven, E_m. This is approximately formulated as a function of k_{EV}.

$$E_m = A_E \cdot (k_{\mathrm{EV}})^{B_E},$$

where the coefficients A_E and B_E change based on the specific type of PHEV. As per the statistical patterns observed in PHEV driving behavior, the daily distance traveled by a PHEV, M_d, tends to conform to a lognormal distribution.

$$M_d = e^{(\mu_m + \sigma_m N)}.$$

Here, N represents a standard normal variable. The parameters μ_m and σ_m of the lognormal distribution are derived from the mean μ_{M_d} and the standard deviation σ_{M_d} of M_d.

$$\mu_m = \ln\left[\frac{\mu_{M_d}^2}{\left(\mu_{M_d}^2 + \sigma_{M_d}^2\right)^{\frac{1}{2}}}\right], \quad \sigma_m = \left[\ln\left(1 + \frac{\sigma_{M_d}^2}{\mu_{M_d}^2}\right)\right]^{\frac{1}{2}}.$$

Ultimately, following the establishment of the energy consumption per mile driven E_m and the daily driving range M_d, the daily recharge energy of a PHEV, D_E, is expressed as follows.

$$D_E = \begin{cases} C_{\mathrm{Bat}} & \text{if } M_d \geq M_E, \\ M_d \cdot E_m, & \text{otherwise}, \end{cases}$$

where a constant M_E represents the maximum driving distance of a PHEV in an all-electric mode, *i.e.*,

$$M_E = \frac{C_{\mathrm{Bat}}}{E_m} = \frac{C_{\mathrm{Bat}}}{A_E \cdot (k_{\mathrm{EV}})^{B_E}}.$$

Queuing theory is used to depict the collective charging process of multiple PHEVs connected to load buses [7]. Various queuing models are selected to describe different PHEV charging scenarios. This work analyzes charging scenarios for an EV charging station.

The operation of PHEVs at an EV charging station can be likened to queuing customers served in an $M/M/c$ queue. In this context, the first M signifies the inter-arrival time of customers, modeled by an exponential distribution with a mean denoted as T_λ | with $T_\lambda > 0$. The second M represents the service time for each customer, which is assumed to follow an exponential distribution with a mean denoted as T_μ | with $T_\mu > 0$. The parameter c denotes the maximum number of simultaneously connected customers. The use of the exponential distribution in this context is justified by the assumption that PHEVs operate independently in terms of both their arrival and charging duration. This independence implies a Poisson process for the arrival of PHEVs at the charging station and the duration of their charging sessions. Additionally, for simplicity in modeling, it is assumed that the number of customers waiting at the EV charging station is infinite.

In queuing theory, the discrete distribution governing the number of simultaneously charging PHEVs in an $M/M/c$ queue, represented by the variable n, can be expressed as follows:

$$p_n = \begin{cases} \left(\displaystyle\sum_{i=0}^{c-1} \frac{(c\rho)^i}{i!} + \frac{(c\rho)^c}{c!} \cdot \frac{1}{1-\rho}\right)^{-1} & n = 0, \\ \dfrac{(c\rho)^n}{n!} \cdot p_0 & n = 1, 2, \ldots, c, \end{cases}$$

where ρ is the occupation rate per server, expressed as

$$\rho = \frac{T_\mu}{c T_\lambda}.$$

It should be highlighted that, typically, ρ is expected to be less than 1 in order to prevent the PHEV queue from becoming unmanageably long. The service time T to charge a PHEV in the aforementioned queue model adheres to an exponential distribution with a mean value of T_μ. Then,

$$T = -T_\mu \cdot \ln(U),$$

where U is a uniformly distributed variable in $(0, 1)$. Nevertheless, as it is impractical for a PHEV to undergo an extremely brief charging period, and considering that the charging duration is constrained by the vehicle's battery capacity or service limitations, the parameter T is constrained within a specified range $[T_{\min}, T_{\max}]$. This yields

$$T = \begin{cases} T_{\min} & \text{if } T \le T_{\min}, \\ -T_\mu \cdot \ln(U) & \text{if } T_{\min} < T < T_{\max}, \\ T_{\max} & \text{if } T \ge T_{\max}. \end{cases}$$

After establishing the charging power level, the charging voltage V and the maximum charging current $I_{\max}$ are determined. Therefore, the average charging current for a PHEV can be computed as follows:

$$I = \min\left\{\frac{D_E}{V \cdot T}, I_{\max}\right\}. \tag{1}$$

Ultimately, the collective charging demand (denoted as P) of the n PHEVs at an EV charging station is calculated as follows:

$$P = \sum_{i=1}^{n} V \cdot I_i,$$

where I_i denotes the charging current of the i-th EV, as obtained from (1).

Results

This study provides actionable insights for strategically locating EV charging stations to optimize system efficiency and user accessibility, supporting the integration of electrified mobility into existing power infrastructures.

IEEE-14 bus system (base case)

This work considered the IEEE-14 bus system, represented through a single-line diagram in Fig. 2, which illustrates the electrical interconnections within the system, providing information about the spatial arrangement of the buses and branches listed in Tables 1 and 2 [26]. These detailed data on the system buses and branches describe the physical layout of the grid and provide a complete description of its configuration and behavior.

From the DPF applied to the base case, we obtained active power losses and efficiency values of 13.3930 MW and 95.0843%, respectively. The power flow results are shown in Table 1. Meanwhile, Table 2 provides details regarding the impedance, admittance, and configuration of the power lines and transformers, offering information on the physical connections and characteristics of the network components. It should be noted that this analysis provides steady-state data on the power system's behavior. As for the PPF, this research work extends beyond a deterministic analysis. Therefore, we incorporated the charging station's PDF.

Table 1. System bus data

Bus number	Final voltage (p.u.)	Final angle (°)	Load (MW)	Load (MVAR)	Generation (MW)	Generation (MVAR)
1	1.060	0.0	0.0	0.0	232.4	-16.9
2	1.045	-4.98	21.7	12.7	40.0	42.4
3	1.010	-12.72	94.2	19.0	0.0	23.4
4	1.019	-10.33	47.8	-3.9	0.0	0.0
5	1.020	-8.78	7.6	1.6	0.0	0.0
6	1.070	-14.22	11.2	7.5	0.0	12.2
7	1.062	-13.37	0.0	0.0	0.0	0.0
8	1.090	-13.36	0.0	0.0	0.0	17.4
9	1.056	-14.94	29.5	16.6	0.0	0.0
10	1.051	-15.10	9.0	5.8	0.0	0.0
11	1.057	-14.79	3.5	1.8	0.0	0.0
12	1.055	-15.07	6.1	1.6	0.0	0.0
13	1.050	-15.16	13.5	5.8	0.0	0.0
14	1.036	-16.04	14.9	5.0	0.0	0.0

Table 2. System branch data

From Bus	To bus	Branch resistance (p.u.)	Branch reactance (p.u.)	Line charging (p.u.)
1	2	0.01938	0.05917	0.0528
1	5	0.05403	0.22304	0.0492
2	3	0.04699	0.19797	0.0438
2	4	0.05811	0.17632	0.0340
2	5	0.05695	0.17388	0.0346
3	4	0.06701	0.17103	0.0128
4	5	0.01335	0.04211	0.0
4	7	0.0	0.20912	0.0
4	9	0.0	0.55618	0.0
5	6	0.0	0.25202	0.0
6	11	0.09498	0.19890	0.0
6	12	0.12291	0.25581	0.0
6	13	0.06615	0.13027	0.0
7	8	0.0	0.17615	0.0
7	9	0.0	0.11001	0.0
9	10	0.03181	0.08450	0.0
9	14	0.12711	0.27038	0.0
10	11	0.08205	0.19207	0.0
12	13	0.22092	0.19988	0.0
13	14	0.17093	0.34802	0.0

The selected power system assumes base values of 100 MVA for apparent power, 33 kV for low voltage (LV), and 115 kV for high voltage (HV). These predefined parameters establish the initial configuration of the system under study, providing a reference point for the subsequent subsections. Additionally, these values served as input parameters for various calculations and simulations, ensuring a standardized and consistent basis for evaluating the system's performance and behavior.

Representative scenarios

Introducing uncertainties in load profiles led to a more realistic power system representation, improving the robustness of the analysis. Considering the charging station PDF allowed for a probabilistic perspective, offering information about different load scenarios and their impact on active power losses and system efficiency. This extension improved the comprehensiveness of our understanding, paving the way towards a more informed power system design.

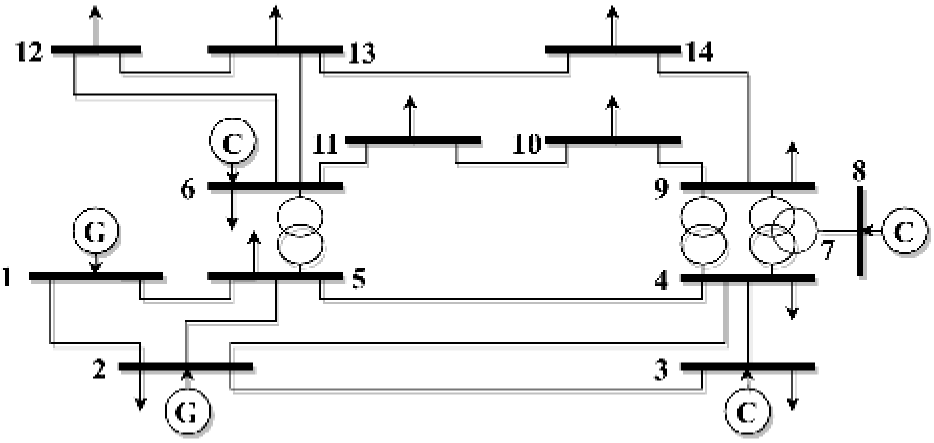

Figure 2. IEEE-14 bus system
Source: Authors

An equivalent load profile of 4500 EVs was used, yielding $nb = 4000$ realizations. These correspond to the collection of sampled datasets $\mathcal{X}$. The 20 most representative Gaussian families are shown in Fig. 3. These scenarios contain $d = 13$ features, where x_1 represents the charging station's load profile (MW), and x_2 to x_{13} describe the network's active power losses (MW) and efficiency (%) at specific bus locations (buses 9 through 14). These features are shown in Table 3. The inputs from x_2 to x_{13} correspond to PQ and LV buses within the modified IEEE-14 bus system, whose corresponding Gaussian families are depicted in Figs. 5 and 6. For the original dataset, denoted as $\mathbf{X}_0$, and $n = 200000$ observations were considered.

It was assumed that the sampled data for all features in Table 3 were independent and identically distributed (iid), and they were considered as an unknown PDF. The hyperparameters were obtained using a MLE framework. The corresponding values are listed in Table 4. This approach enables a robust exploration of the sampled data, incorporating statistical considerations and estimation parameters to improve reliability.

Charging station placement

The PDF of each feature (x_2 to x_{13}) significantly contributes to the decision-making process, offering a statistical representation of the distribution of the network, minimized active power losses, and improved efficiency in locating the charging station load profile x_1 at the PQ and LV buses. We identified the most robust bus regarding active power losses and efficiency, considering the input $p(x_1 \mid \mu_{x_1}, \sigma_{x_1}) = \mathcal{N}(86.0094, 1.4800)$. By analyzing all PDFs, we were able to make informed decisions, ensuring that the charging station operated within grid capacity constraints.

Considering the lowest expected active power losses value and the highest efficiency from Table 4, we selected the most robust bus in the analyzed power system. This strategic decision, exemplified by the features x_2 and x_3, respectively, involved placing the charging station at bus 9. It should be added that the variance is related to energy dissipation, and it is essential for enhancing power system stability and allowing the system to withstand disturbances and quickly recovering from them.

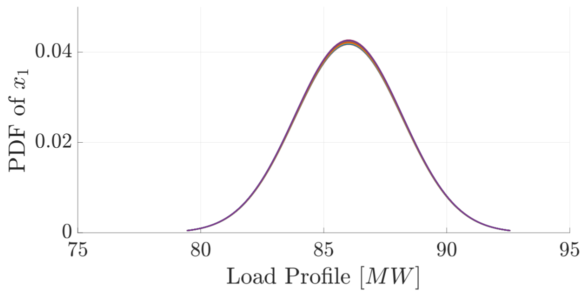

Figure 3. Gaussian family plots for the charging station load profile
Source: Authors

Table 3. Features considered for each sampled dataset

Feature	Description	Units
x_1	Charging station load profile	[MW]
x_2	Active power losses after locating x_1 at bus 9	[MW]
x_3	System efficiency after locating x_1 at bus 9	[%]
x_4	Active power losses after locating x_1 at bus 10	[MW]
x_5	System efficiency after locating x_1 at bus 10	[%]
x_6	Active power losses after locating x_1 at bus 11	[MW]
x_7	System efficiency after locating x_1 at bus 11	[%]
x_8	Active power losses after locating x_1 at bus 12	[MW]
x_9	System efficiency after locating x_1 at bus 12	[%]
x_{10}	Active power losses after locating x_1 at bus 13	[MW]
x_{11}	System efficiency after locating x_1 at bus 13	[%]
x_{12}	Active power losses after locating x_1 at bus 14	[MW]
x_{13}	System efficiency after locating x_1 at bus 14	[%]

Table 4. PDFs of network power losses and efficiencies obtained using MLE

Feature / Bus	$p(P_L \mid \mu_{P_L}, \sigma_{P_L})$	$p(\eta \mid \mu_\eta, \sigma_\eta)$
9	$\mathcal{N}(26.46, 0.65)$	$\mathcal{N}(92.87, 0.25)$
10	$\mathcal{N}(28.67, 0.73)$	$\mathcal{N}(92.32, 0.30)$
11	$\mathcal{N}(29.65, 0.78)$	$\mathcal{N}(92.08, 0.32)$
12	$\mathcal{N}(35.26, 0.97)$	$\mathcal{N}(90.72, 0.41)$
13	$\mathcal{N}(30.76, 0.80)$	$\mathcal{N}(91.81, 0.33)$
14	$\mathcal{N}(37.04, 1.00)$	$\mathcal{N}(90.30, 0.42)$

Discussion

Some related works, such as [27], have delved into the probabilistic harmonic load flow (PHLF) within the same test system. However, this research diverges by concentrating on decision-making aspects related to the optimal placement of charging stations for EVs at the fundamental frequency. The base case DPF outlines a distinct set of conditions, analyzing the power system under fixed parameters. In contrast, the expected value of the PPF, computed through MLE, represents the average or mean outcome across a spectrum of realizations, incorporating a PDF to quantify uncertain parameters. A probabilistic approach offers a deep comprehension of system behavior, capturing several scenarios derived from uncertainties in the electrical network. Considering the confidence interval (Table 5) enables a wide exploration of the distance between average and extreme scenarios, as well as a realistic analysis and a more informed approach to decision-making and system planning in the context of inherent uncertainties [17].

Table 5. Confidence intervals for network active power losses MW at buses x_2, x_4, x_6, x_8, x_{10}, and x_{12}

Node	Active power losses { confidence interval
x_2	26.5 ± 0.5
x_4	28.7 ± 0.65
x_6	29.6 ± 0.9
x_8	35.5 ± 1
x_{10}	30.8 ± 0.7
x_{12}	37 ± 1

Considering the lowest expected active power losses value and the highest efficiency is a key factor for selecting the most robust bus in the power system. This is especially notable when placing the charging station at bus 9, as shown in Table 6. The associated variance, connected to energy dissipation, is essential for improving steady-state system stability, enabling the system to withstand disturbances and recover rapidly.

Table 6. Confidence Intervals for Network Efficiencies [%] in Nodes x_3, x_5, x_7, x_9, x_{11}, and x_{13}.

Node	Efficiency { confidence interval
x_3	92.87 ± 0.08
x_5	92.34 ± 0.11
x_7	92.08 ± 0.12
x_9	90.66 ± 0.19
x_{11}	91.81 ± 0.05
x_{13}	90.3 ± 0.3

Conclusions

The methodology proposed in this research includes a probabilistic model for EV charging demand that incorporates MLE to quantify uncertainties and establish robust confidence intervals for active power losses and efficiency. After applying this strategy to the IEEE-14 bus system, considering the analysis of the resulting PDFs, we identified bus 9 as the most robust location for charging infrastructure.

Determining reasonable locations for charging stations provides a computationally efficient framework that allows planners and policymakers to minimize grid losses and maximize efficiency. Consequently, the numerical simulations conducted exhibit an improvement in the overall grid robustness, contributing to a resilient power infrastructure that can fulfill future sustainable transportation demands.

For the analysis, we used the standardized IEEE-14 bus test system with assumed EV demand profiles. The numerical results validate the proposed framework, which closely resembles real-world networks. Considering different topologies and load characteristics may require further validation. It should be noted that, while the bootstrapping method is more computationally efficient than traditional Monte Carlo simulations, its application to very large-scale systems could still pose computational challenges that were not explored herein. Future work will focus on validating this procedure on larger test systems and real-network data, incorporating sources of uncertainty such as non-conventional generation variability while exploring its application for planning vehicle-to-grid (V2G) infrastructure.

CRediT author statement

Harrynson Ramírez-Murillo: investigation, methodology, validation, and writing (review).
Ricardo Rincón: investigation, methodology, validation, and writing (review).
Fabián Salazar-Cáceres: conceptualization, formal analysis, and writing (original draft).
Martha Patrica Camargo-Martínez: conceptualization, formal analysis, and writing (original draft).
Natalia Rojas-Medina: visualization, and writing (editing).
Camilo Leal-Rincón: visualization, and writing (editing).

References

[1] G. Dileep, \A survey on smart grid technologies and applications," *Renew. Energy*, vol. 146, pp. 2589{2625, 2020. [Online]. Available: https://doi.org/10.1016/j.renene.2019.08.092.

[2] B. R. Prusty and D. Jena, \A critical review on probabilistic load flow studies in uncertainty constrained power systems with photovoltaic generation and a new approach," *Renew. Sust. Energy Rev.*, vol. 69, pp. 1286{1302, 2017. [Online]. Available: https://doi.org/10.1016/j.rser.2016.12.044.

[3] W. N. A.-D. Abed, \Solving probabilistic optimal power flow with renewable energy sources in distribution networks using fire hawk optimizer," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 6, p. 100 370, 2023. [Online]. Available: https://doi.org/10.1016/j.prime.2023.100370.

[4] A. Younesi, H. Shayeghi, Z. Wang, P. Siano, A. Mehrizi-Sani, and A. Safari, \Trends in modern power systems resilience: State-of-the-art review," *Renewable and Sustainable Energy Reviews*, vol. 162, 112397. https://doi.org/10.1016/j.rser.2022.112397, 2022.

[5] V. Singh, T. Moger, and D. Jena, \Uncertainty handling techniques in power systems: A critical review," *Electric Power Systems Research*, vol. 203, 107633. https://doi.org/10.1016/j.epsr.2021.107633, 2022.

[6] M. H. Amini, A. Kargarian, and O. Karabasoglu, \Arima-based decoupled time series forecasting of electric vehicle charging demand for stochastic power system operation," *Electric Power Systems Research*, vol. 140, 378{390. https://doi.org/10.1016/j.epsr.2016.06.003, 2016.

[7] G. Li and X.-P. Zhang, \Modeling of plug-in hybrid electric vehicle charging demand in probabilistic power flow calculations," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, 492{499. https://doi.org/10.1109/TSG.2011.2172643, 2012.

[8] Q. Guo, S. Nojavan, S. Lei, and X. Liang, \Economic-environmental analysis of renewable-based microgrid under a cvar-based two-stage stochastic model with efficient integration of plug-in electric vehicle and demand response," *Sustainable Cities and Society*, vol. 75, 103276. https://doi.org/10.1016/j.scs.2021.103276, 2021.

[9] B. Tan, H. Chen, X. Zheng, and J. Huang, \Two-stage robust optimization dispatch for multiple microgrids with electric vehicle loads based on a novel data-driven uncertainty set," *International Journal of Electrical Power & Energy Systems*, vol. 134, 107359. https://doi.org/10.1016/j.ijepes.2021.107359, 2022.

[10] A. Danese, B. N. Torsæter, A. Sumper, and M. Garau, \Planning of high-power charging stations for electric vehicles: A review," *Applied Sciences*, vol. 12, no. 7, 3214. https://doi.org/10.3390/app12073214, 2022.

[11] V. Anadón Martínez and A. Sumper, \Planning and operation objectives of public electric vehicle charging infrastructures: A review," *Energies*, vol. 16, no. 14, 5431. https://doi.org/10.3390/en16145431, 2022.

[12] S. E. Bibri, J. Krogstie, K. Amin, and A. Alahi, \Smarter eco-cities and their leading-edge artificial intelligence of things solutions for environmental sustainability: A comprehensive systematic review.," *Environmental Science and Ecotechnology*, vol. 19, 100330. https://doi.org/10.1016/j.ese.2023.100330, 2024.

[13] G. Fotis, \An improved arithmetic method for determining the optimum placement and size of ev charging stations," *Computers and Electrical Engineering*, vol. 120, 109840. https://doi.org/10.1016/j.compeleceng.2024.109840, 2024, issn: 0045-7906.

[14] S. Deeum et al., \Optimal placement of electric vehicle charging stations in an active distribution grid with photovoltaic and battery energy storage system integration," *Energies*, vol. 16, no. 22, 1{26. https://doi.org/10.3390/en16227628, 2023, issn: 1996-1073.

[15] S. Deeum, P. Bhumkittipich, N. Janjamraj, S. Romphochai, Y. Kongjeen, and K. Bhumkittipich, \Monte carlo based optimal placement of multiple pv/bess units in power distribution system with varying electric vehicle load penetration," *International Review of Electrical Engineering* (*IREE*), vol. 20, no. 1. https://doi.org/10.15866/iree.v20i1.25522, 2025.

[16] S. Sakthivel and K. Gayathri, \A novel pelican bird optimization algorithm based optimal allocation of combined dgs and evcss for improving voltage stability of rds," *Indian Journal of Science and Technology*, vol. 17, no. 34, 3522{3531. https://doi.org/10.17485/IJST/v17i34.2170, 2024.

[17] M. D. Arango Serna, C. A. Serna, and G. Pérez Ortega, \Parametric linear programming for a materials requirement planning problem solution with uncertainty," *Ingeniería e Investigación*, vol. 30, 96{105. https://doi.org/10.15446/ing.investig.v30n3.18181, 2010.

[18] C. D. Zuluaga and M. A. Álvarez, \Bayesian probabilistic power flow analysis using jacobian approximate bayesian computation," *IEEE Transactions on Power Systems*, vol. 33, no. 5, 5217{5225. https://doi.org/10.1109/TPWRS.2018.2810641, 2018.

[19] R. Zimmerman, C. Murillo-Sánchez, and D. Gan, \Free, open-source tools for electric power system simulation and optimization," *Available*, vol. online: https://matpower.org/, no. Accessed on 25 August 2024, 1997.

[20] A. Arif, Z. Wang, J. Wang, B. Mather, H. Bashualdo, and D. Zhao, \Load modeling|a review," *IEEE Transactions on Smart Grid*, vol. 9, no. 6, 5986{5999. https://doi.org/10.1109/TSG.2017.2700436, 2018.

[21] A. Pessoa, G. Sousa, L. Maués, F. Alvarenga, and D. Santos, \Cost forecasting of public construction projects using multilayer perceptron artificial neural networks: A case study," *Ingeniería e Investigación*, vol. 41, no. 3, 1{11. https://doi.org/10.15446/ing.investig.v41n3.87737, 2021.

[22] F. Salazar-Caceres, H. Ramirez-Murillo, C. A. Torres-Pinzón, and M. P. Camargo-Martínez, \Performance estimation technique for solar-wind hybrid systems: A machine learning approach," *Alexandria Engineering Journal*, vol. 87, 175{185. https://doi.org/10.1016/j.aej.2023.12.029, 2024.

[23] A. Markensteijn, J. Romate, and C. Vuik, \A graph-based model framework for steady-state load flow problems of general multi-carrier energy systems," *Applied Energy*, vol. 280, 115286. https://doi.org/10.1016/j.apenergy.2020.115286, 2020.

[24] H. Wang, Z. Yan, X. Xu, and K. He, \Probabilistic power flow analysis of microgrid with renewable energy," *International Journal of Electrical Power & Energy Systems*, vol. 114, 105393. https://doi.org/10.1016/j.ijepes.2019.105393, 2020.

[25] S. F. Mokhtar, Z. M. Yusof, and H. Sapiri, \Confidence intervals by bootstrapping approach: A significance review," *Malaysian Journal of Fundamental and Applied Sciences* (*MJFAS*), vol. 19, no. 1, 30{42. https://doi.org/10.11113/mjfas.v19n1.2660, 2023.

[26] IEEE, \14 bus power flow test case," *Illinois Center for a Smarter Electric Grid* (*ICSEG*), vol. Available online: https://icseg.iti.illinois.edu/ieee-14-bus-system, no. Accessed on 25 August 2024, 1962.

[27] A. A. Romero, H. C. Zini, and G. Ratta, \An overview of approaches for modelling uncertainty in harmonic load-flow," *Ingeniería e Investigación*, vol. 31, 18{26. https://doi.org/10.15446/ing.investig.v31n2SUP.25207, 2011.