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Hosting Capacity Enhancement of Photovoltaic Sources, Using Voltage Controller Devices and Energy Storage Systems

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ABSTRACT: This paper presents a mathematical model for the Distribution Network (DN) expansion, planning to increase the penetration of Photovoltaic (PV) energy sources in the Distribution Network. The presented model determines the optimal place of PVs in coordination with Energy Storage Systems (ESS). It also identifies the optimal power generation of PVs as well as the optimal amount of energy that must be purchased from the upstream utility grid. The aim of this optimization problem is to maximize the penetration capacity of PVs that the technical constraints of the Distribution Network are satisfied. The proposed optimization problem is formulated as a Mixed-Integer Nonlinear Programming (MINLP) problem, and is solved using SBB solver under GAMS. The uncertainties associated with PV production and electricity demand are modeled by generating different scenarios. The K-means clustering technique is used to reduce the number of scenarios to make the problem tractable. The effectiveness of the presented model is verified on a standard IEEE 33-bus distribution system. The numerical results show that using ESS capabilities On-Load Tap Changer (OLTC), and the reactive power production capability of PVs for controlling voltage profile, increasing the Hosting Capacity of PVs, improving the voltage profile, and thereby decreasing the total investment and operation costs.

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1- Introduction

Renewable Energy Sources (RES) have experienced rapid growth in recent years due to their environmental and economic advantages. Despite these advantages, the high penetration of RES in a Distribution Network (DN) introduces many challenges from a technical point of view. It can jeopardize the stability of the system and cause several power quality problems. It is expected that these problems will solve in the coming years, since the traditional DNs are being converted into active ones. However, this is a complicated process and requires a large investment. Therefore, the entire process (i.e., altering an inactive DN into an active one) may take several decades to complete. However, considering environmental problems, the deployment of RES is inevitable. The operation and investment strategy of RESs should be coordinated with reactive power sources, ESSs, and voltage control devices in DN which facilitate the usage of RES. To do so, it is necessary to design a coordinated strategy to maximize the penetration of RES in the DN.

The increasing demand for electricity on one hand and the concerns about weather conditions and environmental changes on the other hand, has made the governments change their relevant energy policy throughout the world. It is expected that the integration of RES into DN to increase significantly with decisions made on COP21 held in Paris. It is forecasted that the RES production level in Europe will reach 50% of the total produced energy in the year 2050.

Hosting Capacity (HC) is an essential factor that plays a vital role in the assessment of DNs capability to integrate RES. Generally, the HC can be defined as “the maximum amount of RES generation that can be connected to the DN without deteriorating the power quality and reliability of the electricity customers”.

The growing penetration of RES in DNs introduces new uncertainties and causes power oscillation. Moreover, the improper sizing and sitting of RESs in DNs causes inefficient operation and leads to an increase in Energy Cost and power losses.

It should be emphasized that due to technical issues, a specific number of PVs can be connected to each node of a DN. The higher values will increase the power losses, jeopardize the system stability, and jeopardize the power quality. Reliability is another essential issue that can get worse if the RES penetration is higher than the desired expected value. Using ESS has been introduced as an appropriate and efficient tool to remove the concerns, as mentioned earlier. [1]

Currently, there is no particular rule in connecting RESs to DNs. RESs are usually connected to buses in which the electricity load is higher, or connected to the furthest point

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of a radial DN. Many researches have been carried out to determine the best location and size of RES in a DN.

In [2], a comprehensive review is done with regards to the DG optimal location in the DN. In [3], the optimal sizing and sitting problems of DGs are investigated. In [4], the optimal place and location of DGs are determined, considering voltage stability index and power losses. The optimal place and size are identified in [5-6] using metaheuristic algorithms. In [7-9] and [10], the ESS location and size are determined to enhance the HC of RES. The maximum HC of PVs considering reactive power compensators and active transformers is analyzed [11-12]. In [13], a multi-criterion planning approach is proposed to improve the HC of PVs, considering the power quality equipment. In ref. [14] and [15], the optimal size and location of DGs and ESSs are coordinated with capacitor banks planning to maximize the HC.

In this paper, a new optimization model is presented to determine the optimal placement of PVs, considering the voltage controller devices (i.e., OLTC) as well as the reactive power production and absorption capability of inverter-based PVs aiming at enhancing the HC. These aspects have not been considered by other published works.

In various articles, increasing the Hosting Capacity of Photovoltaic sources has been investigated using multiple devices. The optimal size and location of scattered generators have been analyzed in terms of voltage stability index and losses for use in the network. However, in our work, in addition to determining the optimal location of the Photovoltaic generator and storage, voltage control devices and absorption, and supply of reactive power through inverters of Photovoltaic sources have also been used to increase Hosting Capacity while reducing the cost of Distribution Network. This method has not been used previously. The work has been revised completely and a new section has been added to the simulation part.

The proposed model determines the optimal location of PVs in coordination with ESSs and voltage controller equipment (i.e., OLTC). The reactive power generation of PVs is also considered. The objective of this optimization problem is to maximize the HC of PVs in DN that the investment and operation cost is minimized and the prevailing technical constraints are met. The proposed optimization problem is formulated as a Mixed-Integer Nonlinear Programming problem (MINLP). To determine the candidate points for the installation of Photovoltaic sources and storage, GAMS software has been used so that the buses that have a higher investment value are identified as candidate buses after simulating the proposed model. The Objective Function includes annual operating and investment costs. The constraints considered in the problem are also the typical constraints of Distribution Networks, including feeder restrictions, substation restrictions, bus voltage restrictions, etc. Losses are also modeled and added to the Objective Function. In the proposed model, the uncertainty of Photovoltaic sources, load, and how to model them is discussed. The modeling method is random programming, in which uncertainties are modeled by generating different scenarios. The scenarios are generated by the normal distribution function, and because the number of scenarios is large, the K-means clustering method is used to reduce the number of scenarios. The sensitivity analysis is also performed to investigate the results further. The effectiveness of the presented model is verified on a standard IEEE 33-bus Distribution Network [16].

The rest of this paper is organized as follows: Section 2 presents the mathematical formulation of the proposed model. Section 3 demonstrates the simulation results, and section 4 concludes the article.

2- Problem Formulation

2- 1- Objective Function

The problem is formulated as an MINLP to maximize the HC such that investment and operation cost is minimized. The Objective Function (OF) in (1) shows the Net Present Value (NPV) of investment and operation cost, plus the power loss cost. The different terms of OF are multiplied by the corresponding weighting coefficients, which represent the importance of each term from the operator perspective. The AC power flow is used to model the DN behavior. The first term of OF shows the investment cost, while the second is the Energy Cost. Energy Cost is the cost of energy, purchased from the upstream network plus the depreciation cost of ESS. The last term is the power loss cost [9,17,18].

$$Minimize\, C = Inv\, C + EC + Loss\, C \tag{1}$$

The annual total investment cost is demonstrated by Eq. (2), which consists of the annual investment cost of PVs (Eq. 3), ESS (Eq. 4), and substations (SS) (Eq. 5), respectively.

$$Inv\, C = \text{Inv}\, C^{PV} + \text{Inv}\, C^{ESS} + \text{Inv}\, C^{SS} \tag{2}$$

$$\text{Inv}\;\; C^{PV} = \sum_{PV}\sum_{i} \frac{r\left(1+r\right)^{LTpv}}{\left(1+r\right)^{LTpv} - 1}\;\; IC_{PV,i} \tag{3}$$

$$\text{Inv}\, C^{ESS} = \sum_{ESS}\sum_{i} \frac{r\left(1+r\right)^{LTess}}{\left(1+r\right)^{LTess} - 1}\;\; IC_{ESS,i} \tag{4}$$

$$\text{Inv}\, C^{SS} = \sum_{SS}\sum_{i} \frac{r\left(1+r\right)^{LTss}}{\left(1+r\right)^{LTss} - 1}\;\; IC_{SS,i} \tag{5}$$

where r is the interest rate. LT is the lifetime of the corresponding equipment. ESS is the storage, PV is the Photovoltaic source, SS is the upstream grid post, i is the bus number, and IC is the equipment investment cost in the considered bus.

The annual total Energy Cost (EC) is depicted by (Eq. 6), which consists of the annual Energy Cost of PVs (Eq. 7), ESS (Eq. 8), and substations (SS) (Eq. 9), respectively.

$$EC = w_{e1}\left(EC^{PV}\right) + w_{e2}\left(EC^{ESS}\right) + w_{e3}\left(EC^{SS}\right) \tag{6}$$

$$EC^{PV} = \sum_{s} Prob_s \sum_{PV}\sum_{h} \lambda_{PV,h} P_{PV,s,h} \tag{7}$$

$$EC^{ESS} = \sum_{s} Prob_s \sum_{ESS}\sum_{h} \lambda^{dch}_{ESS,h} P^{dch}_{ESS,s,h} \tag{8}$$

$$EC^{SS} = \sum_{s} Prob_s \sum_{SS}\sum_{h} \lambda_{SS,h} P_{SS,s,h} \tag{9}$$

where h is the index for the hour, s is the index for the scenario, $Prob_s$ is the probability of scenario s, λ_{PV} is the operation cost of PV, P_{PV} is the active power produced by PVs, λ^{dch}_{ESS} is the degradation cost of ESS, P^{dch}_{ESS} is the power discharged from the storage system, λ_{SS} is the cost of energy of the upstream grid and P_{SS} is the active power imported from grid. w_{e1} و w_{e2} ، w_{e3} are weighting factors. The operation cost of PVs is assumed to be zero in our study.

The power losses cost is calculated as:

$$Loss\ C = w_{loss} \sum_{s} Prob_s \sum_{h}\sum_{i}\sum_{j} 0.5*\left(P_{ij,s,h} + P_{ji,s,h}\right) \tag{10}$$

where P_{ij} is the active power flow from bus i to bus j. P_{ji} is the active power flow from bus j to bus i. and w_{loss} is the weight coefficient of losses.

2- 2- Technical Constraints

Constraints of the optimization problem are thoroughly described in this section.

2- 2- 1- Power Balance Constraints

Active and reactive power balance equations are defined as Eqs. (11) and (12):

$$\sum_{PV\in i} P_{PV,i,s,h} + \sum_{ESS\in i}\left(P^{dch}_{ESS,i,s,h} - P^{ch}_{ESS,i,s,h}\right) + P^{SS}_{s,h} - \sum_{\forall j} P_{ij,s,h} = PD^{i}_{s,h} \tag{11}$$

$$\sum_{PV\in i} Q_{PV,i,s,h} + Q^{SS}_{s,h} - \sum_{\forall j} Q_{ij,s,h} = QD^{i}_{s,h} \tag{12}$$

where P_{PV} is the active power produced by PVs , P^{dch}_{ESS} is the power discharged from storage system, P^{ch}_{ESS} is the power charged from storage system, P_{SS} is the active power imported from grid, P_{ij} is the active power flow from bus i to bus j, Q_{PV} is the Reactive power consumed/produced by PVs, Q_{SS} is the reactive power imported from grid and Q_{ij} is the reactive power flow from bus i to bus j.

2- 2- 2- Power Flow Constraints

Active and reactive power flow through feeder ij can be calculated as follows:

$$P_{ij,s,h} = TC^2_{ij,s,h} V^2_{i,s,h} g_{ij} - TC_{ij,s,h} V_{i,s,h} V_{j,s,h} \left(g_{ij}\cos\theta_{ij,s,h} + b_{ij}\sin\theta_{ij,s,h}\right) \tag{13}$$

$$Q_{ij,s,h} = -TC^2_{ij,s,h} V^2_{i,s,h} b_{ij} + TC_{ij,s,h} V_{i,s,h} V_{j,s,h} \left(b_{ij}\cos\theta_{ij,s,h} - g_{ij}\sin\theta_{ij,s,h}\right) \tag{14}$$

Where P_{ij} is the active power flow from bus i to bus j, TC is the tap changer, V_i and V_j are the voltage magnitudes at nodes i and j , g is the conductance, b is the suspension, θ_{ij} is the voltage angle and Q_{ij} is the reactive power flow from bus i to bus j.

2- 2- 3- Constraints of Voltage Magnitude, Feeders and Substations Capacity, and Tap Changer Setting

Technical limitations related to voltage magnitude, feeders, and SS capacity as well as the tap changer setting, is denoted as:

$$V^{min}_{i} \le V_{i,s,h} \le V^{max}_{i} \tag{15}$$

$$P_{ij,s,h}^2 + Q_{ij,s,h}^2 \le \left(S_{ij}^{max}\right)^2 \quad (16)$$

$$S_{SS}^{min} \le S_{SS,s,h} \le S_{SS}^{max} \quad (17)$$

$$TC_{OLTC,ij}^{min} \le TC_{OLTC,ij,s,h} \le TC_{OLTC,ij}^{max} \quad (18)$$

Where V_i^{min} and V_i^{max} are the minimum and maximum voltage magnitudes at node i , P_{ij} ,Q_{ij} & S_{ij} are the active, reactive & apparent power flow from bus i to bus j, S_{SS} is the apparent power imported from grid and TC is the tap changer.

2- 2- 4- Energy Storage Systems-related Constraints

The equations associated with ESS constraints can be formulated as below:

$$P_{ESS}^{ch,min} U_{Ess,s,h}^{ch} \le P_{ESS,s,h}^{ch} \le P_{ESS}^{ch,max} U_{Ess,s,h}^{ch} \quad (19)$$

$$P_{ESS}^{dch,min} U_{Ess,s,h}^{dch} \le P_{ESS,s,h}^{dch} \le P_{ESS}^{dch,max} U_{Ess,s,h}^{dch} \quad (20)$$

$$U_{Ess,s,h}^{ch} + U_{Ess,s,h}^{dch} \le 1 \quad (21)$$

$$U_{Ess,s,h}^{ch} \le U_{Ess} \quad (22)$$

$$U_{Ess,s,h}^{dch} \le U_{Ess} \quad (23)$$

$$SOC_{Ess,s,h} = SOC_{Ess,s,h-1} + \eta_{ESS}^{ch} P_{Ess,s,h}^{ch} - \frac{1}{\eta_{ESS}^{dch}} P_{Ess,s,h}^{dch} \quad (24)$$

$$SOC_{ESS}^{min} \le SOC_{Ess,s,h} \le SOC_{ESS}^{max} \quad (25)$$

where P_{ESS}^{dch} is the power discharged from storage system, P_{ESS}^{ch} is the power charged from storage system, SOC_{Ess} is the ESSs state of charge, η_{ESS}^{ch} & η_{ESS}^{dch} are the charging and discharging efficiencies of a storage system, and U_{Ess} & U_{ss} are the binary investment variables.

Eqs. (19) -(20) constrain the charging and discharging power of the ESS. Otherwise, it is bounded by its upper and lower limits. Eq. (21) shows that the ESS cannot be charged and discharged simultaneously. If the ESS is not installed, the investment binary variables should be zero, and thus Eqs. (22) and (23) enforce the ESS binary variable related to the charging and discharging power to be zero. State of charge equations is denoted by Eq. (24), which is limited by (25).

The optimization problem formulated above contains two different decision variables: binary investment variables (here and now decision variables), and continuous operation variables (wait and see). The binary investment variables are U_{Ess} , U_{ss} and U_{PV} . The continuous operation variables are $P_{PV,i,s,h}$, $P_{ESS,i,s,h}^{dch}$, $P_{ESS,i,s,h}^{ch}$, $P_{s,h}^{SS}$, $V_{i,s,h}$ and $\theta_{ij,s,h}$.

2- 3- Uncertainty Modeling

There are two types of uncertainty in the presented model: demand uncertainty and the generation uncertainty of the PVs. Since these uncertainties primarily affect the results, it is inevitable to model them.

The electricity demand scenarios are generated using historical data. To do so, the daily load curve is predicted for the last year planning horizon. The same approach is applied to the daily production of PVs. Thus, there are 365 scenarios for loads and PVs. Each scenario represents 24-hours electricity consumption and its corresponding 24-hours PV generation. Since the problem would be intractable for many scenarios, the K-means clustering technique is used to reduce the number of scenarios. This way, the correlation between load consumption and PV generation is preserved. Using K-means, the primary 365 scenarios are converted into three representative scenarios.

Production and load scenarios have been determined in such a way that 365 rows of 24-hour information related to one year of load, and also 365 rows of 24-hour information related to PV production are available. Each day of the load scenario along with the same day of the PV generation scenario is considered as one scenario. Afterwards, using the K-means method, the total of 365 existing scenarios has been reduced to three scenarios. Therefore, since day one load and PV information is considered as a scenario, the correlation between PV and load scenario is considered.

Table 1. Investment and operation costs data

	capacity	OC**3** ($/MWh)	DC**2**($/MWh)	IC**1**($/MW)
SS**4**	6.6MVA	Ref. [20]	0	650000
PV	1.5MW	0	0	470000
ESS	1MWh	0	0.015	300000

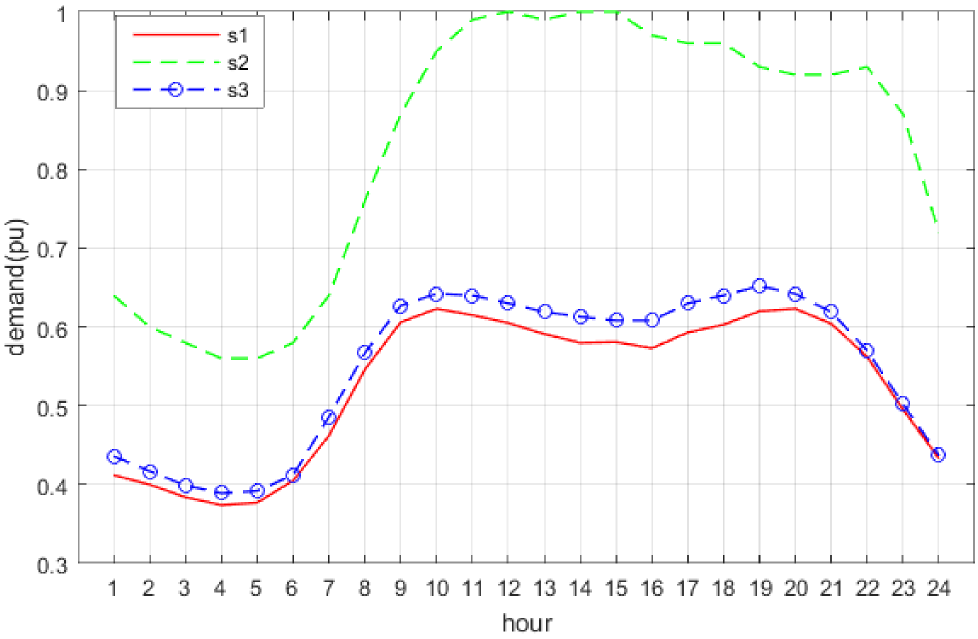

Fig. 1. Daily load curves of different scenarios

2- 4- Determination of Candidate Location

Considering all nodes of DN as a candidate for the installation of PV and ESS, produces a large number of binary variables in the MINLP problem, which increase the computation time considerably.

To determine the locations with more investment value, the relaxed MINLP problem is solved. This means that investment-related binary variables are relaxed ($0 \le U_{Ess}, U_{PV} \le 1$). If the relaxed binary variable at a node remains near one after solving the problem, it shows that this node has more investment value. On the contrary, if a binary variable remains near 0, this node has less investment value. The operator should choose a threshold, and thus the locations with corresponding binary variables higher than this pre-specified value must be selected as candidate places. It should be noted that this approach is not exact. However, it provides appropriate candidate locations.

3- Numerical Study

3- 1- System Data and Assumptions

The proposed model is applied to IEEE 33-bus radial DN. System data can be found in [19]. SBB solver is used under GAMS to solve the problem. The simulation is performed on a windows-based computer with a 4G RAM, and a 2.66 GHz CPU. The interest rate is assumed to be 7%. Voltage magnitude is considered to be between 0.95 and 1.05 pu. The battery efficiency is 90%.

The total active and reactive loads are 3.715 MW and 2.3 MVar, respectively. The nominal voltage of DN is 12.66 kV. The capacity of feeders is assumed to be 300 A. The capacity of PVs and ESS are 1.5 MW and 1 MW, respectively. Lifetimes of ESS, PV, and SS are 15, 25, and 30 years, respectively. However, 1 is the reference bus. Emission cost is not considered in this study. We fix the voltage bus 1 in 1.05 pu. The investment and operation costs are shown in Table. 1.

PV and load data can be found in [21,22]. As stated before, the K-means clustering technique using MATLAB software is employed to decrease the number of scenarios. The probabilities of the three remaining scenarios (1,2 &3) are 61%, 26% and 13%, respectively.

The daily load curves, as well as the daily PV generations in different scenarios, are shown in Fig. 1 and 2, respectively. As shown in Fig. 2, the maximum production of a PV is 76%.

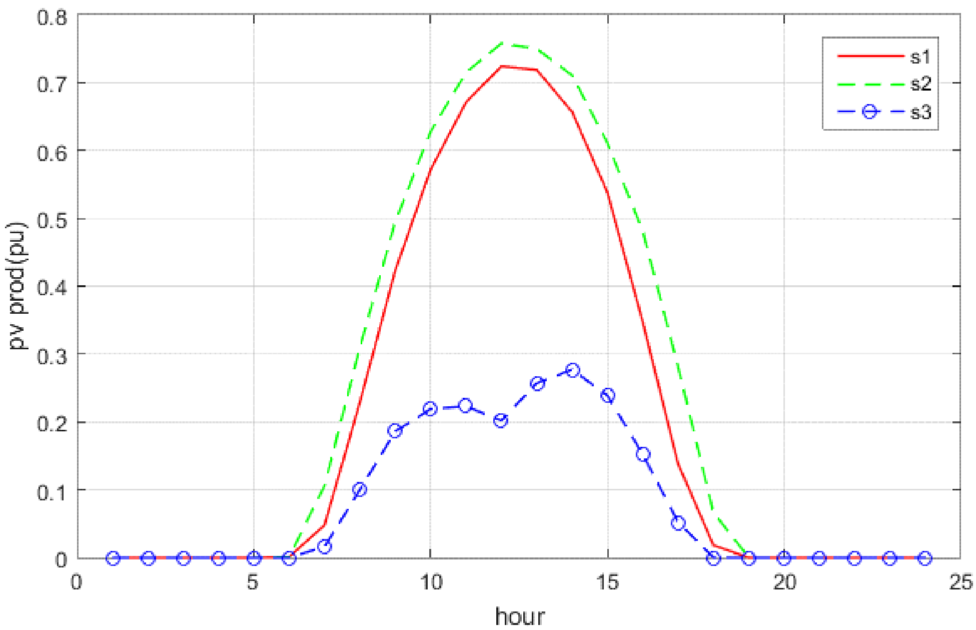

Fig. 2. Daily production curve of PV's generation in different scenarios

To obtain the candidate locations for ESS and PV, as previously demonstrated, the relaxed MINLP problem is solved. In this regard, the CONOPT solver is used. The threshold is fixed at 0.35 for PV and 0.15 for ESS. The value of relaxed binary variable or investment value for PV is depicted in Fig. 3 [3].

the candidate location of PV and ESS which has been obtained in the previous section include buses (2,3,19,23,30,32) & (2,3,7,24,25), respectively.

Moreover, two OLTCs are considered, one between nodes 5 and 6, and the other one between nodes 27 and 28 [5]. The tap of the OLTC can change from a minimum of 0.95 to a maximum of 1.05. It is assumed that PV sources can both generate and absorb reactive power. The power factor of PV sources is supposed to change between 0.9 and 1. Note that both leading and lagging power factor is modeled.

3- 2- Simulation Results

This section contains three subsections: section 3.2.1 shows the results for the basic case. Section 3.2.2 discusses the effect of OLTC on HC. The effect of ESS is also demonstrated in section 3.2.3.

3- 2- 1- Basic Model

The basic model consists of PV, OLTC, and ESS. The PV optimal place is bus 2, 3, 23, 30& 32, and PV at bus 19 is not selected. ESS is only located on bus 3. The optimal capacity of PVs, except for node 32, which is computed 1.2 MW, is 1.5 MW. Therefore, 7.2 MW PV is installed in scenario 2. It can be mentioned that in our case study, the total installed capacity of PVs is twice the total demand of DN. The ESS is also selected to be installed at bus three where a PV is located. Hence, the ESS can be charged when there is an excess power generation in PV and vice versa.

The total investment and operation costs are provided in Table 2.

The maximum generation of PV, SS, and ESS, and power losses for different scenarios, are shown in Table 3.

The charging curve for 24 hours is illustrated in Fig. 4.

As shown in Fig. 4, ESS is charged at hours 7 to 17, and hence the excess power generation of PVs is absorbed. Consequently, the HC of PVs is increased. In off-peak hours, the ESS is also charged since the electricity price is low. At hour 20, where the electricity price is maximum, the ESS is discharged.

The voltage curve is shown at hour 12 for all nodes and scenarios in Fig. 5. As shown, the minimum voltage occurs at node 18 and scenario two, which is the furthest bus from the SS. It should be noted that scenario 2 is the worst-case scenario.

The voltage curve of bus 32 is shown for 24 hours in Fig. 6. Since PV is installed at this node, the voltage of this node is maximum when the PV produces power.

3- 2- 2- Effect of On-Load Tap Changer on Hosting Capacity

The presented model is solved without OLTC. Simulation results that the optimal location of PV and ESS, investment and operation cost remain unchanged. However, the optimal

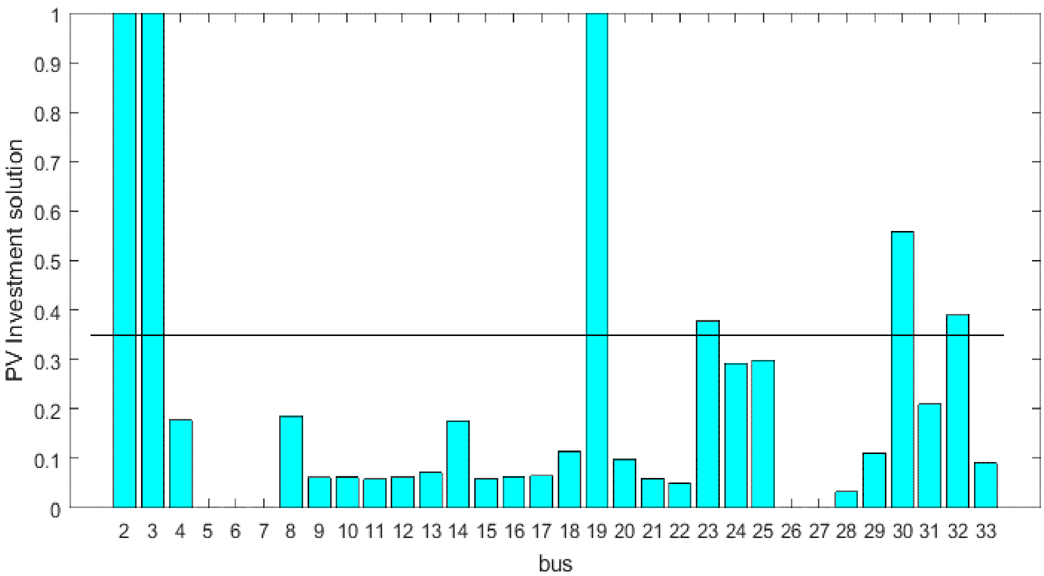

Fig. 3. Investment solution for PVs at each node

Table 2. Investment and operation cost

Investment cost (M$)				
PV	ESS	Substation	Total	
3.5	0.3	2.5	6.3	
Annual operation cost (M$)				
PV	ESS	Substation	Loss	Total
0	0.00028	0.39	0.038	0.43

Table 3. Maximum generation and loss

	S1	S2	S3
Maximum generation PV(MW)	6	7.2	2.7
Maximum production ESS(MW)	1	1	1
Maximum SS production (MW)	2.37	3.6	3.02
Maximum power loss (MW)	0.067	0.154	0.074

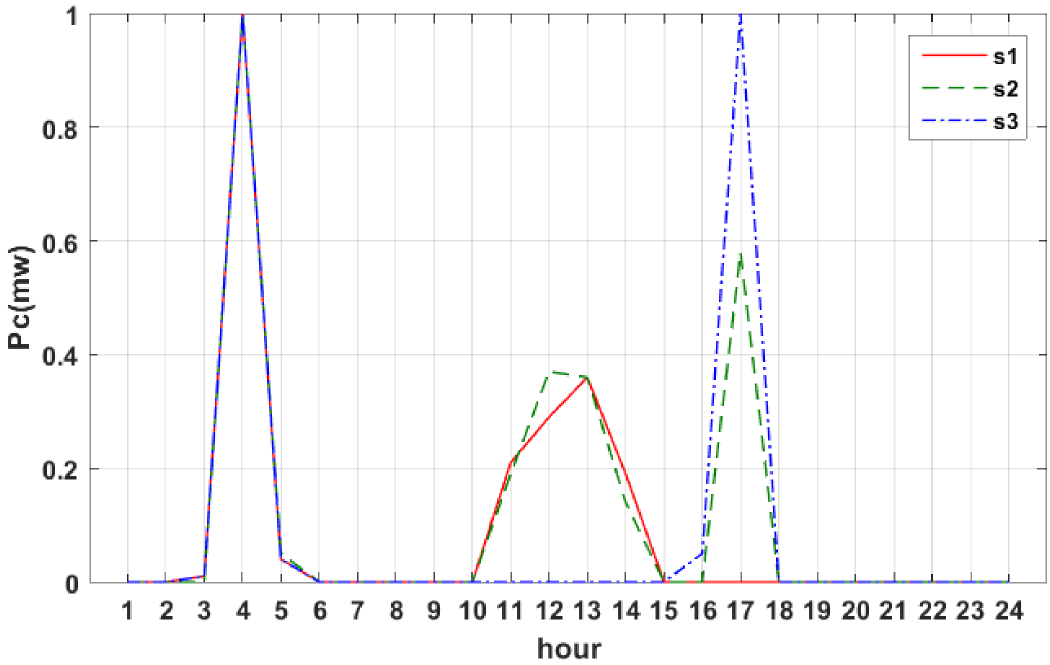

Fig. 4. Daily charging curve of ESS in different scenarios

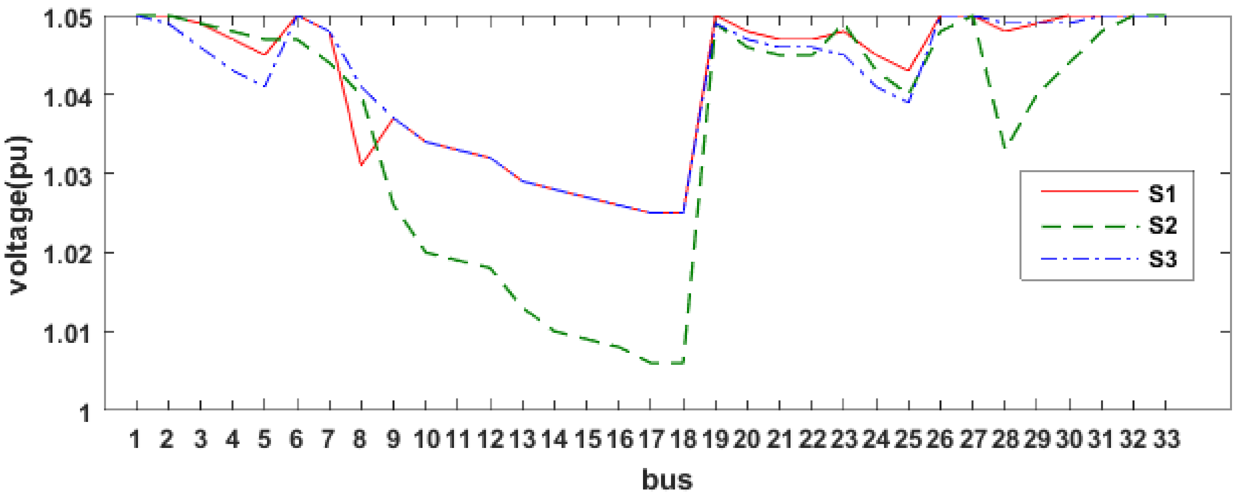

Fig. 5. Voltage profile at hour 12 in different scenarios

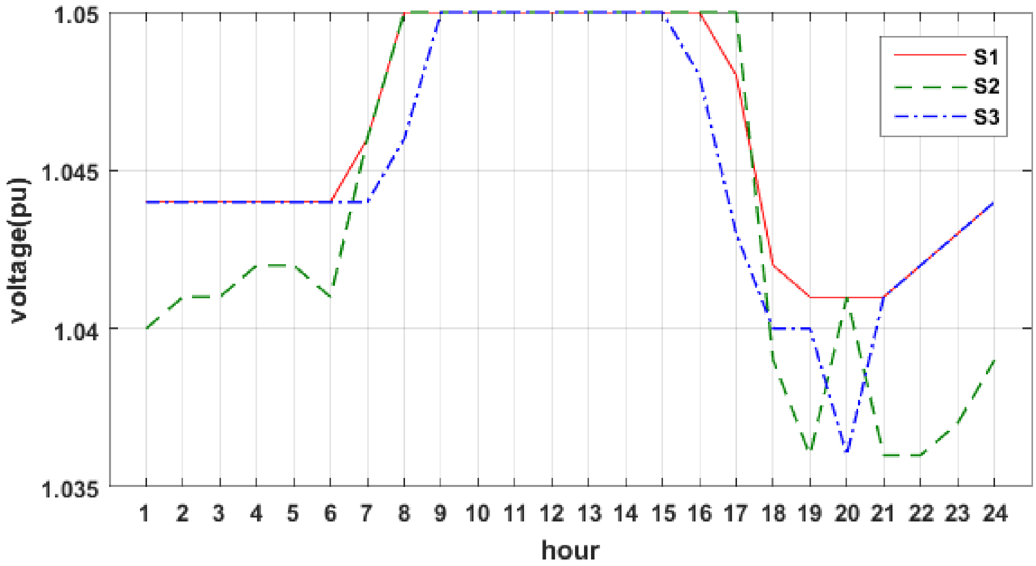

Fig. 6. Voltage profile at node 32 in different scenarios

Table 4. Maximum generation, loss, and costs

Total operation cost (M$)	Total investment cost (M$)	Maximum Power losses (MW)	Maximum generation of substation (MW)
0.57	7.4	0.226	4.37

PV capacity is slightly increased.

It is observed that using OLTC does not affect the HC. However, if the load at each node is multiplied by 1.2, the results of the base case and the case without OLTC would be different. In this state, no ESS is installed, and the HC is increased to 8.6 MW (1.5 MW at nodes 2, 19, 23, and 30, 1.4 MW at bus 3, 1.2 MW at bus 32).

Investment and operation cost, the maximum substation production, and power losses are indicated in Table 4. As can be observed, the operation cost is significantly increased.

3- 2- 3- Effect of Energy Storage Systems on Hosting Capacity

The model is simulated without ESS. The PV optimal place is bus 2, 3, 23, 30& 32 and PV at bus 19 is not selected. The maximum PV capacity at nodes 2, and 3 is 1.5 MW, at nodes 23, and 30 is 1.2 MW and at nodes 32 is 1 MW. The investment cost is \$6M, and the operation cost is \$0.47M. Thus, compared to the base case, HC is decreased from 7.2 MW to 6.4 MW. The total cost is also reduced from 6.73M\$ to 6.47M\$. It can be inferred from the results, that ESS will increase the HC (for our case study about 0.8 MW).

If the investment cost of ESS is reduced by 20%, The maximum capacity of PV is 1.5 MW at bus 2, 3, 30, and 32, and 1.4 MW at bus 19 and PV at bus 19 is not selected. ESS is only located on buses 2& 24. Compared to the base case, the HC is increased from 7.2 to 7.4 MW, and the total cost (investment cost plus the operation cost) is decreased from 6.73 M\$ to 6.59M\$.

3- 2- 4- Effect of Weighting Coefficient on Hosting Capacity

To investigate the effect of changing the weighting factor on the results, new coefficients are set as $w_{e1}=0$,$w_{e2}=0.05$,$w_{e3}=0.05$, $w_{loss}=0.9$. This setting means that the power losses are of utmost importance for the planner. The results are provided in Table 5.

As the results show, no PV and ESS are chosen to be built. Therefore, the investment and operation cost shown in Table 5 are those related to the SS. As can be seen, the operation costs are three times greater than the calculated one in the

Table 5. Power losses and costs

Total operation cost (M$)	Total investment cost (M$)	Power losses cost (M$)	Maximum Power losses (MW)
1.2	2.5	0.055	0.179

basic case. This is due to the lower weighting coefficient with concerning the basic case.

If the weighting coefficient is changed to $w_{e1}=0$,$w_{e2}=0.05$,$w_{e3}=0.9$, $w_{loss}=0.05$, then running the simulation shows that the results are similar to those of the basic case. It is clear that as the w_{e3} is decreases, the HC is also reduced.

4- Conclusion

This paper presents a new method to increase the Hosting Capacity of PVs in a Distribution Network. To increase the Hosting Capacity, two different tools were used: 1- OLTC and 2- ESS. The candidate locations for PV and ESS are obtained by relaxing the MINLP model. However, it is assumed that the OLTC exists in the DN. Generally, OLTC has no impact on HC, unless the load is increased. Under these circumstances, the effect of OLTC on HC will be more apparent.

It is also observed that ESS will enhance the HC, since ESS can be charged during the periods that PV produces excess power. The capability of reactive power generation and absorption by PVs is another factor that improves the HC, as observed in the simulation results.

As future work, we want to model the role of electric vehicles, given the significant impact of ESS.

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