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Utilisation of electric vehicles and battery energy storage systems for the enhancement of PV hosting capacity in a distribution network

Zulu Esau, Hara Ryoichi and Kita Hiroyuki
Graduate School of Information Science and Technology, Hokkaido University, Hokkaido, Japan

ABSTRACT

To foster decarbonisation of the transportation sector, there is a growing widespread global adoption of electric vehicles (EVs) as a clean, environmentally friendly alternative to fossil-fuel-dependent internal combustion engine vehicles (ICEV). This has required the electrical power system to distribute power to EV charging stations. In addition, battery energy storage systems (BESSs) have also been deployed to improve network resilience. Both EVs and BESSs on distribution networks (DNs) may be charged using photovoltaic (PV) resources. Subsequently, huge numbers of PV plants have been installed globally over the past decade. With excessive PV penetration into the distribution network (DN), the consequences are risks of operational constraint violations such as over-voltages, feeder line congestion, protection maloperation and high harmonics. This requires limiting the amount of installed PV to alleviate these risks. The maximum amount of PV which can be integrated into the DN without violating these network operational limits is the PV hosting capacity (PVHC). This paper proposes models for quantifying the impacts of EVs and BESSs on the PV hosting capacity of DNs using the stochastic particle swarm and gradient descent algorithm (PSO-GD). The simulation results of case studies have shown that the proposed method is accurate, fast, and efficient.

KEYWORDS Battery energy storage system; distribution network; electric vehicle; hosting capacity; particle swarm and gradient descent algorithm; photovoltaics; stochastic analysis
CONTACT Esau Zulu zulu.esau3@gmail.com
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1. Introduction

At the power distribution network (DN) level, photovoltaic (PV) power generation is a promising renewable energy power generation alternative due to its high scalability and ease of installation (Atwa et al., 2010). On the other hand, PV penetration into the DN comes with risks of operational constraint violations such as over-voltages, feeder line congestion, protection maloperation due to reverse power flows, and increased harmonics (Mohammad et al., 2017). The PV hosting capacity (PVHC) is the maximum capacity of PV which can be integrated into the DN without violating the operational limits of the DN (Luomeng et al., 2022). In Khumar et al. (2019), the authors argue that battery energy storage systems (BESSs) are integrated into the residential sector for the self-consumption of PV output and resiliency improvements. With the presence of BESSs, the net active generation, which is the actual generation of PV minus the BESS charging, must be considered in the hosting capacity evaluation, as reported in Robin et al. (2022) and Su et al. (2019).

While the future of electric power generation is moving towards PV-based power generation with incorporated BESSs, the future of mobility technology is shifting towards electric vehicles (EVs). Charging for EVs occurs mainly at the DN level. Because of the inter- and co-dependences of EVs and BESSs on PV, there is a potential effect on the DN's PV hosting capacity (Vega-Fuentes et al., 2019). Therefore, there is an urgent need to develop models that quantify and qualify the potential benefits and downsides of EV and BESS deployment in DNs.

Abad et al. (2018) and Darwin et al. (2020) proposed a two-stage stochastic Mixed Integer Linear Programming (MILP) method to estimate the PVHC of DN. This method produces interesting results but risks losing practicality due to linearisation of the power flow equations. (Zhao et al., 2017) proposed an EV hosting capacity maximisation model based on aggregating the EV load in the chargeable region. This model has a high practical value; however, it is very difficult to solve problem involving an enormous number of uncertainties. The Monte Carlo Simulation (MCS)-based stochastic analysis of uncertainties in PV, BESSs and EVs was attempted by (Ayyadi, 2019). In that paper, uncertainties in EV and BESS charging were modelled using the probability density functions of the parameters and variables of the PV plants, EVs and BESSs, respectively. This was then used to generate scenarios for which the hosting capacity was subsequently estimated.

The disadvantage of MCS-based calculations is that they impose a huge computational burden because they are required to simulate a huge number of scenarios to accurately model a system (Melioupoulos, et al., 1990).

This paper proposes a stochastic method of estimating the potential PV hosting capacity enhancement due to EV and BESS deployment in a DN using the stochastic particle swarm and gradient descent algorithm (PSO-GD) developed by the authors (Zulu et al., 2023a).

2. Uncertainty characterisation of variables

The PVHC of a DN is the maximum amount of PV which can be installed in/injected into the network without violating the network's operational constraints on voltages, line capacities, harmonics, reverse power, etc. It is a very important metric for planning DN expansion and distributed generation (DG) by distribution system operators (DSOs).

With the advent of EVs and BESSs being deployed in the network, which are subsequently charged by the installed PV systems, it is cardinal to underpin the positive impacts that EVs and BESSs could have on the PVHC.

The charging and discharging of EVs and BESSs are uncertain phenomena which depend on different uncertain variables and parameters. The PV output is intermittent because of its dependence on solar irradiation, which is intermittent in nature and, the load demand is usually stochastic in nature and varies from one level to another in each timeframe. Thus, all these variables are uncertain and must be characterised using random variables.

To accurately estimate the PVHC of DNs with the advent of EV and BESS deployment, there is a need to model the uncertainties in the variables mentioned above. In the subsequent sections, these uncertainties are modelled in this context as well as their mathematical connections to the PVHC problem.

2.1. Uncertainty characterisation of EV load

EV charging is characterised by its arrival time (plug-in time), mounted-battery capacity, plug-in period, the initial state of charge (SoC) of the EV storage, and EV departure time (plug-out time). The aggregate charging load presented by the EV also depends on the type of EV. According to Su et al. (2019), there are five distinct EV types as shown in Table 1.

Table 1. Charging characteristics of five types of EVs.

EV type	Battery capacity (kWh)	Charging power (kW)		Endurance mileage (km)
		Slow	Fast	
Private	24/40	6.6	11	150/250
Utility	40	6.6	11	250
Public	40	-	11	250
Bus	202	-	50	200
Truck	240	-	80	250

The actual charging period of the EV is dependent on the initial state of charge (SoC) of the EV at the plug-in time of the EV and its capacity. The SoC of an EV at a time t is given by Equation (1).

$$SoC_{t,j}^{EV,k} = SoC_{(t-1),j}^{EV,k} + \eta_{ch}^{k} P_{t,j}^{ch,k} t_{ch}^{EV,k} - \frac{P_{t,j}^{dis,k} t_{dis}^{EV,k}}{\eta_{dis}^{k}} , \quad (1)$$

where $SoC_{(t-1),j}^{EV,k}$ is the initial SoC of the EV storage before time t; $SoC_{t}^{EV,k}$ is the SoC of EV storage at time t; η_{ch}^{k} and η_{dis}^{k} are the EV charging and discharging efficiencies, respectively; $t_{ch}^{EV,k}$ and $t_{dis}^{EV,k}$ are the EV charging and discharging time periods, respectively; k represents the EV type; j is the number assigned to the EV in the fleet.

Ahmadian et al. (2015) argue that the SoC of an EV can be modelled using a normal distribution as in Equation (2).

$$f(SoC) = \frac{1}{\sqrt{2\pi\sigma_{soc}^{2}}} e\left\{-\frac{(SoC-\mu_{soc})^{2}}{2\sigma_{soc}^{2}}\right\} , \quad (2)$$

where σ_{soc} is the standard deviation of the EV storage SoC; μ_{soc} is the mean of the EV storage SoC.

An EV's charging demand is thus estimated for the time between the plug-in and plug-out times. This is approximated using the available charging option of either slow or fast charging. Thus, EV charging demand is given by Equation (3).

$$P_{ch,j}^{EV,k}(t) = \begin{cases} P_{ch}^{EV,k} , & t_{pi} \le t \le t_{po} \\ 0, & otherwise \end{cases} , \quad (3)$$

where $P_{ch}^{EV,k}$ is the variable charging power demand by an EV in fleet k; t_{pi} and t_{po} are the plug-in and plug-out times of the EV respectively.

Therefore, for the EVs in the pool, the aggregate charging demand is given by Equation (4).

$$P_{ch}^{EV} = \sum_{k=1}^{N_{type}} \sum_{j=1}^{N_j} P_{t,j}^{ch,k} , \quad (4)$$

where N_{type} is the number of EV types (=5); N_j is the total number of EVs of a particular type.

2.2. Uncertainty characterisation of BESSs

Like EVs, the charging requirements of a BESS depend largely on the initial SoC of the BESS and the charging time and discharging time of the BESS. Equation (5) gives the variation of the SoC of a BESS in a particular time.

$$SoC_{t,h}^{BESS}(t) = SoC_{(t-1),h}^{BESS} + \xi_{h}^{BESS}\left\{\frac{\eta_{ch}^{BESS} P_{ch,t}^{BESS,h} \tau_{ch,h}}{E_{max}^{BESS}}\right\} - (1-\xi_{h}^{BESS})\left\{\frac{P_{dis,t}^{BESS,h} \tau_{dis,h}}{\eta_{ch}^{BESS} E_{max}^{BESS}}\right\} , \quad (5)$$

where $P_{ch,t}^{BESS,h}$ is the charging load for the BESS h at time t; P_{ch}^{BESS} is the constant charging power of the BESS; $SoC_{(t-1),h}^{BESS}$ is the initial state of charge of the BESS before time t; $SoC_{t,h}^{BESS}$ is the state of charge of the BESS at time t; SoC_{max}^{BESS} is the maximum BESS capacity; $SOC_{(t-1),h}^{BESS}$ is the state of charge of the BESS before time t; τ_{ch} is the BESS charging duration; ξ is the binary variable for BESS charging/discharging, $\xi \in \{0,1\}$; $\eta_{\mathrm{ch}}^{\mathrm{BESS}}$ and η_{ch}^{BESS} are the BESS charging and discharging efficiency, respectively;

E_{max}^{BESS} is the BESS energy storage capacity.

The aggregate charging demand for all BESSs in a DN is thus the sum of all BESSs connected in the network.

$$P_{ch,t}^{BESS} = \sum_{h=1}^{N_{BESS}} P_{ch,h}^{BESS} . \tag{6}$$

2.3. Uncertainty characterisation of normal load

The normal load demand is modelled using truncated normal distribution as highlighted by Zulu, et al. (2023). Equation (7) indicates this representation.

$$f(P_L) = \begin{cases} 0, & P_L < a \\ \frac{1}{\sqrt{2\pi\sigma_L{}^2}} e\left\{-\frac{(P_L-\mu_L)^2}{2\sigma_L{}^2}\right\}, & a < P_L < b \\ 0, & P_L > b \end{cases} , \tag{7}$$

where P_L is the normal load of the system; μ_L is the mean of the load; σ_L is the standard deviation of the load demand; a and b are the minimum and maximum values of the load respectively.

The mean of the load, μ_L , is the aggregate load demand of the network. The standard deviation, σ_L, the minimum load value, a, and the maximum load value, b are determined from historical data collected from existing DNs. These values vary from network to network and may result in different results depending on which network is considered.

In this study, historical data from the Ota city solar-powered community in Japan is used for determining typical values of the standard deviation, and the values of a and b.

2.4. Uncertainty characterisation of PV generation

According to (Mohammad, et al. 2017), the output of PV systems depends on many factors including the time of day, season, and geographical location. The most compelling variable on which the output of PV systems depends is the irradiation of the sun incident on the PV arrays. Therefore, because the solar irradiation can be characterised by the beta distribution, (Mohammad, et al. 2017 and Zulu, et al. 2023b) modelled the PV output according to the beta PDFs. Mathematically, the probabilistic output of PV is, then, modelled using Equation (8).

$$f(P_{pv}) = \begin{cases} KP_{pv}^{(\alpha-1)}(1-P_{pv})^{(\beta-1)}, & \alpha \geq 0, \beta \geq 0 \\ 0, & otherwise \end{cases} , \tag{8}$$

where K is a scaling factor: $K = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha).\Gamma(\beta)}$ given by the gamma functions $\Gamma(\cdot)$; P_{pv} is the per unit PV output power; α and β are curve sharpening parameters.

3. Problem formulation

Dubey et al. (2017) and Luomeng et al. (2022) proposed that the PVHC estimation can be formulated as a deterministic problem as in Equation (9).

$$PVHC = max\left\{\sum_{i=1}^{N_{pv}} P_{pv,i}\right\} . \tag{9}$$

This formulation, however, fails to account for the uncertainties in the input variables of the problem.

Zulu et al. (2023) proposed a two-stage formulation employing hybrid deterministic and stochastic methods. This problem was then solved using the MCS-based analysis.

In this paper, the PVHC estimation problem is formulated as a probabilistic mixed integer nonlinear programming (MINLP) problem whose objective is to maximise the installed PV capacity in the DN. Equation (10) is the probabilistic maximisation formulation of the PVHC estimation problem considered.

$$PVHC = max\left\{\sum_{i=1}^{N_{pv}} P_{pv,i} \,|(\Pr\, [V_{max}^{n} \geq V_{lim}\,])\right\} . \tag{10}$$

Subject to:

$$P_m = \sum_{n=1}^{N} V_m V_n \{G_{mn} cos(\delta_m - \delta_n) + B_{mn} sin(\delta_m - \delta_n)\} , \tag{11}$$

$$Q_m = \sum_{n=1}^{N} V_m V_n \{G_{mn} sin(\delta_m - \delta_n) - B_{mn} cos(\delta_m - \delta_n)\} , \tag{12}$$

$$P_{pv,i} \geq 0 , \tag{13}$$

$$V_{min} \leq V_n \leq V_{max} , \tag{14}$$

$$Q_{min,n} \leq Q_n \leq Q_{max,n} , \tag{15}$$

$$S_{mn}^{min} \leq S_{mn} \leq S_{nm}^{max} , \tag{16}$$

$$SOC_{Min}^{EV,k} \leq SOC_t^{EV,k} \leq SOC_{Max}^{EV,k} , \tag{17}$$

$$SOC_{Min}^{BESS,h} \leq SOC_t^{BESS,h} \leq SOC_{Max}^{BESS,h} , \tag{18}$$

$$P_m = P_{pv,m} + P_m^G - P_{L,m} - P_{ch}^{EV} - P_{ch}^{BESS} , \tag{19}$$

where V_{max}^{n} is the maximum node voltage; V_{lim} is the voltage limit allowable; N_{pv} is the total number of nodes with PV installation; Equations (11) and (12) are the power flow equations for node m; Equations (14)-(16) are the operational limits on the network dependent and independent variables (voltage, reactive power, and line flows, respectively). Equations (17) and (18) are the limits on the amount of energy that can be stored or extracted from the EV and BESS, respectively. Equation (19) is the power balance requirement at bus m. $P_{pv,m}$ is the PV power injected into bus m; P_m^G is the power generation from other sources at bus m; $P_{L,m}$ is the conventional load at bus .

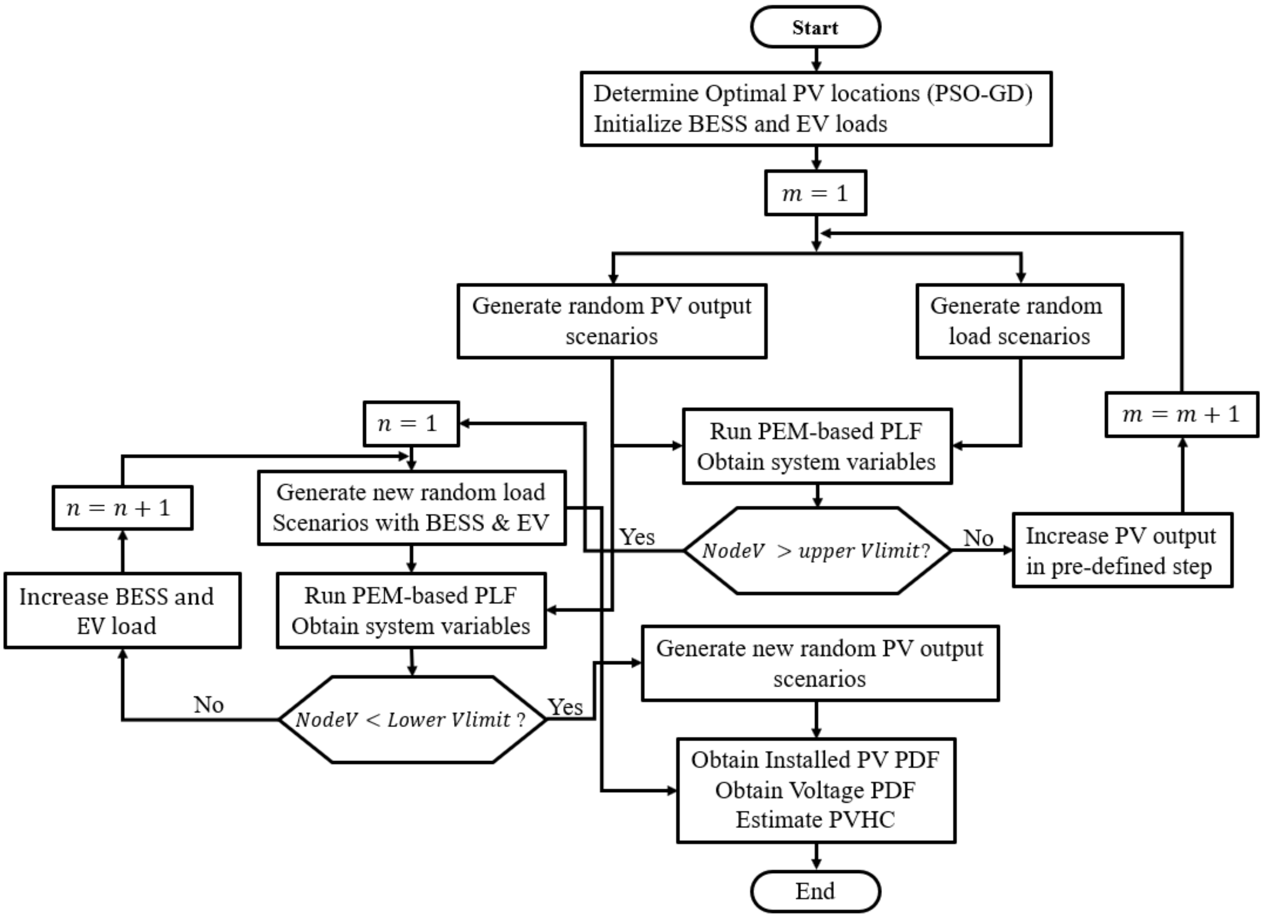

Figure 1. Flowchart of the multi-stage algorithm for estimating the PVHC of distribution networks.

4. Proposed method

Figure 1 shows the flow chart of the proposed method to solve the PVHC problem in the presence of EV and BESS deployment in the DN. The solution proceeds by first determining the optimal locations for PV installation using the Particle Swarm Optimization and Gradient Descent (PSO-GD) algorithm (Zulu et al., 2023). For the locations obtained in the first step, several PV output scenarios are generated using the uncertainty characteristics in Equation (8). The loads at all nodes also generate stochastic scenarios based on the characteristics in Equation (7).

Once the stochastic scenarios of the PV output and load demand are generated, they are analysed to determine the node voltages, line power flows and other network variables using probabilistic load flow (PLF) analysis based on the point estimate method (PEM).

One of the outcomes of the preceding procedure is a series of installed PV sizes and resulting node voltages. These are then plotted to determine the highest installed PV size which results in the network operating at the node voltage upper limit. This point is deemed the PVHC of the DN without the deployment of BESSs and EVs.

The next phase involves adding BESS and EV deployment in the network as charging loads given by Equations (3) and (6). At the locations with PV installation, the BESS and EV sizes are increased by adding the number of EVs and BESS in predetermined sizes until the network voltage falls below the specified lower voltage limit.

Afterwards, the BESS and EV charging load (with their stochastic characteristics) are augmented to the normal load at the locations with PV installation. The augmented load's stochastic behaviour is modelled, and new PV output scenarios are generated. With the new stochastic PV output and load demand scenarios, the procedure for estimating the PVHC, described earlier, is undertaken. The resulting PVHC is the hosting capacity of the network with BESS and EV deployment in the system.

5. Case studies

The procedure outlined in Section 4 was applied to the IEEE 33 bus test distribution network. The technical data for the IEEE 33 bus can be found in MATPOWER (Zimmerman et al., 2011).

Two case studies were conducted: a base case study to establish the PV hosting capacity of the network without BESS and EV load and a case to establish the PV hosting capacity when BESS and EV charging load is stationed at locations where PV is installed.

The voltage operational upper and lower limits of 1.05 [pu] and 1.00 [pu], respectively, were taken as the principal limits for basing the PVHC estimation.

5.1. Case I: PVHC without BESS and/or EV load

In the case without BESS and EV load, the PV hosting capacity of the DN is determined by estimating the installed PV sizes which do not result in node voltage limit violations, and their respective locations. The installed PV sizes and their locations in the IEEE-33 bus DN are shown in Figure 2.

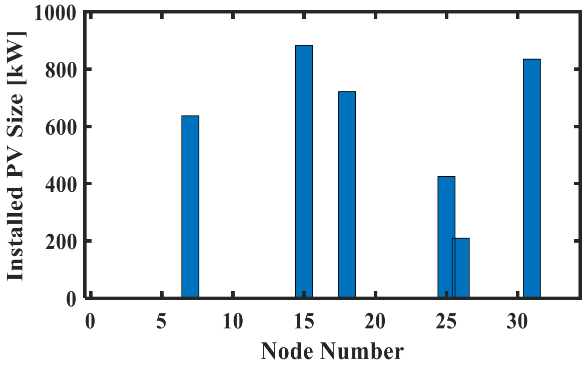

Figure 2. Installed PV sizes and locations without BESS and EV load in IEEE 33 bus test DN.

It is observed that the PV sizes range from 209.72 kW at bus 26 to 882.62 kW at bus 15. The aggregate installed PV is about 3709.40 kW.

5.2. Case II: PVHC with BESS and EV charging deployment

In the second case, BESS and EV charging load is augmented to the conventional load in case I. The augmentation process is as described in Section 4 and is elaborated with Figure 1.

The following assumptions were made for the estimation of BESS and EV load:

1. All BESSs and EVs are privately owned and controlled.
2. BESS charging is exclusively performed using installed PV.
3. EV charging takes place in a specially designated time window by the private owner (usually 6:00pm to 7:00am the following day) (Su et al., 2019).

Assumption 1 means that only locations (or network nodes) with installed PV have battery storage installation and EV charging capability. Assumption 2 makes it easier to control the BESS charging. Assumption 3 is based on the expectation that private EVs would be in transit during the day and exclusively parked during the night.

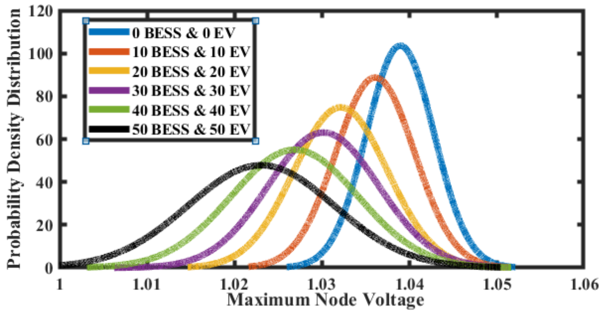

Figure 3. PDF of node voltages for different BESS and EV numbers.

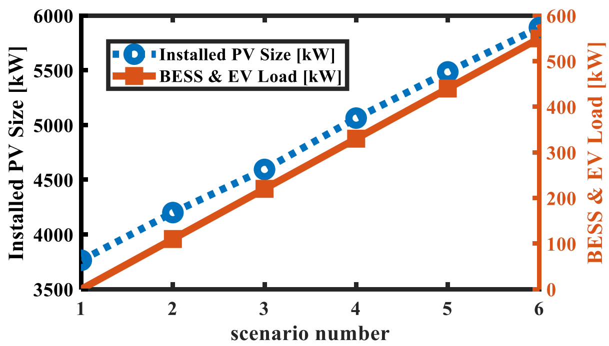

Figure 4. Variations of Installed PV size with increases in BESS and EV load.

From Table 1 and Robin et al. (2022), private EVs have capacities ranging from 24 to 40 kWh and are charged at 6.6 kW power. The BESS for home installations has about 4 to 5 kW charging power. With these taken into consideration, EVs and BESSs were added in batches of 10 for each location. Figure 3 shows the variations of the voltage PDFs as each batch of BESSs and EVs is added. It is observed that the minimum node voltage recorded on the PDF decreases steadily as the batches are added.

When the final batch of 50 BESSs and 50 EVs is added, the minimum observed node voltage drops below the preset minimum of 1.0 [pu] (reference value). Thus, the total charging load required to bring the observed minimum node voltage below the reference value is 530 kW. Figure 4 shows the variation of installed PV sizes with the changes in the BESS and EV charging load. BESS and EV charging load increases from 0 kW to 530 kW while installed PV size increases from 3709 kW to about 5850 kW, an increase of about 57.72%.

Figure 4 also shows that there is a very high correlation between the EV and BESS charging load and the estimated PVHC of the DN. In fact, for this case, there is a 99.98% correlation between the two variables.

However, the increase in the installed PV size is not a perfect straight-line correlation (99.98%) with increases in BESS and EV charging load because of uncertainties in both the conventional load and the BESS and EV charging load which slightly affect the PVHC estimation outcomes.

6. Conclusion

This paper has presented stochastic models for incorporating BESSs and EVs in the PVHC estimation process in DNs. It attempts to model the BESS and EV as charging loads and uses the probabilistic characterisations to model their uncertainties. These models are then joined with the normal load probability density functions (PDFs) for overall point estimate probabilistic load flow analyses.

The paper has also presented a method for estimating the PV hosting capacity (PVHC) of a distribution network (DN) using PEM-based probabilistic load flow analysis to obtain important dependent and independent variables required for PVHC estimation.

Furthermore, the paper shows how battery energy storage systems and electric vehicles increase the PVHC of a DN. This is validated through the application of the algorithm to the IEEE-33 bus test distribution network.

It has been shown that incorporating BESSs and EVs increases the overall PVHC of a DN substantially. In the case study presented, the PVHC increased by just below 60% when several private EVs and BESSs were included as charging loads in the DN.

Financial interest disclosure

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

Notes on contributors

Dr Esau Zulu is a member of IEEJ and IEEE, and was born in 1986, in Zambia. He graduated with B.Eng. Electrical Eng. from The Copperbelt University, Kitwe, Zambia, in 2010, and a MSc. Electrical Engineering degree from Curtin University, Perth, Australia, in 2013. In December 2023, he graduated with a Ph.D. degree in Information Science and Technology, Hokkaido University.

Prof Ryoichi Hara is a member of IEEJ and IEEE, and completed his Ph.D. in engineering research and planning, operation, and control of power systems in 2003 at Hokkaido University. In 2006 he was appointed as Associate Professor at Hokkaido University in the Graduate School of Information Science and Technology.

Prof Hiroyuki Kita is a senior member of IEEJ and IEEE, and received his M.E. and Ph.D. degrees from Hokkaido University, Sapporo, Japan, in 1988 and 1994, respectively. Since 2005, he has been working as a Professor at Hokkaido University in the Graduate School of Information Science and Technology under the division of Systems Science and Informatics.

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