

Hosting capacity in smart distribution systems using OpenDSS tool and Monte Carlo-based methodology

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Abstract. The increased installation of distributed generators in the electrical network presents significant challenges for system planners and operators, demanding strategic adaptations to accommodate diverse energy sources while ensuring grid stability and operational efficiency. HC analysis has recently been proposed as an essential tool capable of guiding investments into the areas of the network, most likely to offer optimal benefits. This paper presents a method for the estimation of photovoltaic HC of the distribution network. For this purpose, the OpenDSS program, employing the Monte Carlo-based method, is utilised to quantify the HC of the electrical distribution network. The simulation is conducted using a real electrical MV network and then verified against the IEEE Test System for validation. The paper reports HC of 166.5%, which is higher in comparison with similar methods and models, investigates the influence of constant generation in daily simulation and proves that voltage constraint is violated before line loading. A considerable increase of the circuit losses is recorded if the optimal penetration of PV is exceeded. The main contribution of this work is the development, testing and implementation of the HC estimation method in complex power systems using open-source tools and integrating them in an innovative fashion. The results of this research will contribute to collective endeavours of energy transition and a sustainable future.

Keywords: Distributed power generation, Energy, Photovoltaic systems, Power system planning, Power system simulation.

1 Introduction

A growing number of renewable energy-based distributed generators (DGs) in power distribution networks have appeared recently [1], due to environmental concerns, electrical energy market liberalisation, and energy transition policies. The integrated energy system of gas, heat, electricity and cold has a vast amount of potential schedulable resources. Unfortunately, the majority of these energy sources are now run independently, which results in low system flexibility, low energy usage, and a significant decline in the use of solar and wind power. In order to increase the capacity for the consumption of Renewable Energy Sources (RES) and the flexibility of integrated energy systems, a community-integrated energy system's cost-effective dispatch while taking demand-side coordinated response into account is proposed in [2].

Distributed Generation (DG) systems in general, can provide numerous benefits and at the same time challenges for the system operator. Decreased capital costs, loss

reduction, and support for voltage profiles are some of the benefits which the replacement of conventional generation with DGs brings to power distribution grids [3]. Utilising RES more frequently is more than most likely to persist in the future powered by wind and solar energy being at the forefront of a historical shift in energy-producing technologies.

By 2024, solar PhotoVoltaic (PV) is anticipated to be the most widely employed renewable generation technology, accounting for almost 60% (about 697 GW) of the projected 33% of global electricity generated from renewable sources [4]. Building-Integrated PV (BIPV) systems offer an additional electrical energy source, but even in perfect climate circumstances, their power output is dependent on outside variables such as solar insolation, weather, location, and earth's rotation. Variations in grid demand are caused by this variability in systems that are connected to the grid. Each BIPV and rooftop PV system is photovoltaic-based; however, how they are installed produces different energy characteristics of a generation. At the peak of the energy season of the rooftop, the BIPVs are producing the least amount of energy, and the other way around.

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In order to address this, a novel method for optimal incorporation of BIPV and rooftop photovoltaic systems by utilising their disparate nature of energy production is proposed in [5].

The notable growth of PV generation is caused by reduced carbon footprint, decreasing costs of the installations [6] which is relatively fast and easy, prosumer policy promotion and technical merits. Despite that, the distribution networks are not intended to support widely distributed PVs [3]. Because of increased rooftop solar PV integration, networks with Low Voltage (LV) have been experiencing operational challenges such as imbalance and overvoltage [7]. Networks must be continuously improved, modernised, and innovative in order to support the trend of DG expansion. The Hosting Capacity (HC) analysis, which was customarily excluded from system studies, is one instance.

PhotoVotalic Hosting Capacity (PVHC) refers to the maximum PV generation that can be connected to a distribution system without violating network limitations [8]. Diverse factors affect the maximum PV penetration limit such as the capability of the network to manage power fluctuations caused by intermittent solar generation [9], three-phase or single PV connection, load type, network topology and layout, methods and constraints defined in decision-making framework, amongst others. All methods employed for HC calculation rely on power flow computations to ascertain voltage and current values within the distribution network. They are classified as stochastic, deterministic, optimisation, streamline, and recent hybrid [10] methods. Hybrid methods decrease the complexity or computational simulation time of conventional methods while combining their many benefits [11]. For a wide range of scenarios and feeders, additional Distributed Energy Resource (DER) uncertainties and different limiting limitations can be studied. Furthermore, these methods can provide a single HC value as opposed to many distribution values. As a result, a number of research papers have used hybrid methodologies to achieve particular goals [12–17].

Monte Carlo simulation (MCS) is the most frequently used stochastic method for generating random scenarios. A large number of MCS DG scenarios of allocation encourages sufficient HC precision. Setyonegoro et al.'s study [18] suggests utilising the MCS to determine PV using real feeders as case studies for urban and rural areas. Concluding that the HC of urban areas with many business and industrial customers is larger than that of the feeder representing rural areas, with 31% and 18% of full load, respectively. [19] applied convergence tests to different feeders and discovered that, on average, a 1000-scenario MCS is precise to within a tolerance of 2%. [20] presented that hourly and half-hourly resolution analyses provide an imprecise estimate of the voltage impact of domestic PV. If HC considers only from 10 am to 2 pm sunny hours, it underestimates the entire day by 11% [21]. In [22], it was shown that the number of nodes has a significant impact on the HC of the feeder. The HC increased as the number of nodes increased. By the use of MCSs to address the uncertainties and unpredictable loading behaviour in addition to the placement and size uncertainty of PV. [23] examined the

economical HC improvement method as a trade-off between curtailment and upgrade through an MCS procedure. The research was concentrated on finding the most cost-effective option between upgrades and curtailment from a Distribution System Operator's (DSO) perspective for increasing the HC of distribution networks. Concluding that DSOs with adequate upgrade capabilities can view a network upgrade as a favourable return on investment in terms of increasing HC, rather than using curtailment. Curtailment, on the other hand, can be demonstrated as a means of waiting for the DSOs to discreetly allot resources for boosting PV penetration in cases where resource availability for network improvements is reduced.

Power system constraints must be defined to determine acceptable HC. Existing literature shows the utilisation of various combinations of limiting factors for HC estimation, reflecting the diverse HC values that result from different constraints. Voltage value (48%), temperature limit (26%), voltage imbalance (19%), harmonics (4%) and flickers (3%) are limits associated with the HC calculation [7]. When examining distribution networks with a large number of PV power plants, it was evidenced in [24] that there are non-conventional installation criteria that enable better net PV production without violating network constraints. Voltage variation is still the primary issue related to HC, even though there are many other issues as well.

HC is not a fixed quantity. Usually, it can be enhanced with a variety of tools and techniques, including control of voltage [25], reactive power control [26], and grid reconfiguration [27]. Whereas active operational approaches according to the regulation of reactive and active power are provided in [28], [29] suggests reconstructing the network to improve HC. Active power curtailment [30], battery energy storage systems (BESS) [8], and enhancement of power quality [31] are further techniques for HC improvement. While numerous research suggested different methods for evaluating the DG-HC, only [32–38] took into consideration how Grid-Connected Electric Vehicles (GCEV) integration affected the DG-HC problem [39].

Considerable gaps and research possibilities in the area of HC estimation have been revealed according to the recent literature's knowledge and findings. These gaps relate to load generation modelling, methodologies, and tools. As a result, the creation of new models and techniques for HC computations is suggested. During load flow analysis, greater emphasis must be placed on precise generation and load modelling. Given the importance of data granularity, load and generation modelling should utilise curves with data at intervals finer than half-hourly precision. A part of these efforts is the research that is provided in this paper. It provides a method to estimate the photovoltaic HC of the distribution network.

The most deployed PV module types in the real network are monocrystalline and polycrystalline, with a rated power of 500 W. This study aims to estimate the HC capacity of a typical European network, focusing on a case study of a standard medium voltage system. This study applies the European Standard 50160 [40] for the stochastic method, not commonly used in similar studies, thus contributing unique results to the research community

and providing a model that can be utilised in future studies. The findings of this study will enhance the process of DG planning by providing insights for power utility companies regarding potential negative outcomes if the deployment of RES is not carefully planned. This contribution supports the advancement of sustainable and renewable energy generation practices. The following sections explain the study through problem formulation which is followed by methodology, model application, results and discussion, and conclusion.

2 Problem formulation

Since PV is expected to be the most commonly employed renewable generation in the future, estimating the PVHC of the distribution network is imperative. Broadly speaking, HC is the highest quantity of DG, whereas respecting the technological constraints of the power system, that can be added to the network in its existing configuration. A specific power system parameter is used to define HC. It is incorrect to identify HC exclusively in terms of total MW. This method makes it difficult to compare different networks and diminishes the uniqueness of each system. The percentage of customers who own PVs (20%), the power transformer rating (20%), the peak load percentage (47%), the overall energy usage (7%), PV roof space (2%) and active power (5%) are only a few of the various ways that HC can be expressed in relation to parameters [7].

The desired level of accuracy and network configurations influence the HC value. Given the inherent tolerance of human judgement to imprecision, achieving an excessively precise HC value isn't always essential. This flexibility is beneficial as it reduces calculation complexity by accommodating imprecision. The level of risk that DSOs are willing to accept is closely tied to HC, particularly influenced by DG allocation, which is pivotal for HC computation and enhancement [41]. Previous studies have proven that HC calculation parameters tend to reduce (by up to 20%) in low dispersion and high penetration scenarios and to increase at medium DG penetration and high DG dispersion levels.

In this paper HC value is defined as the maximum PV installation capacity (P_{PV}) to the feeder's maximum load ($P_{\max}^L$), so HC can be represented as:

$$HC(\%) = \frac{P_{PV}}{P_{\max}^L} \times 100. \quad (1)$$

In the following section, objective function and constraints are defined and explained.

2.1 Mathematical definition of the problem

The main objective of this paper is estimation of photovoltaic HC of the distribution network. Considering the radial network with N buses:

$$N = \{0, 1, 2, \dots, n\} \quad (2)$$

and DG installed where $DG \subset N$ [42], buses with DG can be represented as:

$$DG = \{B_1^{DG}, B_2^{DG}, B_3^{DG}, \dots, B_n^{DG}\}. \quad (3)$$

If B is represented by all branches' set, and the branch between (a) and (b) is represented with (a, b) , the impedance of such a line is equal to:

$$z_{ab} = r_{ab} + ix_{ab}. \quad (4)$$

If we consider that at each bus $a \in N$, the load becomes:

$$s_a^L = p_a^L + iq_a^L. \quad (5)$$

Whereas DG complex power for each bus $a \in DG$ can be represented as:

$$s_a^{DG} = p_a^{DG} + iq_a^{DG}. \quad (6)$$

Complex power between buses (a) and (b) will be:

$$S_{ab} = P_{ab} + iQ_{ab} \quad (7)$$

where I_{ab} represents complex current.

If complex voltage at bus (a) is assigned as:

$$v_a = |V_a|^2 \quad (8)$$

based on Ohm's law we can write:

$$V_a - V_b = z_{ab}I_{ab} \quad \forall (a, b) \in B. \quad (9)$$

By multiplying each side by its conjugate, this expression leads to:

$$v_b = v_a - 2(r_{ab}P_{ab} + x_{ab}Q_{ab}) + |z_{ab}|^2 \frac{P_{ab}^2 + Q_{ab}^2}{v_a}, \forall (a, b) \in B. \quad (10)$$

Equations of the nodal power balance gives:

$$P_{ab} = \sum_{c:b \rightarrow c} P_{bc} + p_b^L - p_b^{DG} + r_{ab} \frac{P_{ab}^2 + Q_{ab}^2}{v_a} \quad (11)$$

$$Q_{ab} = \sum_{c:b \rightarrow c} Q_{bc} + q_b^L - q_b^{DG} + x_{ab} \frac{P_{ab}^2 + Q_{ab}^2}{v_a}. \quad (12)$$

If we consider multiple paths from substation to each bus, the bus (b) voltage will be:

$$v_b = v_0 - \sum 2(r_{ab}P_{ab} + x_{ab}Q_{ab}) + \sum |z_{ab}|^2 \frac{P_{ab}^2 + Q_{ab}^2}{v_a}, \quad \forall (a, b) \in B. \quad (13)$$

In this paper to estimate HC, power flow equations must be combined with voltage and overloading constraints. Voltage constraint at some bus a :

$$V_{\min} \leq V_a \leq V_{\max}, \quad \forall a \in N \quad (14)$$

where $V_{\min}$ and $V_{\max}$ are the voltage minimum and maximum [43]. Overloading constraint:

$$I_{ab} \leq I_{\max}, \quad \forall (a, b) \in N. \quad (15)$$

where I_{ab} is current flowing through a line connecting buses a and b , $I_{\max}$ represents maximum current of the

considered component. The method used in this article estimates HC, by using a stochastic method which is based on iterative random allocation of PV into the network.

3 Methodology

Research simulations were performed by the Open Distribution System Simulator (OpenDSS) [44] tool in a co-simulation with Python programming language. In particular, the medium voltage test power system was modelled and simulated in OpenDSS, whereas the Monte Carlo (MC) based algorithm was developed and written in the free and open-source scientific environment Spyder to quantify the HC of the electrical distribution network. A “primitive” nodal admittance (Y) matrix represents each component of the system. In OpenDSS, daily mode was used for time-series three-phase power flow execution, which follows the daily load curves for performing a series of solutions [45].

OpenDSS is implemented as a Component Object Model (COM) DLL that may be driven by a range of software platforms, as well as a stand-alone executable program. Python is used as an object-oriented programming language to perform data optimization, whereas the medium voltage grid was simulated in OpenDSS. After each simulation, some elements were needed to be returned to the initial state, since their state remains remembered. Figure 1 outlines the structure of the co-simulation of OpenDSS and Python. Average values were calculated by MCS, for which input values must be defined in advance. MCS repeats the simulation of the model, using different random input values giving a set of possible output values in each iteration. As a result, average ($\bar{x}$) value is calculated as:

$$\bar{x} = \frac{\sum_{k=1}^n x_k}{n} \quad (16)$$

where x_k represents the result of each simulation, n stands for the number of simulation runs. The results were validated on IEEE 37 Test System.

4 Model application, results and discussion

In this section, the test power system model is presented, followed by a detailed description of load and generation characteristics. Then, computational procedure and simulation scenarios are presented, followed by a detailed investigation of obtained results.

4.1 Model of the test power system

For this study a test power system which is included in a standard medium voltage (MV) distribution network was used. The modelled network presented in Figure 2 is a 9 Bus 35 kV electrical distribution network, which is

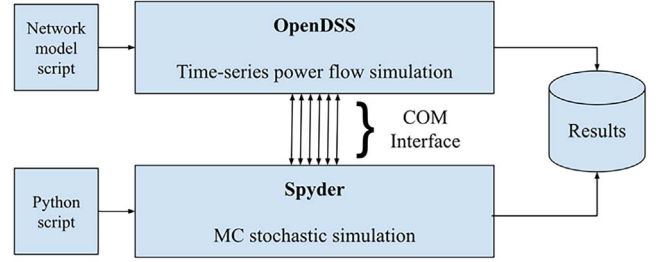


Fig. 1. Co-simulation structure.

supplied by a 110/35 kV transformer of 30 MVA installed power from the public electricity distribution network. Total active load power of the grid is 10400 kW, whereas the total reactive power is 5880 kVAr. Two-port lines and cables are presented in Table 1, whereas numbers in object names correspond to bus numbers which it connects.

4.2 Power system load modelling

The load modelling is depicted through normalised daily load profiles and their distribution among network buses which is crucial for assessing the grid performance. Normalised daily load profile, presented in Figure 3 with 15-minute resolution data assigned to all customers, serves as a fundamental representation. The total active power and reactive power of the five loads are 10.40 MW and 5.88 MVar respectively, resulting in a total power demand of 11.95 MVA. Figure 4 displays the distribution of the maximum load among buses in the network, whereas more details regarding the peak demand of each load at the respective bus are represented in Table 2. Figure 5 illustrates the 24-hour per unit voltage profiles of each bus within the grid. It is obvious that the peak power demand occurs at bus 7.

4.3 PV system output power

OpenDSS offers a built-in PV system, which consists of a model of PV array and the PV inverter. The active power (P) is a function of irradiance (E), temperature (T) and rated power at the maximum power point (P_{mpp}) at E of 1000 kW/m² and a selected T . Additionally, efficiency of the inverter at the operation power and voltage is applied. All of these values are defined as an array of points and for this research were used predefined values in [46]. The graph in Figure 6 illustrates the daily output curve of a photovoltaic power station which is typical for summer, revealing volatility characterised by fluctuations dependent on environmental conditions. A decline in cell efficiency results from a decrease in the cell's electrical output as temperature rises [47]. The performance of the PV module's output power can drop by 0.4–0.5% for every 1 °C increase in operating temperature [48]. The PV output power, depicted with 15-minute resolution data in Figure 6, shows that the maximum power output occurs at 14:45, reaching 22.95 kW. For the study cases where PV is considered to produce constant power, output power is equal to 27.73 kW.

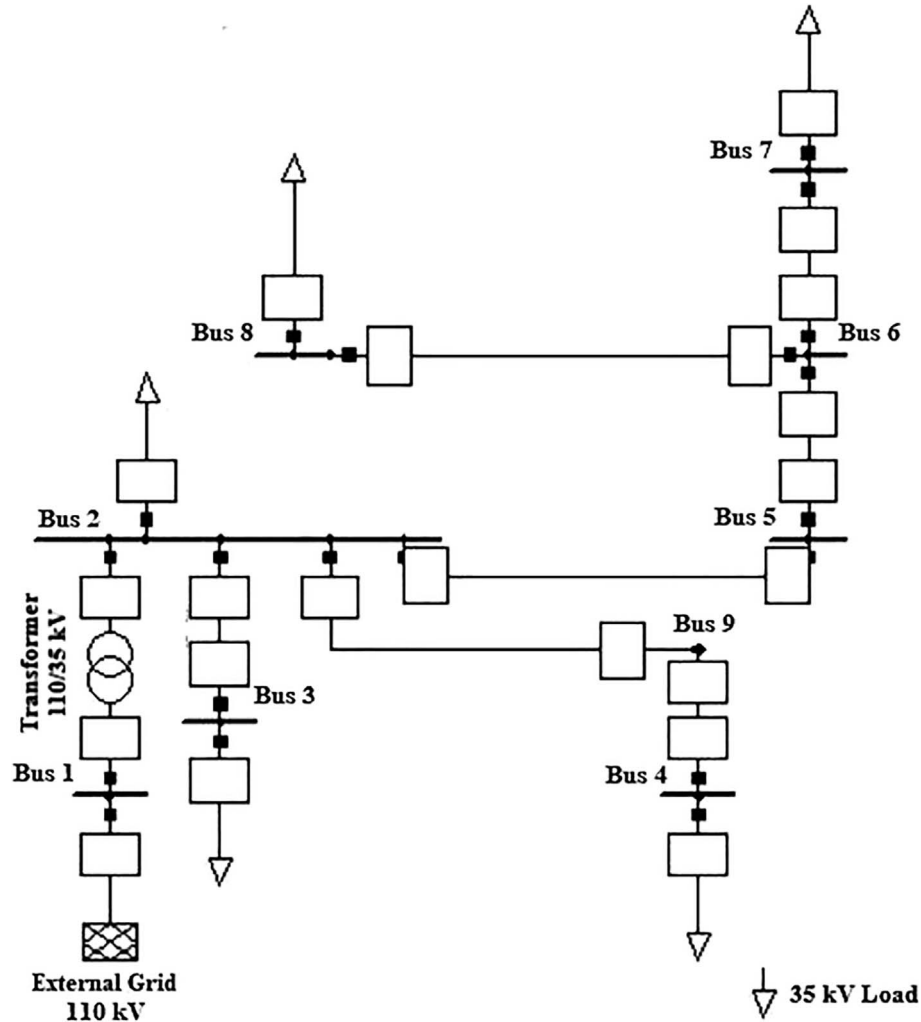


Fig. 2. Single line diagram of the analysed network.

Table 1. Parameters of the network objects.

Object	Length [km]
Line 23	16.90
Line 25	2.53
Line 29	3.25
Line 94	0.58
Line 56	0.02
Line 67	0.93
Line 68	0.75

4.4 Details of computational procedure

The MC stochastic method outlined in Figure 7 was developed for HC estimation, employing an iterative random allocation of PV into the network to generate random scenarios. Thus, simulating the unpredictable behaviour of consumers. As a result, the HC of the grid is estimated in

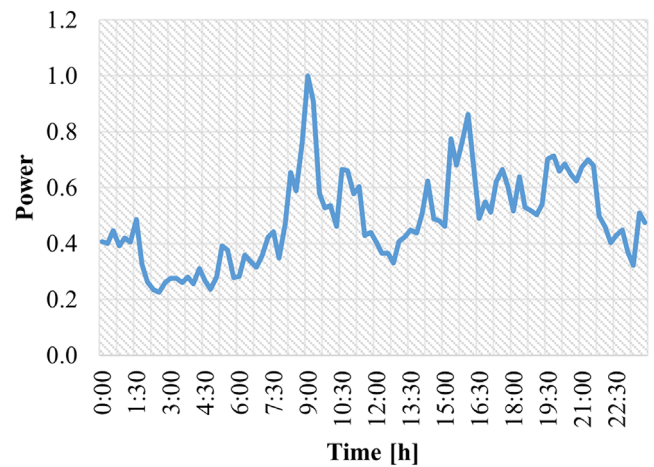


Fig. 3. Normalised daily load profile of domestic consumers in real electrical MV network.

accordance with the defined constraints. Figure 7 presents different steps involved in MC based algorithm.

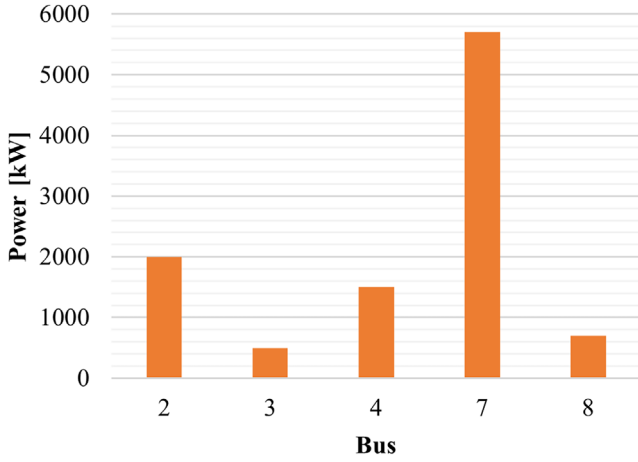


Fig. 4. Maximum load power per bus.

In the first step initial conditions are defined:

- (A) A maximum number of simulations is set to 1000, since repeating the procedure 1000 times for a MC analysis reduces the probability of yielding wrong results.
- (B) Selecting a performance index: voltage or/and line loading.
- (C) Setting a limit of the index in accordance with the accurate standards.

Then, the performance index is calculated as a function of DG amount and the network is initialised in the

Table 2. Peak demand for each load.

Bus number	Nominal power of the load [MW]	Nominal load power factor
2	2.0	0.89
3	0.5	0.78
4	1.5	0.93
7	5.7	0.84
8	0.7	0.96

OpenDSS. PV penetration is incremented in the network by 1%, connecting PV on randomly chosen one of 35 kV grid nodes. After each increment of PV integration, time-series power flow is executed in OpenDSS and checked if one of the grid limits is violated. Calculations were performed in a 15-minute time step for a whole day. If one of the grid limits is violated, the HC value and node voltage is recorded. The procedure is repeated until the maximum number of simulations is reached.

4.5 Definition of simulation scenarios

Three study cases (S1-1, S1-2 and S2) were developed, as presented in Table 3. Study cases S1-1 and S1-2 consider the integration of PV with constant output power, whereas study case S2 considers PV with a daily output curve. Both case S1-2 and case S2 consider only voltage as a constraint, according to EN50160 [40] which allows $\pm 10\%$ deviation from nominal value. The minimum voltage limit in the grid is set to 0.9 p.u., while maximum is 1.1 p.u. In the scenario S1-2, line loading was set as a constraint.

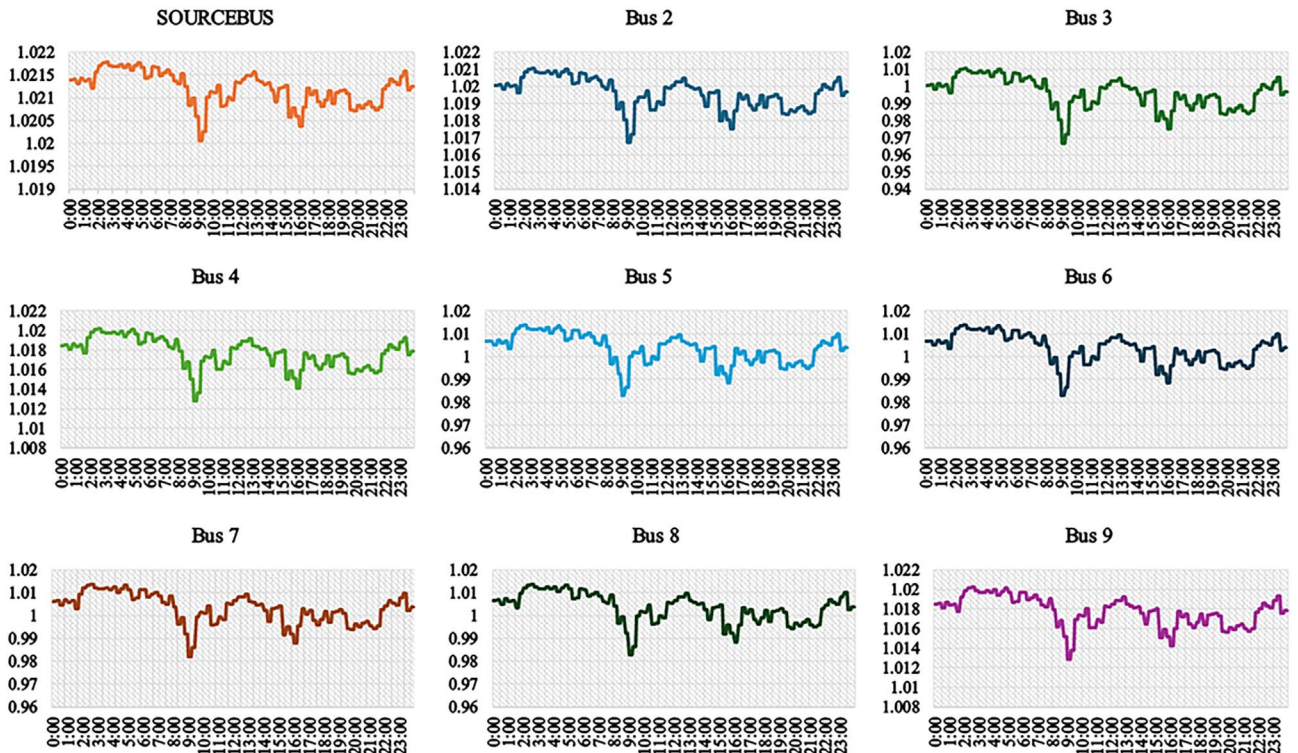


Fig. 5. 24 h voltage profile of MV distribution grid.

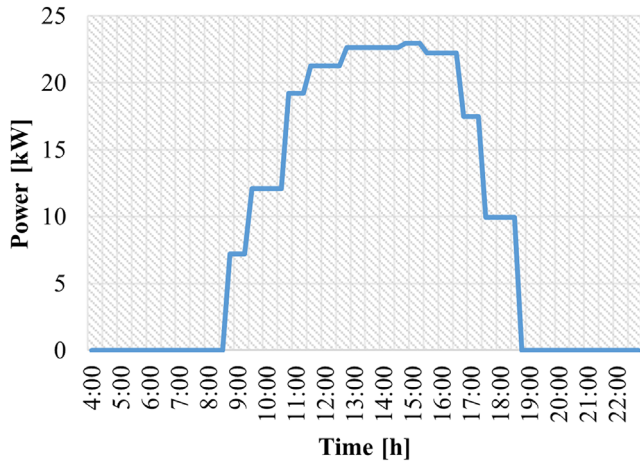


Fig. 6. Active power provided by 1% PV penetration in the network.

4.5.1 Scenario – S1-1

After 1000 simulations for the S1-1 scenario, the HC of a standard medium voltage network is estimated to be 127.0%. P.u. voltage per bus in the grid is illustrated by the solid line in Figure 8 during the last iteration in the simulation where maximum penetration of the PV was 139%, dashed line represents the voltage profile of each bus before deployment of PV. When comparing the voltage in the grid with and without RES and considering the highest PV penetration level in this study, a significant increase in the daily network voltage is observed. This increase ultimately breaches voltage limits due to the high injection of active power into the grid. Figure 9 represents penetration of PV in %, per bus. It is noted that for most of the cases in accordance with the penetration level of PV per bus, voltage increase occurs. Bus 3 has the longest feeder in the network, which gives additional explanation for highest voltage increment. What confirms results reported in [49], is that the maximum location penetration is underestimated if only the farthest locations are considered.

4.5.2 Scenario – S1-2

After 1000 simulations for the S1-2 scenario, the HC of a real standard medium voltage network is estimated to be 470.4%. P.u. bus voltage in the grid is demonstrated in Figure 10 during the last iteration in the simulation where the maximum penetration of the PV was 478%, together with the voltage profile of each bus before deployment of PV which is represented by a dashed line. The results lead to the conclusion that voltage constraints are violated much earlier than line loading, owing to the higher voltages observed in the grid, with a maximum per unit (p.u.) voltage of 1.3 and a smoother voltage curve. Table 4 represents the overloaded power delivery element, positive sequence current and the percentage of overload. “Normal Amps” refers to normal ampacity amperes, while “Emerg Amps” refers to emergency ampacity amperes. Equation 17 represents the relation between normal ampacity amperes and emergency ampacity amperes.

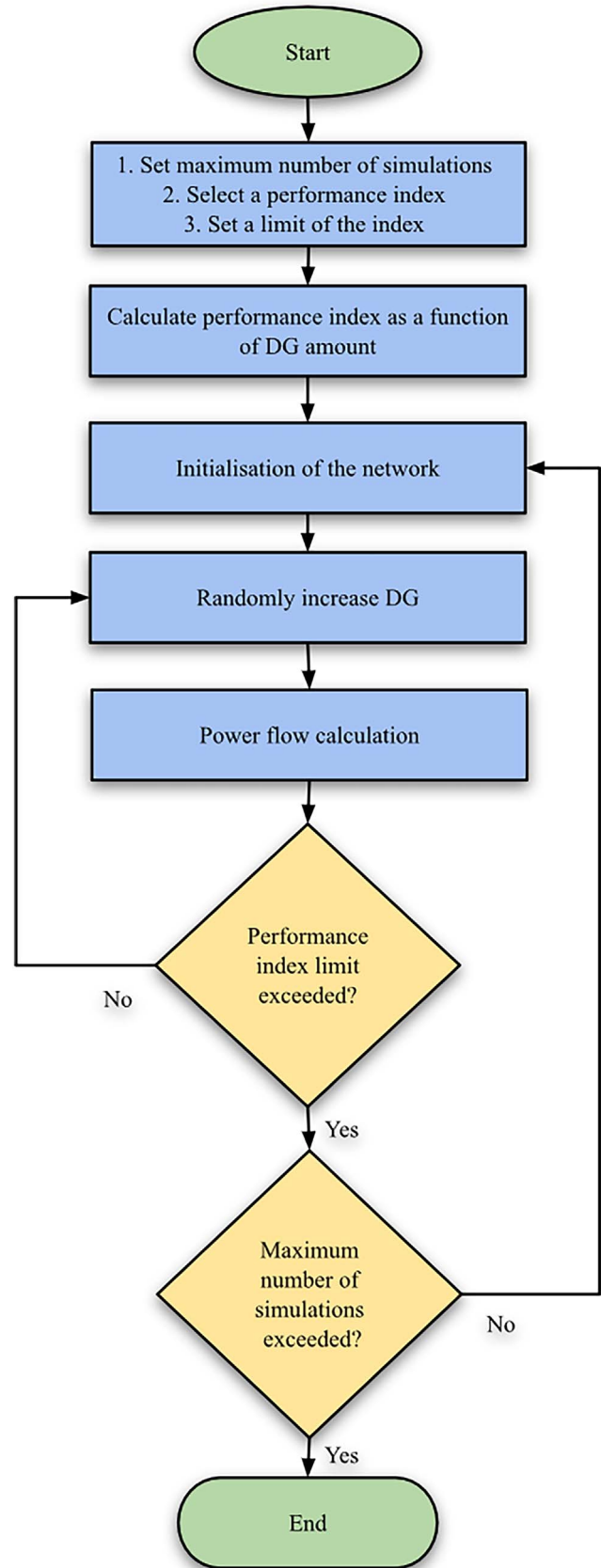
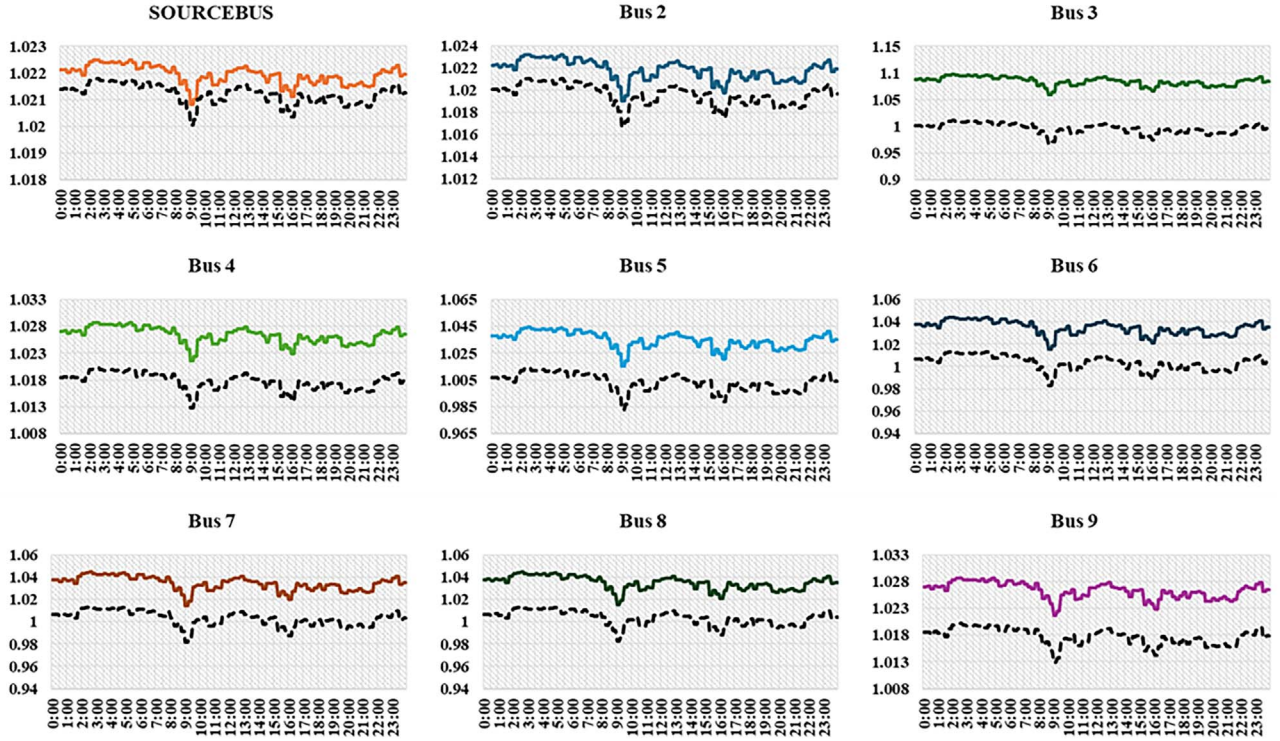


Fig. 7. MC based algorithm.

Table 3. HC estimation scenarios.

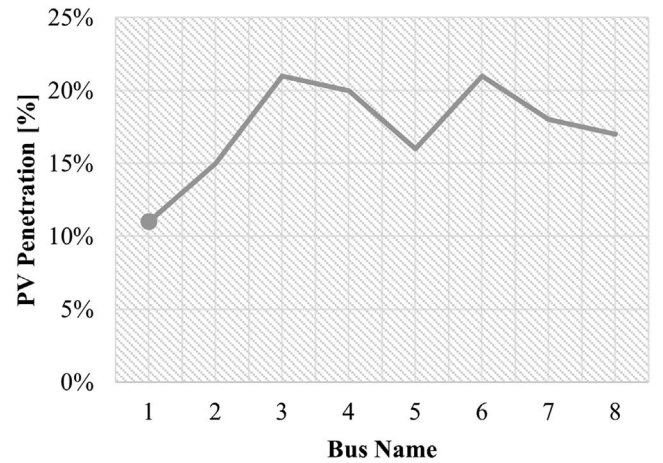
Scenario	Criteria	Violation limit
S1-1	Voltage	$0.9 \leq V \leq 1.1$
S1-2	Line loading	$\leq 100\%$
S2	Voltage	$0.9 \leq V \leq 1.1$

**Fig. 8.** P.u. bus voltage for 139% of PV penetration.

$$\text{Emerg Amps} = 1.5 \cdot \text{Normal Amps.} \quad (17)$$

4.5.3 Scenario – S2

After 1000 simulations for the S2 scenario, the HC of the standard medium voltage network is equal to 166.5%. P.u. voltage per bus in the grid is illustrated in [Figure 11](#) during the last iteration in the simulation where maximum penetration of the PV was 154%. Dashed line represents the voltage profile of each bus before deployment of PV. When comparing the voltage in the grid before and after the deployment of RES, a decrease in network load is observed. This reduction contributes to the network by assisting in peak load shaving. Given the examination of the highest PV penetration level in the study, a notable increase in network voltage can be observed during daily PV generation, primarily due to the high injection of active power into the grid. This increase ultimately leads to the violation of voltage limits during peak power production hours. In order to validate obtained results, the same algorithm was applied on a modified IEEE 37 Test System [50], increasing

**Fig. 9.** PV penetration per bus.

PV penetration of constant output power by 1% on randomly chosen one of 4.8 kV grid nodes. As a result, HC is 200.4%, and in each simulation 1.1 p.u. the voltage limit

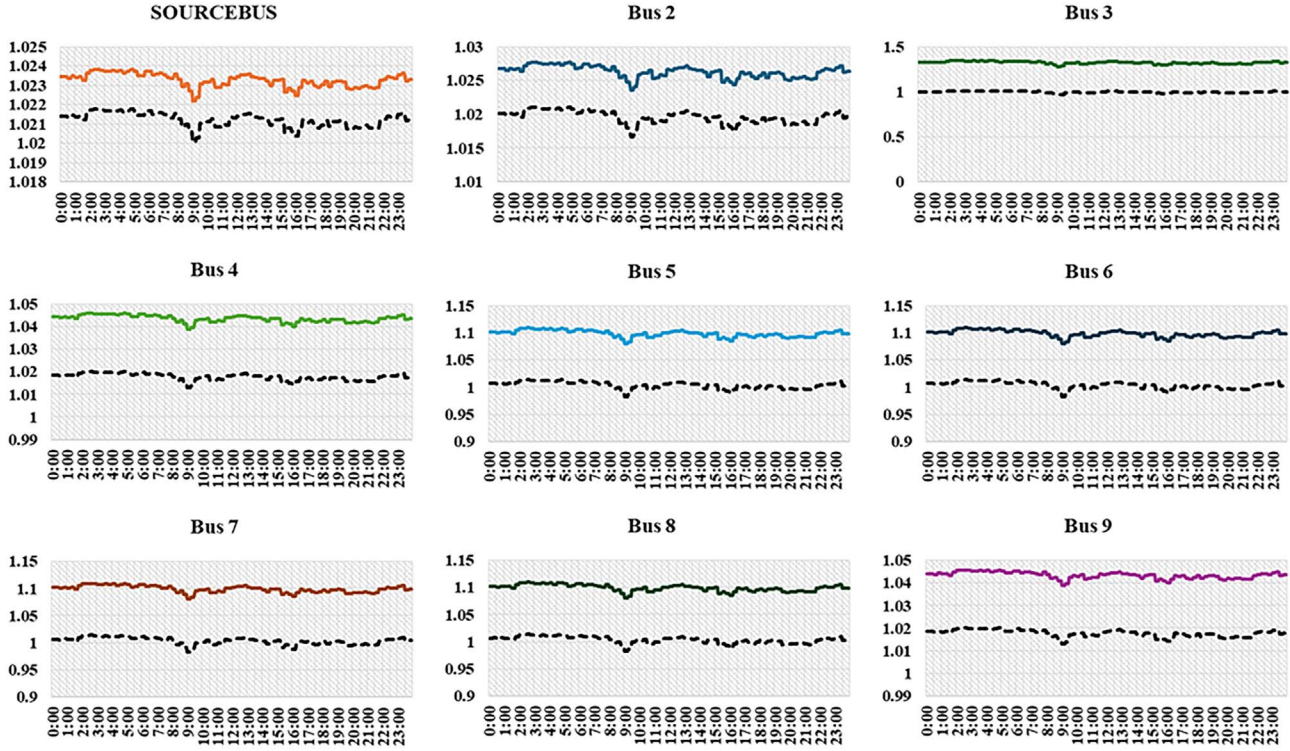


Fig. 10. P.u. bus voltage for 478% of PV penetration.

Table 4. Overload report.

Element	Normal Amps	Emerg Amps	% Normal	% Emerg	kVBase	I1 [A]	I2 [A]	I3 [A]
Transformer	173.21	236.19	100.02	73.34	63.51	173.23	173.23	173.23

was violated. Further validation of the results is provided by confirming the observation made in [51] that voltage levels typically rise, although they do not surpass the thermal capacity of the distribution system. In [52] it is quantitatively confirmed that overvoltage is the most restrictive limit.

4.6 Main findings of the present study

Results of scenario S2 showed favourable impact of PV, contributing to peak load shaving on the grid. On the other hand, voltage increment is noted, since huge penetration of PV in the distribution system results in reverse power flow causing overvoltage. Comparing results from S1-1 and S1-2 scenarios, one can notice that the voltage limit is much earlier violated than line loading, in that way, confirming reported results from some previous research on this topic. Comparing results of scenarios S1-1 and S2, the HC value is underestimated by 39.5%, if constant PV generation is taken into consideration instead of the daily load curve, whereas estimating HC.

Table 5 contemplates all study cases for the purpose of comparison and highlights total circuit losses. It can be observed that adequate penetration of PV decreases circuit

losses, while inadequate penetration of PV considerably increases circuit losses, due to the reverse power flow. Lack of local reactive power may increase the distribution network's overall energy loss [53]. It is calculated that HC can be significantly higher than power system load. In practical distribution systems, this operating condition is possible as determined in similar research. However, additional operational parameters must be investigated in order to ensure efficient exploitation, including power system losses and transformer back feed. In addition, power delivery from distribution to the transmission system could potentially cause voltage control issues, decrease the inertia of the system and therefore lead to power system stability issues. In order to prevent any potential issues, appropriate coordination with the transmission system operator must be performed.

4.7 Comparison with other studies

For the comparison purposes Table 6 represents values of the HC applying MCS for generating PV locations and sizes on different networks considering voltage constraint. In [54] is reported the highest HC value in comparison to others, since the authors applied Active Distribution Network

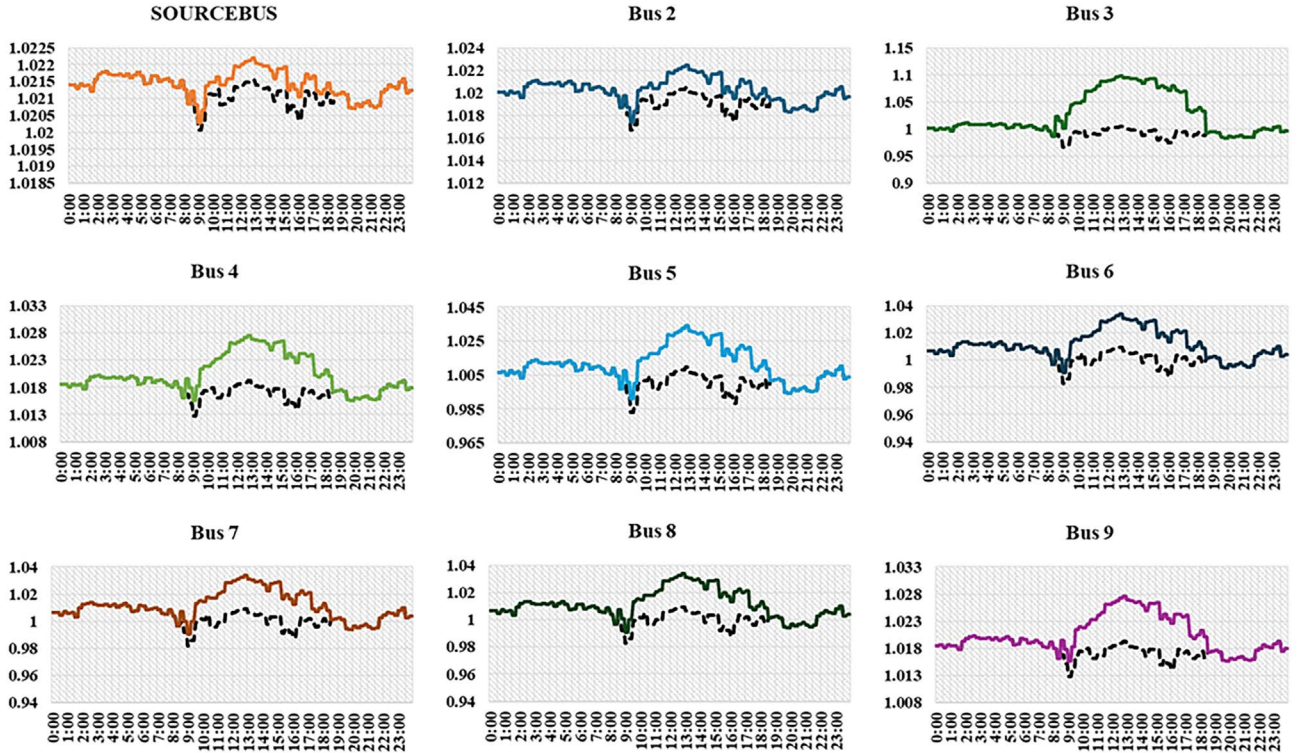


Fig. 11. P.u. bus voltage for 154% of PV penetration.

Table 5. Losses of the active circuit elements.

	Without PV [kW]	139% PV [kW]	154% PV [kW]	478% PV [kW]
Line losses	312.4	118.2	165.7	1816.9
Transformer losses	19.4	4.5	4.9	95.5
Total losses	331.7	122.7	170.5	1912.4
Percent losses for circuit	3.19%	1.18%	1.64%	18.39%

Table 6. Studies that uses MC method for HC estimation.

Network	Voltage limit	HC	Reference
MV	Upper limit 1.05	40%	[49]
LV	0.92–1.05	38.20%	[52]
MV	0.95–1.05	97.30%	[54]
LV	0.95–1.05	30%	[55]
MV	0.95–1.058	50%	[56]
MV	Upper limit 1.05	70%	[57]

Management (ADNM). The reported values of HC are lower than the estimated values in this research, as a result of the stricter voltage constraints and the utilisation of an oversized real medium voltage network in this paper.

4.8 Implication and explanation of findings

The results of this study will give insight for power utility companies, pointing to the importance of planning the deployment of RES in the system in order to mitigate

possible negative outcomes such as overvoltage, overload and high circuit losses, which are investigated in the paper. This method can be applied by distribution network planners and operators to explore the limitations and capability of PV deployment.

4.9 Strengths and limitations

The benefits of integrating RES were confirmed by this research, which was carried out with open-source

technologies. On the other hand, measurements of temperature and irradiance as well as actual load data for each customer would provide even more accurate results.

5 Conclusion

The HC of a real standard medium voltage network is estimated using two open-source software packages in the paper. HC value is considered to be defined as the maximum capacity of the PV installation to the feeder's maximum load. For that purpose, 1000 scenario MC stochastic methods have been developed and applied for daily simulations in a 15-minute time stamp. Voltage and line loading constraints were considered. Results proved that voltage constraint is violated much earlier than line loading. Maximum penetration of PV in the real standard medium voltage system is 166.5% by EN50160. Results demonstrated that if constant generation of PV in daily simulation is considered, it underestimates HC by 39.5%. Losses of the circuit considerably increase when optimal penetration of PV is overcome. Results were validated in IEEE 37 Test System. However, real load data of each customer and measured data of irradiance and temperature would give even more precise results. For this research voltage and line loading constraints were considered, despite the network deployed DG in accordance with those limits, whereas analysing results increase in circuit losses were reported using line loading as a constraint, which implies that additional constraints would be beneficial if taken into the consideration such as harmonic distortion and distribution losses. This work confirmed benefits of integration of RES for the network as decrement in network load. But on the other side pointed out the importance of planned deployment of energy sources in the system by giving the model that can be applied in future studies, which could be valuable insight for power utility companies. For this research voltage and line, loading constraints were considered, despite the network deployed DG in accordance with those limits, whereas analysing results increase in circuit losses was reported using line loading as a constraint, which implies that additional constraints would be beneficial if taken into the consideration such as harmonic distortion and distribution losses. As a future extension, economic analysis of PV deployment could be studied. Future study on HC estimation will include uncertainty and inaccuracy of the PV models as an inherent feature.

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