IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received January 7, 2020, accepted January 11, 2020, date of publication January 14, 2020, date of current version January 24, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2966571

Modified African Buffalo Optimization for Strategic Integration of Battery Energy Storage in Distribution Networks

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ABSTRACT This article presents a two-layer optimization scheme for simultaneous optimal allocation of wind turbines (WTs) and battery energy storage systems (BESSs) in power distribution networks. The prime objective of this formulation is to maximize the renewable hosting capacity of the system. For outer-layer, a new objective function is developed by combining multiple objectives such as annual energy loss in feeders, back-feed power, BESSs conversion losses, node voltage deviation, and demand fluctuations caused by renewables subject to various system security and reliability constraints. Furthermore, a modified variant of African buffalo optimization (ABO) introduced to overcome some of the limitations observed in its standard variant. The proposed modifications are first validated and then introduced for simultaneous optimal integration of multiple distributed energy resources in distribution systems. The proposed modified ABO is employed to determine the optimization variables of outer-layer. Whereas, a heuristic is proposed to solve the inner-layer optimization problem aiming to determine the optimal dispatch of BESSs suggested by outer-layer optimization. By considering the high investment and operating cost of BESSs, minimum energy storage capacity has been ensured during the planning stage. To present the efficacy of developed model, it is implemented on a 33-bus, benchmark test distribution system for various test cases. The comparative simulation results show that the proposed optimization model and modified ABO is very promising to improve the performance of active distribution systems.

INDEX TERMS African buffalo optimization, battery energy storage system, distribution systems, distributed generation, optimization, renewables.

NOMENCLATURE

$B^{\max}$	Maximum BESS capacity allowed to integrate at any node (kWh)
B_j^r	Rated capacity of BESS to integrate at node j (kWh)
$b_{\min}, b_{\max}$	Minimum and maximum permissible location limits of buffaloes in ABO
h_{best}	Best fitness values of buffalo herd
$I_{jk}^{\max}$	Maximum current limit of the line connecting nodes j and k (A)
I_{jk}	Current of branch connecting nodes j and k (A)
I_{ss}	Back feed current (A)
L_D	Maximum allowed load deviation
l_{p1}, l_{p1}	Learning factors of ABO
m_i, w_i	Exploitation & exploration moves of ABO
N	Total number of nodes in the system.
n_p	Population size in ABO
P_j	Real power injection at bus j (kW)
P_{grid}	Amount of power purchase from the grid (kW)
P_G^T	Total power generation of the system (kW)
P_D^T	Total real power demand of the system (kW)
$\overline{P_{\text{grid}}}$	Mean of grid power purchase over time period T (kW)
P_D^{peak}	Annual peak demand of the system (kW)

The associate editor coordinating the review of this manuscript and approving it for publication was Fabio Massaro.

$P_{dis}^{\max}$	Maximum discharging power of BESS at any time (kW)
$P_{char}^{\max}$	Maximum charging power of BESS at any time (kW)
P_{C/D_j}^{bess}	Real power dispatch of BESS at node j (kW)
P_j^{wt}	Wind power generation at node j (kW)
P_{D_j}	Load demand at node j (kW)
$P_{wt_j}^r$	Rated capacity of WT installed at node j (kW)
$P_{wt}^{\max}$	Maximum capacity of WT allowed to integrate at any node (kW)
Q_j	Reactive power injection at bus j (kVAr)
r_{jk}	Resistance of the line connecting nodes i and j (per-unit)
r	Randomly selected buffalo from upper half population
r_1, r_2	Random numbers between 0 & 1
$s_{best,i}$	Individual best fitness of buffalo i
SOC_j	State of charge of BESS at node j
$SOC^{\max}$	Maximum SOC limit of the BESS
$SOC^{\min}$	Minimum SOC limit of the BESS
T	Number of load levels considered in a day
t	Time
V_{ss}	Grid substation bus voltage (per-unit)
V_j	Voltage magnitude at node j (per-unit)
$V^{\min}$	Minimum specified node voltage limit (per-unit)
$V^{\max}$	Maximum specified node voltage limit (per-unit)
v_j	Wind velocity at node j (m/s)
$v^{\text{cut-out}}$	Cut-out velocity of WT (m/s)
$v^{\text{cut-in}}$	Cut-in velocity of WT (m/s)
v^r	Rated velocity of WT (m/s)
Y_{jk}	Elements of Y_{bus} matrix (mho)
η	Round trip efficiency of BESS conversion system
$\Re$	Real part of the expression
Φ	Daily to annual conversion factor
δ_j	Voltage angle at node j (rad.)
σ_j	Binary decision variable of WT integration at node j
ρ_j	Binary decision variable of BESS integration at node j
α_j	Binary decision variable for BESS charging at node j
θ_{jk}	Impedance angle of line between nodes j and k

I. INTRODUCTION

In last few decades, the rapid advancements in distributed energy resource (DER) technologies have made modern distribution systems more upgraded in terms of reliability, security and robustness [1]–[5]. The inclusion of DER, along with modern information and communication technologies, has been changed the traditional consumer only image of distribution networks while improving the efficiency of power delivery in more controlled way. The globally deteriorating environmental condition and limiting conventional energy resources along with the availability of different DERs have promoted the large-scale integration of renewable energy resources (RER) in distribution networks [6]–[9]. The optimally or strategically deployed RER based DERs can generate numerous amount of technical, environmental and economical benefits for distribution network operator (DNO), consumer and DER owner. Some of these can include power/energy loss reduction [4], power quality improvement, reduced greenhouse gas emission, voltage profile [10], stability [4], [11] and reliability improvement, and investment postponement. However, the non-optimal allocation of DERs can produce counter-productive results.

On the other hand, the high penetration of renewables can jeopardize the system stability and security as traditional distribution systems were not designed to host the high renewable penetration. The high penetration of renewables increases the fault level and a surplus generation during light load hours can blind the conventional unidirectional protection schemes. The power generation from solar photovoltaic (PV) and wind turbine (WT) is limited by high intermittency associated to solar irradiation and wind speed respectively. The fluctuating power generation from such DERs can cause erroneousness in power scheduling of DNO at grid supply point, sometimes attract unscheduled interchange (UI) charges. Moreover, the quick growth of solar PVs also reduces the system inertia which may affect the grid stability if adequate technologies have not been adopted.

To overcome some of the limitations of variable solar and wind power generations, various planning and operational management models, and strategies have been studied in existing literature [12]–[15]. In [6], [9], optimization frameworks have been devised to integrate high renewable penetration in distribution systems. Some optimal switching arrangements are proposed for solar photovoltaic and wind power generations to utilize these resources as dispatchable energy resources. Furthermore, the continuous advancements in battery energy storage technology have led to the large-scale integration of battery energy storage system (BESS) in distribution systems. The optimal deployment of BESS can provide various techno-economic benefits as good as other DERs. The energy storage units not only supply/consume power in critical hours but also provide virtual inertia and improve the operational flexibility of the system by effective charging and discharging algorithms. Nowadays, the BESS is also supporting some of the grid ancillary services known as ‘distributed ancillary services’ [16]. Additionally, the effective management of BESS generates profit from energy arbitrage, peak-load shaving, load-shifting, demand response programs, and improved operational flexibility of the system.

The optimal and effective integration of BESS is a challenging task and not simple as distributed generations (DGs). Unlike DG, the optimal integration of BESS is limited by timely availability of state-of-charge (SOC), its associated constraints, charging-discharging decisions, number of life cycles, and dispatch control. In literature, various planning and operation strategies have been suggested for optimal integrate the BESS in distribution systems. Some optimization problems are developed in [15], [17], [18] for optimal BESS allocation in active distribution system with wind power generation. The Monte-Carlo simulation, and a chance-constrained optimization model is developed in [15] to determine optimal site and size of BESS ensuring maximum utilization of energy resources in small distribution system. A negative sensitivity index based approach is proposed in [17] to optimally deploy BESS in distribution networks, aiming to minimize power loss and voltage deviation. Sedghi *et al.* [18] presented an optimization problem for optimal integration of BESS to improve the system performance and reliability by considering the uncertainty of wind power generation. A two-stage optimization problem is presented in [19] for optimal planning of distributed generation and energy storage in distribution networks. By considering nodes, sizes, and timely estimation of SOC, the optimal BESS allocation turns out be a complex mixed-integer, non-linear and no-convex two-layer optimization problem.

In literature, various analytical and artificial intelligence (AI) based optimization techniques have been suggested to solve the optimal allocation of different DERs simultaneously. The analytical methods are based on some simplified assumptions therefore sometimes fails to solve the complex real-life engineering optimization problems. On the other hand, the AI-based techniques can solve such complex engineering optimization problems efficiently but require high computations. Some of the popularly known AI-techniques adopted for DER integration can include genetic algorithm (GA) [4], [6], [9], [12], particle swarm optimization (PSO) [4], teaching-learning-base optimization (TLBO) [11], [20], moth search optimization (MSO) [21], etc.

However, some problem specific limitations have been observed in many standard optimization techniques. To overcome some of the limitations observed in standard variants of AI techniques, many improved and hybrid methods are also suggested such as dynamic node priority based GA [10], quasi-oppositional TLBO [11], hybrid Tabu search/particle swarm optimization algorithm [18], ant lion optimization [19], hybrid grey wolf optimization [22], nondominated sorting genetic algorithm (NSGA-II) [23], gradient particle swarm optimization (GPSO) and bacteria foraging (BFA) hybrid algorithm [24], etc.

As discussed, the most of existing studies are focused either on single or limited aspects of BESS deployment in distribution networks. These can be optimization framework, problem formulation, optimization method, objective function, deployment strategies, and operation/dispatch schemes. In order to explore the maximum benefit of BESS integration, the planning and some of the crucial operational strategies which maximize daily profit should be investigated simultaneously. On the other hand, the recently developed optimization techniques should also be explored to overcome some of the limitations of existing methods and to maximize benefits of DER integration.

The contribution of this article is two-fold. A two-layer optimization problem has been devised to determine optimal sites and capacities of multiple WTs and BESSs simultaneously. The goal of outer or upper layer is to determine optimal sites and sizes of WTs and BESSs, aiming to minimize multiple objectives such as annual conversion loss, feeder loss, back-feed power into main grid transformer, and node voltage deviation and standard deviation of system demand while ensuring effective utilization of BESS. In inner or internal layer, an optimal hourly power dispatch problem is formulated to maximize energy arbitrage benefits of deployed BESSs. The proposed optimization model is implemented on a benchmark 33-bus distribution system. Secondly, a recently developed African buffalo optimization (ABO) is introduced to solve the optimal DER integration problem of distribution systems. Two modifications have also been suggested to overcome some of the limitations observed in its standard variant. The suggested modifications are validated by comparing the performance of proposed ABO with its standard variant. After validation of suggested improvements, the modified ABO (MABO) is introduced to solve the proposed outer-layer optimization problem of WTs and BESS integration. Furthermore, a heuristic is proposed to solve the inner-layer optimization problem of BESS power dispatch, for the BESSs suggested in each iteration of MABO. The simulation results obtained for different test cases are revealed that the suggested modifications have been improved the solution searching abilities of standard ABO, in terms of mean fitness, best fitness, worst fitness, and standard deviation. Moreover, the proposed two-layer optimization model effectively enhanced the wind power hosting capacity of the system by 23.55%.

II. PROPOSED TWO-LAYER OPTIMIZATION PROBLEM

The traditional distribution networks were designed by assuming unidirectional power flows. Similarly, the existing protection and operation schemes are also following the same network topology therefore the renewable hosting capacity of these systems are limited. Nowadays, the inclusion of DERs is changing the nature of these distribution networks from passive to active. Following the above discussed facts, sites and sizes of different DERs should be determined optimally, aiming to minimize some of the risks associate to high renewable penetration. The optimal integration of different DERs has always been a challenging task for DNOs. By considering sites, sizes and types of DERs, this problem turns out to be a complex mixed-integer, non-linear, and non-convex optimization problem. The integration of BESS further increases the complexity of this problem.

In order to reduce the problem complexity up to some extent, a two-layer optimization framework has been devised in this section, aiming to determine optimal sites and sizes of WTs and BESSs simultaneously. The objective functions and constraints, devised in each layer, are discussed in following sections.

A. OUTER-LAYER OPTIMIZATION FRAMEWORK

This layer can be named as a 'DER integration-layer' or 'outer-layer'. It aims to provide the final solution of the problem which includes optimal sites and sizes of different DERs, i.e., WTs and BESSs. In this layer formulation, various DER planning objectives have been considered. It includes minimization of annual energy loss (f_1); node voltage deviation (f_2); demand deviation index (f_3); and daily charging-discharging energy mismatch index of BESS (f_4). Due to the different scale and nature of these objective functions, a multiplicative penalty function based approach is used to transform this multiobjective problem to single objective optimization problem [25]. However, a multiobjective optimization based on Pareto front can also be introduced for more realistic problem formulation. The combined objective function of this layer is expressed in (1) and individual objectives have been discussed in following sections.

$$\min F_1 = (\Phi f_1) * (1 + f_2) * (1 + f_3) * (1 + f_4) \tag{1}$$

subject to:

$$0 \le P^r_{wt_j} \le P^{\max}_{wt} \quad \forall j \tag{2}$$
$$0 \le B^r_j \le B^{\max} \quad \forall j \tag{3}$$
$$\sum_{j=1}^{N} \sigma_j P^r_{wt_j} \le P^{\text{peak}}_D \tag{4}$$

Equations (2) to (4) are representing the maximum WT and BESS capacities deployment constraint at any node, and total WT hosting capacity of the system respectively.

1) MINIMIZATION OF ANNUAL ENERGY LOSS

It is well-known that the maximum annual energy loss occurs in distribution networks which results into revenue loss for an utility. In modern distribution systems, various energy conversion equipment are being deployed which also contribute to the power delivery losses, e.g., AC-DC and DC-DC converters associated with different DERs. The high penetration of renewables back-feeds the transmission substations therefore, the back-feed power into the main grid is also minimized in proposed work. The purpose of this objective is to determine the adequate capacities of WT and BESS simultaneously. For example, if high renewable penetration is suggested with lesser BESS capacity then this objective will help the optimization algorithm to reject this solution and vice versa. The objective function of daily energy loss in the system, f_1, is expressed as

$$\min f_1 = \sum_{t=1}^{T} P_{Line}(t) + P_{Conv}(t) + P_{Back}(t) \tag{5}$$

where,

$$\begin{aligned} P_{Line}(t) = \sum_{j=1}^{N}\sum_{k=1}^{N} \frac{r_{jk}\cos\left(\delta_j(t) - \delta_k(t)\right)}{V_j(t)V_k(t)}\big[P_j(t)P_k(t) \\ +Q_j(t)Q_k(t)\big] + \frac{r_{jk}\sin(\delta_j(t) - \delta_k(t))}{V_j(t)V_k(t)}\big[Q_j(t)P_k(t) \\ -P_j(t)Q_k(t)\big] \end{aligned} \tag{6}$$

$$P_{Conv}(t) = P^{bess}_{C/D_j}(t)(1 - \sqrt{\eta}) \quad \forall j \tag{7}$$

$$P_{Back}(t) = \begin{cases} \left|\Re[V_{ss}(t)I_{ss}(t)^*]\right|, & \text{if } I_{ss}(t) < 0 \\ 0, & \text{else} \end{cases} \tag{8}$$

Equations (6), (7), and (8) are representing the total power loss in branches, energy loss of BESS conversion systems, and back-feed power to main grid respectively, all at time t.

2) MINIMIZATION OF NODE VOLTAGE DEVIATION

The voltage regulation has always been an important concern for utilities to ensure quality power supply to consumers. Usually, it has been suggested that node voltage deviation should be minimized while determining optimal power dispatch of various DERs and performing any tap changing operation of voltage regulators. The high penetration of renewables results into node over voltages in the system. In the proposed study, the minimization of node voltage deviation is also considered as an objective function, f_2, expressed as

$$f_2 = \max\left\langle \Delta V_j(t) \right\rangle \quad \forall j, t \tag{9}$$

where,

$$\Delta V_j(t) = \begin{cases} 0, & \text{if } V^{\min} \le V_j(t) \le V^{\max} \\ \left|1 - V_j(t)\right|, & \text{else} \end{cases} \tag{10}$$

3) MINIMIZATION OF DEMAND DEVIATION INDEX

Nowadays, the growing penetration of intermittent power generation is increasing the risk of overdraw/under-draw with respect to scheduled power. Sometimes, excessive overdraw of power can put the upstream transmission networks at risk. Generally, a warning is issued by load dispatch centers to a system operator that overdraws during a period when supply frequency dips below its nominal range and vice versa [26], [27]. Moreover, UI charges are also applied on energy purchase if any constraint has been violated. In the proposed model, it is difficult to investigate the dynamic behavior of the system therefore a close approximation has been used. To maintain the supply frequency with the specified limits, a demand deviation index (DDI) is proposed comprising of the standard deviation of power drawing from the main grid or scheduled power over a time period T. The DDI is minimized and expressed as

$$\min f_3 = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(\frac{P_{grid}(t)}{P^{\text{peak}}_D} - \frac{\overline{P_{grid}}}{P^{\text{peak}}_D}\right)^2} \tag{11}$$

where,

$$P_{grid}(t) = \sum_{j=1}^{N} P_{D_j}(t) + P_{Line}(t) - \sum_{j=1}^{N} \sigma_j P_j^{wt}(t) - \sum_{j=1}^{N} \rho_j P_{C/D_j}^{bess}(t) \tag{12}$$

Equation (12) expresses the amount of power purchase by DNO from main grid, at time t, i.e., $P_{grid}(t)$.

4) MINIMIZATION OF DAILY CHARGING-DISCHARGING ENERGY MISMATCH INDEX

The number of charging-discharging cycles is limited for the BESS therefore it is important to minimize the number of cycles to maximize its life-time. However, it is a challenging task to determine and minimize the number of cycles at planning stage therefore one charging and discharging cycle is assumed over a time interval of T. However, these cycles may be varied in daily system operations based on techno-economic benefits. Moreover, it is also important to ensure adequate BESS capacity deployment. To fulfill these requirements, the mismatch between charging and discharging energies of deployed BESS, over T hours or levels, is minimized and expressed as

$$f_4 = \max\left\langle \Delta B_j \right\rangle \quad \forall j \tag{13}$$

where,

$$\Delta B_j = \rho_j \frac{\left| \sum_{t=1}^{T} P_{C_j}^{bess}(t) - \sum_{t=1}^{T} P_{D_j}^{bess}(t) \right|}{B_j^r} \tag{14}$$

This objective function also ensures that the battery SOC should reach to its initial value at the end of everyday to perform next day operations.

B. INNER-LAYER OPTIMIZATION FRAMEWORK

In previous section, the outer-layer optimization framework has been designed and presented to determine the optimal sites and sizes of different DERs. In each iteration, the promising sites and sizes of DERs are suggested which need to be justified. In order to determine the fitness value of function F_1 expressed in (1), the value of objective functions f_1 to f_4 has to be determined first. These functions involve time depended variables which need to be optimized or calculated for each $t \in T$. The optimization variables include optimal dispatch of suggested BESSs, i.e. P_{C/D_j}^{bess}, whereas other time dependent variables can be updated and calculated by using power-flow calculations. To ensure the optimality of these variables at each time t, an inner-layer optimization framework is developed. The objective function of this inner-layer or operational-layer optimization is comprised of the power loss, back-feed power and load deviation. The same penalty function based approach is adopted to combine all the objectives. A combined objective function is expressed in (15) for inner-layer optimization.

$$\min F_2(t) = \left(P_{Line}(t) + P_{Back}(t)\right) * \left(1 + f_d(t)\right) \quad \forall t \tag{15}$$

subject to:

$$SOC^{\min} \le SOC_j(t) \le SOC^{\max} \quad \forall j, t \tag{16}$$

$$P_{char_j}^{Lim}(t) \le P_{C/D_j}^{bess}(t) \le P_{dis_j}^{Lim}(t) \quad \forall j, t \tag{17}$$

$$SOC_j(t) = SOC_j(t-1) + \alpha_j \sqrt{\eta} P_{C_j}(t) + (1-\alpha_j)\frac{P_{D_j}(t)}{\sqrt{\eta}} \quad \forall j, t \tag{18}$$

$$I_{jk}(t) \le I_{jk}^{\max} \quad \forall j, k, t \tag{19}$$

$$P_j(t) = V_j(t) \sum_{k=1}^{N} V_k(t) Y_{jk} \cos\left(\theta_{jk} + \delta_k(t) - \delta_j(t)\right) \quad \forall j, t$$

$$Q_j(t) = -V_j(t) \sum_{k=1}^{N} V_k(t) Y_{jk} \sin\left(\theta_{jk} + \delta_k(t) - \delta_j(t)\right) \quad \forall j, t \tag{20}$$

where, $f_d(t)$ represents the relative fraction demand deviation with respect to previous time $t-1$ and expressed as

$$f_d(t) = \left| \frac{P_{grid}(t) - P_{grid}(t-1)}{P_{grid}(t-1)} \right| \tag{21}$$

Equations (16) to (20) are expressing the constraints of SOC limits, charging/discharging power limits, SOC balancing, feeders thermal limits, real and reactive nodal power balance respectively. For each time t, the maximum allowed discharging, i.e. $P_{dis_j}^{Lim}(t)$, and charging, i.e. $P_{char_j}^{Lim}(t)$, limits of BESSs used in (17) are determined by using (24) and (25) as shown at the bottom of the next page, respectively. The charging and discharging efficiencies are calculated as square root of round trip efficiency.

C. WIND POWER GENERATION

The wind velocity is highly unpredictable that results into fluctuating power generation from WTs. In planning stage, it is difficult to consider all the states of wind power generation in optimization therefore hourly power generation is generally considered. The wind power production from WTs is the function of wind speed along with some WT parameters [9]. If technical specifications of a WT such as swapping area, pitch angle, etc. remain constant with the time then wind power production would be proportional to the cubic function of wind velocity. As suggested in [16], the mathematical expression of wind power generation at node j and time t is modeled as

$$P_j^{wt}(t) \propto v(t)^3 \tag{22}$$

By using (22), the kW power production from WT can be determined as

$$P_j^{wt}(t) = \begin{cases} 0, & \text{if } v_j(t) < v^{\text{cut-in}} \text{ or } v_j(t) > v^{\text{cut-out}} \\ \left(\dfrac{v_j(t)}{v^r}\right)^3 P_{wt_j}^r, & \text{if } v^{\text{cut-in}} < v_j(t) < v^r \\ P_{wt_j}^r, & \text{if } v^r \le v_j(t) < v^{\text{cut-out}} \end{cases} \tag{23}$$

D. PROPOSED BESS DEPLOYMENT AND MANAGEMENT STRATEGIES

In this section, following rules and strategies are proposed or adopted for optimal deployment and dispatch management of BESS.

- It has been ensured that a minimum possible number of BESSs should be deployed to reduce the associated high investment and maintenance costs.
- Due to the limited number of charging-discharging cycles, only one complete charging-discharging cycle is assumed in a day. It helps to enhance the battery life and reduces the conversion losses to some extend.
- Further to keep the number of cycles at minimum, no BESS is allowed to discharge once it starts charging and reaches to maximum SOC level (except emergency), i.e., $SOC^{\min}$ and vice versa.
- No BESS is discharged beyond its minimum SOC level, i.e. $SOC^{\min}$.
- Strategically, only two BESSs are assumed to be deployed in the system known as central and distributed energy storages. The central BESS is deployed at grid substation and its size is determined by optimization. Both site and size of distributed BESS have to be determined.
- For inner-level optimization, the upper, i.e. $P_{dis_j}^{Lim}(t)$, and lower, i.e. $P_{char_j}^{Lim}(t)$ limits of BESS power dispatch at any time t are determined by using (24) and (25) respectively.

III. PROPOSED AFRICAN BUFFALO OPTIMIZATION

The African buffalo optimization method is a swarm-based, meta-heuristic, and nature-inspired optimization technique, developed by Odili *et al.* [28], in 2015. It is inspired from the social and herding behavior of African buffaloes. In ABO, three major characteristics of these animals are basically modeled into some set of mathematical equations which help to ensure safety, find shelters and meadows for their herd [29]. They have inherent broad memory that helps them to guide and tracking the path in vast land space of Africa. Furthermore, these buffaloes are very social and cooperative animal, prefer to live in herds. The African buffaloes have very special inbuilt characteristics to help and shield their herd members if anyone is in danger.

Second attribute of this mammal is its harmony towards fellow members of the herd. This beast communicates with other members of the group by means of two vocal sounds '*waa*' and '*maa*'. The *waa* sound is an alarming call in the herd which means to explore new places or sometime to help the needy member. This sound is an indication for the herd members to keep walking as current region is unfavorable or dangerous. Sometimes, this sound is also produced by a buffalo who is in danger and needs help from its fellow beings. On the other hand, *maa* sound is a pleasant sound which indicates that current location is delightful and safe for the herd. By this sound, fellow members are ensured that they can stay to exploit the location. Third and the last attribute is representing the parliamentary characteristics of the herd. If there are different opinions in the herd then they take the decision by help of election and majority takes the next line of action. In this paper, the basic ABO is presented and then some improvements are suggested in following sections.

A. Standard Variant of African Buffalo Optimization

In this section, a standard variant of ABO algorithm is presented. In 2015, J.B. Odilid *et al.* have developed this simple and effective optimization technique by considering above discussed characteristics of African buffaloes [28]. This algorithm comprises unique capabilities of this animal for effective exploration and exploitation in the given search space. It tries to solve pre-mature convergence problems by making sure that each buffalo is updating its location with respect to the previous experience. Another unique characteristics of ABO is its adequate exploitation by reinitializing the entire herd when leader (the best buffalo) is not improving with iterations.

The basic steps of ABO algorithm is given below.

1. Initialize the objective functions $F(x)$, $x \in S$, population size n_p, and algorithm parameters such as l_{p1} & l_{p2}, etc.
2. Randomly produce the feasible population of buffaloes and set on random nodes within the search space.

$$P_{dis_j}^{Lim}(t) = \begin{cases} 0, & \text{if } SOC_j(t) \le SOC^{\min} \text{ or } I_{gs}(t) \le 0 \\ \sqrt{\eta}P_{dis}^{\max}, & \text{if } SOC_j(t) - \dfrac{P_{dis}^{\max}}{B_j^r} \ge SOC^{\min} \text{ and } I_{gs}(t) > 0 \\ \sqrt{\eta}B_j^r(SOC_j(t) - SOC^{\min}), & \text{if } SOC_j(t) - \dfrac{P_{dis}^{\max}}{B_j^r} < SOC^{\min} \text{ and } I_{gs}(t) > 0 \end{cases} \quad \forall j \tag{24}$$

$$P_{char_j}^{Lim}(t) = \begin{cases} 0, & \text{if } SOC_j(t) = SOC^{\max} \\ -\Big(\dfrac{P_{char}^{\max}}{\sqrt{\eta}}\Big), & \text{if } SOC_j(t) + \dfrac{P_{char}^{\max}}{B_j^r} \le SOC^{\max} \\ -\Big(\dfrac{B_j^r(SOC^{\max} - SOC_j(t))}{\sqrt{\eta}}\Big), & \text{if } SOC_j(t) + \dfrac{P_{char}^{\max}}{B_j^r} > SOC^{\max} \end{cases} \quad \forall j \tag{25}$$

3. Now update the fitness value of ith buffalo by using (26).
$$m_{i+1} = m_i + l_{p1}(h_{best} - w_i) + l_{p2}(s_{best,i} - w_i) \quad (26)$$
where, m_i and w_i are representing the exploitation and exploration moves of ith buffalo ($i = 1, 2, 3, \ldots, n_p$), respectively. l_{p1} and l_{p2} are the learning factors varying from 0.1 to 0.6. Furthermore, h_{best} and $s_{best.i}$ are the best fitness value of herd and individual best fitness of buffalo i respectively.
4. Update the position of ith buffalo and $[h_{best}, s_{best,i}]$, as follows
$$w_{i+1} = \frac{w_i + m_i}{\pm 0.5} \quad (27)$$
5. Is h_{best} improving? If yes, move to next step, otherwise return to step 2.
6. Repeat steps 3 to 5 until stopping criteria is not achieved otherwise move to next step.
7. Print the optimal solution.

B. MODIFIED AFRICAN BUFFALO OPTIMIZATION

Although, the ABO algorithm outperformed on benchmark functions in [28] but shows some limitations when applied to real-life engineering optimization problems. It has been observed that standard variant of ABO is unable to find the global optimal solution, already determined by some of the existing optimization methods. In order to overcome some of the limitations observed in standard variant of ABO, two modifications are suggested without altering the basic mechanism of standard ABO. These shortcomings and corresponding corrections are discussed below.

Limitation-1 (Parliamentary Characteristic of The Herd): As discussed, the herd of African buffaloes shows parliamentary characteristic when they have different opinions in the herd. The majority population takes next line of action by using election. However, it is observed that the parliamentary characteristics of the herd has not been modeled in standard variant of ABO.

Suggested modification-1 (Inclusion of parliamentary characteristic): In order to introduce the democratic behavior of the herd, buffalo population is sorted according their fitness values and then divided into two groups. The upper half population will be considered as leader group of the herd. These leaders will follow the main leader of the herd, i.e., h_{best}, known as 'pathfinder'. Similarly, a buffalo from the lower half population will follow its adjacent or local leader. The community legislator will be chosen randomly from the parliamentary group of upper half population. These modifications are presented in the modified ABO (MABO) algorithm steps 4 to 6b.

Limitation-2 (Reinitialization of complete population): The standard variant of ABO has shown strong exploration and exploitation capabilities while solving benchmark functions. However, the frequent and random reinitialization of complete population limits the directional search of the herd when applied to solve the complex engineering optimization problems with large solution space. It is basically generating completely new population when best solution is not improving with iterations. Therefore, a modification is required to provide the guidance to buffalo population towards global region.

Suggested Modification-2 (Guided Reinitialization of Partial Population): To provide the target search direction to weak population of the herd, partial number of buffaloes is only reinitialized under parliamentary characteristic, unlike standard variant of ABO. The proposed corrections will provide the guidance to poor buffaloes to move towards their strong or leading fellows. The proposed correction is presented in step 6c.

The suggested modifications will improve the potential of ABO to seek the global optima. Steps of proposed MABO is presented below.

1. Set the algorithm control parameters and objective function(s).
2. Generate random but feasible population of buffaloes and place these to random locations within the search space.
3. Calculate fitness value for all buffaloes.
Proposed modifications start here...
4. Sort the buffalo population according to their fitness values.
5. Update the fitness and location of buffalo i; where, $i \in \{$sorted upper half buffalo population, $i = 1, 2, 3, \ldots, \frac{n_p}{2}\}$, by using (26) and (27) respectively.
6. Now, update the fitness and location of buffalo j; where, $j \in \{$lower half of the sorted population $j = (\frac{n_p}{2} + 1), \ldots, n_p\}$ as follows.
Generate a random number, $r_1 \in [0, 1]$,
   a) If $r_1 \geq 0.5$ then update the fitness of buffalo j, from lower half population, as suggested below
   $$m_{j+1} = m_j + l_{p1}(h_{best} - w_r) + l_{p2}(s_{best,j} - w_r) \quad (28)$$
   where, r is the randomly selected buffalo from the upper half population $r \in \{i = 1, 2, 3, \ldots, \frac{n_p}{2}\}$, called as local legislator. The suggested modification in (28) will help the upper half group of buffaloes to guide their fellows in the lower half population. The modification will also support the help seekers buffaloes of the herd.
   b) Update the location of jth buffalo by using (27), as follows
   $$w_{j+1} = \frac{w_j + m_j}{\pm 0.5} \qquad \forall\, j = (\frac{n_p}{2} + 1), \ldots, n_p \quad (29)$$
   c) If $r_1 < 0.5$ then randomly update the location of buffalo j within the search space, as suggested in (30).
   $$w_{j+1} = b_{\min} + (b_{\max} - b_{\min})r_2 \quad (30)$$
   where, $b_{\min}$, $b_{\max}$, and $r_2 \in [0, 1]$ are the minimum and maximum permissible location limits of buffaloes, and random number respectively.

...proposed modifications end here

7. Repeat the step 3 to 6 until stopping criteria is achieved.

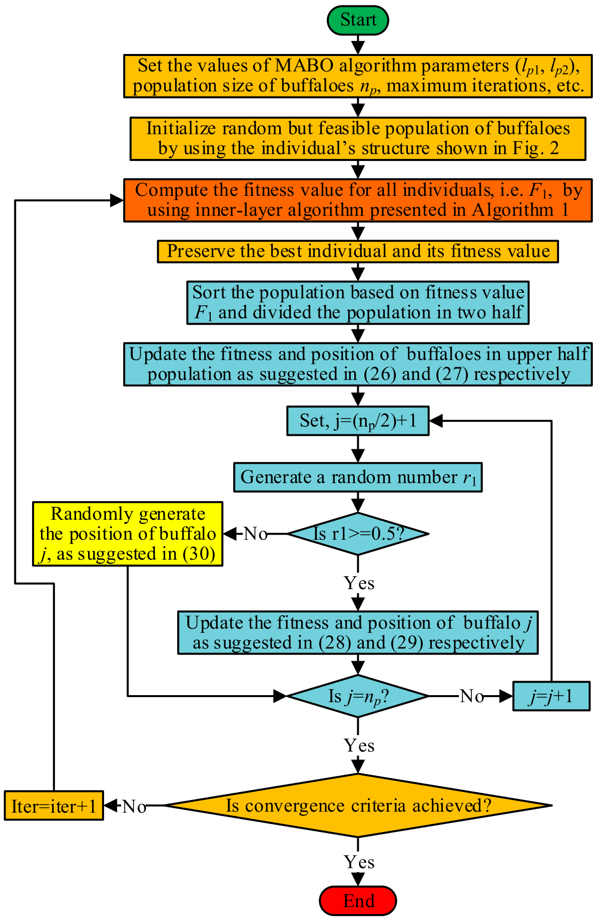

FIGURE 1. Flowchart of proposed MABO.

IV. PROPOSED MODIFIED AFRICAN BUFFALO OPTIMIZATION FOR WT AND BESS INTEGRATION

In this section, the proposed MABO is applied to solve the real-life DER integration problem of distribution systems, presented in Section II. The optimization problem is formulated in two levels, i.e., outer and inner layer frameworks, therefore two optimization techniques will be needed. The decision variables of outer-layer optimization include optimal sites and sizes of WTs, site and size of distributed BESS. As discussed in Section II-D, the central BESS is strategically integrated at grid substation thus its node/site will be known. However, its capacity should be included in optimization variables. Suppose, DER investor wants to deploy n_w number of WTs, and 2 BESS (1 central and 1 distributed) then the total number of optimization variables would be $(2n_w + 3)$. By considering the sites and sizes of these DERs and system complexity, this problem turns-out to be mixed-integer, non-linear, and non-convex optimization problem. The proposed MABO employs to solve this outer-layer optimization problem aiming to determine sites and sizes of these DERs. The structure of buffalo individual used in MABO is presented in Fig. 2. Further, the flow chart of proposed MABO method used for DER integration is presented in Fig. 1.

On the other hand, the decision variables of inner-layer optimization include optimal dispatch of BESSs suggested by out-layer optimization method, as a solution of optimal planning. This is a two-variable problem with reduced complexity therefore meta-heuristic approach is ignored, instead a heuristic is used. The pseudo-code of proposed strategies for optimal hourly dispatch control of deployed BESSs is presented in Algorithm 1.

Algorithm 1 Pseudo-Code of Proposed BESS Management

Receive the DER sites and sizes from MABO and deploy in the system; set objective $F_2(t)$;
set $t = 0$;
for each time t **do**
  $t = t + 1$;
  forecast/determine the total power generation from all WTs by using (23) (i.e. $P_G^T(t) = \sum_{j=1}^{N} \sigma_j P_j^{wt}$) and total system demand (i.e. $P_D^T(t)$) at time t;
  determine the upper and lower BESS dispatch limits $[P_{dis_j}^{Lim}(t), P_{char_j}^{Lim}(t)]\ \forall j$ by using (24) and (25) respectively;
  if $P_G^T(t) > P_D^T(t)$ **then**
    determine the optimal dispatch of distributed BESS, $P_C^{bess}(t)$ for minimum value of $F_2(t)$. It is determined by varying the power dispatch of the BESS from $P_{char_j}^{Lim}(t)$ to 0 kW, in step size of 10 kW; ▷ First priority will be given to distributed BESS because it contributes in power loss minimization.
    if $P_G^T(t) > \left(P_D^T(t) + P_C^{bess}(t)\right)$ **then**
      determine the optimal dispatch of central BESS if any, $P_C^{bess}(t)$ by minimizing $P_{Back}(t)$ only;
    else
      determine the optimal dispatch of central BESS, $P_C^{bess}(t)$ by minimizing $f_d(t)$ only;
    end if
  else
    determine the optimal dispatch of distributed BESS $P_D^{bess}(t)$ for minimum value of $F_2(t)$, by varying the BESS power dispatch from 0 to $P_{dis_j}^{Lim}(t)$ in step size of 10 kW;
    if $f_d > L_D$ **then** ▷ L_D denotes the maximum allowed load deviation by load dispatch center.
      then determine the optimal dispatch of central BESS $P_D^{bess}(t)$ for minimum value of $f_d(t)$;
    end if
  end if
  perform the power flow calculations and determine the objective functions of outer-layer optimization for at time t, by using these BESS dispatch;
end for
return objective function F_1 to outer-layer optimization as a fitness value.

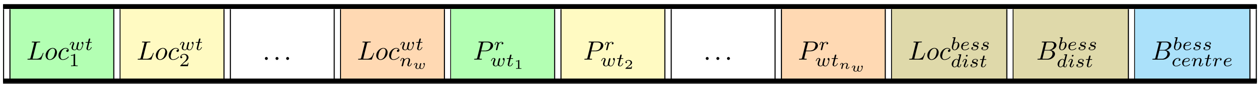

FIGURE 2. Structure of an individual used in MABO (decision variables of outer-layer optimization problem.)

V. CASE STUDY

In this section, the MABO method is applied to solve the proposed complex two-layer optimization problem of WT and BESS integration in benchmark test distribution system of 33 buses [30]. It is a 12.66 kV distribution system with total real and reactive power demand of 3715 kW and 2300 kVAr respectively. Total real power loss of the system at nominal loading is 202.67 kW [10]. As discussed, the contribution of this paper is two-fold, proposed modifications in ABO and optimization framework for WT and BESS integration. Therefore, the MABO is validated first and then used to solve the proposed DER integration problem in following sections.

A. VALIDATION OF PROPOSED MODIFICATIONS IN ABO METHOD

To validate the proposed modifications in ABO, the performance of MABO is compared with its standard variant. For this validation, a single objective dispatchable DG integration problem is formulated for active power loss minimization in 33-bus distribution system. The problem is solved by using both standard [28] and modified variants of ABO. The meta-heuristic methods have certain randomness in final solutions therefore 50 independent trials are performed. Table 1 presents a comparison of some performance parameters of these algorithms, obtained in 50 independent trials of ABO and MABO. The maximum number of iterations and population size considered for both the approaches are 100 and 50 respectively. This table summarizes the value of best fitness, mean fitness, worst fitness, standard deviation, and CPU time for ABO and MABO. The comparison reveals that the suggested modifications have enhanced the best solution searching ability and overall performance of standard ABO. However, the simulation time is slightly increased because of extra steps introduced in the basic algorithm.

Furthermore, the convergence characteristics of these methods are also compared for the best and mean solutions, and presented in Fig. 3, for a single run. It can be seen from these figures that the proposed MABO has better solution searching abilities. In order to investigate the scalability of the proposed MABO, the simulation time has been observed with increased size of this problem. Fig. 4 shows that the simulation time is slightly accelerative with increasing number of variables. Now this method is used to solve the proposed two-layer optimization problem in following section.

TABLE 1. Performance comparison of ABO and MABO for 50 independent trails.

Method	Best Fitness (MW)	Worst (MW)	Mean Fitness (MW)	Stand Deviation	CPU time(s)
ABO	0.0729	0.0811	0.0768	0.0022	7.21
MABO	0.0715	0.0785	0.0751	0.0014	7.44

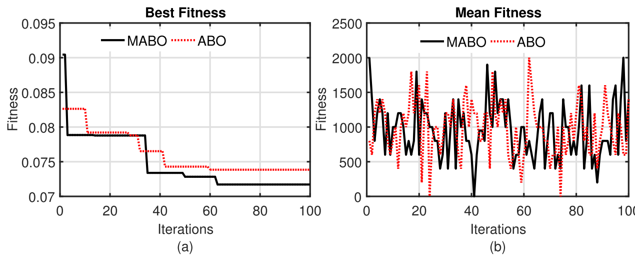

FIGURE 3. Best and mean convergence characteristics of ABO and MABO for power loss minimization in 33-bus distribution system.

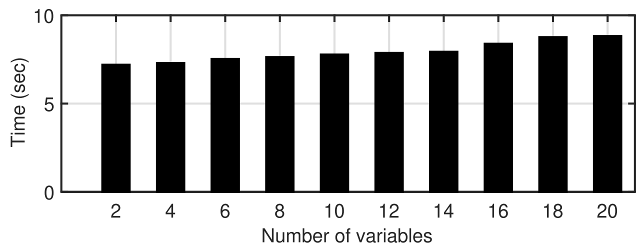

FIGURE 4. The effect of problem-size on modified African buffalo optimization.

B. SIMULATION RESULTS OF WT AND BESS INTEGRATION

After validation of MABO, it is now implemented for proposed simultaneously optimal accommodation of WTs and BESSs in the same 33-bus test distribution system. The optimization framework developed in Section II is solved by using the proposed optimization methods in Section IV. The values of parameters used in this study are summarized in Table 2. The hourly wind power, and load multiplying factors (LMF), used in the study, are referred from [16] and shown in Fig. 5. The load data has mixed power demand of residential, commercial and industrial loads. In order to determine the hourly load profile in kW, the LMF is multiplied with the peak load of the system. Peak load is assumed as 1.6 times of nominal load [10]. Similarly, hourly kW power generation of a WT is calculated by multiplying the hourly wind power multiplying factor with rated capacity of corresponding WT. The distribution system is assumed to be dispersed in a small geographical area therefore all nodes can have same wind profile. In practice, WTs are only available in specific sizes therefore discrete sizes of WTs have been considered in this study. The considered WT sizes are as follows: 250 kW, 850 kW, 1250 kW, 1500 kW, 1800 kW, and 2000 kW [31].

TABLE 2. Simulation parameters used in the study.

Parameter	Value
Φ	365 days
T	24 hours
L_D	20%
$V^{\max}$, $V^{\min}$	1.05 p.u., 0.95 p.u.
η	90%
$SOC^{\min}$, $SOC^{\max}$	10%, 100%
$P_{char}^{\max}$, $P_{dis}^{\max}$	1 MW each
$P_{wt}^{\max}$, $B^{\max}$,	2000 kW, 6500 kWh
$v^{\text{cut-out}}$, $v^{\text{cut-in}}$, v^{r}	20 m/s, 4 m/s, 15 m/s

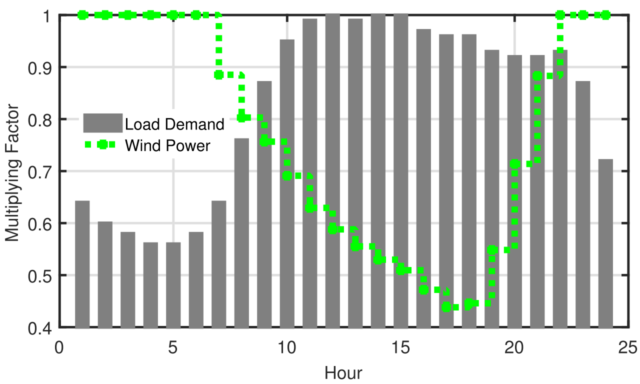

FIGURE 5. Hourly multiplying factors for load demand and wind power generation.

To investigate the effect of battery energy storage integration with different strategies, following cases are framed and solved.

- **Case–I:** Base case, no DER
- **Case–II:** optimal integration of WTs only
- **Case–III:** simultaneous optimal integration of WTs and one distributed BESS
- **Case–IV:** simultaneous optimal integration of WTs, one distributed and one central BESSs.

The simulation results of these cases are presented in Table 3. It includes the optimal sites and sizes of different DERs, renewable penetration, standard deviation of the demand, total energy loss in feeders and BESS conversion system, maximum voltage, and percentage annual energy loss reduction. In case-I, the load profile shown in Fig. 5 is simulated for this system, without considering any DER. As observed from Table 3, the mean voltage profile of the system is very poor in base case condition.

In case-II, three WTs are assumed to deploy, as this number is found to be compromising for this system [10]. The outer-layer optimization only (i.e., MABO) is used to solve this case since there no dispatchable source presents to optimize in inner-layer. The optimal integration of WTs only has significantly reduced the annual energy loss of the system as compared to base case, i.e., case-I. The maximum potential of wind power generation has been found during light load hours in night, as can be observed from Fig. 5. Therefore, the maximum WT penetration is limited by the minimum load demand of the system appeared in 4:00–5:00 hours. However, the inclusion of WTs has increased the fluctuations in power drawing from the main grid, as observed from the value of standard deviation which is very high as compared to case-I. It can be possible since no dispatchable/controllable energy source presents to minimize the fluctuations caused by wind power generation in this case.

To improve the techno-economic performance of active distribution systems, some dispatchable DERs may be required such as diesel engines, gas micro-turbines, combined heat and power, BESS, etc. Among these, only BESS provides dual characteristic of both generation and load whenever required. It is a very promising DER to store and release the clean energy generated from renewables. Therefore, the optimal integration of WTs is re-investigated in case-III by simultaneously deploying one BESS along with three WTs. Table 3 shows that the presence of this BESS has not been changed the optimal sites of WTs much, just shifted two WTs to their adjacent nodes. The WT of node 14 moves to its adjacent node 15, and WT of node 31 to 30 which are topologically nearest to previous nodes. The inclusion of this BESS has increased the sizes of two WTs and also reduced the annual energy loss of feeders as compared to case-I and II but at the cost of extra energy loss in BESS conversion system. Though, the total annual energy loss reduction is less as compared to case-II however the presence of BESS significantly reduced the effect of wind power generation fluctuation as can be observed from the standard deviation. From this case, it has been concluded that one distributed BESS within the system significantly contributes in demand deviation reduction caused by WTs, voltage profile improvement, and feeders annual energy loss reduction. The proposed optimal BESS management scheme is outperformed for these objectives.

From case-III, it has been observed that the standard deviation of hourly load demand at grid supply point is still higher than the base case. The distributed BESS is not sufficient to minimize the fluctuations in hourly power purchase from the upstream grid. Therefore, one more BESS is dedicatedly planned at grid supply point itself to minimize back-feed power and fluctuation in power supplied to distribution system. Secondly, it is also advantageous to deploy and manage the BESS at grid substation because it will reduce the requirements of extra land and substation equipment. Thirdly, it will be easy to determine/measure back-feed power and demand deviation from the substation at grid supply point. In this case, the site of integration is already known for central BESS therefore nine variables (3 WT sites, 3 WT sites, 1 site and 2 capacities of BESS) have to be determined. The addition of central BESS significantly reduces the fluctuations in hourly power purchase from the main grid. It is interesting to notice that the sites and capacities of WTs are same as obtained in case-III except the node of one WT that shifts from node 8 to node 3. The possible reason for this shift is central BESS at node 1 that mainly charged by the WT at node 3.

TABLE 3. Simulation results of proposed two-layer optimization problem of WT and BESS integration obtained by MABO.

Cases	WT Nodes	WT Sizes (kW)	WT Penetration (%)	BESS Node(s)	BESS Size(s) (kWh)	Annual Energy Loss in Feeders (MWh)	Standard Deviation of Demand	Conversion Losses (MWh)	Mean Voltage (p.u.)	Total Annual Energy Loss reduction (%)
I	NA*	NA*	NA*	NA*	NA*	3493.27	1165.21	NA*	0.93	00.00
II	08, 14, 31	850, 850, 1250	49.63	NA*	NA*	1717.99	1659.00	NA*	0.96	**50.82**
III	08, 15, 30	850, 1500, 2000	**73.18**	17	5197.30	1617.69	1395.70	490.74	**0.98**	39.64
IV	03, 15, 30	850, 1500, 2000	**73.18**	17, 1	4818.30 6231.00	**1595.33**	**991.52**	435.36 578.31	**0.98**	25.31

*NA = not available; (bold data indicates the promising solutions)

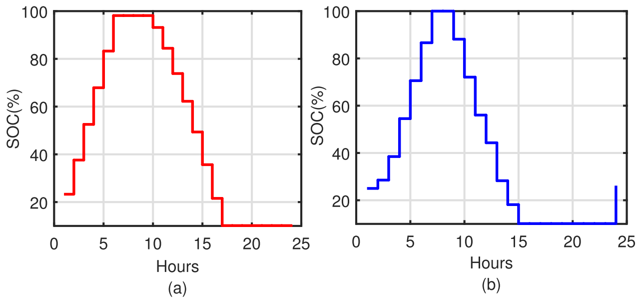

FIGURE 6. Hourly state-of-charge (%) of (a) central BESS at node 1, and (b) distributed BESS at node 17 in case-IV.

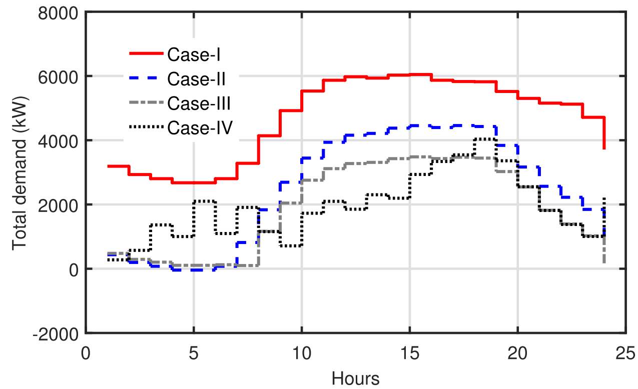

FIGURE 7. Hourly load demand of distribution system for all cases.

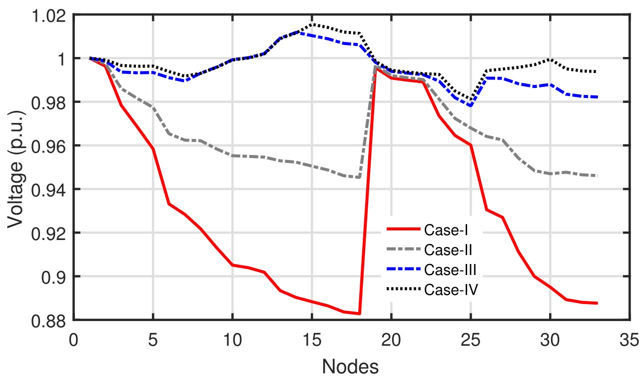

FIGURE 8. Mean node voltage profiles of 33-bus distribution system for different cases.

Technically speaking, the power generation from central BESS should not contribute in feeder energy loss reduction instead can increase it when charging from a WT at node 3. However, the feeder power loss reduction is more in this case (except conversion losses). It could be possible when distance and amount of power delivery is minimum between WTs and BESSs. The hourly optimal power dispatch of BESSs are presented in Fig. 6. It shows that the power dispatch profiles of central and distributed BESSs are very similar, except amount of power dispatch. It is due to the involvement of common objectives in these hours, i.e., load deviation and back-feed power. From hours 00:00 to 6:00, both the BESSs are simultaneously charging to reduce the back-feed power caused by excess renewable power generation during this period. The central and distributed BESSs remain in idle mode (at maximum SOC) from hours 6:00 to 10:00 and 7:00 to 9:00 respectively. In the day time, central BESS controls the demand deviation whereas distributed BESS minimizes demand deviation, node voltage deviation, and annual energy loss in branches simultaneously.

The simultaneous integration of BESSs and WTs is significantly reduced the annual energy loss in feeders and fluctuation in hourly power purchase from the grid. The node voltage profile and renewable hosting capacity of the system have also been improved. Although, the total annual energy loss reduction is more in case-II but at lower WT penetration. On the other hand, the most of performance parameters of system are improved in case III and IV at high WT penetration. The inclusion of central BESS provides additional flexibility to system by managing the scheduled power within its nominal value. The resultant hourly demands of the system are shown in Fig. 7. It shows that the distributed BESS alone is unable to shift the resultant system demand from peak load hours to light load hours. Whereas, the central BESS has shifted some of the peak demand to light load hours.

Similarly, the mean node voltage profile (over 24 hours) of all these cases are presented in Fig. 8. It shows that the optimal integration of DERs has significantly improved the node voltage profile of the system, especially in cases III and IV.

VI. CONCLUSION

In this paper, a two-layer optimization framework has been developed for simultaneous optimal accommodation and management of WT and BESS in distribution systems. Some new objectives and security constraints are introduced to improve the renewable generation hosting capacity of distribution networks. The objective functions proposed in outer-layer optimization include minimization of annual power loss in feeders, back-feed power into grid substation transformer, BESS conversion system loss, node voltage deviation, demand deviation index, and daily charging-discharging energy mismatch index. The operational objectives such as hourly power loss, back-feed power, and demand deviation are minimized in inner-layer. The case studies and simulation results reveal that the proposed model effective managed to accommodate the maximum wind power generation in 33-bus test distribution system without violating any system constraints. Similarly, the strategic integration of BESS has been optimized multiple DNO objectives effectively.

On the other hand, a recently developed ABO algorithm has been introduced to solve the DER integration problem of distribution systems while suggesting some modifications. The suggested corrections are significantly improved the solution searching ability of ABO in terms of performance parameters such as best, mean and worst fitnesses, and standard deviation. In the future work, the proposed MABO can be applied to solve some more complex real-life engineering optimization problems.

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