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Optimal Allocation of PV-STATCOM to Improve the Operation of Active Distribution Network

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Abstract— *This paper presents a novel method to improve the efficiency of active distribution networks (ADNs) by optimal placement of distributed energy resources (DERs) and utilizing the unused capacity of inverter-interfaced photovoltaic (PV) units for reactive power compensation. After investigating the mathematical model of PV systems, wind turbines, other non-renewable distributed generations, energy storage systems, and responsive loads, a genetic algorithm (GA)-based approach is used to find the optimal placement and allocation of all units. The modeling also takes into account the uncertainty of PV units and wind turbines to represent real-world operational conditions more accurately. Additionally, although the IEEE 33-bus system is used to formulate the presented method, one can easily extend it to any other network with an arbitrary number of buses. The effectiveness of the proposed method is verified by designing three different scenarios. The simulation results obtained based on MATLAB clearly show the capability of the proposed method to improve the voltage profile and the cost of losses in ADN. This is done by properly utilizing the excess capacity of inverter-interfaced PV units as a static compensator (STATCOM), even in the absence of sunlight. The findings indicate that the inclusion of DERs and PV-STATCOM results to a notable enhancement of approximately 68.46% in power losses reduction and around 65% in the voltage deviation minimization.*

Keywords—Energy management, active distribution network, PV-STATCOM, distributed energy resources, genetic algorithm.

1. INTRODUCTION

Future distribution networks require the use of new structures that lead to the presentation of the concept of microgrids and smart electrical networks in the distribution network [1]. Factors such as the expectations of consumers to receive high-quality and reliable electrical energy have increased the desire of policymakers in the field of the electricity industry to utilize renewable energies and distributed generations (DGs) along with energy storage systems (ESSs) [2, 3]. Furthermore, growing concerns about greenhouse gas emissions and encouraging distribution network operators to invest in advanced and more efficient technologies have given rise to the emergence, development, and evolution of active distribution networks. [4, 5].

An ADN consists of several DERs and control systems that interactively work to maintain the safe and economic operation of the network in order to manage energy optimally. The use of DERs at the level of distribution networks can have many technical and economic benefits for distribution networks [6, 7].

The use of clean renewable DERs is growing worldwide in order to produce electricity with less environmental impact. One of the most popular and influential types of these resources is PV solar energy. However, the utilization of this energy source poses a major challenge due to its low efficiency. In order to improve and solve the efficiency problems of the solar PV system, a system with a smart PV inverter is usually used as a static compensator (PV-STATCOM) in the distribution network, where the PV inverter can be controlled as a dynamic reactive power compensator. This system can be used to provide 24-hour voltage control during critical network conditions [8].

If the excess capacity of the inverter is used as a STATCOM, the voltage of the network buses can be improved even in the absence of sunlight. In the event of no compensation, the voltage of ADN buses falls within the allowed range only during daylight hours. This leads to the possibility of some buses having out-of-range voltages during periods of sunlight deficiency. Thus, employing STATCOM can prove beneficial for enhancing ADN operation [9].

Reactive power compensation is one of the tools for minimizing energy costs and quick return of invested capital. STATCOM can be used for voltage regulation or power factor correction, ultimately to maintain voltage stability. When the network voltages drop significantly, the STATCOM has to work at its maximum capacity, and its reactive power remains constant despite further voltage drops. Therefore, it can be deduced that in out-of-acceptable-range voltages, the STATCOM exhibits a constant-current characteristic [10].

In this study, in addition to PV-STATCOM, other DERs such as non-renewable DG, ESS, wind turbine (WT), and demand-side participation in the form of responsive load (RL) are considered. ESS can participate in energy management on the demand side by charging energy in low-peak hours with low electricity tariffs and injecting energy in high-peak hours with high electricity tariffs, thus gaining profit through arbitrage. Also, the participation of the demand response in the form of RL can significantly help energy management during peak hours [11].

The presence of DERs, such as WT and PV systems, can affect energy management and improve ADN's technical and economic objectives. It should be noted that these DERs have an intermittent nature, leading to an indeterminate power output. Thus, it is imperative to employ advanced mathematical methodologies to calculate the expected definite power of these DERs for optimal operation.

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1.1. Literature review

In Ref. [8], the integration of grid-connected PV systems that use DERs to reduce active and reactive power demand from the grid has been investigated. This research has tried to develop the integration of PV-STATCOM for VAR compensation with other renewable DERs. Ref. [9] presents a strategy for a novel smart inverter PV-STATCOM, in which a PV inverter can be controlled as a dynamic reactive power compensator. In the proposed strategy, during the periods when there is a fault in the network, the inverter in the photovoltaic system can be used to adjust the reactive power and improve the voltage profile. In Ref. [10], the authors present a synchronverter-based PV system as PV-STATCOM. In this model, the inverter can exchange active and reactive power with the distribution networks. In the presented model, reactive power compensation is used for the whole day, even at nighttime. The utilization of PV inverters in power distribution systems as PV-STATCOM during nighttime operations is investigated in Ref. [11]. This study utilizes a novel method, namely the hunter–prey optimization (HPO) algorithm, for optimal allocation of PV-STATCOM devices in distribution systems. Inspired by animal hunting behavior, HPO introduces several scenarios for how animals behave when hunting, some of which are randomly expanded. The findings of this study underscore the potential of PV-STATCOMs as an effective solution for improving network performance.

Ref. [12] presents a novel non-linear optimization approach for implementing an energy management strategy in distribution networks. The main objective of the presented method is the efficient utilization of PV-STATCOM units for the dynamic compensation for active and reactive power produced by each renewable energy resource. However, the presence of other energy resources at the distribution network level has been neglected.

Ref. [13] points out that solar farms, despite the substantial investments in infrastructure, are generally non-operational at night. However, utilized as a PV-STATCOM unit, solar farms can unlock their full potential by actively participating in the regulation of voltage during critical periods of high power demand. The study introduces an optimized smart inverter for reactive power compensation in distribution networks. The proposed method ensures effective regulation of current and voltage, along with reactive power control.

The coordinated operation between a distribution network and distribution-level microgrids is addressed in Ref. [14], which introduces a distributed robust optimization method for the energy management of microgrids to reduce the operating cost of the distribution network.

Although the studies mentioned above, along with various other papers in the literature, have provided innovative methods to address various technical and economic challenges in the energy management of distribution networks, most of them fail to address the presence of PV-STATCOM with the purpose of attaining the desired voltage profile of ADN, considering minimized daily loss cost. Moreover, the simultaneous participation of RLs and other DERs in order to observe the impact of each DER in improving the goals of ADNs has yet to be investigated.

1.2. Contributions

The primary objectives of this research includes the strategic positioning and application of DERs within an ADN, with a focus on maximizing their operational efficiency and enhancing reactive power generation. The proposed methodology herein elucidates the synergistic impact of PV-STATCOM in conjunction with other DERs in ameliorating diurnal energy losses and enhancing voltage stability. Subsequent section undertakes a comprehensive scrutiny of the proposed model. The following points can be considered as novel contributions of this study:

- Offering energy management strategies in ADN to develop operation studies to achieve the technical and economic goals;
- Analyzing the received signals of the ADN and adjusting DER's optimum commitments accordingly;
- Minimizing the cost of daily losses and improving the voltage profile at each time period;
- Utilizing the unused capacity of inverter-interfaced PV units as PV-STATCOM with the purpose of reactive power compensation;
- Optimizing the DER's day-ahead operation.

1.3. Organization of the manuscript

The remainder of the paper is organized as follows: in Section 2 describes the proposed strategy. Mathematical formulations are specified in Section 3. In Section 4 defines different cases related to the simulation results. Finally, in Section 5 presents the conclusions related to the results.

2. Proposed Energy Management Approach

The proposed energy management strategy is based on the complete ADN model, considering the presence of renewable and non-renewable DERs and also RLs to represent demand-side impact. The main objective of the current study is to design an energy management strategy to improve the voltage profile and reduce the daily loss costs of the ADN. This involves minimizing a defined cost function while considering the power constraints of the ADN components. In the proposed strategy, when needed, the PV-linked inverters can act as a STATCOM and participate in reactive power compensation by dynamically injecting reactive power.

Moreover, it is possible to achieve minimum energy cost for the ADN itself at each time period by considering the time-of-use prices. Therefore, the results obtained from each DER are sent to the ADN operator to optimize ADN objectives. Additionally, the remaining capacity of the PV inverter is utilized to correct the power factor of the network. However, the entire capacity of the inverter is used for STATCOM operation during the nighttime. This study uses the genetic algorithm, a meta-heuristic optimization algorithm, to solve the multi-objective optimization problem and minimize the objective function.

3. Mathematical Formulation of the Proposed Strategy

The following sections will cover the formulation of mathematical equations associated with the DERs in the ADN and the objective function. Subsequently, a detailed description of each equation is provided.

3.1. Objective function modeling

Since the primary objective of this study is the optimal placement and allocation of DERs in an ADN, ensuring their efficient use and improving reactive power injection, it is necessary to priory formulate technical and economic objectives as a multi-stage optimization problem. Therefore, as stated in the formula below, the objective function consists of two terms: the first term denoted by OF_1 is to reduce the cost of ADN's daily losses, and the second term denoted by OF_2 is to improve the hourly voltage profile in a daily planning.

$$OF_{Total} = w_1 \times \overbrace{\left[\left(\sum_{h=1}^{24}(P_{Loss_h} \times Cost_h \times Hour_h)\right)\right]}^{OF_1=P_{LOSS}^{Cost}} + \\ w_2 \times \overbrace{\left[\left(\sum_{h=1}^{24}\sum_{i=1}^{33}|V_{i,h}-1|\right)\right]}^{OF_2=VPD} \\ w_1 = w_2 \\ w_1 + w_2 = 1 \tag{1}$$

$$P_{Loss} = \sum_{b=1}^{32}\left(R_b \times I_b^2\right) \tag{2}$$

Where $Cost_h$ and $Hour_h$ in the first term represent the amount of electricity price and the number of time intervals of the h^{th} hour, respectively. The second term of the objective function is the sum of hourly voltage deviations from the per-unit nominal voltage for all buses. $V_{i,h}$ is the i^{th} bus voltage value at the h^{th} hour. Also, R_b and I_b indicate the resistance and current of the b^{th} branch, respectively.

The following constraint regulates the permissible voltage profile for all buses in the ADN. For the substation bus, the voltage magnitude is considered to be equal with 1p.u. Therefore:

$$\begin{cases} V_{min} \le |V_{i,h}| \le V_{max} & \forall i,h \\ |V_{1,h}| = 1\ p.u & \forall h \end{cases} \tag{3}$$

3.2. Energy storage system modeling

The following equation refers to the amount of energy stored in the ESS and the amount of energy injected into the ADN. Therefore, the following equation should be considered [15].

$$\sum_{h \in h_{dis}} Hour_h \times P_{ESS_h}^{dis} = \\ \sum_{h \in h_{ch}} Hour_h \times P_{ESS_h}^{ch} \times \rho_{ESS} \tag{4}$$

Where $P_{ESS_h}^{dis}$ and $P_{ESS_h}^{ch}$ show the amount of discharging and charging power by ESS during the h^{th} hour, respectively. Additionally, ρ_{ESS} is the efficiency of ESS which is considered to be % 80. The maximum acceptable daily charge of the ESS can be considered as follows:

$$\sum_{h \in h_{ch}} Hour_h \times P_{ESS_h}^{ch} \times \rho \le E_{ESS}^{Capacity} \tag{5}$$

Where $E_{ESS}^{Capacity}$ shows the maximum permissible existing energy of the ESS. Likewise, the maximum and minimum acceptable rates for ESS charging and discharging at each hour h can be calculated as follows:

$$0 \le P_{ESS_h}^{dis}, P_{ESS_h}^{ch} \le P_{ESS} \qquad \forall h \tag{6}$$

3.3. Distributed generation modeling

Grid code connection requires DGs to have obligatory contributions in reactive power support. Therefore, DG should be operated with an adaptive power factor. The power constraints of DGs can be expressed as follows:

$$Q_h^{DG} = P_h^{DG} \times \tan(arcos(PF_h^{DG})) \quad \forall h \tag{7}$$

$$P_{h,min}^{DG} \le P_h^{DG} \le P_{h,max}^{DG} \qquad \forall h \tag{8}$$

$$Q_{h,min}^{DG} \le Q_{h,t}^{DG} \le Q_{h,max}^{DG} \qquad \forall h \tag{9}$$

$$\sqrt{(P_h^{DG})^2 + (Q_h^{DG})^2} \le S_{max}^{DG} \qquad \forall h \tag{10}$$

$$PF_h^{DG} = \frac{P_h^{DG}}{\sqrt{\left((P_h^{DG})^2 + (Q_h^{DG})^2\right)}} \quad \forall h \tag{11}$$

$$PF_{h,min}^{DG} \le PF_h^{DG} \le PF_{h,max}^{DG} \quad \forall h \tag{12}$$

Where, P_h^{DG} and Q_h^{DG} are the DG's active and reactive power dispatch at h^{th} hour, respectively. S_{max}^{DG} denotes the maximum apparent power capacity of the DG. Also, $PF_{h,min}^{DG}$ and $PF_{h,max}^{DG}$ are the minimum and maximum permissible power factor of the DG at the h^{th} hour.

3.4. Responsive load modeling

The RL's percentage of load reduction (% per) will reduce both active ($P_{h,RL}$) and reactive power ($Q_{h,RL}$) [16, 17]. Therefore, RL is supposed to have a constant power factor (PF_t^{rl}). The related equations to the RL's participation and the corresponding adaptive power factor are stated below.

$$\begin{cases} 0 \le P_{h,RL} \le ((\%per) \times P_{h,demand}^i) & \forall\, h \in per_h \\ P_{h,RL} = 0 & \forall h \notin per_h \end{cases} \tag{13}$$

$$\left[\left(P_{h,RL}\right)^2 + \left(Q_{h,RL}\right)^2\right]^{1/2} \le \frac{PER(\%)}{100} \times S_L \quad \forall\, h \in per_h \tag{14}$$

$$PF_{h,RL} = \frac{P_{\mathrm{h,RL}}}{\left(P_{\mathrm{h,RL}} + Q_{\mathrm{h,RL}}\right)^{1/2}} = cte \qquad \forall\, h \in per_h \tag{15}$$

$$Q_{h,RL} = \tan(\cos^{-1}(PF_{h,RL})) \times P_{h,RL} \quad \forall\, h \in per_h \tag{16}$$

In this study, the type of RL is the direct load control (DLC), which reduces the percentage of load in certain hours by the ADN operator, while RL consumers receive an incentive plan from the ADN operator for reducing their load.

3.5. Wind turbine modeling

The choice of wind turbine location in an ADN relies on the wind speed in a specific area. A WT's output power also varies, depending on the wind speed at a given site [18]. In this modeling, the power produced by a WT is considered to have a Rayleigh probability density function (PDF). Therefore:

$$PDF(V_h) = \frac{(2 \times V_h)}{{C_h}^2}\exp(-(\frac{V_h}{C_h})^2) \quad \forall h \tag{17}$$

Where V_h and C_h are the terms related to the wind speed and the scale factor of the Rayleigh PDF at the h^{th} hour, respectively. The value of C_h is modeled as follows after determining the mean value of wind speed ($V_{h_{mean}}$) at each hour, which is obtained from the historical information of the location.

$$\begin{array}{l} V_{h_{mean}} = \int\limits_0^\infty (V_h \times PDF(V_h) \times dV_h) = \\ \int\limits_0^\infty \frac{(2\times V_h^2)}{C_h^2} \exp(-(\frac{V_h}{C_h})^2) \times dV_h = \frac{\sqrt{\pi}}{2} \times C_h \quad \forall h \end{array} \tag{18}$$

$$C_h = 1.128 \times V_{h_{mean}} \qquad \forall h \tag{19}$$

In order to convert the probabilistic value into the expected value of the WT generated power, the Rayleigh PDF value of each hour is divided into 10 discrete states. According to the modeling and performed calculations, the WT's generated power at each state is obtained according to the following equation:

$$P_h(w) = \begin{cases} 0 v_{mean} \le v_{in}^c \\ \frac{v_{mean}-v_{in}^c}{v_{rated}-v_{in}^c} \times P_r^w v_{in}^c \le v_{mean} \le v_{rated} \\ P_r^w v_{rated} \le v_{mean} \le v_{out}^c \\ 0 v_{out}^c \le v_{mean} \end{cases} \tag{20}$$

Where P_r^w and $P_h(w)$ are the rated and generated power value of the WT. v_{out}^c, v_{in}^c, and v_{rated} are the parameters related to the maximum, minimum, and the nominal speed of the WT, respectively.

The probability of each discrete state to obtain the expected power is modeled as follows:

$$\lambda_{s,h} = \int_{\varphi_{n-1}}^{\varphi_n} PDF(V_h) \times dv_h \qquad \forall s, h \tag{21}$$

Where, φ_n and φ_{n-1} are related to the limits of each discrete state at each hour h. Therefore, the expected output power of the WT at each hour is modeled according to the following equation:

$${P_h}^{WT-\exp ected} = \sum_{s\in S} \left(\lambda_{s,h} \times P_{h,s}(w)\right) \quad \forall h \tag{22}$$

3.6. Photovoltaic system modeling

The allocation of PV system at the level of ADN as renewable DER is one of the requirements of the active management of the demand side. This has a positive effect on energy management, voltage control, and the use of inverter capacity in reactive power injection. Therefore, in order to model the PV system, the solar radiation parameters for every hour of the day should be considered for the location of the PV system. Solar radiation for each hour can be calculated using a beta PDF based on historical data as follows [19, 20]:

$$\begin{array}{l} f_B\left(\varphi_h\right) = \\ \begin{cases} \frac{\Gamma(\alpha_h+\beta_h)}{\Gamma(\alpha_h)+\Gamma(\beta_h)} \left(\varphi_h^{(\alpha_h-1)} \times \varphi_h^{(\beta_h-1)}\right) & \begin{pmatrix} 0 \le \varphi_h \le 1, \\ \alpha_h, \beta_h \ \ge 0 \end{pmatrix} \\ 0 & (otherwise) \end{cases} \\ \forall h \in h_{pv} \end{array} \tag{23}$$

Where $f_B\left(\varphi_h\right)$ is a random variable of solar radiation (kw/m^2) at each hour of sunlight ($h \in h_{pv}$). In this equation, α_h and β_h are related to the value of parameters of the PDF, which are modeled as the following equations to determine the mean and standard deviation of solar radiation at each hour of sunlight.

$$\beta_h = (1-\mu_h) \times \left(\frac{\mu_h\left(1+\mu_h\right)}{\sigma_h^2} - 1\right) \qquad \forall h \in h_{pv} \tag{24}$$

$$\alpha_h = \frac{\mu_h \times \beta_h}{1-\mu_h} \qquad \forall h \in h_{pv} \tag{25}$$

In order to calculate the expected value of the generated power of the PV system, each hour has 10 discrete states and the Beta PDF is generated with this statement. Therefore, the probability of each discrete state can be modeled as follows:

$$\lambda_{s,h} = \int_{\varphi_{n-1}}^{\varphi_n} f_B\left(\varphi_{h,s}\right) \times d\varphi_{h,s} \qquad \forall s, h \in h_{pv} \tag{26}$$

Here, φ_n and φ_{n-1} are solar irradiance limits of state s. The PV system generated power at each discrete state is expressed as follows:

$$P^{PV}\left(\varphi_{s,h}\right) = \eta^{PV} \times S^{pv} \times \varphi_{s,h} \qquad \forall s, h \in h_{pv} \tag{27}$$

Where, η^{PV} and S^{pv} are the efficiency of solar panels and the total area of the panels, respectively. Therefore, the expected generated power (kw/hour) of the PV system across any hours of sunlight can be modeled as a follow.

$${P_h}^{PV-\exp ected} = \sum_{s\in S} \left(\lambda_{s,h} \times P^{PV}\left(\varphi_{s,h}\right)\right) \qquad \forall h \in h_{pv} \tag{28}$$

3.7. PV-STATCOM system modeling

The utilization of the PV system's inverter as a STATCOM throughout different time periods has the potential to boost the PV system's efficiency by generating reactive power. The power constraints of PV-STATCOM regarding the amount of reactive power injection during sunlight and non-sunlight hours, along with power factor limitations are stated in following.

$$\begin{cases} Q_h^{PV-STAT} = P_h^{PV-STAT} \times \tan(arcos(PF_h^{PV-STAT})) & \forall h \in h_{pv} \\ Q_h^{PV-STAT} \le Q_{\max}^{PV-STAT}, \quad P_h^{PV-STAT} = 0 & \forall h \notin h_{pv} \end{cases} \tag{29}$$

$$\sqrt{\left(P_h^{PV-STAT}\right)^2 + \left(Q_h^{PV-STAT}\right)^2} \le S_{max}^{Inverter} \qquad \forall h \in h_{pv} \tag{30}$$

$$PF_h^{PV-STAT} = \frac{P_h^{PV-STAT}}{\sqrt{\left((P_h^{PV-STAT})^2+(Q_h^{PV-STAT})^2\right)}} \qquad \forall h \in h_{pv} \tag{31}$$

$$PF_{h,min}^{PV-STAT} \le PF_h^{PV-STAT} \le PF_{h,max}^{PV-STAT} \quad \forall h \in h_{pv} \tag{32}$$

It should be noted that during the hours of sunlight, the PV system is able to generate active power and reactive power, but during no sunlight hours, the PV system only generates the reactive power required by the ADN through the STATCOM.

3.8. Load flow modeling

Technical controls should be checked to ensure that the ADN is in optimal operation status or not [21–23]. By receiving the data from ADN and DERs, the operator can investigate the power flow. The purpose of load flow is to obtain the voltage of each bus of the ADN at each hour. The modeling related to active and reactive power load flow is considered as the following equations.

$$P_{g,h} + P_h^{DG} + P_{h,RL} + P_h^{WT-\exp ected} + P_h^{PV-STAT} - P_{ESS_h}^{ch} - P_{L_h} = \sum_{j\in\Omega_i} P_{ij}(V_{i,h}, V_{j,h}, Y_{ij}, \theta_{ij}) \quad \forall h \in ESS^{ch} \tag{33}$$

$$P_{g,h} + P_{ESS_h}^{dis} + P_h^{DG} + P_{h,RL} + P_h^{WT-\exp ected} + P_h^{PV-STAT} - P_{L_h} = \sum_{j\in\Omega_i} P_{ij}(V_{i,h}, V_{j,h}, Y_{ij}, \theta_{ij}) \quad \forall h \in ESS^{dis} \tag{34}$$

$$Q_{g_h} + Q_h^{DG} + Q_{h,RL} + Q_h^{PV-STAT} - Q_{L_h} = \sum_{j\in\Omega_i} Q_{ij}(V_{i,h}, V_{j,h}, Y_{ij}, \theta_{ij}) \quad \forall h \tag{35}$$

Here, $P_{g,h}$, $Q_{g,h}$, P_{ij} and Q_{ij} are the amount of active and reactive power inputs to the ADN and the amount of active and reactive power injected to each bus at the h^{th} hour, respectively. i and j are related to ADN buses. Y_{ij} and Q_{ij} are (i, j) element of admittance matrix and the related angle, respectively.

4. Numerical Results

4.1. Input data

The proposed strategy was applied to a modified version of 33-bus 12.66-kV ADN given in [24]. The distribution network with all DERs is shown in Fig. 1.

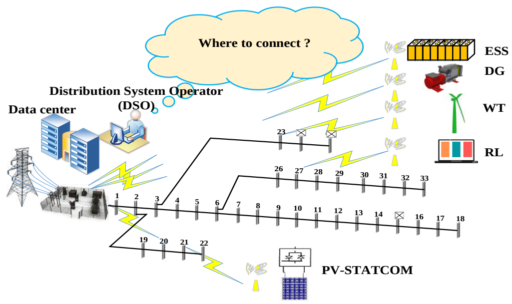

Fig. 1. IEEE 33-bus ADN.

The study examines results over a 24-hour period, assuming each hour has its peak load and electricity price, as depicted in Figs. 2 and 3.

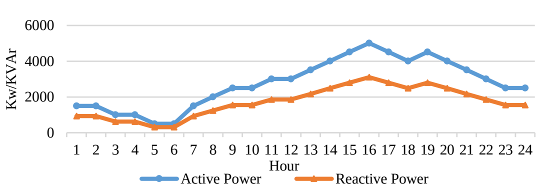

Fig. 2. ADN load profile.

This study was designed for a brief duration, encompassing a single day. The chosen temporal increments were set at one hour, resulting in a total of 24 time periods within the day.

To investigate the impact of the demand side, one bus is determined as RL with constant PF (PF=0.85) which could be reduced by ADN operator up to 30% at hours when the energy consumption is above 70%. DERs' parameters are given in Table 1.

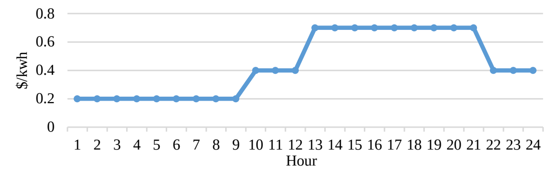

Fig. 3. ADN electricity price.

Table 1. The DERs data.

DG	Active power	800KW
	Power factor	$0.85 < PF < 1$
ESS	Capacity	1000kwh
	Power	1000kw
	Efficiency	$\rho = 0.85$
PV	Power	500kw
	Area	$S^{pv} = 4000\text{m}^2$
	Efficiency	$\eta^{PV} = 18.6\%$
WT	Power	800KW
	Wind speed	$v_{in}^c = 3m/s,\ v_{out}^c = 12m/s,\ v_{rated} = 25m/s$
STATCOM	Power factor	$0.85 < PF < 1$

According to [20], solar irradiance occurs during the time frame of 7 AM to 6 PM. Expected output power of the PV in day-ahead operation is shown in Fig. 4. However, the utilization of the PV system inverter as a STATCOM serves to enhance the overall efficiency of the photovoltaic system by contributing to the generation of reactive power.

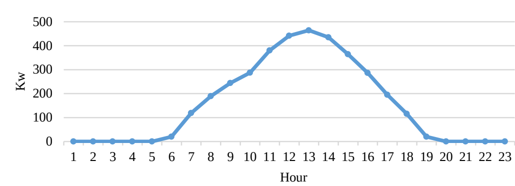

Fig. 4. Expected output power of the PV.

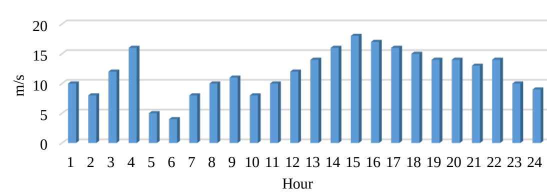

Fig. 5. Mean wind speed.

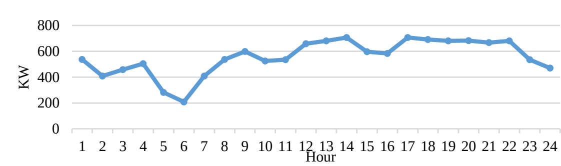

Fig. 6. Expected output power of the WT.

The mean hourly wind speed and expected output power of the WT in day-ahead operation are shown in Figs. 5 and 6, respectively.

4.2. Simulation results

In order to verify the effectiveness of the proposed method, three different cases are simulated. In case 1, none of the DERs

Table 2. The results in case 1.

Parameter	Value
$OF_1 = P_{Loss}^{Cost}$	2076.5
$OF_2 = VPD$	32
OF_{Total}	1054.2
P_{Loss}	3454.6kw
Minimum Voltage	0.86p.u

Table 3. The results of GA in case 2.

DER type	Bus number
DG	28
ESS	23
WT	15
RL	26

are present in the distribution network. In the second case, the effect of the presence of DERs in the improvement of the objective functions is investigated, and in the third case, the effect of the addition of PV-STATCOM in the improvement of the objective functions is studied. In the following, the obtained simulation results are provided and explained.

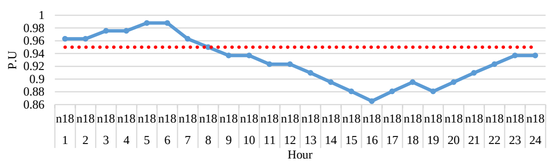

Fig. 7. Minimum bus voltage in case 1.

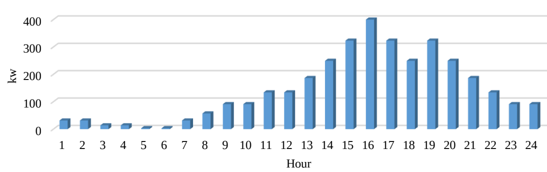

Fig. 8. Active power loss in case 1.

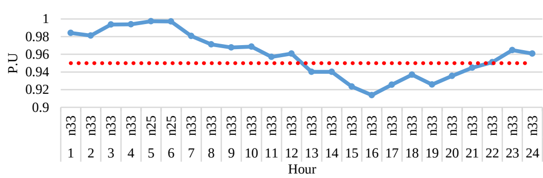

Fig. 9. Minimum bus voltage in case 2.

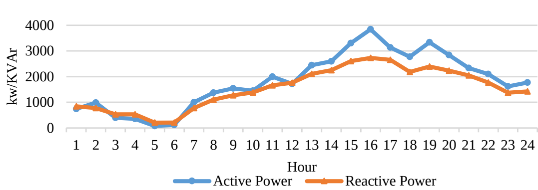

Fig. 10. ADN load profile in case 2.

A) Case 1: Without DERs and PV-STATCOM

This case explores the results in the absence of DERs. The results for case 1 are given in Table 2.

As shown in the Table, the initial objective function attains a value of 2076.5$, while the subsequent objective function registers

Table 4. Results of the objective functions in the case 2.

Parameter	Value	Percentage
$OF_1 = P_{Loss}^{Cost}$	1021.4$	-50%
$OF_2 = VPD$	17.7	-44.68%
OF_{Total}	519.5	-50.72%
P_{Loss}	1687.9kw	-51.14%
Minimum Voltage	0.91p.u	+5.81%

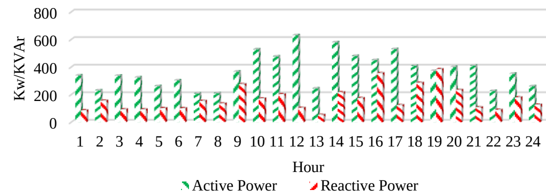

Fig. 11. Active and reactive power of DG in case 2.

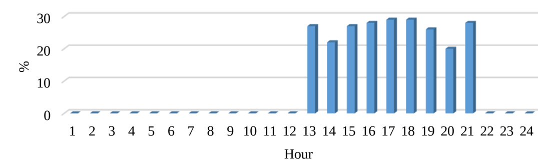

Fig. 12. ESS operation in case 2.

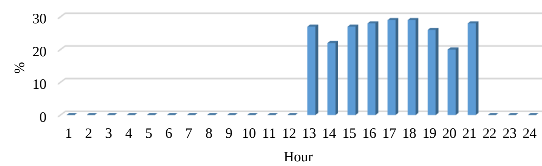

Fig. 13. RL optimal power schedule in case 2.

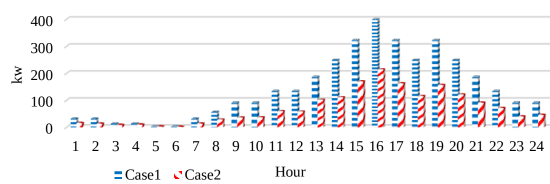

Fig. 14. Active power loss in case 2.

a value of 32. Notably, the minimum voltage obtained in this case stands at 0.86p.u, surpassing the conventional threshold range. The results of this case will serve as a benchmark for comparison with other cases. Fig. 7 shows the bus number related to the minimum ADN bus voltage at each hour.

According to the findings depicted in this figure, the voltage range consistently exceeds the established norm across the majority of temporal hours. Specifically, at 14, a minimum voltage of 0.89p.u is recorded at bus 18, surpassing the conventional threshold. Fig. 8 illustrates the daily power losses for each hour. The data indicates that the amount of power loss is correlated with the ADN's power consumption.

Based on the data presented in this figure, there is a positive correlation between peak energy consumption periods and elevated network losses within the system, indicating a direct relationship between high demand and increased energy dissipation.

B) Case 2: With DERs and without PV-STATCOM

This case focuses on the situations when the ADN contains DERs, without taking the PV-STATCOM into account. Table 3 shows the optimal location of DERs based on GA in this case.

The values of the objective functions, daily power loss and the

Table 5. Simulation and experimental parameters.

DER type	Bus number
DG	31
ESS	11
WT	17
RL	30
PV-STATCOM	13

Table 6. Results of the objective functions in the case 3.

Parameter	Value	Percentage
$OF_1 = P_{Loss}^{\text{Cost}}$	654.8$	-68.46%
$OF_2 = VPD$	11.2	-65%
OF_{Total}	333	-68.40%
P_{Loss}	1110.5kw	-67.85%
Minimum Voltage	0.95p.u	+10.46%

minimum bus voltage in case 2 are given in Table 4. As can be seen, DERs incorporation could reduce the objective functions. The data clearly demonstrates a 50% improvement in the first objective function value, a 44.68% amelioration in the secondary function value, and an approximate 5.81% enhancement in the minimum voltage value observed in the second case. Fig. 9 shows the number related to the minimum ADN bus voltage at each hour.

As Shown in the figure, the minimum bus voltage rises compared to case 1, yet it fails to consistently stay within the permissible range during certain hours, thus the voltage profile is improved. Furthermore, the active and reactive power consumptions of the ADN are shown in Fig. 10.

The comparison of Fig. 2 and Fig. 10 elucidates that within case 2, the inclusion of DERs has precipitated a reduction in the energy consumption of the distribution system. The optimal dispatch of DG, charging and discharging of ESS, and the power schedule of RL at each hour are shown in Figs. 11-13.

As shown in these figures, according to the price of electricity and the amount of consumption, DERs are dispatched to address the ADN's demand requirements and meet the technical constraints. In Fig. 11, the power injection by DG at various temporal hours is contingent upon the exigencies of the distribution system and the optimization criteria. Fig. 12 unequivocally illustrates that the operational conduct of ESS is predicated on the pricing dynamics associated with electricity charging and discharging, where charging activities are undertaken during periods of low price and off-peak hours. Furthermore, Fig. 13 elucidates the requisite contribution from participation RL towards enhancing the optimization objectives during peak consumption intervals and in alignment with the distribution network requirements.

The active power loss of the ADN is shown in Fig. 14. Examining the figure also reveals that when power consumption rises, the power loss of the ADN rises as well, as the branch currents increase accordingly.

The comparative analysis of active power losses between case 1 and case 2 is depicted in the aforementioned figure, revealing a reduction in distribution network losses from 400kw to approximately 200kw during the peak consumption hour at 16.

C) Case 3: With DERs and PV-STATCOM

Considering the last case, where the incorporation of DERs had a beneficial impact on enhancing voltage profile and reducing the objective function, yet the minimum bus voltage occasionally fell outside the acceptable range, this final case aims to explore the impact of incorporating a PV-STATCOM on voltage profile and the overall performance of the system. The optimal DER placement using the GA in case 3 is given in Table 5.

By comparing Table 3 and Table 5, it becomes evident that the integration of PV-STATCOM results to a shift in the optimal placement of DERs. Table 6 presents the values of the objective functions when PV-STATCOM is utilized. Examining this table reveals that incorporating DERs and PV-STATCOM concurrently

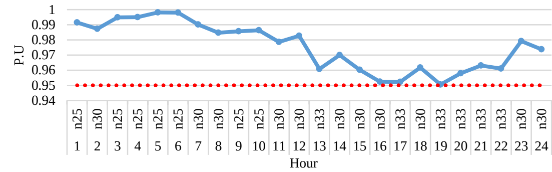

Fig. 15. Minimum bus voltage in case 3.

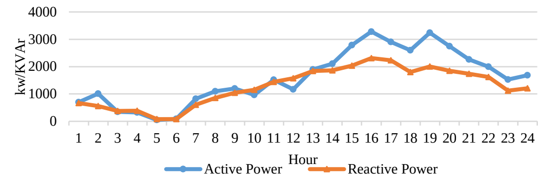

Fig. 16. ADN load profile in case 3.

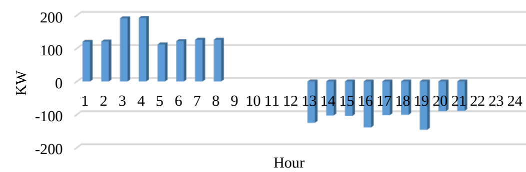

Fig. 17. ESS operation in case 3.

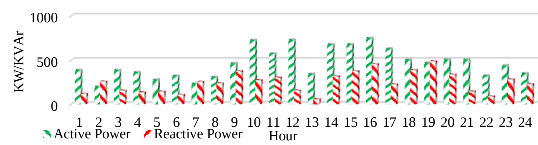

Fig. 18. The optimal dispatch of DG in case 3.

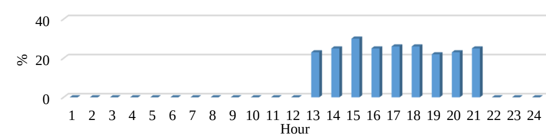

Fig. 19. RL optimal power schedule in case 3.

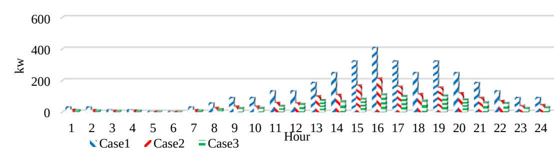

Fig. 20. Active power loss in case 3.

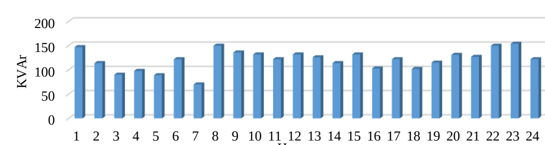

Fig. 21. STATCOM generated power in case 3.

enhances the objective functions. The minimum ADN bus voltage for each hour is illustrated in Fig. 15.

Table 6 demonstrates a noteworthy enhancement of 68.46% in power losses reduction and a substantial 65% advancement in voltage deviation minimization. Furthermore, there is a discernible amelioration of approximately 10.46% in the minimum voltage levels across distribution buses.

It is worth mentioning that the reactive power compensation by PV-STATCOM positively impacts the improvement of objective functions compared to case 2 and helps maintain voltage within acceptable range. Fig. 16 displays the ADN load profile in case 3. As shown in this figure, the ADN has a smoother load profile compared to case 1 and case 2. Considering DERs and PV-STATCOM manage the load profile in peak load hours and use PV-STATCOM with the aim of optimizing the objective functions during the hours when the cost of the electricity price is high.

Figs. 17-19 display the ESS operation, the active and reactive power generated by the DG, and the power schedule of RL at each hour, respectively.

As per Fig. 17 shows, the operational dynamics of ESS are harmonized in alignment with energy price variations and load demands, all in pursuit of optimizing the specified objective functions. Fig. 18 illustrates the DG operation in response to the system's exigencies, exhibiting fluctuations in their utilization across distinct hours. Moreover, Fig. 19 demonstrates the active involvement of RL during peak consumption periods within the network framework. Notably, at 15, there is a documented RL participation rate of approximately 30%, while at 19, this is diminished to around 20%, reflecting the adaptive nature of RL integration in accordance with distribution network requisites.

The active power loss of ADN is shown in Fig. 20. It is evident that the power loss of the ADN in each hour, similar to other cases, depends on the power consumption.

Fig. 21 illustrates the hourly variation in reactive power generated by STATCOM in response to the variations in the ADN's condition. At hour 1, the reactive power output of the PV-STATCOM stands at approximately 140 kvar, whereas by hour 7, it registers a reduced value of around 70 kvar. This discernible difference in power generation underscores the adaptive comportment of the PV-STATCOM in response to the exigencies and operational requisites of the distribution system.

5. CONCLUSION

Due to growing energy needs driven by global developments and technological advancements, managing energy in ADNs for optimal utilization of DERs has become crucial. This study addresses this need by proposing a GA-based optimal placement and power allocation strategy based on efficient mathematical modelling and considering the integration of DERs and PV-STATCOM units. The proposed method leverages the unoccupied capacity of PV-linked inverters as STATCOM (PV-STATCOM) to reduce daily loss cost and improve voltage profile within the ADN. This approach allows for better utilization of the PV systems even during non-sunlight hours by enabling reactive power compensation through PV-STATCOM. Simulations conducted in MATLAB demonstrate the effectiveness of the proposed approach. The findings from the investigation in these cases have demonstrated that the integration of DERs and PV-STATCOM within the distribution system yields a notable enhancement of 68.46% and 65% in power losses and voltage deviation minimization, respectively. Furthermore, from a technical perspective pertaining to the distribution system, a substantial advancement of approximately 10.46% has been realized in the minimum voltage levels.

REFERENCES

[1] S. Mirzamohammadi, A. Jabarzadeh, and M. S. Shahrabi, "Long-term planning of supplying energy for greenhouses using renewable resources under uncertainty," *J. Cleaner Prod.*, vol. 264, p. 121611, 2020.

[2] J. Wei, Y. Zhang, J. Wang, X. Cao, and M. A. Khan, "Multi-period planning of multi-energy microgrid with multi-type uncertainties using chance constrained information gap decision method," *Appl. Energy*, vol. 260, p. 114188, 2020.

[3] L. Luo, S. S. Abdulkareem, A. Rezvani, M. R. Miveh, S. Samad, N. Aljojo, and M. Pazhoohesh, "Optimal scheduling of a renewable based microgrid considering photovoltaic system and battery energy storage under uncertainty," *J. Energy Storage*, vol. 28, p. 101306, 2020.

[4] S. E. Ahmadi and N. Rezaei, "A new isolated renewable based multi microgrid optimal energy management system considering uncertainty and demand response," *Int. J. Electr. Power Energy Syst.*, vol. 118, p. 105760, 2020.

[5] Y. Wang, Z. Yang, M. Mourshed, Y. Guo, Q. Niu, and X. Zhu, "Demand side management of plug-in electric vehicles and coordinated unit commitment: A novel parallel competitive swarm optimization method," *Energy Convers. Manage.*, vol. 196, pp. 935–949, 2019.

[6] F. S. Gazijahani, A. Ajoulabadi, S. N. Ravadanegh, and J. Salehi, "Joint energy and reserve scheduling of renewable powered microgrids accommodating price responsive demand by scenario: a risk-based augmented epsilon-constraint approach," *J. Cleaner Prod.*, vol. 262, p. 121365, 2020.

[7] A. Hussain, V.-H. Bui, and H.-M. Kim, "Microgrids as a resilience resource and strategies used by microgrids for enhancing resilience," *Appl. Energy*, vol. 240, pp. 56–72, 2019.

[8] T. A. Boghdady and Y. A. Mohamed, "Reactive power compensation using statcom in a pv grid connected system with a modified mppt method," *Ain Shams Eng. J.*, vol. 14, no. 8, p. 102060, 2023.

[9] R. K. Varma and E. M. Siavashi, "Pv-statcom: A new smart inverter for voltage control in distribution systems," *IEEE Trans. Sustainable Energy*, vol. 9, no. 4, pp. 1681–1691, 2018.

[10] A. J. Sonawane and A. C. Umarikar, "Voltage and reactive power regulation with synchronverter-based control of pv-statcom," *IEEE Access*, 2023.

[11] A. M. Shaheen, R. A. El-Sehiemy, A. Ginidi, A. M. Elsayed, and S. F. Al-Gahtani, "Optimal allocation of pv-statcom devices in distribution systems for energy losses minimization and voltage profile improvement via hunter-prey-based algorithm," *Energies*, vol. 16, no. 6, p. 2790, 2023.

[12] O. D. Montoya, O. D. Florez-Cediel, and W. Gil-González, "Efficient day-ahead scheduling of pv-statcoms in medium-voltage distribution networks using a second-order cone relaxation," *Comput.*, vol. 12, no. 7, p. 142, 2023.

[13] B. Dubey, S. Agrawal, and A. K. Sharma, "Smart inverter-based pv-statcom power compensation using baphin optimization algorithm," *Int. J. Renewable Energy Res.*, vol. 13, no. 3, pp. 1015–1030, 2023.

[14] F. J. Lachovicz, T. S. Fernandes, and J. A. Vilela Junior, "Impacts of pv-statcom reactive power dispatch in the allocation of capacitors bank and voltage regulators on active distribution networks," *J. Control Autom. Electr. Syst.*, vol. 34, no. 4, pp. 796–807, 2023.

[15] N. Kumar, S. Dahiya, and K. Singh Parmar, "Multi-objective economic emission dispatch optimization strategy considering battery energy storage system in islanded microgrid," *J. Oper. Autom. Power Eng.*, vol. 12, no. 4, pp. 296–311, 2024.

[16] G. Goyal and S. Vadhera, "Solution to objectives of supply side energy management by integrating enhanced demand response strategy," *J. Oper. Autom. Power Eng.*, vol. 12, no. 4, pp. 269–279, 2024.

[17] A. Roy, F. Auger, F. Dupriez-Robin, S. Bourguet, and Q. T. Tran, "A multi-level demand-side management algorithm for offgrid multi-source systems," *Energy*, vol. 191, p. 116536, 2020.

[18] M. Mosayebian, "A new approach for modeling wind power in reliability studies," *J. Oper. Autom. Power Eng.*, vol. 11, no. 2, pp. 144–150, 2023.

[19] R. Avvari and V. K. DM, "A novel hybrid multi-objective evolutionary algorithm for optimal power flow in wind, pv,

and pev systems," *J. Oper. Autom. Power Eng.*, vol. 11, no. 2, pp. 130–143, 2023.

[20] A. Zakariazadeh, S. Jadid, and P. Siano, "Smart microgrid energy and reserve scheduling with demand response using stochastic optimization," *Int. J. Electr. Power Energy Syst.*, vol. 63, pp. 523–533, 2014.

[21] S. Zhu, D. Li, and H. Feng, "Is smart city resilient? evidence from china," *Sustainable Cities Soc.*, vol. 50, p. 101636, 2019.

[22] T. Yasuda, S. Ookawara, S. Yoshikawa, and H. Matsumoto, "Materials processing model-driven discovery framework for porous materials using machine learning and genetic algorithm: A focus on optimization of permeability and filtration efficiency," *Chem. Eng. J.*, vol. 453, p. 139540, 2023.

[23] G. Papazoglou and P. Biskas, "Review and comparison of genetic algorithm and particle swarm optimization in the optimal power flow problem," *Energies*, vol. 16, no. 3, p. 1152, 2023.

[24] S. Chandramohan, N. Atturulu, R. K. Devi, and B. Venkatesh, "Operating cost minimization of a radial distribution system in a deregulated electricity market through reconfiguration using nsga method," *Int. J. Electr. Power Energy Syst.*, vol. 32, no. 2, pp. 126–132, 2010.