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Probabilistic photovoltaic generation and load demand uncertainties modelling for active distribution networks hosting capacity calculations

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ABSTRACT

With the increasing integration of photovoltaic (PV) systems in active distribution networks (ADNs), accurate modelling of PV power generation and the network demand has become essential, especially for system operators (SO). However, existing studies have focused on deterministic representations of hourly profiles for PV generation and load consumption, which cannot thoroughly evaluate the existing uncertainties of PV power output and load demands. In this study, uncertain parameters load demand and PV power output profile will be modelled with forecasted values, and their profile will be obtained over probability density functions (PDFs). Firstly, a vast quantity of realistic load and PV generation profiles are produced over a day with 15-minute resolution, with a scenario generation method using the Monte Carlo methodology. Afterward, the generated scenarios are reduced to a set of scenarios to represent the span of all generated scenarios. A fully local reactive power regulation strategy is used in this study to evaluate the hosting capacity of the ADN. This proposed method is tested on modified 33-bus and 69-bus distribution test systems by using practical solar generation and load data. The proposed methodology results in the hosting capacity improvement by 20% besides the existing Q-Voltage and PF-Power local voltage control methods, where it has the flexibility to be implemented to any distribution feeder.

1. Introduction

The recent trend with the increased integration of photovoltaic (PV) systems into active distribution networks (ADNs), introduces new challenges to the grid by their uncertain characteristics [1]. The uncertainty from the load demand also has an evident variable profile, where the maximum demand profile and PV power output show different trends over the day. The PV power generation in peak generation times, as voltage-related issue and thus, limits the ADNs' PV hosting capacity. The hosting capacity is referred to the allowed PV generation that can be integrated into the network without violating standard limits for voltage, protection, and power quality issues. For further integration of PVs into the network, it is certainly essential to have a precise overview of the PV generation output and load demand to determine the hosting capacity increase accurately.

The deterministic approaches have shortfalls in representing the current profile of the grid with uncertain characters of PV and loads [2]. Sensitivity analysis is a possible solution to determine uncertainty, where the most influencing uncertain parameter can be found, but it can't select optimal design under conditional uncertainties [3]. Uncertainty modelling can be solved by a robust optimization strategy, which works out to minimize or maximize the objective function under the worst-case bounds of random variables [4]. However, this technique is not appropriate for long term applications as well as don't accomplish the complete stochastic behaviour of PVs, because of the variable and independent input profiles. Hence, recently the important research institutes like EPRI, have identified the need for probabilistic assessment to be included for defining uncertainties in future distribution system studies [5]. Therefore, real-time and high-resolution uncertainty modelling is the essential key to be able to allocate more PVs in distribution systems by overcoming variability challenges [6,7]. Probabilistic assessment is a strong alternative to the abovementioned methods, to solve the stochastic behaviour of future energy systems where the outcome of energy is uncertain [8].

Studies [9,10] are conducted to increase the hosting capacity of ADNs with considering the uncertainties of renewables. An extensive formulation is proposed for the hosting capacity enhancement of distribution network by using linear stochastic model, where the Roulette Wheel mechanism (RWM) is used to generate load samples for representing load uncertainties [11]. In [12], the association between the number of PVs connected to distribution network and hosting capacity is

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Nomenclature

Parameters

P_{pvn}	PV system nominal active power
S_{pvn}	PV system nominal apparent power
S_{trn}	Transformer nominal apparent power (kVA)
uk	Transformer short-circuit voltage (%)
V_{hvn}	Transformer high voltage (HV)-side nominal voltage (kV)
V_{lvn}	Transformer low voltage (LV)-side nominal voltage (kV)
V_{max}	Bus voltage magnitude upper limit (*p.u.*)
V_{min}	Bus voltage magnitude lower limit (*p.u.*)
V_{ref}	Bus reference voltage magnitude (*p.u.*)
$V_{b,crit}$	Critical bus voltage magnitude (*p.u.*)
ρ_s	Occurrence probability of scenario s

Variables

NT	Number of time intervals
NP	Number of PV units
P_{pv}	PV system active power
Q_{lim}	PV system reactive power limit
Q_{pv}	PV system reactive power
Q_{us}	Up-stream reactive power
S_{tr}	Transformer apparent power

investigated. Considering the stochastic nature of PV generation and load demand and presenting them with random forms of probabilities, voltage levels were calculated to assess the PV hosting capacity.

Stochastic approaches are presented to improve accuracy of models with the eventual aim of reducing uncertainties in terms of renewable sources and consumption units [13]. To evaluate the uncertain random variables, studies [14–16], ensure that the Monte Carlo simulation (MCS) technique is a widely accepted method for the stochastic analysis. MCS includes several sampling uncertainties to resolve distributions of unknown stochastic parameters. Solving the deterministic model multiple times by MC samples, the uncertain models are repeated to provide more accurate results [17]. A comprehensive review on probabilistic forecasting of PV power production and electricity consumption is given in [18]. Studies show that, an accurate PV output forecast is vitally needed to foresee and adapt the further integration of PVs into the power system [19,20].

To represent PV uncertainties, the solar radiation modelling [21] and solar power output modelling are the two main methods to generate the PV power by time series. The solar radiation technique requires high accuracy of radiation electric power transfer function, which might lead to mismatch between measured and generated data [22]. The power output method uses the real measured power data for creating new PV power time series. In [23], the PV power is characterized by a non-parametric Kernel distribution. However, after fitting the data using kernel distribution, it is hard to exclude data points from the incomplete data record [24]. A Bayesian approach is presented to forecast PV active power by clearness index and PV power output [25]. But then again, the uncertainty approach can lead to error with nonlinear relationship between clearness and power output. Beta distribution of PV generation is a popular assumption among many researchers [26].

A probabilistic approach is based on probabilistic data input and produces a set of results. In other words, instead of a mean value over the time, there would be a distribution function representing occurrence probabilities of different quantities over the same time scale. After obtaining the distribution function, the quantities which are mean values and standard deviations can be derived. A two-stage stochastic programming approach presented the improvement over the deterministic scheduling [27]. As a drawback of this solution, a large number of scenarios can cause a computational burden. This reveals the importance of scenario reduction techniques [28], to reduce the simulations greatly. Overall, the stochastic assessment of PV generation and load demand would provide more independent elaboration of PVs integration to enhance the hosting capacity.

This paper proposes a method for modelling uncertainties related to load demand and available output power of photovoltaic units by using forecasted values to obtain probability density functions (PDFs). Through this method, the inherent stochastic nature of the problem is released and the problem is decomposed into a deterministic one. The rest of the work is focused on a Monte Carlo method to create the desired number of scenarios for representing uncertain variables. Scenario generation will be first step of this study and scenario reduction method will be used to reduce excessive computations. Monte Carlo simulation considering uncertainty scenarios is applied to model the load demand and PV generation in a daily study horizon with the measurements in quarter-hourly time steps. This approach allows for a more thorough evaluation of uncertainties related to PV power output and load demands and can improve the accuracy of distribution network modelling.

On the basis of demonstrating the results with selected uncertainties, the effectiveness of the suggested approach for increasing the ADN hosting capacity is demonstrated through different case studies on 33 node and 69 bus test feeders [29]. The hosting capacity will be evaluated under three metrics explicitly, voltage limits, transformer loadings and line loadings. A novel local voltage controller is used in this paper, based on the work in [30]. In the proposed strategy, the PV units at the end of a distribution feeder provide grid voltage support using the local droop-based controller. In contrast, the available reactive power capability of the other PV systems is deployed to decrease the reactive power flow at the up-stream line of the PVs terminal. This paper will improve the hosting capacity investigations in [30], by considering a stochastic approach, which is crucially important for System Operator (SO) s to account the likelihood of uncertainties.

The structure of the paper is as follows: Section 2 describes the overall stochastic modelling approach. Then, Section 3 will explain the Monte Carlo based stochastic methodology to generate a large quantity of realistic load and PV generation profiles with a 15-minute resolution over a day. This method helps in capturing the variability and uncertainty inherent in PV generation and load consumption. The generated scenarios are then reduced to a manageable set that represents the range of all generated scenarios. This allows for efficient analysis while still encompassing the variability of the data. The study utilizes a fully local reactive power regulation strategy to evaluate the hosting capacity of active distribution networks (ADNs). This strategy is applied to assess the system's ability to accommodate additional PV systems while maintaining stability. The simulation results are provided in Section 4. The method is tested on the modified 33-bus and 69-bus distribution test systems using practical solar generation and load data. Finally, the paper is concluded in Section 5. This real-world testing validates the effectiveness of the approach in improving hosting capacity by 20 % compared to existing local voltage control methods. The methodology demonstrated in the study has the flexibility to be implemented on any distribution feeder, making it applicable across different network configurations and scenarios. This highlights its potential for practical implementation in real-world distribution systems

2. Stochastic modelling of uncertainties in PV generation and load demand

In the literature, there are several approaches to solve existing uncertainty problems. Uncertainty can be defined by different distributions around the nominal value (i.e., Gaussian [31]). The uncertainty is probabilistic, and recognized continuous PDFs used in many studies for PVs and loads are Beta distribution and normal distribution, respectively. Fig. 1 presents the uncertainty modelling steps used in this paper. The studies will be commenced on the given uncertainty profiles for load

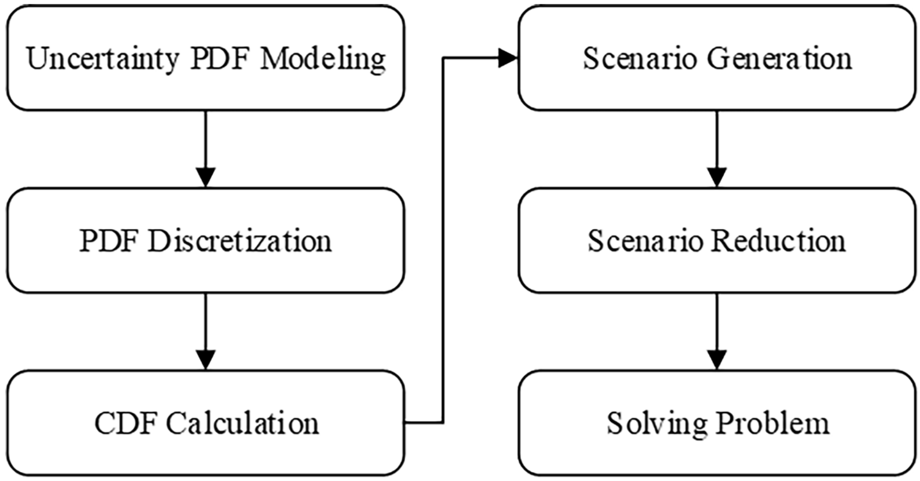

Fig. 1. Uncertainty modelling steps for PV generation and load demand [32].

and PVs of Fig. 3.

The uncertainty modelling for load and PV forecast error and their real time uncertainty realizations are represented by their probability distributions. The paper follows the methodology in [32], for scenario generation & reduction. Scenario generation will be first step of this study and scenario reduction method will be used to reduce excessive computations. While actively controlling the voltage by reactive power capabilities of inverters in the network, it is also very crucial to evaluate stochastic impacts of PVs and load as an alternative to worst-case assessment studies.

3. Computational MCS approach to evaluate ADNs with high PV penetrations

In this work, the computational method for probabilistic assessment is performed by Monte Carlo Simulation (MCS) to enhance the accuracy of results. To solve the proposed problem, this work is focused on a Monte Carlo method by using scenario generation and reduction techniques. To investigate the hosting capacity of the test systems, three security constraints (bus voltage, branch loading and transformer loading limits) have been used. The subsequent subsection outlines the Stochastic Study Procedure as illustrated in Fig. 2.

Create Random Sampling Model & Model Uncertainties by PDFs: For each uncertainty factor (load demand and PV profile), a random sampling model is constructed with MCSs. In order to generate scenarios, random variables should be created for each input random variable, corresponding to a value between 0 and 1. Then, the uncertainties are modelled based on the error obtained by the PDF.

Create Set of Scenarios: An extensive collection of scenarios is created with the MCS technique. Using the Roulette Wheel Mechanism (RWM) [32], a large number of scenarios (thousand) are generated as presented in Equation (1). Intended for each random variable in individual time intervals, a random number is produced between 0 and 1 according to the random number generator.

$$\sum_{j=1}^{r}\left(\frac{k_j}{n_j}\left(\sum_{(i=1)}^{N}v_i\right)mod1, k_j = 1, ..., N, j = 1, ..., r\right. \tag{1}$$

where $v_1,\ldots,v_N$ are vectors with dimension d obtained by the ordinary MCS. Dimension d indicates the number of random values in each scenario. A vector with dimension d of random numbers in the range of [0,1] is constructed by means of a set of values $\{k_j$, j = 1,…,r}.

Following the random numbers and probabilities from PDFs obtained, RWM generates scenarios for each hour represented in vector form recognising load demand and PV power output with binary parameters as Equation (2). Each scenario represents possible combination of load demand & PV profile, reflecting the variability& uncertainty in the system.

$$s = \overbrace{\left\{W^{l}_{(1,t,s)}, ..., W^{l}_{(7,t,s)}, W^{pv}_{(1,t,s)}, ..., W^{pv}_{(7t,s)}\right\}}^{Scenarios}_{(t=1,...,T)} \tag{2}$$

where a vector of binary parameters $W^{l}_{(1,t,s)}\ldots W^{l}_{(7,t,s)}$ and $W^{pv}_{(1,t,s)}\ldots W^{pv}_{(7,t,s)}$ are identifying the load demand and PV power outputs, respectively. t,T are time instance and time intervals.

The random numbers are produced for PV power generation and load demand for each time interval until the desired number of scenarios are generated. Eventually, the normalized probability of each scenario is calculated by Equation (3), where ND is the total number of load levels in each hour. $\beta_{l,t}$, $\beta_{pv,t}$ are the probabilities for the lth load interval and PVth photovoltaic power interval, respectively.

$$\pi_s = \frac{\Pi^{T}_{(t=1)}\left(\Pi^{ND}_{(ld=1)}\left(\sum^{7}_{(l=1)}\left(W^{l}_{(l,t,s)}\beta_{(l,t)}\right)\right)\sum^{7}_{(pv=1)}\left(W^{PV}_{(pv,t,s)}\beta_{(pv,t)}\right)\right)}{\sum^{(N_s)}_{(s=1)}\Pi^{(N_T)}_{(t=1)}\left(\Pi^{ND}_{(ld=1)}\left(\Sigma^{7}_{(l=1)}\left(W^{l}_{(l,t,s)}\beta_{(l,t)}\right)\right)\Sigma^{7}_{(pv=1)}\left(W^{PV}_{(pv,t,s)}\beta_{(pv,t)}\right)\right)} \tag{3}$$

Scenario Reduction Algorithm: The scenario reduction process is performed using the simultaneous backward method and is reduced to 10 scenarios as follows:

Step 1: S are the complete set of scenarios, and DS is the scenarios to be deleted (initially zero). The distances of all scenario pairs are calculated as in Equation (4):

$$DTs, s^{'} = \sqrt{\sum_{i=1}^{d}\left(v_i^{s} - v_i^{s^{'}}\right)^2} \tag{4}$$

where distance scenario pairs (s,s') are represented with $DT_{s,s}{'}$. v_i are vectors with dimension d, which indicates the number of random values in each scenario.

Step 2: For each scenario k, $DT_{k,r} = \min DT_{k,s'}$, $k \in S$ and s'$\neq$ k where r is the scenario index with being closest to scenario k.

Step 3: Calculate $\mathrm{PD}_{k,r} = \pi_k \times \mathrm{DT}_{k,r}$ where $k \in S$. Select d where $\mathrm{PD}_d = min\mathrm{PD}_k,\ k \in S$.

Step 4: $S = S - \{$ d$\}$, DS = DS+ {d},$\pi_r = \pi_r + \pi_d$.

Step 5: Repeat **Step 2 – Step 4** until the desired number of scenarios are left.

Step 6: Stopping rule is applied in order to stop simulations when desired number of samples are achieved by Equation (5).

$$cv_f = \frac{\sigma_f}{\mu_f\sqrt{N_s}} \tag{5}$$

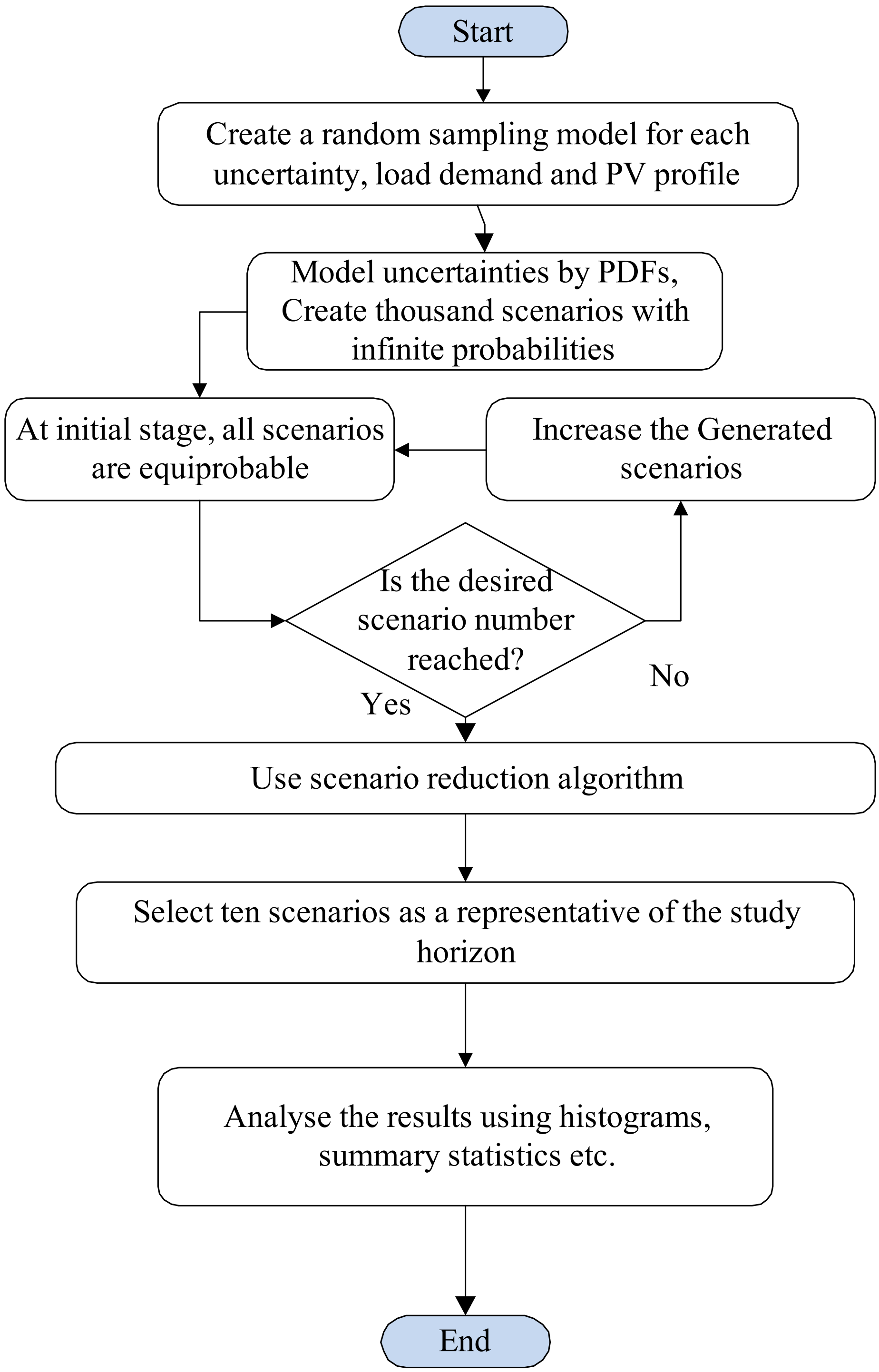

Fig. 2. The flowchart of MCS scenario generation method with scenario reduction.

where σ_f and μ_f are standard deviation and mean values of random variable "f". cv_f is monitored to stop the simulations accordingly.

Increase Generated Scenarios if Necessary: If the desired number of scenarios is not reached or the variability in the system is not adequately captured, the process returns to generating additional scenarios until the desired level of representation is achieved.

Select Representative Scenarios: From the pool of scenarios, a subset of representative scenarios (e.g., ten scenarios) is selected to cover the study horizon. These number of scenarios are chosen to provide a diverse representation of potential system analysed with optimal computational efficiency and without compromising the accuracy of the simulation results.

3.1. Whole system approach & computational method by MCS

For each uncertainty factor (load demand and PV power profile), a random sampling model is constructed. This involves generating random samples that represent potential values for these uncertainties. The parameters and characteristics of the entire active distribution network is considered, including the distribution lines, transformers, PV systems, loads, and other relevant components.

MCS technique generates random variables to establish their PDFs

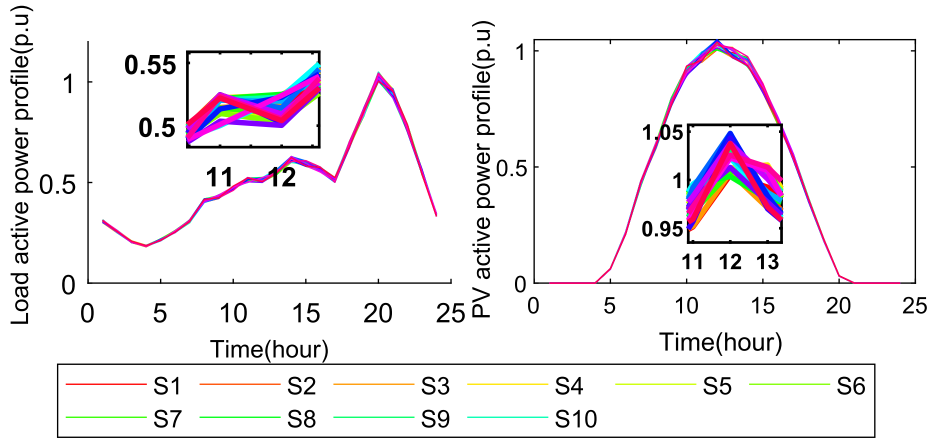

Fig. 3. Representative PV generation output & load profile scenarios.

for solving the problem of nonlinear, complex models. In Fig. 2, the steps are given to create 1000 samples of the simulation model for representing uncertainties as PDFs. Following, a scenario reduction method is used to have the desired number of representative scenarios for illustrating the results.

3.2. Constraints

The network hosting capacity is considered from the perspective of three following performance indexes namely, i) Bus voltage constraints, ii) Transformer loading constraints, iii) Branch flow constraints.

i Bus voltage constraint

Each bus voltage should meet the limits as: the maximum and minimum voltage constraints are defined as follows [33]:

Maximum voltage constraint =

$$100\left(\frac{1}{V_{\max}-1}\right)\sum_{s=S}\rho_s\sum_{ij\in B}[\mathrm{V}_{ij,s}^{\max}(p.u.)-1] \tag{6}$$

Minimum voltage constraint =

$$100\left(\frac{1}{1-V_{\min}}\right)\sum_{s=S}\rho_s\sum_{ij\in B}(\mathrm{V}_{ij,s}^{\min}(p.u.)-1) \tag{7}$$

where, the boundaries of V_{max} and V_{min} are 1.1 and 0.9 per unit (p.u.) in this study, respectively. S and s are set and index of scenarios, respectively and ρ_s is occurrence probability of scenario s, and B is set of network branches ij.

ii Transformer loading constraint

The transformer loading constraint is equal to the maximum loading of the transformer over a day [34]. Its power rating will limit the maximum amount of apparent power flow through the transformer.

$$Transformerloadingconstraint = S_{trf,t,i} < S_{MVA} \tag{8}$$

where $S_{trf,t,i}$ represents the forward apparent power flow across the transformer in each time interval t and for the scenario i, S_{MVA} is the MVA rating of the transformer. In this study, not being in the scope of the study, reverse power flow constraint is not included in the calculations.

iii Branch flow constraint

A branch flow constraint is also defined regarding the network lines loading. The flow of power through the distribution line should be less than its thermal capacity [35,36].

$$Branchflowconstraint = It_{t,i} < \mathrm{I}max \tag{9}$$

3.3. The scenarios

The required number of scenarios are selected in a way to represent the whole set of scenarios, capturing the variability and uncertainty present in the system, and managing computational complexity. These scenarios collectively cover the entire range of possibilities in the system from a diverse range of possible outcomes. Thus, the selected subset provides a comprehensive representation of the study horizon while remaining feasible for analysis within computational constraints the subset aims to capture key features of the system's behaviour, i.e. peak demand periods, variations in generation. For the desired accuracy, ten scenarios will be considered and accordingly will be represented in simulation results. Limiting the number of scenarios to ten ensures computational efficiency without compromising the accuracy of the simulation results. To signify the achieved accuracy in the simulation results, the outcomes will be represented in terms network power losses in kW, can be derived as;

$$\text{network power loss} = \sum_{s\in S}\rho_s\sum_{(ij\in B)}P_{(ij,s)}^{loss} \tag{10}$$

where S and s are set and index of scenarios, respectively and ρ_s is occurrence probability of scenario s. The outcomes will be selected according to their probabilities, consisting of ten scenarios. The daily profiles are represented with fifteen minutes' time intervals, depending on the varying values of the input data. In other words, the studied deterministic results will be extended to representative scenarios for increasing the accuracy of the results. Results are probable to improve accuracy with consideration of the probabilistic forecasts over 15 min horizons. Fig. 3 represents the ten PV power output scenarios reduced from 1000 set of scenarios generated by the Monte Carlo simulations. Table 1, represents the scenario probabilities for given load and PV profiles.

3.4. The stochastic vs. Deterministic approaches

In deterministic studies, system parameters are typically represented using fixed values or deterministic profiles, often based on historical

Table 1
Scenario probabilities for load and PV profiles.

Scenario	Probabilities	Scenario	Probabilities
1	0.3149	6	0.0310
2	0.3065	7	0.0211
3	0.1941	8	0.0140
4	0.0529	9	0.0079
5	0.0489	10	0.0086

data or static assumptions. The analysis involves running simulations or calculations using these fixed parameters, such as power flow. On the other hand, stochastic studies incorporate uncertainty modelling with probability distributions, generating scenarios for simulations that evaluate system performance. These simulations include power flow analyses across a range of scenarios, providing a comprehensive understanding of system behaviour under uncertainty. While deterministic studies offer insights into specific conditions, stochastic studies enable System Operators (SOs) to make more informed decisions.

As the PV and load uncertainties increase the grid losses, also the voltage control might become unmanageable. The stochastic approach allows the SO to account the likelihood of uncertainties, to develop robust strategies for system planning and operation by explicitly considering uncertainty and variability in system parameters, to sustain the safe operation of the power network. To investigate thoroughly, the statistical metrics like the value of stochastic solution (VSS), average uncertainty and expected value are compared in Table 2. These metrics will give a guidance to predict how the stochastic model will perform. Expected value is the summation of the ten stochastic results for each metric. Value of the Stochastic Solution (VSS) measures the loss and voltage deviation to predict the future realizations of the stochastic problem under consideration (load and PV power generation uncertainties). The difference between stochastic solution of the problem and the solution of the stochastic problem with the optimal deterministic solution (obtained with the expected value of the uncertain parameters) computes VSS. For each statistical metric, expected values of losses and voltage deviation over the 10 scenarios are calculated. Also, two contradictory assets of integration of PV power uncertainty and load demand uncertainty will be addressed by the following two performance metrics: average uncertainty grid loss and average uncertainty voltage deviation.

$$\text{AUL(Average Uncertainty Loss)} = \frac{\frac{\widehat{f_1}-f_1}{\sum_{t=1}^{NT}\sum_{p=1}^{NP} P_{Pv,f,t}}}{NT} \tag{11}$$

$$\text{AUVD (Average Uncertainty Vol. Deviation)} = \frac{\frac{\widehat{f_2}-f_2}{\sum_{t=1}^{NT}\sum_{p=1}^{NP} P_{Pv,f,t}}}{NT} \tag{12}$$

where, f_1 and f_2 are the deterministic,$\widehat{f}_1$ and $\widehat{f}_2$ are expected total loss (kW) and expected voltage deviation (p.u.) of the system with $P_{Pv,f,t}$ representing the PV power generation over 24 h. The units for average uncertainty loss and voltage deviation are kW and V, respectively.

The deterministic problem has been solved by considering the most probable scenario of the load and PV demand. Whereas the stochastic scenarios have 10 probable scenarios that constitute expected value. Therefore, the expected values of losses, voltage deviation, loading of branches and transformers have been presented. It should be noted that the four performance metrics have positive values for all the statistical approaches. For each change in deterministic and stochastic solution, their variance is calculated. Losses and transformer loading obtains higher values when uncertainty is considered. However, the voltage deviation and branch loading has negligible difference. These metrics indicates the future realizations of the stochastic problem under consideration of uncertainties (load and PV power) for SO's future planning.

Table 2
Comparison of the results obtained by selected metrics over 24 h for Case 1.

Metrics	Deterministic	Expected	VSS	Average
Loss (kW)	10,884	10,900	15.96	0.00215
Voltage deviation $-V_{b18}$	97.26	97.24	0.022	0.00299
Branch Loading (%)	4392	4388	3.92	0.05
Transformer Loading (%)	3896.3	3920.6	24.34	0.315

4. Simulation results

In this section, the generated scenarios are implemented to the test systems. This paper is a continuation of the work in [30], where a novel local voltage control strategy is proposed for enhancing the hosting capacity of ADNs with high PV penetrations. The comprehensive results for the proposed voltage control strategy with enhanced probabilistic assessment are provided on the 33 node and 69 node feeders as the test networks. After the system description, the case studies will evaluate the performance of the proposed scheme. Then, an assessment study derives the PV hosting capacity in the deployed test systems.

4.1. The studied test systems' description

Considering that PV systems are increasingly used in the ADNs, the 33 node and 69 node test systems are configured by PVs connected to each node for both test systems, is implemented in DIgSILENT PowerFactory. The feeder transformers' rating is selected as the system base power. The transformers in each test system are equipped with an On Load Tap Changer (OLTC), where observed for tap changes per day. Further details regarding the transformer, feeder line data are listed in the paper [30]. The transformer supplying the same number of loads in each system are general loads and their active and reactive powers vary during a day. The base power for the loads profile are their maximum active and reactive power that are provided. Accordingly, the maximum feeder active and reactive power demands are 65 % and 40 % of the system base power. Nominal power factor of each PV system is 0.9. The proposed voltage control strategy introduced in [30], will be compared with the most superior local voltage control techniques in the literature namely Q-voltage and PF-power strategies. The simulation results will be investigated under two case studies where Case 1 and Case 2 will represent 33 and 69 node test systems, respectively.

The investigation of the proposed scheme across both the 33-node and 69-node test systems provides insights into its scalability and generalizability. By evaluating its performance on networks of varying sizes and topologies (radial and meshed), the study demonstrates the robustness and applicability of the methodology across different distribution network configurations. The ability of the proposed scheme to deliver notable improvements in both radial and meshed networks underscores its versatility and practical utility across diverse network structures.

4.2. Case 1: 33 node stochastic simulation results

This section will compare the evaluated stochastic assessment results with the expected values of the existing voltage control techniques to reveal the effectiveness of the proposed technique. Thus, this section will illustrate the PF-Power, Q-Voltage and proposed voltage control methods comparison over their expected values, on the 33 node test feeder. In the case study, the performance criteria for comparing the reactive power control methods are defined in terms of the network losses, the transformer/branches loading.

The voltage variation at bus 18, as the most critical, is portrayed in

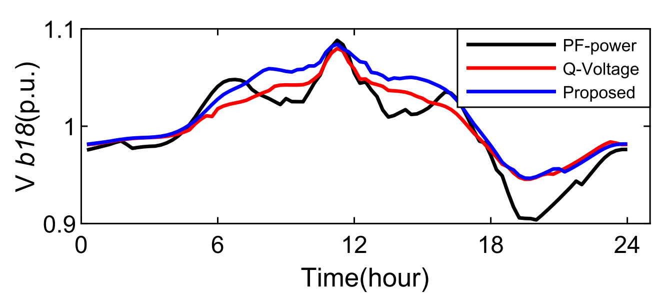

Fig. 4. Voltage amplitude at the (critical) bus 18 for expected values.

Fig. 4. Its voltage is slightly higher than 1.0p.u., over the day. From further numerical studies, this result appears to be reasonable, thus it is preserved within the critical voltage limits. Fig. 5 presents the network power losses in terms of active power, compared with three discrepant scenarios. An interesting aspect is the decrease of losses in standard voltage control techniques, while the generation is increased, thereby can be explained by the excessive reactive power consumption. However, network power losses are much lower in the proposed stochastic results over the daily trend.

In Fig. 6, there is a massive reduction for the medium voltage (MV) grid reactive power requirement from the upstream network, regarding the proposed controller. As illustrated, the PF-power and Q-voltage strategies require an excessive amount of reactive power support from the upstream network. However, the proposed controller results in a significant reduction in MV grid reactive power support, being able to generate the desired reactive power within its own PV units.

Fig. 7 illustrates the loadings for the feeder transformer and the Line 8. For the line, both PF-power and Q-voltage strategies violates the safety limit, and former strategy exceeds the loading limits in the peak generation times during the day. It is clear that the time of the overloading coincide with the period of highest solar generation in standard voltage control techniques.

The enhanced PV hosting capacity with expected values of proposed method is compared to the conventional control methods in Table 3. The hosting capacity defined by maximum voltage is lower compared to deterministic results, due to the increase in the load demand and slight decrease in PV generated power with generated scenarios. For the loading constraints, the proposed strategy, will allow more PV units to be integrated without violating the limits.

For conventional voltage control methodologies, it is anticipated that PVs may cause the grid components to be overloaded under the several scenario considerations. Thus, when loading constraints are observed under several predicted scenarios, it is obvious that the proposed strategy, is the most effective method to increase the hosting capacity.

From the expanded evaluations by stochastic assessment, the results demonstrate that, the proposed method is a reliable and robust way to increase the PV capacity within the network without surpassing the constraints defined in the grid codes.

4.3. Case 2: 69 node stochastic simulation results

To represent the stochastic simulations further and to verify the proposed strategy, the simulations are extended on a 69 node test system. The test system representation and further details are provided in paper [30]. Fig. 8 represents the critical node voltages, which are located at the beginning and the end of the feeder, respectively. It can be seen from the figure that the voltages at buses are respectively higher than those of conventional strategies. Besides, prior to the deployment of the proposed voltage controller, the transformer and line loadings are much higher, presented in Fig. 10. Furthermore, the proposed strategy has the lowest network power losses. As seen in Fig. 9, the power losses

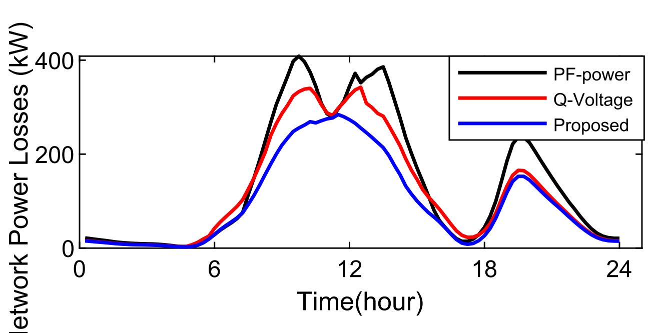

Fig. 5. The 33-node test feeder network power losses (kW) for expected values.

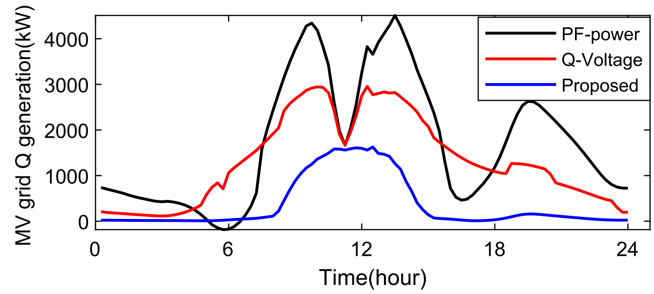

Fig. 6. The 33-node test feeder MV grid reactive power generation for expected values.

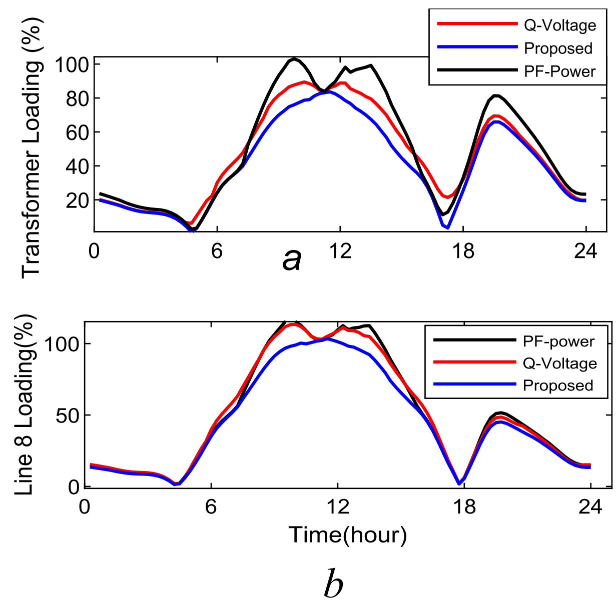

Fig. 7. The 33-node test feeder results with thirty-three PV systems for expected values (a) The transformer loading, (b) The line 8 loading.

Table 3
The PV hosting capacity of the 33-node test feeder with the expected values (in percentage of the system base power 5750 kW).

Control Method	Hosting capacity subject to constraint		
	Max. voltage	Trans. Loading	Branch flow
PF-power	210	112	100
Q-voltage	280	132	105
Proposed	205	152	**120**

decreased dramatically for the proposed technique, when compared to conventional ones.

To substantiate the performance of the proposed scheme with the probabilistic approach, the external dependency on the MV grid is assessed in Fig. 11. The required MV reactive power generation is extremely high for standard control strategies, where the ADN will be mostly dependent to the upstream network. When the proposed strategy is explored, the reactive power support from the upstream network is significantly less.

Tap positions are illustrated in Fig. 12, where the Q-voltage tap numbers are slightly lower than the PF-Power technique. However, the proposed method has the least tap operations over the day, which verifies best performance with only one tap operation per day.

Therefore, the proposed technique has a direct effect on increasing hosting capacity. It can be concluded that the probabilistic investigation

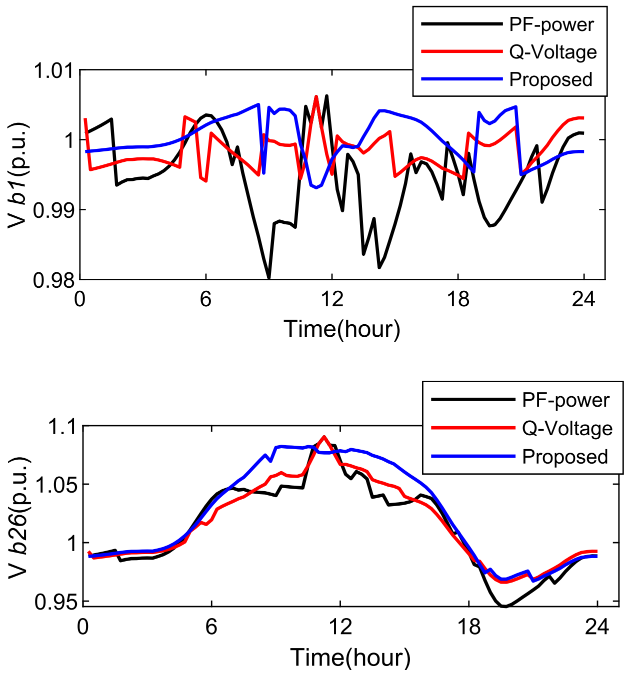

Fig. 8. Voltage amplitude at the (critical) buses Bus1 and Bus26 for expected values.

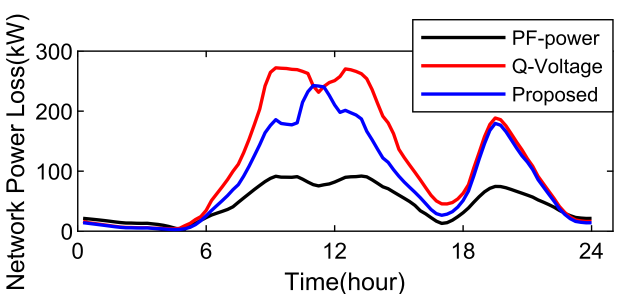

Fig. 9. The 69-node test feeder network power losses (kW) for expected values.

of the proposed algorithm is much more effective to achieve the minimum network loss, less tap changes over the day and enhancing the relative hosting capacity are always above 15 %.

4.4. Comparison of deterministic and stochastic results

The findings are based on some of the most advanced, highly-granular, detailed studies performed on the deterministic and stochastic results of the practical test systems. Fig. 13 and Fig. 14 represents the comparison of deterministic and stochastic evaluations for each control strategy in terms of voltage at critical bus 18 and network power losses, respectively. It is a vital representation that, the SO process will be determined highly by the stochastic assessment results. Especially in the peak generation hours, stochastic results display a significant difference from the deterministic results. The peak generation results in higher voltages in stochastic cases. If deterministic results are taken into consideration by SO, the safe operation of power systems conditions would be possibly interrupted. Therefore, the consideration of PV power generation and load demand uncertainties will become prominent in future, for the safe operation to be fulfilled by SO's.

5. Conclusion

The distributions of the stochastic variables can be approached by a discrete distribution with a limited number of scenarios with the corresponding probabilities. An extensive collection of scenarios are created with the Monte Carlo simulation technique by using the Roulette Wheel Mechanism (RWM). To accurately decrease the number of scenarios and handle the stochastic problem, scenario reduction algorithm is applied. Out of one thousand scenarios with infinite probabilities, these scenarios are reduced to ten set of scenarios with backward scenario reduction method. Several loss and hosting capacity metrics are applied to assess future PV power generation and load demand. On the basis of demonstrating the results with selected uncertainties, the

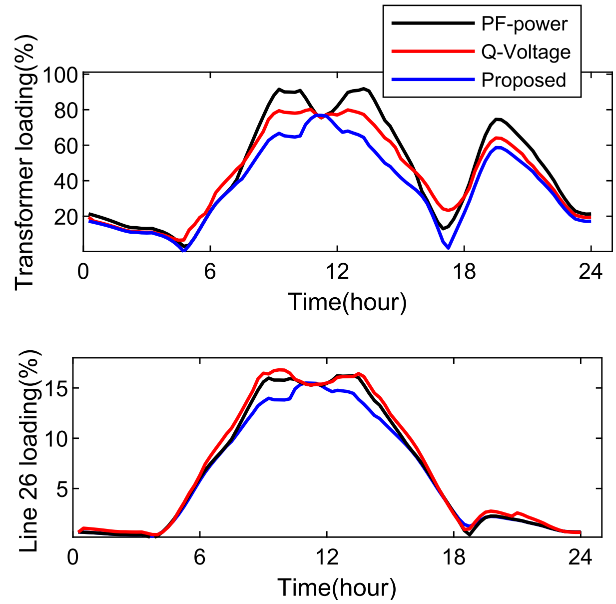

Fig. 10. The 69-node test feeder results with sixty nine PV systems for expected values (a) The transformer loading, (b) The line 26 loading.

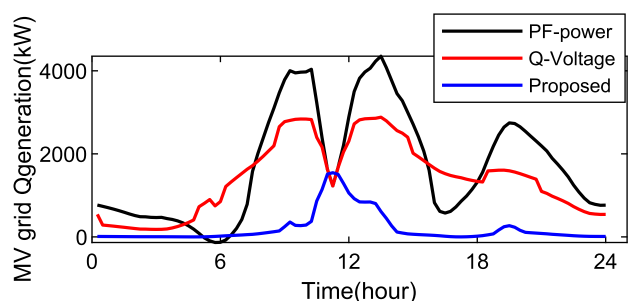

Fig. 11. The 69-node test feeder MV Grid reactive power generation for expected values.

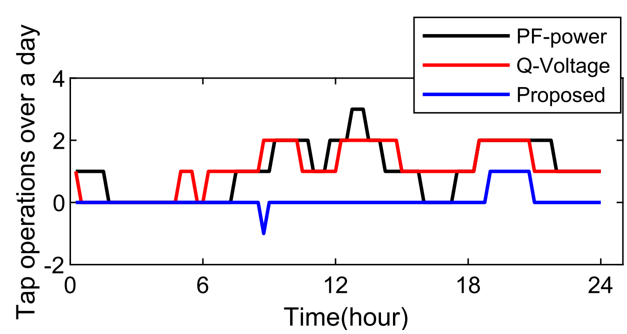

Fig. 12. The 69-node test feeder tap operations over a day.

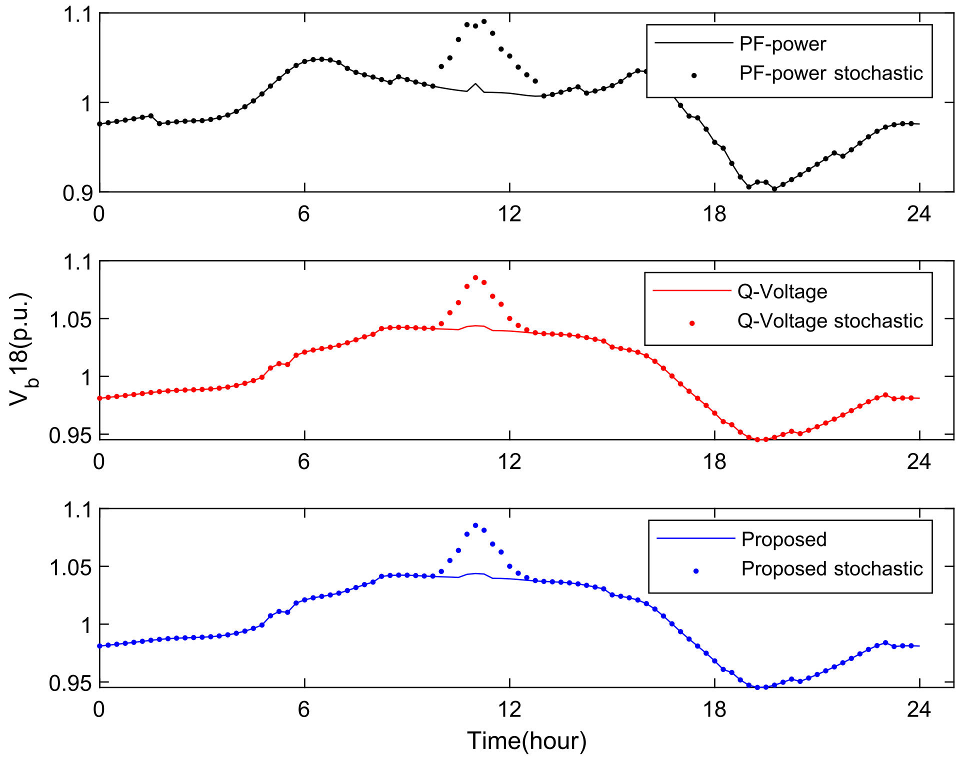

Fig. 13. The 33-node test feeder voltage amplitude at the (critical) bus 18 for expected values of deterministic and stochastic results.

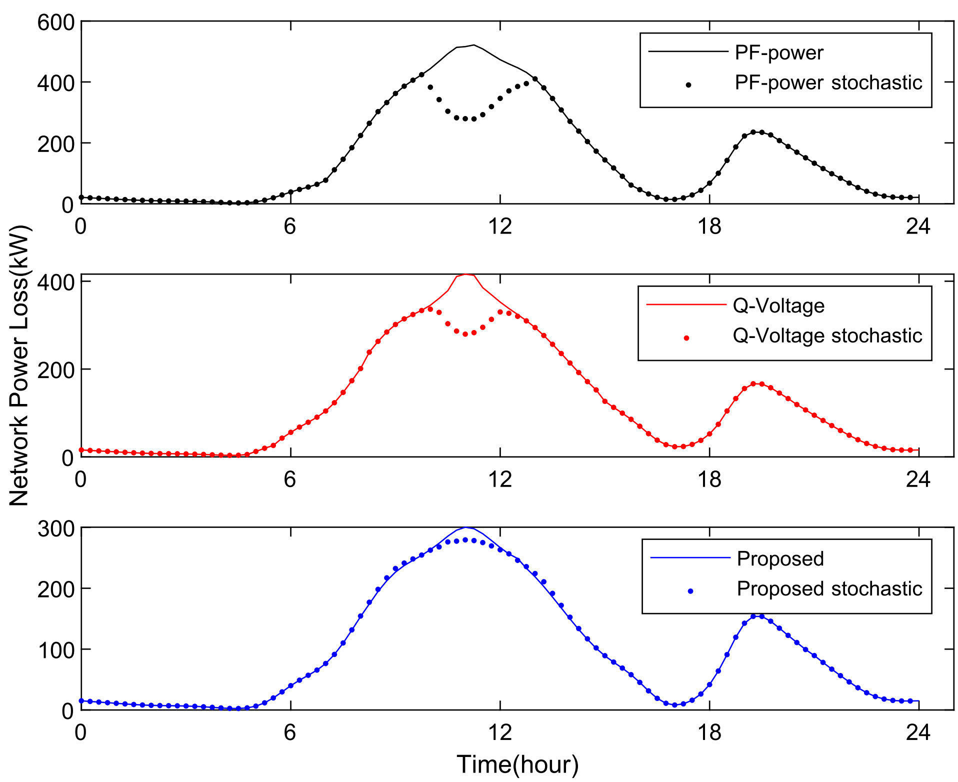

Fig. 14. The 33-node test feeder network power losses (kW) for expected values of deterministic and stochastic results.

effectiveness of the suggested approach for increasing the DN hosting capacity is demonstrated through different case studies on 33 and 69 node test systems. To determine the PV hosting capacity for the studied networks, load flow calculations are derived over 24 h over the time intervals of 15 min for the PVs nominal apparent power. The expected value, which is the summation over the probabilities of given ten scenarios, is compared with the deterministic results. The simulation results confirmed that, the active power losses decreased by 50 % and 40 % compared to PF-power and Q-voltage strategy, respectively. A major reduction was observed over the MW reactive power supplied to the studied 33-node test system, for the proposed controller (75 % less than PF-power and 65 % less than Q-voltage). Hosting capacity expected value observations show that the proposed approach increases the hosting capacity by 20 % in comparison to PF-power case. Moreover, the SOs need for stochastic assessment is demonstrated for the secure and reliable operation of power system. For the safe operation of power systems with high penetration of PVs, the consideration of PV power generation and load demand uncertainties will become prominent in future, and needs to be fulfilled by SO's. Future work will emphasise to consider the correlation metrics, between load and PVs. In the context of evaluating factors impacting hosting capacity, it is vital to consider the impact of energy storage under active distribution network concept. Energy storage, a key element of active distribution networks, which plays a crucial role to enhance hosting capacity by mitigating intermittency issues associated with renewable energy sources such as PV systems. The future work aims to provide insights into how storage technologies can further improve hosting capacity and grid stability, by incorporating energy storage systems to this work.

CRediT authorship contribution statement

Melike Selcen Ayaz: Conceptualization, Data curation, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Mostafa Malekpour:** Formal analysis, Investigation, Software, Visualization, Writing – original draft. **Rasoul Azizipanah-Abarghooee:** Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft, Writing – review & editing. **Mazaher Karimi:** Funding acquisition, Investigation, Software, Visualization, Writing – original draft. **Vladimir Terzija:** Data curation, Methodology, Project administration, Resources, Supervision, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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