Multiobjective Nested Optimization Framework for Simultaneous Integration of Multiple Photovoltaic and Battery Energy Storage Systems in Distribution Networks

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Abstract

The rapid growth of renewables in modern distribution networks results in the spilling of energy due to the limited hosting capacity of these networks, violation of system constraints, reduced network efficiency, and improper utilization of resources. Battery energy storage system (BESS), in spite of its high cost, a shorter life and complex control, offers a techno-economically feasible solution for the problem. In this paper, a multiobjective nested optimization framework is developed for the simultaneous optimal allocation of multiple solar photovoltaics (SPVs) and BESSs in the distribution networks. The framework involves a two-layered structure; the outer layer provides tentative planning solutions to the inner layer that optimizes the desired objectives of network operations and then returns the functional values back to the outer layer. The purpose of the inner-layer is to satisfy the operational constraints of the networks and ensure the optimal utilization of BESS capacities, suggested by the outer layer, at the time of planning itself. A new BESS operating strategy is proposed for optimum utilization of BESS. The nested multiobjective optimization problem is handled by suggesting a new weighted sum approach in conjunction with a recently developed swarm intelligence-based algorithm, i.e. moth search optimization. Overall, the proposed deterministic model essentially ensures the high penetration of SPVs and the optimal utilization of BESSs to justify their installation. The optimization model is investigated on a benchmark 33-bus test distribution network. The application results highlight enhanced energy efficiency, peak load shaving, high renewable penetration, voltage profile improvement, and mitigation of energy spillage or reverse power flow while effectively absorbing the excess renewable power generation during light load hours.

Keywords: Battery energy storage systems, nested optimization framework, integration of RESs, moth search optimization, distribution systems.

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Nomenclature

Parameters and Sets

F_l	lth objective function
$F_p^{in}(s)$	Objective considered in the inner layer during state s, $p = 1, 2, 3$.
F_p^o	Objectives considered in the outer layer, $p = 1, 2, 3$.
P_B^{Min}, P_B^{Max}	Minimum and maximum permissible charging and discharging power limits of BESSs for any state s (kW)
$\eta_{c/d}$	Charging/discharging efficiency of BESSs (%)
P_{DG}^{Max}	Maximum power generation limit of DGs (kWp)
W_B^{Max}	Maximum energy storage deployment capacity of BESS at a node (kWh)
W_B^R	Rated energy storage capacity of BESSs (kWh)
SOC^{Min}, SOC^{Max}	Minimum and maximum state-of-charge (SOC) limits of BESSs (p.u.)
Δt	Duration of state s
r_{ij}	Resistance of branch connecting nodes i and j respectively (ohm)
Y_{ij}	Elements of Y-bus matrix (mho)
θ_{ij}	Impedance angle between nodes i and j (rad)
I_{ij}^{Max}	Maximum line thermal limit (A)
$\overline{P_G}$	Mean power generation from grid (kW)
ϕ	Daily to annual conversion factor

Variables

$P_i(s)$, $Q_i(s)$	Real and Reactive power injection at ith node in sth state (kW or kVAr)
$V_i(s)$, $\delta_i(s)$	Voltage magnitude and angle at ith node in sth state (p.u. or rad)

$I_{ij}(s)$	Current flow between nodes i and j during sth state (A)
$I_1(s)$, $V_1(s)$	Current (A) and voltage (V) magnitude in secondary winding of grid sub-station transformer during system state s
$P_{G,i}(s)$	Power generation from grid at ith node in sth state (kW)
$P_{D,i}(s)$, $Q_{D,i}(s)$	Active and reactive system demand at ith node in sth state (kW or kVAr)
$P_{DG,i}(s)$	Active power generation from DGs at ith node in sth state (kW)
$UB_{ch,i}(s)$, $UB_{dis,i}(s)$	Upper charging and discharging boundaries of BESSs for inner-layer at ith node in sth state (kW)
$P_{ch,i}(s)$, $P_{dis,i}(s)$	Charging and discharging dispatch of BESSs at ith node in sth state (kW)
$W_{B,b}(s)$	Energy dispatch of bth BESS during sth system state (kWh)
$SOC_i(s)$	SOC status of BESS at ith node in sth state (p.u.)
$\delta_1(s)$, $\delta_2(s)$	Voltage angles at bus 1&2 during sth state (rad)

1. Introduction

The increasing energy demand together with the depleting fossil reserves and alarming environmental concerns have necessitated the use and integration of renewable energy sources (RESs) in modern distribution systems. A promising development of active distribution system (ADS) concepts within traditional distribution systems can be made with the help of optimal distributed energy resources (DERs) integration [1, 2]. As a consequence, extensive efforts are being taken to integrate efficient and easily available distributed generations (DGs), i.e. solar photovoltaics (SPVs) and wind turbines (WTs) into distribution systems. The optimal integration of DER units offers several advantages such as minimization of greenhouse gas emission, node voltage deviation and energy loss, reliability, stability and power quality improvement, etc. [3, 4, 5]. On the other hand, their non-optimal integration results in a series of operational difficulties such as reverse power flow, fault current rising, worsening of load deviation index, voltage rise at point of common couplings and many more. [6, 7].

The intermittent power generation from renewables is another big challenge for power system operators aiming to minimize the mismatch between supply and demand. The accurate uncertainty modeling, at the time of planning, is a very complex task that could result in a non-optimal long-term planning solution. Therefore, the benefits of DG integration cannot be fully exploited on account of indeterminacy modeling of renewable power generation. The battery energy storage system (BESS) may provide feasible solution to these problems [8, 9]. It not only absorb intermittency of renewables but can also take advantage of energy arbitrage to generate profit in retail energy markets. Moreover, the reliability, security and efficiency of the system can also be enhanced if BESSs in coordination with DGs are managed effectively [10, 11]. The coordinated management of BESSs in ADS can systematically optimize the network operations, make renewable DGs act as dispatchable sources, can help in improving the load deviation index, etc. [11, 12]. However, the BESS is a costly option and its placement can be justified if it ensures higher RES penetration with other stated technical benefits.

Extensive research has been conducted on the optimal allocation of BESSs using diverse problem frameworks and optimization techniques. In these research efforts, the authors were mostly focused on the optimization of BESSs' capacity without paying much heed to their respective optimal sites. The objective functions considered in these research works aiming to determine optimal BESS sizes in distributions systems include maximization of arbitrage benefits [13], minimization of fuel cost [14], net present cost (NPC) of BESS installation [15], minimization of operational cost and reliability enhancement [16], reduced energy supplied cost [17], cost function minimization [18], peak shaving, valley filling and load balancing [19], etc. The different frameworks and optimization techniques utilized while optimizing these objectives include dynamic programming [13, 14], non-dominated sorting genetic algorithm (NSGA) to effectively deal with multiple objectives [15], two-stage optimization framework [17], Grey Wolf optimization [18], forecast and heuristic based energy storage scheduling system [19], etc. Some other important literary works dealing with the allocation of BESSs in distribution networks considering the optimization of both the sizing and siting problem of BESSs with existing DGs are presented in the following literature. In these works, optimal allocation of BESSs in distribution systems is proposed so as to achieve diverse objectives, viz. mitigation of wind curtailment, energy loss minimization and feasibility enhancement [20], over-voltage minimization [21], minimizing system operational costs or power losses [22], voltage regulation and peak load shaving [23], minimizing NPV of distribution network [24], overall storage cost minimization [25], system cost minimization (arbitrage benefit enhancement, reduction of energy losses and environmental emission, etc.) [26], power loss minimization [27], etc. However, daily optimal dispatch of BESSs is not considered in [21, 23], whereas the optimal integration (sizing and siting) of BESSs is considered sequentially in [22], but simultaneously in [20, 24, 25, 26, 27], along with optimal daily dispatch. In [27], the authors proved that the simultaneous optimization approach of BESS allocation and daily dispatch is much more effective than the sequential approach. It has been shown that practically large scale BESS utilisation can be achieved while optimizing consumption from RESs [25]. It has also been found that high penetration of RESs has positive impact on power losses, node voltage profile and emission reduction [26]. On the contrary, high penetration of RESs can have counterproductive impact. The simultaneous placement of multiple DGs and BESSs can enhance penetration of renewable energy resources and associated techno-economic benefits in distribution systems. Moreover, the coordinated integration of DGs and BESSs in distribution systems also provides several benefits to the DSOs and end-consumers.

The joint optimal allocation of renewables and BESSs, followed by the daily optimal dispatch of suggested BESSs is highly essential for enhancing the techno-economic and operational efficiency of distribution systems while mitigating the detrimental impacts (like reverse power flow) of high renewable penetration. In-turn, there are two approaches by which one can perform joint optimization procedure namely, simultaneous and sequential joint optimizations [28, 29, 30, 31]. In the former, the optimization algorithms simultaneously optimize the decision variables wherein sequential procedure, the optimization algorithms act in sequential steps. However, simultaneous joint optimization is considered to outperform the sequential joint optimization [32, 33, 34, 35, 36, 37, 38]. In [32], a joint optimization algorithm of combining network reconfiguration and capacitor control is proposed for system loss reduction and operational cost minimization. In [35], a multiobjective joint optimization of energy trading and electrical grid efficiency is considered for different stake holders in micro-grids. In fact, a handful of work has been presented in the area of simultaneous joint optimization of dispatchable/non-dispatchable DGs and BESSs in distribution systems [36, 37, 38]. In [36], dispatchable DGs and battery switching stations (BSSs) are optimally allocated simultaneously to obtain system loss minimization without optimizing the location of DGs. In [37, 38], simultaneous joint optimization of energy storage and RESs is performed for system cost minimization. However, only their capacities and operation are optimized and not the location. Therefore, the simultaneous joint allocation (including both sizing and siting) of BESSs and DGs along with the joint operational strategy could provide better optimization results than the existing methodologies in the distribution systems. To the authors' knowledge, a little or no effort has been put in the direction of the joint optimization problem of BESSs and DGs where all the parameters are optimized simultaneously, e.g. sitting and sizing along with daily optimal dispatch validation of deployed BESSs at the time of integration itself. The simultaneous joint optimization problem is a very complex combinatorial problem as the allocation problem is also interlinked with the charging/discharging operational strategies and constraints of BESSs. In other words, it is a nested problem wherein the optimal operation is embedded in optimal planning that necessitates a well-tailored strategy and therefore cannot be solved using conventional optimization framework.

In this paper, a nested optimization framework is proposed for the simultaneous joint accommodation of SPVs and BESSs in distribution systems using Corrected Moth Search Optimization (CMSO) with high exploitation and exploration capabilities. The framework considers optimal operation and utilization of these DERs while deciding the fitness of tentative solutions thus ensures high penetration of SPV without spillage of energy. The sizing and siting of DERs, and charging/discharging dispatch of BESSs are optimized simultaneously while considering optimal operation of BESSs by suitably selecting the network performance objectives rather than using additional constraints. This not only reduces the complexity of the problem but also improves system operation. The obtained sizing, siting, and operation of BESS ensures power loss minimization, mitigation of reverse power flow, improvement in system voltage profile and improvement in grid power demand profile. The salient contributions of this work are:

- A two-layer multiobjective nested optimization framework is developed for simultaneous joint optimal integration of multiple DERs while ensuring most effective utilization of energy storage systems to be deployed in conjunction with renewables in distribution networks.

- A collaborative operation strategy is proposed for optimal and coordinated utilization of BESSs to be deployed in conjunction with SPVs.

- The multiobjective nested optimization problem is handled by suggesting a new weighted sum approach and recently explored swarm intelligence-based algorithm, i.e. CMSO, having well-balanced exploration and exploitation capabilities to search local and global solutions [5].

- The operation of BESSs is optimized by suitably selecting constrained objectives rather than using additional constraints.

- The proposed model is investigated on a benchmark 33-bus test distribution system and the contributions are supported with various case studies.

The organization of this paper is as follows: the proposed optimization methodology is presented in Section 2. The section also addresses BESS operating strategy. The mathematical formulation is presented in Section 3. Section 4 discusses the solution technique for the proposed methodology. The simulation results and discussion are presented in Section 5 and 6 respectively, followed by conclusions drawn in Section 7.

2. Proposed Optimization Model

The prime goal of the proposed DER model is to find the simultaneous siting and sizing of SPVs and BESSs which optimizes desired objectives while satisfying various constraints of the distribution networks, generation, and energy storage. The multiple objectives considered in this optimization model include annual energy loss minimization, load deviation index minimization, and maximization of the BESS utilization index for energy arbitrage benefits. BESSs energy management involves optimal charging and discharging in coordination to power generation from SPV units, and load demand. Thus the sizing and siting problem gets inherently linked to the complex management problem of BESSs, the later one behaves as a constraint while optimizing the siting and sizing problem. The developed model leads to a nested optimization problem. Nevertheless, the effective energy management of BESSs is tedious owing to the sequential optimization of a large number of dynamic states. It happened on account of operating constraints of BESSs that varies with states and has an inter-state dependency, besides network constraints. Therefore, the effective and optimal management of BESSs need adequate control, and dispatch strategies under dynamically varying states.

In this paper, the following assumptions and strategies are well-considered when modeling the proposed optimization framework.

1. A substantial reduction in feeder power loss can be achieved if BESSs are charged locally from SPV units, instead of the grid supply.
2. A heavy reduction in feeder power loss may result if BESSs optimally discharge during peak hours.

3. The power loss reduction is the function of sizing and siting of SPVs and BESSs as well as charging/discharging scheduling of BESSs.
4. The reverse power flow is one of the measures that decide adequate DG penetration and BESSs capacity in the system.
5. In order to justify the daily to annual operations, the state-of-charge (SOC) level of each BESS should reach to its initial value at the end of the day (could differ in practice), e.g., the charging and discharging energy should be equal for the day.
6. To justify the suggested BESS capacity by outer-layer, each of the deployed BESS should be fully utilized in one charging/discharging cycle in a day. The violation of this constraint means the non-optimal capacity of the suggested BESS.
7. By considering the limited number of life cycles of BESSs, only one charging-discharging cycle is considered for a day.

The proposed optimization framework is a nested structure, wherein the behavior of decision maker at a particular layer is influenced by the decision maker at another layer [39, 40, 41, 42, 43, 44, 45, 46]. This framework works sequentially in two layers while optimizing separate multiobjective functions at each layer. The inner-layer optimization problem acts as a constraint to the outer-layer optimization problem, such that, only those individuals are considered feasible that are inner-layer optimal and also satisfy the outer-layer constraints [40, 41, 42, 43]. The outer-layer framework deals with the siting and sizing of SPVs and BESSs by considering the planning objectives such as minimization of annual energy loss, minimization of load deviation index, and maximization of BESS utilization index. The inner-layer framework considers the levels of SOCs and charging/discharging status of BESSs as decision variables with the aim of optimal hourly dispatch management of BESSs against the tentative solution vector suggested by the outer-layer. The objectives considered in this layer are the hourly minimization of feeder power loss, reverse power flow, and node voltage deviation.

3. Proposed Multiobjective Nested Framework and Problem Formulation

The nested multiobjective optimization problems are complex combinatorial problems where it is difficult to optimize multiple conflicting objectives simultaneously, as each objective is equally important with different units and scales. However, the problem can be solved by adopting a suitable multiobjective technique that selects the most compromising solution out of numerous alternatives in Pareto-front usually generated by the optimization methods. Generally, most of these multiobjective problems may be solved as a single objective by combining various objectives into a fitness function by using a weighted sum or fuzzy approach or a combination of both [47, 48, 49, 50, 51, 52, 53, 54, 55]. In the fuzzy framework, the scaling of the objectives may be imperfect on account of unequal slopes of fuzzy membership functions of different objective functions [54]. It happened to owe the diverse range that usually exists with the lower and upper bounds of the objectives. As a consequence, the objective function having more slope of fuzzy membership function may dominate over other objectives. This leads to the wrong reflection of weights being assigned thus affects desired trade-offs in the multiobjective problem. On the other hand, the selection of proper weights to objectives is challenging while employing a weighted sum approach. The approach requires scaling of objectives considered so that weights can be assigned to these objectives. The choice of weights is usually left with the operator, but accurate scaling of objectives is difficult on account of the unknown relationship between the scaling factor and the objective function value. The optimal solution of the weighted sum approach depends on the selected weights. In fact, the functional value of the objective function depends on the proper selection of weighting factors that have been selected after some trial and error [55].

The above-identified limitations may be resolved by appropriate scaling of objectives. With the suitable scaling of multiple objectives, the assigned weights by the operator thus provide a desired trade-off in the multiobjective problem. The proposed suggestion can effectively be employed with a weighted sum approach rather than a fuzzy approach. Moreover, the approach is highly suitable for the conflicting nature of objectives [50]. However, the weighted sum approach may generate an optimal solution with a weak objective which could be possible as the overall fitness is the sum of fitness of all the objectives. Nevertheless, the approach does not show the tendency to restrain the poor functional value of an objective. Therefore, a new weighted sum approach is suggested for the nested multiobjective problem. In this approach, first, the scaling factors are evaluated for each of the objectives in order to have the same relative strength to all the objectives. For this purpose, each of the objectives is optimized independently. The scaling factors are determined from the optimized functional values of these objectives. These scaling factors are very useful while the functional values of objectives are quite dissimilar. To sum up we can say, the scaling factors are made active in this approach by making their dependence on the functional value of all considered objectives. Let, for instance, t, the fitness of the scaled objective function is given by

$$Let,\ k_1(t)F_1(t) + k_2(t)F_2(t) + ... + k_l(t)F_l(t) + ... + k_n(t)F_n(t) = \gamma(t) \tag{1}$$

Where, $k_1(t)...k_n(t)$, are the proposed scaling factors defined such that

$$k_1(t) + k_2(t) + k_3(t) + ... + k_l(t) + ... + k_n(t) = 1 \tag{2}$$

For true reflection of the weighting factors,

$$k_1(t)F_1(t) = k_2(t)F_2(t) = k_3(t)F_3(t) = ... = k_l(t)F_l(t) = ... = k_n(t)F_n(t) \tag{3}$$

Equations (1), (2) and (3) yields,

$$k_l(t) = \frac{1}{F_l(t)\sum\limits_{p=1}^{n}\frac{1}{F_p(t)}}; \forall F_l(t) \neq 0, \forall l, p \in \Omega \tag{4}$$

Further, using (1) and (3),

$$\gamma(t) = nk_n(t)F_n(t) \tag{5}$$

$$\Rightarrow \frac{\partial \gamma(t)}{\gamma(t)} = \frac{\partial F_n(t)}{F_n(t)} \tag{6}$$

Equation (6) shows true reflection in the fitness of the overall objective function being optimized with the change in functional value of the objectives considered. This validates perfect scaling of the objectives. The generic representation of the weighted objective function for the proposed multiobjective problem can be expressed as:

$$Min\, F(t) = \sum_{l=1}^{n} w_l k_l(t) F_l(t); k_l(t) = \left(F_l(t) \sum_{p=1}^{n} \frac{1}{F_p(t)} \right)^{-1}; \sum_{l=1}^{n} k_l(t) = 1, \sum_{l=1}^{n} w_l = 1; \forall l, p \in \Omega \tag{7}$$

In (1)-(7), $k_l(t)$, w_l, n, and Ω are denoting proposed scaling factors and weighting factors of the objectives, number of objectives and set of objectives respectively.

3.1. Inner-layer optimization

The objective function for the inner-layer framework is therefore formulated as

$$\begin{gathered} \text{Min}\, F^{in}(s) = w_1 k_1(s) F_1^{in}(s) + w_2 k_2(s) F_2^{in}(s) + w_3 k_3(s) F_3^{in}(s); \\ k_l(s) = \left(F_l^{in}(s) \sum_{p=1}^{3} \frac{1}{F_p^{in}(s)} \right)^{-1}, \sum_{l=1}^{3} k_l(s) = 1, \sum_{l=1}^{3} w_l = 1; \forall s \in \Omega_s \end{gathered} \tag{8}$$

where,

$$\begin{aligned} F_1^{in}(s) = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{ij}(s)(P_i(s)P_j(s) + Q_i(s)Q_j(s)) + \beta_{ij}(s)(Q_i(s)P_j(s) - P_i(s)Q_j(s)); \\ \forall i \neq j, \;\&\; s \in \Omega_s \end{aligned} \tag{9}$$

$$\alpha_{ij}(s) = \frac{r_{ij}\cos(\delta_i(s) - \delta_j(s))}{V_i(s)V_j(s)} \qquad \beta_{ij}(s) = \frac{r_{ij}\sin(\delta_i(s) - \delta_j(s))}{V_i(s)V_j(s)} \tag{10}$$

$$F_2^{in}(s) = \begin{cases} \Re(V_1(s) I_1^*(s)); \delta_1(s) < \delta_2(s); \forall s \in \Omega_s \\ 1 \qquad\qquad\quad ; \delta_1(s) \geq \delta_2(s); \forall s \in \Omega_s \end{cases} \tag{11}$$

$$F_3^{in}(s) = 1 + \sum_{i=1}^{N} |(V_1 - V_i(s))| \,; \forall i \in \Omega_N, \forall s \in \Omega_s \tag{12}$$

Equations (9), (11) and (12) are corresponding to the objectives of minimizing feeder power losses, reverse power flow and node voltage deviation respectively. In (8)-(12), i, j, N, Ω_N,

$\Re$, s, and Ω_s are representing system nodes, number and set of system nodes, real power flow in the system, system state, and set of system states respectively.

Subject to the following constraints

$$P_{D,i}(s) - P_{DG,i}(s) \pm P_{ch,i}(s)/P_{dis,i}(s) = V_i(s) \sum_{j=1}^{N} V_j(s) Y_{ij} \cos\left(\theta_{ij} + \delta_j(s) - \delta_i(s)\right); \quad \forall i \in \Omega_N, i \neq j, \forall s \in \Omega_s \tag{13}$$

$$Q_{D,i}(s) = -V_i(s) \sum_{j=1}^{N} V_j(s) Y_{ij} \sin(\theta_{ij} + \delta_j(s) - \delta_i(s)); \forall i \in \Omega_N, i \neq j, \forall s \in \Omega_s \tag{14}$$

$$I_{ij}(s) \leq I_{ij}^{Max}; \forall i, j \in \Omega_N, i \neq j, \forall s \in \Omega_s \tag{15}$$

$$0 \leq P_{DG,i}(s) \leq P_{DG}^{Max}; \forall i \in \Omega_N, \forall s \in \Omega_s \tag{16}$$

$$0 \leq W_{B,b}(s) \leq W_B^{Max}; \forall b \in \Omega_b, \forall s \in \Omega_s \tag{17}$$

$$UB_{ch,i}(s) = \begin{cases} 0; SOC_i(s) = SOC^{Max} \;\; or \;\; \delta_1(s) \geq \delta_2(s) \\ P_B^{Max}; SOC_i(s-1) + \frac{\eta_c P_B^{Max}}{W_B^R}\Delta t < SOC^{Max} \;\&\; \delta_1(s) < \delta_2(s); \quad \forall i \in \Omega_N, \forall s \in \Omega_s \\ (SOC^{Max} - SOC_i(s-1))\frac{W_B^R}{\Delta t};\; SOC^{Max} - SOC_i(s-1) < \frac{\eta_c P_B^{Max}}{W_B^R}\Delta t \;\&\; \delta_1(s) < \delta_2(s) \end{cases} \tag{18}$$

$$UB_{dis,i}(s) = \begin{cases} 0; & SOC_i(s) = SOC^{Min} \;\; or \;\; \delta_1(s) \leq \delta_2(s) \\ P_B^{Min}; & SOC_i(s-1) - \frac{P_B^{Min}}{\eta_d W_B^R}\Delta t > SOC^{Min} \;\&\; \delta_1(s) > \delta_2(s); \\ (SOC_i(s-1) - SOC^{Min})\frac{W_B^R}{\Delta t}; & SOC_i(s-1) - SOC^{Min} < \frac{P_B^{Min}}{\eta_d W_B^R}\Delta t \;\&\; \delta_1(s) > \delta_2(s) \end{cases} \tag{19}$$

$$P_B^{Min} \leq P_{ch,i/dis,i}(s) \leq P_B^{Max}; \forall i \in \Omega_N, \forall s \in \Omega_s \tag{20}$$

$$SOC^{Min} \leq SOC_i(s) \leq SOC^{Max}; \forall i \in \Omega_N, \forall s \in \Omega_s \tag{21}$$

$$SOC_i(s) = SOC_i(s-1) + \left(\frac{\eta_c P_{ch,i}(s)}{W_B^R} - \frac{P_{dis,i}(s)}{\eta_d W_B^R}\right)\Delta t; \qquad \forall i \in \Omega_N, \forall s \in \Omega_s \tag{22}$$

Equations (13), (14) and (15) represent nodal power balance and feeder thermal limits respectively, (16) and (17) represent DG and BESS deployment capacity limits at a node. BESS charging/discharging limits are represented by (18), (19) and (20), whereas the SOC limits are denoted in (21) and (22) respectively. It is to be mentioned that the modelling of uncertain power generation from SPV is referred from [56].

3.2. Outer-layer optimization

The objective function for the outer-layer framework is formulated as

$$Min\,F^o = w_1\kappa_1 F_1^o + w_2\kappa_2 F_2^o + w_3\kappa_3 F_3^o; \kappa_l = \left(F_l^o \sum_{p=1}^{3} \frac{1}{F_p^o}\right)^{-1}, \sum_{l=1}^{3} \kappa_l = 1, \sum_{l=1}^{3} w_l = 1 \quad (23)$$

where,

$$F_1^o = \phi \sum_{s=1}^{N_S} F_1^{in}(s); \forall s \in \Omega_s \quad (24)$$

$$F_2^o = \left(\sqrt{\frac{1}{N_s}\sum_{s=1}^{N_S}\left(\overline{P_G} - P_G(s)\right)}^{\,2}\right); \forall s \in \Omega_s \quad (25)$$

$$F_3^o = 1 + \left|\sum_{b=1}^{N_b}\sum_{s=1}^{N_s} P_{ch,i}(s) - \sum_{b=1}^{N_b}\sum_{s=1}^{N_s} P_{dis,i}(s)\right|; \forall i \in \Omega_N, \forall b \in \Omega_b, \forall s \in \Omega_s \quad (26)$$

Here (24), (25) and (26) are corresponding to the objectives of minimizing annual energy loss, load deviation index (LDI), and maximizing utilization index of BESSs to be deployed respectively. Also, N_b, Ω_b, and N_s are denoting number and set of deployed BESSs and number of system states respectively. Since inner-layer optimization is nested with outer-layer optimization, the constraints defined by (13)-(22) are equally valid for the outer-layer framework.

4. Optimization Technique

Moth Search Optimization (MSO) is a swarm intelligence based optimization technique introduced by Gai-Ge Wang in 2016 [57]. MSO is based upon the hypothesis that moth will instinctively tend to do its best to adjust the flight orientation so as to move towards the light source all the time, causing the airborne moths to come plummeting downward thus leads to a spiral flight path that gets closer and closer to the light source (the global optima) [58]. Phototaxis and Levy flights are the essential features of MSO that provide exploration and exploitation of the problem search space. The levy flight motion is adopted to update the positions of the moth population close to light sources (final aim). On the other hand, the straight flight motion is used to update the positions of the moth population very far away from the light source. The control equations of MSO as suggested in [57] can be briefly described as below.

4.1. Levy flights

The position of ith moth with levy flight motion is updated as

$$z_i^{t+1} = z_i^t + \gamma L(s); \qquad \text{where, } \gamma = \frac{S_{\max}}{t^2}; \text{ and, } L(s) = \frac{(\beta-1)\Gamma(\beta-1)\sin\frac{\pi(\beta-1)}{2}}{\pi s^{\beta}} \tag{27}$$

Where, z_i^t and z_i^{t+1} are representing the current and updated positions of the ith moth in t and $(t+1)$th generations, respectively. $L(s)$, γ, and S_{max} are step-size drawn from Levy flights, scale factor, and maximum walk step, respectively. β is taken as 1.5 and $\Gamma(x)$ denotes the gamma function for s be a positive number.

4.2. Phototaxis

In straight flight, the position of a moth can be updated using the following modelling.

$$z_i^{t+1} = \begin{cases} \lambda(z_i^t + \varphi(z_{best}^t - z_i^t)); \; rand(.) > 0.5 \\ \lambda(z_i^t + \frac{1}{\varphi}(z_{best}^t - z_i^t)); \; rand(.) \leq 0.5 \end{cases} \tag{28}$$

Where, φ is an acceleration factor that is being set to golden ration, usually taken as $(\sqrt{5}+1)/2$, and λ is a scale factor being selected randomly to enhance diversity in population.

Recently, the Ref. [5] has pointed out that the standard MSO poorly converges for large-scale complex engineering optimization problems. According to authors the modeling of straight flights, i.e. (28) may mislead moth as the modelling also scales its previous position in addition to its distance from the light source. Eventually, the algorithm converges to local optima. This limitation is overcome by proposing Corrected MSO (CMSO) in [5] by suggesting the following modified modelling for straight flight.

$$z_i^{t+1} = \begin{cases} z_i^t + \varphi(z_{best}^t - z_i^t)\lambda; \; \text{rand}(.) > 0.5 \\ z_i^t + \frac{1}{\varphi}(z_{best}^t - z_i^t)\lambda; \; \text{rand}(.) \leq 0.5 \end{cases} \tag{29}$$

In the present work, CMSO is employed to solve the proposed nested optimization problem for optimally placing DERs in distribution system. For further details, Ref. [57, 5] may be referred. The generalized structure of an individual employed in the outer-layer CMSO algorithm is presented in Fig. 1. It shows the information about the siting and sizing of n_p SPVs and n_b BESSs to be deployed. Similarly, the structure of an individual used in the inner-layer CMSO algorithm is presented in Fig. 2. It contains the inner-layer optimization variables of state s, i.e. charging/discharging power of suggested n_b BESSs. Further, the complete structure of the proposed nested optimization framework, employing CMSO in both the layers, is presented in the flow chart as shown in Fig. 3

5. Simulation Results

In this section, the proposed methodology is validated by implementing it on 12.66 kV, 33-bus test distribution system [59]. The active and reactive peak demand for this

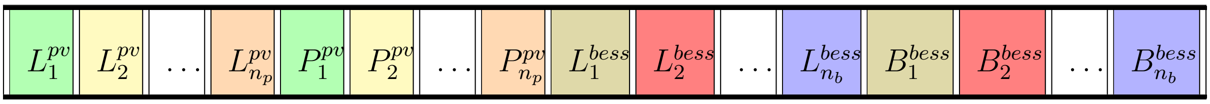


Figure 1: Structure of an individual used in outer-layer CMSO (decision variables of outer-layer optimization problem)

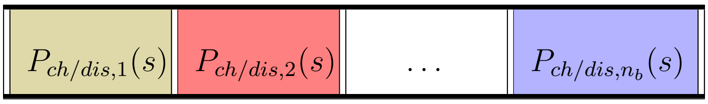


Figure 2: Structure of an individual used in inner-layer CMSO (dispatch decision variables of BESSs in state s)

system is 3715 kW and 2300 kVAr, respectively. The power losses and minimum node voltage, with this network loading, are 202.67 kW and 0.9131p.u, respectively. The detailed bus and line data of the system may be referred from [59]. Various technical parameters pertaining to power generation from SPV and charging/discharging of BESS are presented in Table 1. Three SPVs and three BESSs are assumed to be placed in the system as they are found to be optimal for 33-bus test system [60]. The upper limits of each SPV and BESS to be installed on a single node are taken as 2 MWp and 5 MWh, respectively. The node voltage limits are set as ± 6%. The annual hourly load demand and illumination intensity of solar irradiation are taken from [61, 62]. The nested DER integration problems are highly complex and computationally intensive already without considering any types of uncertainties [41, 43, 44]. The optimality will be achieved but at the cost of the excessively high computational burden. Therefore, the most likely scenarios are considered from the annual load and generation profiles [61, 62]. To minimize the simulation scenarios, the annual load demand, and solar irradiation data are hourly averaged and then divided with their respective annual peak values to obtain the hourly multiplying factors, as shown in Fig. 4. These factors are multiplied with the corresponding peak loads and suggested PV capacities to obtain the load and generation profiles respectively. From the figure, it can be inferred that peak load demand does not coincide with the peak power generation from SPV units which shows the high potential of energy storage deployment to exploit associated arbitrage profits. The promising feature of this model is that the BESSs deployed with the PV systems absorb major uncertainties caused by fluctuating PV power generation and load demand.

The proposed methodology is applied to optimize the objective functions defined by (8) and (23). The selection of weights in the proposed methodology is left with the choice of the operator. The weights of all the objectives have been taken identical in the present work. The population size and maximum iteration count of CMSO are taken as 100 and 200, respectively for each layer of optimization. The other parameters of the algorithm may be referred from [5]. The backward/forward sweep distribution power flow method is employed to solve power flow equations of distribution system.

The application results of the proposed method for optimal sizing and siting of SPVs and BESSs are shown in Table 2. Incidentally, optimal locations of SPV and BESS units

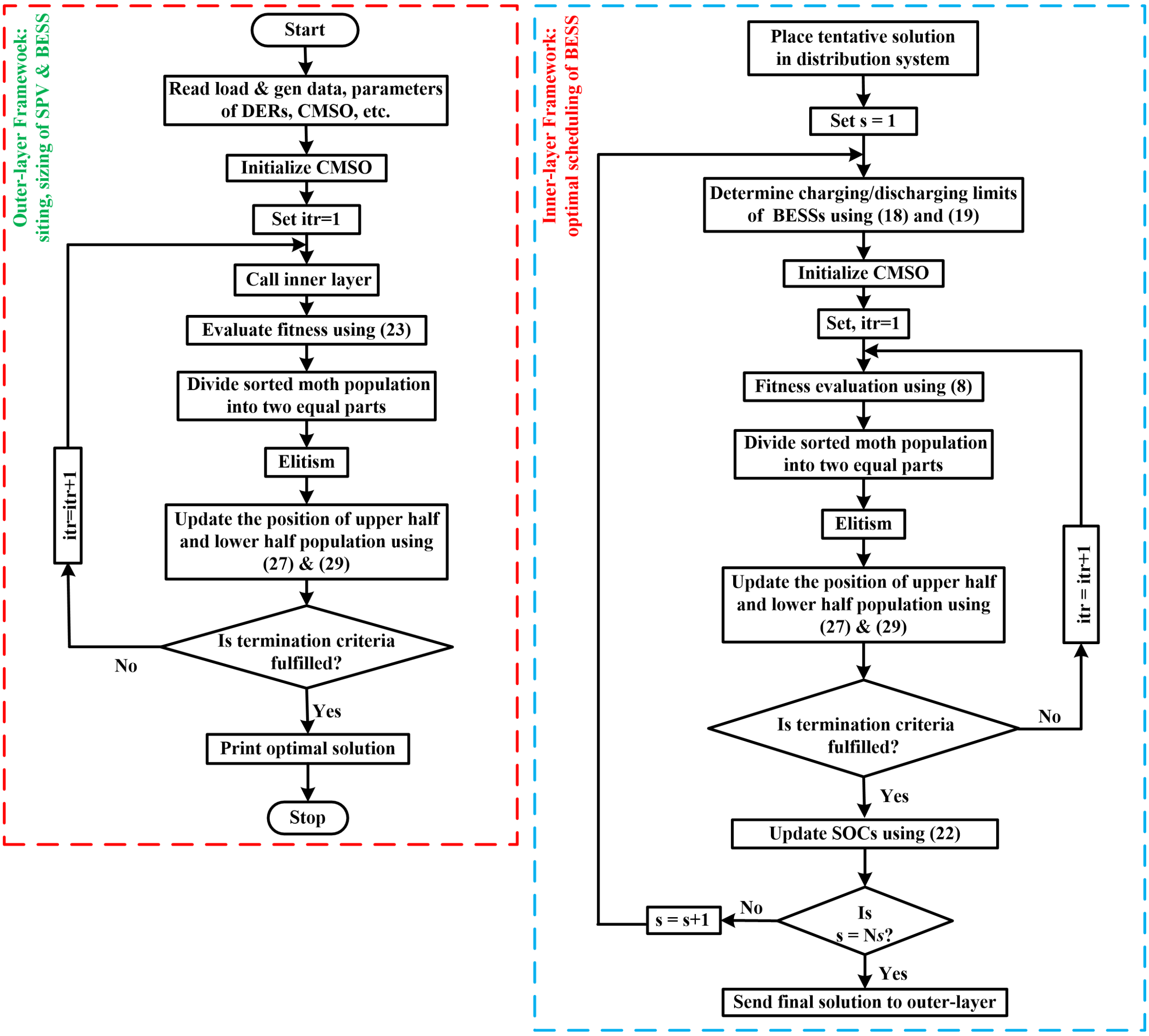


Figure 3: Flow chart of the proposed nested optimization framework employing Corrected MSO (CMSO) in both the layers

are found to be the same. It could be possible since the charging and discharging of BESSs would minimize the power loss if deployed at PV nodes. It also validates the assumptions proposed in Section 2, regarding the charging of BESSs from renewables only. It may be observed from the table that penetration of SPV is found to be 3551 kWp which is nearly 95.6% of the peak demand. To facilitate this high penetration, the total optimal capacity of BESS units is found to be 7320 kWh.

The obtained optimal charging/discharging status of BESSs is presented in Fig. 5. From Fig. 4 and Fig. 5, it may be observed that the charging of BESSs follows the power generation profile of SPVs and their discharging follows the demand profile of peak hours. The utilization of BESSs is found to be almost 100% i.e., BESS units charges to their

Table 1: Technical parameters considered for simulation purpose

Parameter(s)	Value(s)
T	24 H
$\eta_{c/d}$	85%
P_B^{Min}/P_B^{Max}	1 MW/1 MW
SOC^{Min}/SOC^{Max}	0.1/ 1.0
P_{DG}^{Max}/W_B^{Max}	2 MW/5 MWh

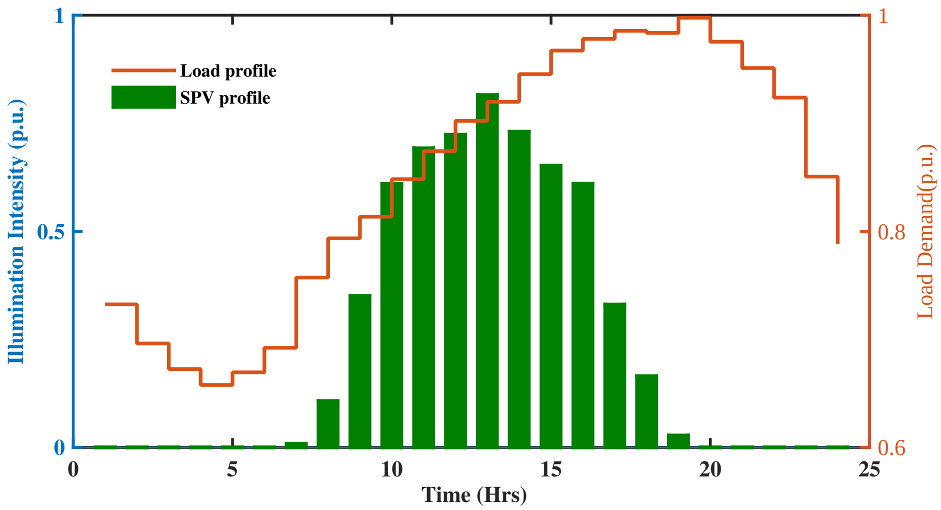


Figure 4: Load demand and illumination intensity of solar irradiation

Table 2: The optimal siting and sizing of SPVs and BESSs

Node	SPV (kWp)	BESS (kWh)
10	1831	4530
17	520	300
32	1200	2490

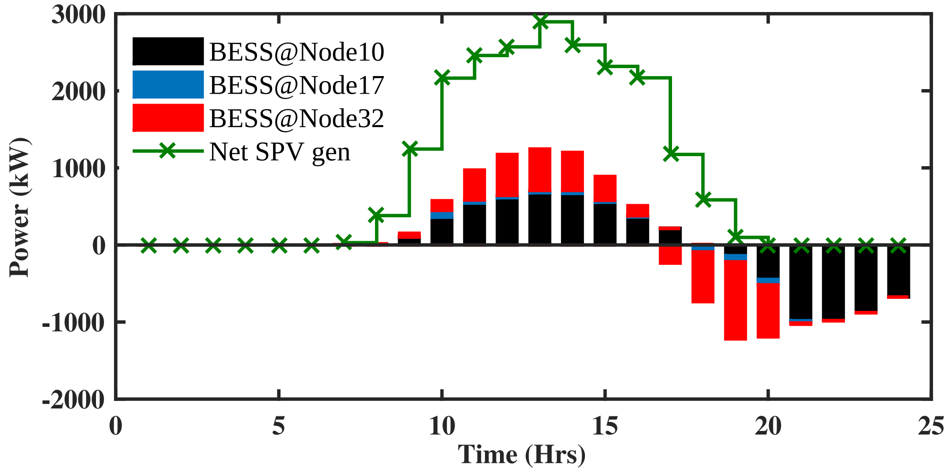
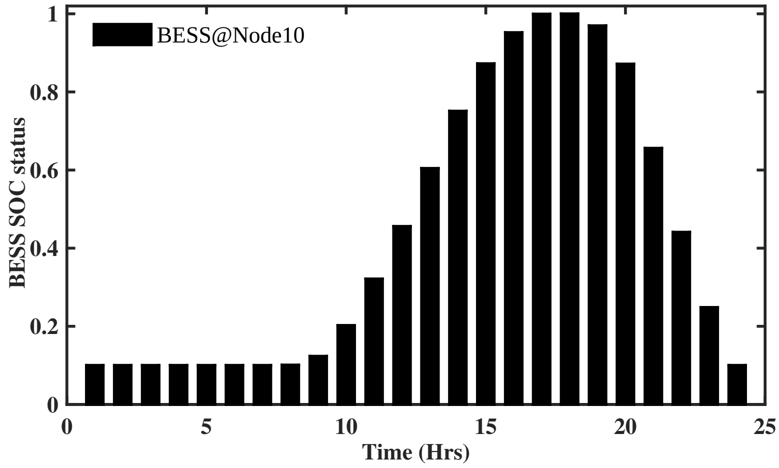


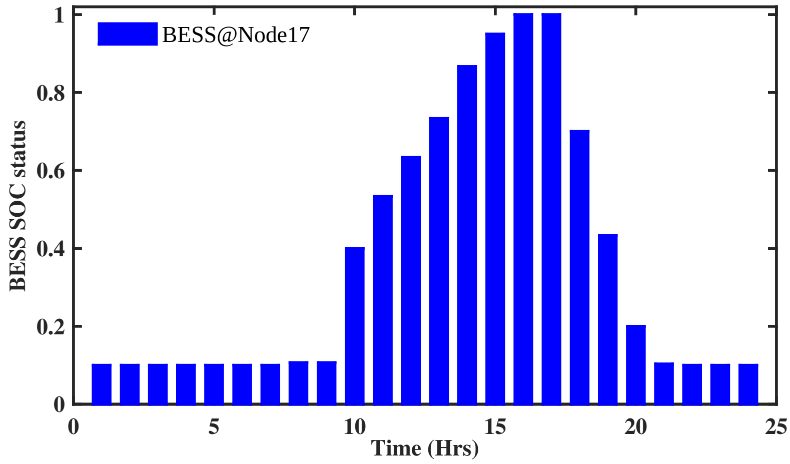
Figure 5: Optimal charging and discharging status of individual BESS over one dispatch cycle and daily net generation from SPVs

Table 3: Simulation results

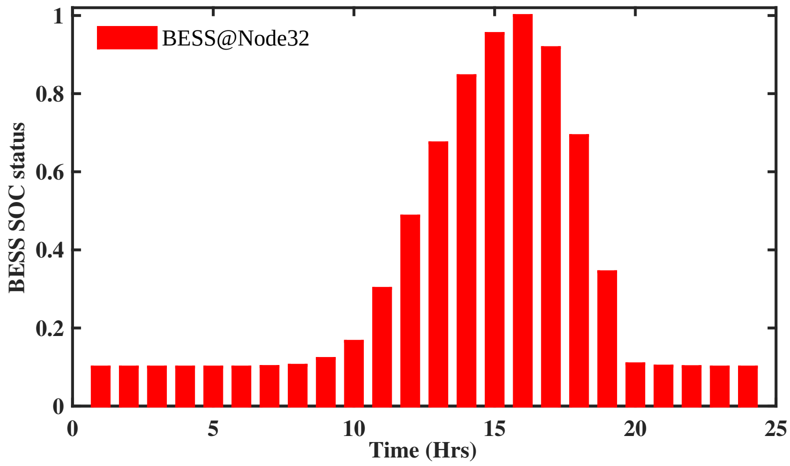
Scenario(s)	Peak power demand (kW)	Annual energy loss (MWh)	LDI (kW)	Reverse power flow (kW)
Before	3908.03	1279.60	467.30	NA
After	2900.00	950.93	277.07	Nil



(a) BESS at node 10



(b) BESS at node 17



(c) BESS at node 32

Figure 6: SOC status over one dispatch cycle of BESSs

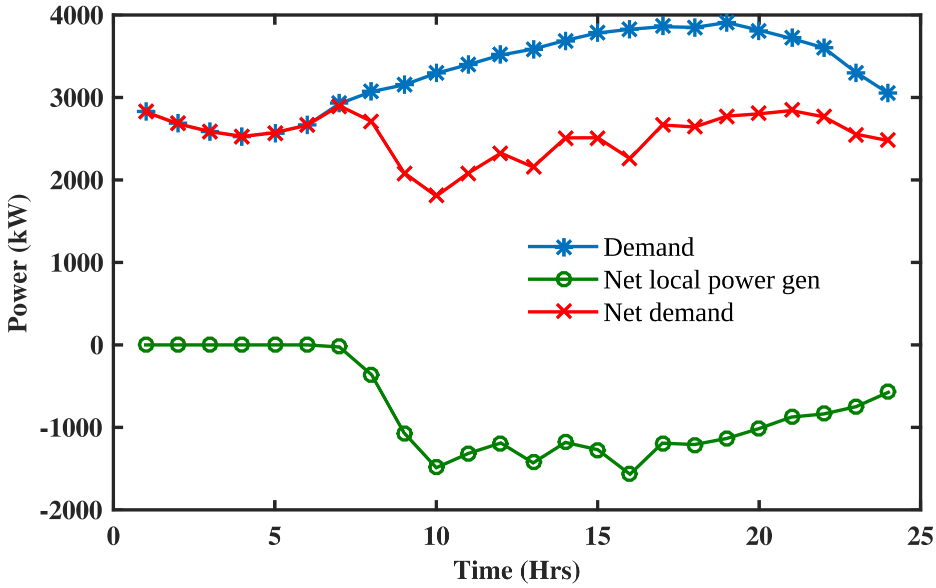


Figure 7: Impact on load demand using proposed method

capacity and discharges to their lower limits in a dispatch cycle of 24 hrs. The SOC status through one cycle of individual BESSs is presented in Fig. 6. It can be depicted from the figure that the SOC status of each BESS varies from pre-set lower limit to pre-set higher limit and the pre-set lower limit is again reached at the end of dispatch cycle. Thus proposed methodology ensures optimum utilization of each BESS unit.

The impact of proposed method on the load demand profile of the station is presented in Fig. 7. The figure shows the load demand on the station before DER placement, the net local power generation of SPVs and BESSs taken together and the net load demand of the grid after DERs placement for a typical day. It can be observed that load demand profile improves. The results of peak power demand, annual energy loss (AEL), load deviation index (LDI) and reverse power flow (energy spillage) are shown in Table 3. From the table it may be observed that the LDI is improved by 40.71%, i.e. from 467.30 kW to 277.07 kW. As a consequence, peak load demand as well as AEL reduction is found to be significantly reduced by about 26%. Moreover, the difference between peak and valley point demand is reduced by 21%. However, the peak loading hour is shifted from 19:00 Hrs to 7:00 Hrs. Proposed solution always maintains a positive net demand from the grid. As a result there is no reverse power flow (energy spillage) as shown in Table 3. It is noteworthy that the proposed methodology completely mitigates reverse power flow in spite of almost 95.6 % penetration of SPV power.

The optimal solution obtained by employing the proposed methodology provides better operational management of storage system while mitigating the intermittency in renewable power generation and variability in system demand. This ultimately results in power loss reduction and node voltage profile enhancement. The hourly feeder power losses before and after DER integration are shown in Fig. 8. From the figure, it can be noticed that the hourly

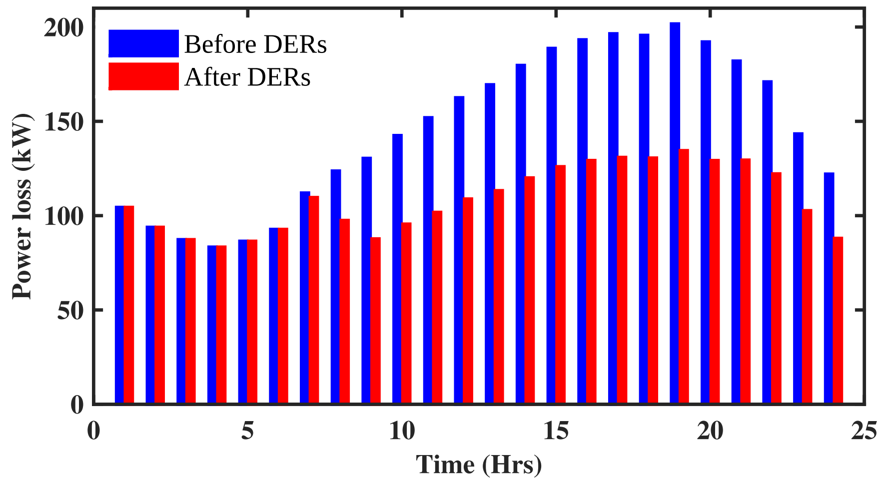


Figure 8: Impact on hourly feeder power losses using proposed method

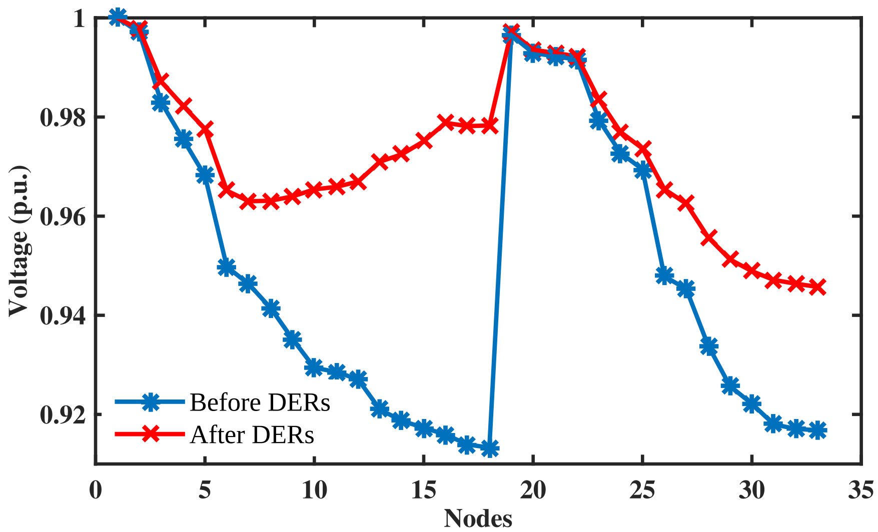


Figure 9: Improvement in node voltage profile during peak load condition

power losses are reduced by about 30 % during the utilization period of SPVs and BESSs, which is a significant figure. Also, from Table 3, it can be observed that the annual quantity for this loss reduction is around 329 MWh. The node voltage profiles of the distribution system, during peak hours, before and after the implementation of proposed methodology are depicted in Fig. 9. It may be observed that even during peak load hours, the voltage profile of the distribution system substantially improves and all the node voltages remain within predefined limits of ± 6%. Thus, the optimal solution obtained using proposed methodology faithfully meets all intended objectives.

Finally, in order to highlight the impact of simultaneous joint allocation and operational management of SPVs and BESSs in distribution systems, three cases are considered. In case-I, only SPVs are optimized, in case-II, BESSs are optimized assuming existing SPVs as in case-I, and proposed simultaneous joint optimization of SPVs and BESSs in case-III. Further, two more cases (case-IV and case-V) are explored so as to show the effectiveness and applicability of the proposed multiobjective nested optimization problem. In case-IV and case-V, joint integration of SPVs and BESSs is considered while satisfying objectives of

Table 4: Comparison results obtained for cases I to V, with respect to the base case

Case(s)	**Optimal solution**		**DG penetration** (%)	**Peak demand reduction** (%)	**AEL reduction** (%)	**LDI enhancement** (%)
	SPVs siting/sizing (kWp)	**BESSs siting/sizing (kWh)**				
I	16/271 24/500 31/325	-	29.50	0.77	15.88	07.99
II	16/271 24/500 31/325	16/940 24/2245 31/1846	29.50	2.94	19.48	26.42
III	10/1831 17/520 32/1200	10/4530 17/300 32/2490	95.58	25.79	25.68	40.71
IV	14/1740 24/770 30/1165	14/4720 24/940 30/1920	98.92	26.51	36.43	-2.82
V	10/1430 16/571 31/906	10/3621 16/870 31/1741	78.25	25.83	17.54	58.84

annual energy loss minimization and minimization of LDI respectively.

The comparison results obtained for these five cases with respect to the base case are presented in Table 4. The table clearly shows no significant improvement in results obtained while comparing case-II with case-I. This shows that if BESSs are optimized alone after optimally placing DGs, it may not cause much improvement in the system operation. However, if employing proposed joint optimization, as in case-III, the results are found to be improved significantly with DG penetration of 95.58%, peak demand reduction of 25.79%, AEL reduction of 25.68%, and LDI enhancement of 40.71%. It happened because the optimal solution obtained in case-III is different than that obtained in case-II. Now, comparing case-IV with case-III, it can be observed that AEL minimization is achieved highly in case-IV as compared to case-III, but the load deviation gets worsen (negative sign indicates diminution in LDI), which is a serious concern for the power system operators. On contrary, in case-V, LDI enhancement achieved is much more than in case-III, but AEL reduction achieved is less. From this comparison, it can be observed that case-III provides most compromising and promising results, thus proving the effectiveness of the proposed multiobjective optimization problem. Moreover, the proposed nested optimization approach allows more penetration of both SPVs and BESSs (in the last three cases) owing to nested optimization strategy where BESSs are managed more efficiently with the dynamically varying system states.

6. Discussion

The results obtained using proposed methodology are promising because of constrained objectives suggested in the inner-layer framework. The proposed methodology simultaneously optimizes the sizing-siting of SPVs and BESSs in the outer-layer while keeping an eye on the optimal utilization of BESSs through inner-layer optimization. Feeder power losses depend upon line flows which are strict function of placement of DERs and their power transaction with distribution buses. The power transaction of SPVs is uncontrolled but that of BESSs is optimally managed to minimize power losses as well as reverse power flow. The minimization of these two objectives governs not only sizing and siting of DERs but also helps to explore the best possible dispatch from BESSs as all these decides distribution flows for the given load demand. Thus proposed optimization strategy indirectly, but effectively, resolved the complex constraints pertaining to optimal BESS dispatch over dynamically varying system states.

7. Conclusions

In this paper, a nested optimization framework is proposed for the coordinated placement of SPVs and BESSs in distribution systems that ensures high penetration of SPV without spillage of energy and optimum utilization of obtained BESS units. The proposed methodology enhances various performance objectives of distribution systems. The application results show that the proposed methodology provides significant peak load shaving and feeder power loss reduction and also improves load demand and node voltage profile of the system by optimally coordinating the dispatches of BESSs with dynamically varying power generation from SPVs and load demand. Since the optimization of sizing and siting of these DERs is carried while considering optimal operation of BESSs, the optimal solution restrains reverse power flow and causes best possible utilization of energy storage devices while absorbing intermittency in renewable power generation and dispatch the same during most stringent system operating conditions. The selection of objectives for the proposed inner-layer framework is responsible for better results as the proposed method is free from any additional constraints being applied for desired operation of BESSs under dynamically varying states. The proposed method is highly simplified and effective to determine sizing and siting of SPVs and BESSs as cost effectiveness of DERs is ignored. The present work can be extended to the joint optimization operational planning problem of other types of renewable DGs, energy storage systems, PEVs etc.

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