Optimal Smart Inverter Control for PV and BESS to Improve PV Hosting Capacity of Distribution Networks Using Slime Mould Algorithm

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This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIP) (No. 2018R1A2A1A05078680).

ABSTRACT  
In this study, an optimal reactive power (Volt/Var) control of smart inverters for photovoltaic (PV) and battery energy storage systems (BESSs) to improve the PV hosting capacity (PVHC) of distribution networks is proposed. The primary objective of the proposed method is to improve the PVHC of a distribution network by determining the optimal oversize, dispatch, and control setting of the Volt/Var functions of the smart inverters for both PVs and BESSs. Concurrently, the optimal locations of the PVs and BESSs are determined. The problem is formulated as a multi-objective mixed-integer nonlinear optimization to maximize the PVHC and minimize the voltage deviation simultaneously. A bio-inspired metaheuristic optimization method, i.e., the slime mould algorithm (SMA), is employed to solve the optimization problem. To assess the efficacy of the proposed PVHC improvement method, extensive simulations are conducted on an IEEE 33-node system using MATLAB software. The simulation results verify that the proposed method improves the PVHC of the distribution network compared to different cases and the default Volt/Var control settings of the smart inverters. Furthermore, the SMA optimization method provides superior performance in finding the optimal PVHC of a distribution network compared to the conventional metaheuristic optimization methods.

INDEX TERMS  
Distributed energy resources, distribution network, hosting capacity, smart inverter, slime mould algorithm, Volt/Var control.

ACRONYMS  
BESS: Battery energy storage systems  
DER: Distributed energy resource  
DNO: Distribution network operator  
HC: Hosting capacity  
OLTC: On-load tap changers  
OS: Over size  
PVHC: PV hosting capacity  
PV: Photovoltaic  
SI: Smart inverter  
SMA: Slime mould algorithm  
SOC: State of charge  
SVC: Static VAr compensator  
VD: Voltage deviation  
VVCS: Volt/Var control setting

INDICES  
i: Index of system buses ∀i ∈ Nb  
j: Index of system buses ∀j ∈ Nb  
k: Index of PV system  
t: Index of time

PARAMETERS AND VARIABLES  
δi,j: The voltage angles at buses i or j  
ηch/dis: Charging/discharging efficiencies of a BESS  
ω: The weighted factor  
σ: Binary decision variables

The associate editor coordinating the review of this manuscript and approving it for publication was Guijun Li.
I. INTRODUCTION

The penetration of distributed energy resources (DERs), particularly photovoltaic (PV) systems in distribution networks, has been increasing with the growing demand for reliable, sustainable, and clean energy. The efficient penetration of PV systems in a distribution network can provide system stability, power reliability, and quality improvement and can reduce energy losses [1]. Nevertheless, there are technical constraints that arise due to the increasing penetration of PV systems in the distribution network, such as an under/overvoltage, reverse power flow, overloading of feeders and transformers, and protection problems [2]–[4]. These constraints limit the maximum deployment of PVs in the distribution network, which is called the PV hosting capacity (PVHC) of the distribution network. The PVHC is a measure of the maximum amount of PVs that the network can accommodate without negatively impacting on the power quality and reliability of the distribution network [5]. An assessment of the PVHC in the distribution network has significant advantages for distribution network operators, DER owners, and consumers. The PVHC of the distribution network has been enhanced by network augmentation, network reconfiguration, and using different external devices to maintain the technical constraints within the permissible limit. One of the main constraints that limit the PVHC of a distribution network is the increase in voltage due to the high penetration of the PVs. Therefore, optimal voltage regulation can improve the PVHC of the distribution network. Conventionally, the voltage is regulated using on-load tap changers (OLTCs), voltage regulators, and switched capacitors. However, these devices have a limited number of switches and slow response times.

The new IEEE standards (IEEE 1547-2018) suggest that inverter-interfaced DERs can actively participate in grid support functions, such as voltage and frequency regulations [6]. The voltage regulation functionalities of the smart inverters are obtained by operating either active power control or reactive power control function modes [7]. The active power (Volt/Watt) control functions of the smart inverter regulate the local voltage by curtailing the active power. However, this function mode wastes energy and revenue and should be used as infrequently as possible. The reactive power control functions of the smart inverter regulate the local voltage by supplying or absorbing reactive power. It operates in different modes, including constant power factor mode, constant reactive power mode, active power reactive power mode (Watt/VAr), and voltage-reactive power mode (Volt/VAr).

In the Volt/VAr reactive power function mode, the smart inverter supplies or absorbs reactive power as a function of the local bus voltage using a predefined Volt/VAr control setting curve. The reactive power outputs and voltage regulation capability of the Volt/VAr mode of the smart inverters depend on the control setting curve. Hence, determining the optimal control of the Volt/VAr setting of the smart inverters can further improve the PVHC of a distribution network.

Battery energy storage systems have been a viable option for voltage regulation, smoothing the intermittent output of PVs, peak load shaving, and reducing power losses and line loading in distribution networks [8], [9]. However, the BESS has provided these services by only controlling the reactive power. The BESS provides a further ancillary service by controlling the reactive power of the smart inverter in the BESS and by selecting the optimal BESS size, power dispatch, and locations in the distribution networks [10]. The smart inverter functionality and interoperability of the BESS are tested in [11]. Therefore, a smart inverter for the BESS can provide grid support functionality similar to the smart...

|Symbol| Description |
|------|-------------|
|$\theta_{ij}$| Impedance angle of the line between bus $i$ and $j$ |
|$d$| Dead band |
|$E_B$| Battery energy |
|$F_1$| The objective function of maximization of the total PVHC |
|$F_2$| The objective function of minimization of the total VD |
|$I_{MPP}$| Current at the maximum power point |
|$I_{SC}$| Short-circuit current |
|$K_i$| Current temperature coefficient |
|$K_v$| Voltage temperature coefficient |
|$m$| Slope |
|$N_b$| Bus number |
|$N_PV$| Number of PV systems |
|$N_{total}$| Total number of modules |
|$N_T$| Total time |
|$NOCT$| Nominal operating cell temperature |
|OF| The total multi-objective function |
|$P_{BESS}$| The active power for the charging or discharging of a BESS |
|$P_{ch/disch}$| Charging/discharging power of a BESS |
|$P_D$| The active power demand |
|$P_{PV}$| Output power of the PV |
|$P_{PV,i}$| The daily maximum active output power of the PVs |
|$Q_D$| The reactive power demand |
|$Q_{PV/BESS}$| The reactive power from the PV/BESS smart inverters |
|$S_{ird}$| Solar irradiance |
|$S_{PV(OS)/BESS(OS)}$| The apparent power of oversized smart inverter for PV/BESS |
|$T_{amb}$| Ambient temperature |
|$T_{cell}$| Cell temperature |
|$U_{B_{ch/disch}}$| Maximum active power limit for the charging/discharging |
|$V_{min/max}$| Minimum/maximum value of voltage |
|$V_{MPP}$| Voltage at maximum power point |
|$V_{OC}$| Open circuit voltage |
|$V_r(v_r)$| Reference voltage |
|$W$| Weight of slime mould |
|$X$| Optimal location of slime mould |
|$Y_{ij}$| Element of the Y-bus matrix |
inverter for the PVs. In this study, the term “smart inverter for a BESS” is used to refer to the bidirectional converter with additional advanced features. Numerous methods have been studied in the literature to assess and improve the distribution network hosting capacity (HC) [12]. In [13], a stochastic analysis method was conducted to determine the HC of distribution networks. In this study, an active distribution network management method that includes the reactive power control of smart inverters for a PV system was used to improve the HC of the distribution network. In [14], static and dynamic network reconfigurations were used to improve the HC. In [15], the HC of the distribution network was improved using a robust optimal operation of the OLTC and static VAr compensator (SVC). In [16], reactive power control for central battery storage systems was used to improve the HC of the distribution network. This method reveals the effect of the size of the battery storage and inverter units on the HC of a distribution network. However, the coordination effect of the reactive power control of the PVs and BESSs on the HC of a distribution network was not studied in this method. In [17], a probabilistic method for hosting a high PV penetration in a distribution network using optimal oversized smart inverters with Watt/VAr functions was studied. In [18], smart inverter control strategies and a BESS were used to assess the practical margin PVHC. However, the effect of reactive power control of the smart inverter for a BESS on the PVHC of the distribution network was not considered with this method. Metaheuristic optimization methods have recently been used for assessing the optimal HC, such as the particle swarm optimization (PSO) [19], genetic algorithms (GA) [20], coyote optimization algorithm [21], modified African buffalo optimization [22], Grey wolf optimization [23], etc. Although the aforementioned methods assessed and improved the HC of the distribution networks, there is still room for further improvement by addressing the issues mentioned above.

In this paper, a method for improving the PVHC of a distribution network based on the optimal reactive power control of a smart inverter for PVs and BESSs is presented. An optimization approach is used to determine the optimal oversize, dispatch, and control setting of the Volt/VAr functions of smart inverters for the PVs and BESSs. In addition, the optimal locations, sizes, and power dispatch for the PVs and BESSs are determined simultaneously. The problem is formulated as a multi-objective optimization method with the objective of maximizing the PVHC and minimizing the voltage deviation (VD) at the same time. A swarm intelligence-based metaheuristic optimization method, i.e., a slime mould algorithm (SMA), is used to solve the optimization problem. Six test cases were simulated on the IEEE 33-node systems using MATLAB software. The simulation results show that the optimized Volt/VAr functions of the smart inverter for the PVs and BESSs have the highest improvement in the total PVHC of the distribution network.

The main contributions of this study are as follows:
1) Smart inverter control: An optimal size, dispatch, and control setting of the Volt/VAr functions of smart inverters for both PVs and BESSs are determined to improve the PVHC.
2) Optimal allocation of PVs and BESSs in the distribution network: The proposed method determines the optimal locations, sizes, and power dispatches of PVs and BESSs in the distribution network.
3) Improving PVHC and minimizing VD of the distribution network: The proposed method improves the PVHC and minimizes the VD of the distribution network at the same time by optimally coordinating PVs and BESSs smart inverter and determining the optimal locations of PVs and BESSs.

Furthermore, comparisons with the default Volt/VAr control settings and conventional metaheuristic optimization methods show that the proposed method has the maximum improvement in the PVHC of the distribution network. The rest of the paper is structured as follows: Section II describes the modeling of solar irradiance, PV systems, BESS, and smart inverter. The proposed PVHC improvement method is presented in Section III. The problem formulation and the SMA optimization algorithm are also described in Section III. Section IV presents the simulation results. Finally, the paper is concluded in Section V.

II. SYSTEM MODELING
A schematic diagram of the system is presented in Fig. 1. The studied system consists of PV arrays, battery banks, smart inverters for PVs and BESSs, different types of loads, the main grid, and transformers. The active and reactive power flow directions are indicated by the black and red arrows, respectively. The BESS can absorb or supply both active and reactive power, whereas the PV system can supply active power to the system and absorb or supply reactive power. The subsequent subsections thoroughly describe the modeling of solar irradiance, PV systems, BESS, and smart inverters.

A. MODELING OF SOLAR IRRADIANCE
The solar irradiance is modeled using a beta distribution to adequately represent variations in solar irradiance [24]. The

FIGURE 1. Schematic diagram of the studied system.
probabilistic density function of the beta distribution for \( \alpha, \beta \geq 0 \), is given as follows:

\[
f(S_{ird} | \alpha, \beta) = \begin{cases} \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \Gamma(\beta)} \times S_{ird}^{\alpha-1} \times (1 - S_{ird})^{\beta-1}, & \text{for } 0 \leq S_{ird} \leq 1 \\ 0, & \text{otherwise} \end{cases}
\]

(1)

where \( \Gamma \) is the gamma function and \( \alpha \) and \( \beta \) are the shape parameters of the beta distribution. The values of the \( \alpha \) and \( \beta \) parameters are estimated using the maximum likelihood estimation from the available data. Subsequently, the Monte Carlo simulation is used to generate samples from the beta distribution.

**B. MODELING OF PV SYSTEMS**

PV systems consist of PV arrays, which generate power from sunlight, and smart inverters, which convert the DC output power of the PVs into AC power with additional functionalities. The PV output power depends on the solar irradiance and ambient temperature. The calculation for the output power of the PV (\( P_{pv} \)) from the solar irradiance and the ambient temperature is described in (2)–(5) [24]:

\[
T_{cell} = T_{amb} + \frac{S_{ird}}{0.8} \times (NOCT - 20) \\
I_{cell} = S_{ird} \times (I_{sc} + K_i \times (T_{cell} - 25)) \\
V_{cell} = V_{oc} - K_i \times T_{cell} \\
P_{pv} = N_{total} \times \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}} \times V_{cell} \times I_{cell}
\]

(2)

(3)

(4)

(5)

**C. MODELING OF BESS**

The BESSs consist of battery banks, charge controllers, and bidirectional smart inverters. Batteries are the primary component of a BESS, which stores electrical energy in the form of chemical energy. The state of charge (SOC) of the battery, which indicates the available energy in the battery, can be calculated as follows:

\[
SOC_i(t) = SOC_i(t-1) + \left( \frac{\sigma_i \eta_{ch} P_{ch,i}(t)}{E_{B_i}} \frac{E_{B_i}}{(1 - \sigma_i) P_{dis,i}(t)} \right) \Delta t
\]

(6)

In this study, we use a BESS model that helps to optimally utilize BESS and accurately determine the reactive output power of a BESS smart inverter. The battery banks are assumed to start charging when the total generated power of the PVs is greater than the total load and discharge when the total generated power of the PVs is less than the total load. This helps to charge the batteries during off-peak hours and discharge during peak hours. The battery banks are not charging above the maximum SOC (\( SOC_{max} \)) and discharging below the minimum SOC (\( SOC_{min} \)).

Furthermore, only one complete charging and discharging cycle is executed daily to increase the life span of the batteries. The maximum active power limit for the charging (\( UB_{ch,i} \)), discharging (\( UB_{dis,i} \)) of the BESS, and the binary decision variables (\( \sigma_i \)) at a given time \( t \) can be expressed as (7)–(9) [10]:

\[
UB_{ch,i}(t) = \begin{cases} 0, & \text{if } SOC_i(t) = SOC_{max} \\
-\frac{P_{max_{ch,i}}}{\eta_{ch,i}} \frac{E_{B_i}}{\Delta t} & \text{if } SOC_i(t) + \frac{\eta_{ch,i} P_{max_{ch,i}}}{E_{B_i}} \Delta t \leq SOC_{max} \forall i, t \\
-\frac{P_{max_{ch,i}}}{\eta_{ch,i}} \frac{E_{B_i}}{\Delta t} & \text{if } SOC_i(t) + \frac{\eta_{ch,i} P_{max_{ch,i}}}{E_{B_i}} \Delta t > SOC_{max} \end{cases}
\]

(7)

\[
UB_{dis,i}(t) = \begin{cases} 0, & \text{if } SOC_i(t) \leq SOC_{min} \\
-\frac{P_{max_{dis,i}}}{\eta_{dis,i} E_{B_i}} \Delta t & \text{if } SOC_i(t) - \frac{P_{max_{dis,i}}}{\eta_{dis,i} E_{B_i}} \Delta t \geq SOC_{min} \forall i, t \\
-\frac{P_{max_{dis,i}}}{\eta_{dis,i} E_{B_i}} \Delta t & \text{if } SOC_i(t) - \frac{P_{max_{dis,i}}}{\eta_{dis,i} E_{B_i}} \Delta t < SOC_{min} \end{cases}
\]

(8)

\[
\sigma = \begin{cases} 1, & \text{if } \sum_{k=1}^{N_{pv}} P_{PV_k}(t) \geq P_{D_T}(t) \\
0, & \text{if } \sum_{k=1}^{N_{pv}} P_{PV_k}(t) < P_{D_T}(t) \end{cases}
\]

(9)

**D. SMART INVERTER MODELING FOR PV AND BESS**

A smart inverter is used to interface the DC output of the DERs, such as the PVs and BESSs, into the AC grid with additional grid supportive functionality. This functionality includes the adoption of reactive power functions to provide adequate local voltage regulation for a voltage variation caused by the intermittent nature of the DERs. In this study, the Volt/Var function of a smart inverter for both PVs and BESSs is considered to improve the PVHC of the distribution network.

The Volt/Var function mode of the smart inverter can provide a certain amount of reactive power as a function of the local voltage according to the control setting curve, as shown in Fig. 2. From this control setting curve, the smart inverter does not supply any reactive power during the dead band (\( d \)) range. If the voltage is below \( v_2 \), the smart inverter operates in a capacitive mode, thereby supplying reactive power. In addition, if the voltage is above \( v_3 \), the smart inverter operates in an inductive mode, thereby absorbing the reactive power. Moreover, when the voltage is between \( v_1 \) and \( v_2 \) as well as \( v_3 \) and \( v_4 \), the smart inverter supplies and absorbs reactive power as a function of the slope (\( m \)), respectively. Conventionally, the control setting curve points of the smart inverter are set to the default values [25]. In this study, the optimal control setting curve points (\( v_1, v_2, v_3, \) and \( v_4 \)) for both PV and BESS smart inverters are determined based on the dead band.
The oversized smart inverter for a PV and a BESS can be increased the headroom for the reactive power of the power output and inverter size. Hence, oversizing the inverter this mode wastes the generated active power. The reactive inverters.
during the day and night for both the PV and BESS smart inverters. However, curtailing the active power when there is insufficient headroom for the reactive power in the smart inverter. However, this mode wastes the generated active power. The reactive power output of the smart inverter depends on the active power output and inverter size. Hence, oversizing the inverter can increase the headroom for the reactive power of the smart inverter. The maximum available reactive power from the oversized smart inverter for a PV and a BESS can be expressed as follows:

\[ Q_{PV}^{\text{max}} = \sqrt{S_{PV(OS)}^2 - P_{PV}^2} \] \hspace{1cm} (11)

\[ Q_{BESS}^{\text{max}} = \sqrt{S_{BESS(OS)}^2 - P_{BESS}^2} \] \hspace{1cm} (12)

where \( S_{PV(OS)} \) and \( S_{BESS(OS)} \) are the apparent power of the oversized smart inverter for a PV and a BESS, respectively; \( P_{BESS} \) is the active power for the charging or discharging of a BESS; and \( Q_{PV}^{\text{max}} \) and \( Q_{BESS}^{\text{max}} \) are the maximum reactive power of a PV and BESS, respectively. In this study, the watt-priority Volt/VAr function mode of the smart inverter is considered, and the reactive power is generated or absorbed during the day and night for both the PV and BESS smart inverters.

III. PROPOSED PVHC IMPROVEMENT METHOD

This section presents an optimization approach for determining the proposed PVHC improvement method. The PVHC improvement is assessed by acquiring the optimal Volt/VAr function mode of the smart inverter for both PV and BESS. A multi-objective optimization method is utilized to simultaneously establish the maximum PVHC and minimum VD by determining the optimal oversize, dispatch, and control setting of the Volt/VAr functions of the smart inverters for PVs and BESSs. Concurrently, the optimal locations of the PVs and BESSs are also determined. SMA is used to obtain the optimal values of the decision variables for improving the PVHC. The formulation of the problem and the SMA optimization method are described in the subsequent subsections.

A. PROBLEM FORMULATION

The problem of the proposed PVHC improvement method is formulated as a multi-objective mixed-integer nonlinear optimization problem. The considered multi-objective functions and the operational constraints are described as follows:

1) OBJECTIVE FUNCTIONS

Two objective functions were considered in this study. The first objective function \((F_1)\) is the maximization of the total PVHC of the distribution networks, as presented by (13), and the second objective function \((F_2)\) is the minimization of the total VD in the distribution networks, as presented by (14).

\[ F_1 = \max PVHC = \sum_{k=1}^{N_{PV}} P_{PV_k}^M \] \hspace{1cm} (13)

\[ F_2 = \min VD = \sum_{i=1}^{N_T} \sum_{t=1}^{N_b} \left( \frac{V_i(t) - V_r}{V_r} \right)^2 \] \hspace{1cm} (14)

where \( P_{PV_k}^M \) is the daily maximum active output power of the PVs, \( N_{PV} \) is the number of PV systems, \( k \) is the PV system index, \( N_b \) is the bus number, \( N_T \) is the total amount of time, \( V_i(t) \) is the magnitude of the voltage at bus \( i \) and time segment \( t \), and \( V_r \) is the reference voltage for all buses. To solve these two objective functions simultaneously, a weighted sum-based multi-objective optimization method is used as shown in (15).

\[ \max OF = \omega_1 F_1 - \omega_2 F_2 \] \hspace{1cm} (15)

where \( \omega_1 \) and \( \omega_2 \) are the weighted factors for each objective function and the sum of their values should be 1. Selecting different combination values for the weighted factors provides different optimization results. In this study, the weighted factors were selected by trial and error.

2) CONSTRAINTS

The optimization problem is subjected to the following equality and inequality constraints.

\[ P_{Grid}(t) + P_{PV}(t) + P_{BESS}(t) - P_D(t) \]
\[ V(t) = \sum_{j=1}^{N_b} V_j(t) Y_{ij} \cos(\theta_{ij}) + \delta_j(t) - \delta_i(t) \]  
\[ Q_{\text{Grid}}(t) + Q_{PV}(t) \pm Q_{\text{BESS}}(t) - Q_D(t) \]
\[ = -V(t) \sum_{j=1}^{N_b} V_j(t) Y_{ij} \sin(\theta_{ij}) + \delta_j(t) - \delta_i(t) \]

where (16) and (17) represent the power balance constraint at each node. In addition, \( P_{\text{Grid}} \) and \( Q_{\text{Grid}} \) are the active and reactive power of the grid at the slack bus, respectively; \( P_{\text{PV}} \) and \( Q_{\text{PV}} \) are the active power from the PV and \( \text{BESS} \), the reactive power of the grid at the slack bus, respectively; \( I_{i,j} \) are the active and reactive power of demand at bus \( i \) and time \( t \), respectively; \( Y_{ij} \) is the element of the Y-bus matrix; \( \theta_{ij} \) is the impedance angle of the line between bus \( i \) and \( j \); and \( \delta_i \) and \( \delta_j \) are the voltage angles at buses \( j \) and \( i \), respectively. Equation (18) indicates that the voltage at each node must be within the minimum voltage \( (V_{\min}) \) and maximum voltage \( (V_{\max}) \) limit. The limit of the current carrying capacity (ampacity) of the line between buses \( i \) and \( j \) is given in (19). Equations (20) and (21) represent the integration limit of PVs power and \( \text{BESS} \) energy at bus \( i \), respectively. Equations (21)–(24) describe the \( \text{BESS} \) constraints. The difference between the SOC at an \( N_T \) time interval and the initial SOC should be minimized to fully utilize one complete charging and discharging cycles daily. Equations (25)–(28) express the constraints of the smart inverter for both PVs and BESSs. The oversized smart inverters for PV and \( \text{BESS} \) (\( S_{\text{PV}(os)} \) and \( S_{\text{BESS}(os)} \)) are limited between the minimum \( (S_{\text{PV,min}}) \) and \( (S_{\text{BESS,min}}) \) and maximum \( (S_{\text{PV,max}}) \) and \( (S_{\text{BESS,max}}) \) values as shown in (25) and (26), respectively. The slope \( (m) \) and dead band \( (d) \) of the Volt/VAr control setting of the smart inverter for both PV and \( \text{BESS} \) are limited to the minimum \( (m_{\min}) \) and \( (m_{\max}) \) and maximum \( (m_{\max}) \) and \( (d_{\max}) \) values as shown in (27) and (28), respectively.

### B. SLIME MOULD ALGORITHM

The SMA is a new biologically inspired metaheuristic optimization method proposed in [26]. The SMA mimics the foraging of slime mould to find the optima of the problem. The slime mould searches for food by producing a propagating wave based on bio-oscillations, creating the optimal route for connecting food. The SMA mathematically expresses the slime mould food searching ability using adaptive weights that simulate the slime mould bio-oscillator. The food approach behavior of a slime mould can be imitated through the following mathematical expression:

\[ X(l+1) = \begin{cases} 
\text{rand} \cdot (UB - LB) + LB, & \text{rand} < y \\
X_b(l) + u_b \cdot (W \cdot X_A(l) - X_b(l)), & r < p \\
u_c \cdot X(l), & r \geq p 
\end{cases} \]

Here, \( LB \) and \( UB \) are the lower and upper bound, respectively, \( r \) and \( \text{rand} \) are the random numbers between \([0, 1]\), and \( y \) is the constant parameter. The parameter \( u_b \) is within a limit of \([-a, a]\), \( u_c \) decreases linearly from 1 to 0, in which \( l \) denotes the current iteration, and \( X_b \) and \( X_b \) are the location of the slime mould and the location of the individual slime mould with the highest odor concentration, respectively. In addition, \( X_A \) and \( X_b \) denote randomly selected individuals from the swarm and \( W \) is the weight of slime mould. The value of \( p \) is given by (30).

\[ p = \tanh |S(z) - D_F| \]

where \( z \in 1, 2, \ldots, n \), \( S(z) \) and \( D_F \) are the fitness of \( X \), and the best fitness obtained in all iteration, respectively. The value of \( u_b \) obtained as follows:

\[ u_b = [-a, a] \]

\[ a = \text{arctanh} \left( -\left( \frac{1}{\max_l} \right) + 1 \right) \]

The positive and negative feedback between the slime mould vein width and food concentration is simulated mathematically as follow:

\[ W(\text{SmellIndex}(l)) = \begin{cases} 
1 + r \log \left( \frac{b_F - S(z)}{b_F - w_F} + 1 \right), & \text{condition} \\
1 - r \log \left( \frac{b_F - S(z)}{b_F - w_F} + 1 \right), & \text{others} 
\end{cases} \]

\[ \text{SmellIndex} = \text{sort}(S) \]

Here, \( b_F \) and \( w_F \) are the best and worst fitness values during the current iterative process, respectively, \( r \) is a random number between \([0, 1]\), \( \text{condition} \) indicates that \( S(z) \) ranks the first half of the population. \( \text{SmellIndex} \) denotes the sorted fitness values. The SMA pseudo-code is presented in Algorithm 1.
Algorithm 1 Pseudo-Code of SMA [26]

Initialize the population size and max iteration \((max_l)\);
Initialize the position of slime mould \(X_z (z=1,2,…,n)\);

While \((l\leq max_l)\)

Calculate the fitness of all slime mould;
Update bestFitness, \(X_b\);
Calculate the \(W\) by Eq.(33);
For each search portion
Update \(p, u_b, u_c\);
Update position by Eq.(29);
End For
\(l=l+1\);
End While
Return bestFitness, \(X_b\);

FIGURE 3. Flowchart of the proposed method.

A flowchart representation of the proposed method is shown in Fig. 3. The flowchart of the proposed method can be explained as follows. First, the data, such as the power system data, the solar irradiance, and load data are collected. Then, the SMA maximum population, decision variables, and maximum iterations \((max_l)\) are specified for the optimization process and initialize the random positions of the slime mould. The SMA search agent can be represented as vector \(X_z\) whose elements are the values of the decision variable i.e., location of PVs and BESSs, the oversize and Volt/Var control settings of the smart inverters, and the charging and discharging power of BESSs. This search agent represents the position of the slime mould. Then, apply the load flow calculation for the 24-h duration and check the constraints are within the limit in each time interval. If the constraints are not met, the objective function will be penalized. Subsequently, the value \(a, p, u_b, u_c\), and \(W\) of SMA are updated as given in (30–33) until the maximum iteration is reached. In each iteration, the objective function is estimated for each of the slime mould and the best position is updated as given in (29). Finally, select the best position of slime mould, i.e., location of PVs and BESSs, the oversize and Volt/Var control settings of the smart inverters, and the charging and discharging power of BESSs, which give the best objective function i.e., maximum PVHC and minimum VD.

IV. SIMULATION RESULTS

Extensive simulations were conducted using MATLAB software to demonstrate the effectiveness of the proposed PVHC improvement method. The details of the test system, case studies, comparison with the default Volt/Var control settings
TABLE 2. Simulation results of the optimal size and location of PVs and BESSs, total PVHC, VD, and smart inverter oversize (OS) for PVs and BESSs.

| Cases | PV No. | Optimal location of PVs | \( P_{PV}^M \) (MW) | BESS No. | Optimal location of BESS | Energy of BESS (MWh) | Total PVHC (MW) | VD (pu) | \( S_{PV(OS)} \) (%) | \( S_{BESS(OS)} \) (%) |
|-------|--------|-------------------------|----------------------|----------|------------------------|---------------------|----------------|---------|----------------|------------------|
| 1     | PV1    | 28                      | 0.8379               | —        | —                      | —                   | 1.1783         | —       | 92.89           | —                |
| 2     | PV1    | 2                       | 6.6482               | —        | —                      | —                   | 7.9150         | 0.0637  | 20.15           | —                |
|       | PV3    | 14                      | 0.4288               | —        | —                      | —                   | 85.39          | —       | —                | —                |
| 3     | PV1    | 16                      | 5.4919               | BESS1    | 12                     | 4.5339              | 8.3459         | 0.2504  | —                | —                |
|       | PV3    | 31                      | 1.7780               | —        | —                      | —                   | —              | —       | —                | —                |
| 4     | PV1    | 13                      | 0.4112               | BESS1    | 4                      | 5.2626              | 98.05          | —       | —                | —                |
|       | PV1    | 2                       | 7.4155               | BESS2    | 23                     | 4.6848              | 8.5991         | 0.0602  | 20.63           | —                |
|       | PV3    | 30                      | 0.7724               | —        | —                      | —                   | 95.00          | —       | —                | —                |
|       | PV3    | 3                       | 4.6058               | BESS1    | 5                      | 5.0769              | 8.6838         | 0.0526  | 92.81           | —                |
|       | PV1    | 3                       | 8.4063               | BESS2    | 8                      | 5.3903              | 9.2833         | 0.0139  | 95.89           | 54.01            |

FIGURE 5. Hourly sampled solar irradiance and load profile data.

and with conventional metaheuristic optimization methods are described in the subsequent sections.

A. TEST SYSTEMS

The IEEE 33-node test system was used to assess the efficacy of the proposed PVHC improvement method. This test system operates at a base voltage of 12.66 kV and a base apparent power of 10 MVA. This test system has 33-buses, 3 laterals, and 32 branches. Detailed specifications of the line and bus data of the IEEE 33-node system were obtained from [28]. The single-line diagrams of the IEEE 33-node systems along with the assigned load types are demonstrated in Fig. 4. Loads of the IEEE 33-node test systems are assigned based on the daily residential, commercial, and industrial load profiles during summer with a 1-h interval obtained from [29]. To determine the uncertain solar irradiance samples, hourly summer solar irradiance data of 5 years (2015–2019) obtained from the National Renewable Energy Laboratory (NREL), National Solar Radiation Database (NSRDB) [30] were used in this study. Fig. 5 illustrates the hourly sampled solar irradiance and load profile data.

As suggested in [31], three distributed PVs are selected as the optimal number of PVs for the IEEE 33-node test system. The parameters of the PV module are obtained from [9]. The total number of modules is determined optimally for each PV to determine the optimal size of the PVs integrated into the test system. Two distributed BESSs are selected as the economical and optimal number of BESSs for the IEEE 33-node test system. The PVs and BESSs are integrated as a negative load and can connect to all buses except bus 1 (slack bus). The backward/forward sweep load flow method was used to solve the load flow equation. The minimum and maximum voltage magnitudes across all buses are considered within the ANSI standard limit (0.95 pu \( \leq V \leq 1.05 \text{ pu} \)). The maximum current carrying capacity limit of each branch of the IEEE 33-node test system is obtained from [32]. The maximum active and reactive power exchange with the upstream utility grid is 6 MW and 3 MVar, respectively. Table 1 summarizes the values of the parameters used in the optimization algorithm.

B. CASE STUDIES

Six cases were executed in the IEEE 33-node test system to verify the effectiveness of the proposed method. The first case (case 1) represents the base case where PV and BESS are not integrated into the test system. Cases 2 and 3 examine the PVHC of the test system by optimally controlling the smart inverter for the PVs and by optimally integrating the BESSs, respectively. In case 3, the reactive power function of the smart inverter is not considered for both the PVs and the BESSs. In case 4, the PVHC of the test system is examined using BESSs and optimal smart inverter control for only the PVs. In case 5, the PVHC of the test system is investigated using BESSs and optimal smart inverter control for only the BESSs. In case 6, the optimal smart inverter control for both PVs and BESSs is used to improve the PVHC of the test system.
Table 2 presents the simulation results obtained for each case. Case 1 shows the VD of the IEEE 33-node test system without integrating the PVs and BESSs. It can be observed that the optimal integration of PVs with optimal smart inverter control in case 2 reduced the VD in comparison with that in case 1. The results of case 3 show that the PVHC is
improved, whereas the VD is increased compared with that of case 2. The optimal integration of the BESSs and optimal smart inverter control for the PVs in case 4 further improved the PVHC and minimized the VD compared to those in cases 2 and 3. The results of case 5 show that using the BESSs with optimal smart inverter control improves the PVHC and minimizes the VD compared with cases 2–4. The case proposed in this study is case 6, which determined the PVHC and VD by finding the optimal location, Volt/VAr control setting, and by oversizing the smart inverter for both PVs and BESSs. The results show that case 6 exhibited the highest improvements in the PVHC and minimum VD in comparison with the other cases.

Fig. 6 shows the optimal Volt/VAr control setting for each smart inverter of the PVs and BESSs for cases 2, 4, 5, and 6, respectively. It can be seen that the control setting for each smart inverter is autonomously determined based on the local voltage. Fig. 7 shows the reactive power output of the smart inverter for the PVs and BESSs at the optimal location on the test system for cases 2, 4, 5, and 6, respectively. It was observed that the smart inverters for the PVs and BESSs also provides reactive power during night time and when there is no charge or discharge of the BESSs. This shows that the smart inverter for the PVs and BESSs can operate as a STATCOM at night and during the ideal time period.

Fig. 8 shows the status of the hourly SOC for the two distributed BESSs at the optimal location of the test system in case 6. The figure shows that both distributed BESSs are charged during a high generation of PVs and discharged during on-peak load hours, providing peak shaving. Fig. 9 shows the bus voltage for all buses at each time interval for all cases.
TABLE 3. Comparison of optimal Volt/VAr control setting with default Volt/VAr control setting.

| Cases | Optimal location of PVs | Optimal location of BESS | Total PVHC (MW) | VD (pu) | Optimal location of PVs | Optimal location of BESS | Total PVHC (MW) | VD (pu) |
|-------|--------------------------|--------------------------|-----------------|--------|--------------------------|--------------------------|-----------------|--------|
| 2     | 33, 18, and 2            | 9 and 8                  | 7.5752          | 0.1228 | 28, 2, and 14            | 4 and 23                | 7.9150          | 0.0637 |
| 4     | 32, 3, and 16            | 18 and 33                | 8.3993          | 0.1200 | 13, 2, and 30            | 5 and 8                | 8.5991          | 0.0602 |
| 5     | 16, 2, and 28            | 16 and 33                | 8.5997          | 0.1328 | 3, 10, and 19            | 5 and 8                | 8.6838          | 0.0526 |
| 6     | 31, 2, and 15            | 16 and 33                | 8.9621          | 0.0501 | 5, 31, and 12            | 24 and 11              | 9.2833          | 0.0139 |

TABLE 4. Comparison with conventional metaheuristic optimization methods.

| Cases | Optimal location of PVs | Optimal location of BESSs | Total PVHC (MW) | VD (pu) | Optimal location of PVs | Optimal location of BESSs | Total PVHC (MW) | VD (pu) |
|-------|-------------------------|----------------------------|-----------------|--------|-------------------------|----------------------------|-----------------|--------|
| 2     | 10, 30, and 2           | 33, 9, and 2              | 6.0412          | 0.0876 | 9, 2, and 14           | 28, 2, and 14           | 7.7991          | 0.0839 |
| 3     | 21, 6, and 27           | 6, 19, and 2              | 7.3999          | 0.1228 | 12, 29, and 2           | 6 and 30              | 7.8999          | 0.0891 |
| 4     | 12, 29, and 2           | 3, 15, and 33             | 8.3495          | 0.1328 | 12, 29, and 2           | 9, 12, and 24         | 8.3499          | 0.0839 |
| 5     | 19, 4, and 30           | 5, 16, and 2              | 7.4999          | 0.0501 | 5, 16, and 2            | 27 and 7             | 7.4999          | 0.0501 |
| 6     | 9, 2, and 33            | 2, 10, and 32             | 9.1945          | 0.0139 | 9, 2, and 33            | 20, 12, and 32        | 9.2833          | 0.0139 |

From the Fig. 9, case 6 provides nearly flat voltage profile with a minimum voltage of 0.9860 pu and a maximum voltage of 1.0148 pu compared to other cases.

C. COMPARISON WITH DEFAULT VOLT/VAr CONTROL SETTINGS OF SMART INVERTER

The proposed optimal oversize, dispatch, and control settings of the Volt/VAr functions of smart inverters for PVs and BESSs are compared with the default Volt/VAr control settings. Accordingly, the default Volt/VAr control points are set as \( v_1 = 0.92 \text{ pu} \), \( v_2 = 0.98 \text{ pu} \), \( v_3 = 1.02 \text{ pu} \), \( v_4 = 1.08 \text{ pu} \), and \( v_r = 1 \text{ pu} \) with an inverter oversize of 10% [25].

D. COMPARISON WITH CONVENTIONAL METAHEURISTIC OPTIMIZATION METHODS

The performance of the proposed SMA optimization is compared with the existing conventional metaheuristic optimization methods (GA and PSO). For this comparison, GA with the population size and the maximum generations of 100, the crossover and mutation probability of 0.8 and 0.01, respectively were used [20]. Similarly, PSO with the population size and the maximum iteration of 100, acceleration factor \( (c_1 \text{ and } c_2) \) of 2, and the inertia weight \( (\omega_{\text{max}} \text{ and } \omega_{\text{min}}) \) of 0.4 and 0.9, respectively were used [19].

The results are summarized in Table 4 and from the comparison, it can be concluded that the SMA optimization methods can outperform GA and PSO in finding the globally optimal values in each cases.

V. CONCLUSION

Based on the advent of smart inverters that provide grid support functions, this paper proposed an optimal reactive power (Volt/VAr) control of the smart inverters for PVs and BESSs to improve the PVHC in distribution networks. The proposed method optimally coordinate PVs and BESSs smart inverter oversize, dispatch, and control settings to improve the PVHC of the distribution network. In addition, the optimal locations, sizes, and power dispatches of the PVs and BESSs were determined. The problem was formulated as a multi-objective mixed-integer nonlinear optimization to simultaneously maximize the PVHC and minimize the VD. The recent bio-inspired metaheuristic optimization method called SMA was used to solve the optimal solutions. Moreover, six test cases were simulated on an IEEE 33-node test system using MATLAB software. The simulation results showed that the proposed optimal Volt/VAr control of the smart inverters for both PVs and BESSs case maximize the PVHC and minimize the VD compared to other cases. Furthermore, the proposed method has superior performance compared to the default control setting of the Volt/VAr functions of the smart inverters and conventional metaheuristic optimization methods. In future work, the effects of optimal smart inverter settings on distribution network faults and the coordination of smart inverter with legacy active network management to improve PVHC will be studied.

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