Optimal Integration and Management of Solar Generation and Battery Storage System in Distribution Systems under Uncertain Environment

Rayees Ahmad Thokar*‡, Nikhil Gupta*, K. R. Niazi*, Anil Swarnkar*, Sachin Sharma*, Nand K. Meena**

*Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur (302017), Rajasthan, India

**School of Engineering and Applied Science, Aston University, Birmingham, UK

(raishameed427@gmail.com, nikhilgupta.ee@mnit.ac.in, krniazi.ee@mnit.ac.in, mnit.anil@gmail.com, sachineesharma@gmail.com, nkmeena@ieee.org)

‡ Rayees Ahmad Thokar, Department of Electrical Engineering, Malaviya National Institute of Technology, Jaipur (302017), Rajasthan, India, Tel: +91 8725985722, raishameed427@gmail.com

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Abstract- The simultaneous placement of solar photovoltaics (SPVs) and battery energy storage systems (BESSs) in distribution systems is a highly complex combinatorial optimization problem. It not only involves siting and sizing but is also embedded with charging and discharging dispatches of BESSs under dynamically varying system states with intermittency of SPVs and operational constraints. This makes the simultaneous allocation a nested problem, where the operational part acts as a constraint for the planning part and adds complexity to the problem. This paper presents a bi-layer optimization strategy to optimally place SPVs and BESSs in the distribution system. A simple and effective operating BESS strategy model is developed to mitigate reverse power flow, enhance load deviation index and absorb variability of load and power generation which are essential features for the faithful exploitation of available renewable energy sources (RESs). In the proposed optimization strategy, the inner layer optimizes the energy management of BESSs for the sizing and siting as suggested by the outer layer. Since the inner layer optimizes each system state separately, the problem search space of GA is significantly reduced. The application results on a benchmark 33-bus test distribution system highlight the importance of the proposed method.

Keywords Battery energy storage systems, multi-objective optimization, bi-layer optimization strategy, distribution systems, RES integration.

1. Introduction

The world now is facing an energy crisis and rising climatic threats that impose a large scale integration of renewable energy resources and considerable changes on the way how to operate the future power system. As a consequence, the integration of renewable distributed generations (DGs), such as solar photovoltaics (SPVs) and wind turbines (WTs) is trending in contemporary distribution systems. Also, the concept of active distribution systems (ADSs) within the vertically integrated system can be possible only by integrating different DER technologies and to analyze their impact on the system operational efficiency [1-4]. Several benefits achieved by the integration of these DGs include alleviation of node voltage deviation, reduced system losses, reduced CO2 emission, improved reliability, and security, etc. [5-8]. However, there arise certain issues with the rapid integration of these DGs which may include worsening of load deviation index, reverse feed, voltage rise, blinding of protection, fault current rising, etc. [5, 6]. Although renewable DGs can help in improving the system performance, however, the full utilization is not possible because of their intermittent and non-dispatchable nature. To alleviate the above-mentioned issues, battery energy storage systems (BESSs) may act as potential candidates by absorbing the intermittent nature of renewable DGs, help them to act as dispatchable sources and can systematically optimize the system operations through coordinated management process. Moreover, the proper coordination among these DERs i.e. BESSs and DGs can also help to enhance the system reliability, stability, and efficiency [5, 6, 9-12]. In addition, the proper management, coordination, and allocation of these DERs seems to be the only alternative that can help to realize the development of ADSs within the vertically integrated system and can bring several advantages to the contemporary distribution systems [13, 14]. This reflects that BESSs can provide great operational flexibility to ADSs but at the cost of sufficiently high investment [15]. Thus the BESS placement can only be justified if it ensures sufficient renewable DG penetration with associated technical benefits. Also, the untimely placement of these DERs may be counterproductive for all stakeholders. Therefore simultaneous optimal coordination and allocation of these DERs may be an interesting choice but is a highly complex, combinatorial and computationally demanding exercise that needs well-tailored methodology and solution technique.

Considerable work has been presented by several researchers in the area of optimal BESS allocation by employing several techniques of optimization [16-20]. The optimal BESS sizing was the main concern of authors in these research works while giving merely any importance to the siting problem of BESS. In [16, 17], dynamic programming is utilized to optimally allocate BESSs in distribution systems while maximizing energy arbitrage benefits. The impact of BESS capacity on system net present value, operational cost and reliability is studied in [18, 19]. In [18], a non-dominated sorting genetic algorithm (NSGA) is used as a multiobjective optimization technique. Authors' in [20, 21] proposed two-stage optimization framework and Grey Wolf optimization to minimize system cost function while optimally assessing the sizing problem of storage systems. For optimal allocation of energy storage systems in distribution system integrated with distributed generation authors proposed a methodology in order to alleviate wind curtailment and to minimize the energy cost function [22]. A short-term operational planning for optimal scheduling of allocated BESSs in distribution systems is performed while considering uncertainties in deployed renewable power generation [23]. In several published works [24-27], researchers succeed in achieving various objectives while optimally allocating BESSs in distribution systems. But, in neither of the works have been seen the simultaneous sizing and siting of BESSs in coordination with DGs, in fact, a few published literature, still not covering the whole aspect, is available in this domain [28-31]. In [28], authors simultaneously allocated battery switching stations and DGs optimally for mitigating system losses but only dispatchable DGs were taken into consideration. To determine sizing and siting of only BESSs in distribution system while mitigating net present cost of system and BESSs a new optimization framework is proposed in [29]. A dynamic programming technique is proposed in [30] to optimally allocate BESSs in order to mitigate the existed abandoned solar and wind energy. The study revealed that total benefits from large scale storage systems can be increased by utilizing distributed generations optimally. Lately an optimization framework is proposed [31] for simultaneous optimal allocation and charge/discharge dispatch of BESSs for mitigating the undesired impacts of existing high PV penetration in distribution systems. In this study both techno-economic as well as emission objectives were achieved. In [29-31], simultaneous placement and sizing with daily charge/discharge dispatch of BESSs is presented but with the existing renewable energy sources (RESs). However, it may be more beneficial and realistic if the allocation of DGs and BESSs is performed simultaneously, which to the best of authors' knowledge has not been presented yet in the literature. Also, the undesired placement of DGs may lead to counterproductive solutions for all the stakeholders. Therefore, the simultaneous allocation of DGs and BESSs can be greatly helpful in enhancing the penetration of RESs and alleviating their undesired impacts in distribution systems already discussed above. Further, the operational efficiency of contemporary distribution systems can also be enhanced with added benefits to utility, consumers, and DER owners by performing the simultaneous allocation process [32].

From the aforementioned discussion, it may be summarised that simultaneous optimal placement and sizing of renewable DGs and BESSs with daily charge/discharge dispatch of BESSs may be an interesting but complex opportunity that needs to be investigated. Simultaneous allocation of BESSs and DGs is a highly complex combinatorial optimization problem as it not only involves their optimal placement but is also embedded with optimal charging and discharging dispatch of BESSs under dynamically varying system states while satisfying network operational constraints. Furthermore, the simultaneous optimization problem is highly computationally demanding owing to the huge search space offered to metaheuristic solution techniques. Therefore, a comprehensive optimization strategy needs to be developed to simultaneously site, size and manage these DERs so as to extract maximum possible benefits from these resources and justify their installation.

In this article, authors' are proposing a bi-layer optimization strategy for simultaneous sizing and siting of SPVs and BESSs in distribution systems by considering optimum utilization of BESSs under uncertain environment. A multi-objective formulation is suggested in fuzzy-framework by considering the minimization of feeder power loss, node voltage deviation, reverse power flow, load deviation index, etc. The optimal placement of SPVs and BESSs is determined in the outer layer whereas the inner layer optimally manages the operation of BESSs while considering several network operation constraints. In addition, the authors' modified the existing self-adaptive polyhedral uncertainty sets to efficiently handle uncertain data of load and generation.

The key takeaways of the proposed methodology include:

1. A new optimization strategy is developed for simultaneous sizing, siting, and management of multiple DER technologies, i.e. SPVs and BESSs under uncertain environment.
2. A modified self-adaptive polyhedral uncertainty sets is developed to efficiently handle intermittency and variability in DG power generation and load demand.
3. A simple, flexible and adaptive dynamic operating strategy for efficient utilization of BESS is proposed.

The proposed methodology is applied on a standard 33-bus test distribution system. The results of study highlight the importance of the proposed method.

In the following section the proposed bi-layer optimisation methodology is presented. The section contains multiple sub-sections such as BESS utilization strategy, synthetic data generation and mathematical modelling including multi-objective formulation. In Section 3, the solution technique for the proposed methodology is discussed. The simulation results and discussions are presented in Section 4, followed by conclusions drawn in Section 5.

2. Proposed Optimization Methodology

The objective of the proposed methodology is to allocate SPVs and BESSs so as to ensure full utilization of SPV and optimize the performance of active distribution systems in terms of economic and technical benefits while satisfying the network's operational constraints. The primary concern of the distribution system operator (DSO) is to make sure that the network is reliable, secure and efficient. The large variation between peak and valley period in load profile of the distribution system results in various issues like demand-supply mismatch, increased penalties, reduction in reliability and efficiency, underutilization of grid assets and investments. Therefore, one of the objectives of distribution performance could be minimization of the deviation in load demands. The minimization of feeder power loss has a positive impact on relieving substation transformers and feeders during peak load periods, improving node voltage profile and providing additional economic and environmental benefits [33]. The SPV units with all its benefits are uncertain and may cause reverse power flow into the grid due to excess local generation. This can give rise to overheating of feeders, excessive losses, blinding of protection, etc. In order to solve this problem, proper allocation and coordination of different SPVs and BESSs is the need of the hour [1, 13-14]. In comparison to regular DER technologies, the installation and running cost of BESS is very high with a comparatively lesser lifetime. Therefore, minimum required storage capacity should be deployed with a limited number of charging and discharging cycles within 24-hour duration [29, 30]. The optimum utilization of BESSs is ensured by coordinating their charging and discharging cycles throughout the day while satisfying several constraints. This requires the consideration of all system states which may prevail during the day. Considering the complex combinatorial nature of the SPV and BESS allocation problem, a bi-layer optimization strategy is proposed.

The bi-layer optimization strategy represents a nested structure where the inner layer is embedded within the outer layer [34]. In this strategy, the decision making process at the inner layer is affected by the decision making process at the outer layer and vice-versa. The strategy constitutes of two layers; the outer-layer and the inner-layer. The outer-layer deals with the optimal siting and sizing of SPVs and BESSs by considering the mean annual scenario. The inner-layer considers mean day scenario in order to optimally manage the hourly dispatch of BESSs for the placement of SPVs and BESSs suggested by the outer layer. A separate multi-objective function is suggested for each layer in the fuzzy framework. The objectives considered for the outer layer are minimization of annual energy loss, minimization of load deviation index and maximization of BESS utilization. And for the inner layer, the objectives considered are minimization of feeder power loss, minimization of node voltage deviation and minimization of reverse power flow. These objectives are executed for all possible operating conditions while satisfying system operational constraints. The decision variables for the outer-layer include DERs sizes and sites; whereas, decision variables for the inner-layer are SOC and charging/discharging power of BESSs.

2.1. BESS Utilization Strategy

The intermittency and variability in power generation from SPVs and load demand may cause a lot of operational problems. By employing BESSs, the variability of DGs and load can be absorbed. For this, an optimal and flexible hourly operating strategy of BESS in the inner-layer of strategy is proposed. On the basis of accurate information on generation from SPVs and demand profile, the length of charge and discharge periods on a daily basis should be optimized [35]. The proposed operating strategy of BESSs is summarized as under.

1. The BESSs are charged by SPV units only. This ensures that intermittency of SPV generations is absorbed by BESS units and no additional loss takes place on account of BESS charging from the grid. This strategy also ensures that there is no reverse power flow.

2. The discharging of BESS takes place during on-peak hours and therefore results in peak shaving with consequent reduction in power loss. It is made sure that all available energy in BESSs up to their lower limits of SOCs is fully utilized.

3. The charging and discharging are governed by SOC limits, efficiency and time periods of charging/discharging of the BESSs, mathematically expressed as given in equations (1) and (2).

4. The charging and discharging dispatches after the 24-hour duration should be balanced so that the energy stored in the deployed storage systems must be exploited fully.

In equation (1) and (2), P_B^{Min} & P_B^{Max}, SOC_i^h, SOC^{Min} & SOC^{Max}, $\eta_{c/d}$, W_B^R, I_G^h, Ω, and T are representing minimum and maximum permissible charging/discharging power limits of BESS, SOC status of BESS at i^{th} node in h^{th} hour, minimum and maximum SOC limits of BESS, charging/discharging efficiency of BESS,

$$P_{ch_i}^{h} = \begin{cases} 0; & SOC_i^h = SOC^{Max} \text{ or } I_G^h \geq 0 \\ P_B^{Max}; & SOC_i^{h-1} + \frac{\eta_c P_B^{Max}}{W_B^R}\Delta t < SOC^{Max} \;\&\; I_G^h < 0 \\ (SOC^{Max} - SOC_i^{h-1})\frac{W_B^R}{\Delta t}; & SOC^{Max} - SOC_i^{h-1} < \frac{\eta_c P_B^{Max}}{W_B^R}\Delta t \;\&\; I_G^h < 0 \end{cases} \quad ,\forall i \in \Omega, \forall h \in T \tag{1}$$

$$P_{dis_i}^{h} = \begin{cases} 0; & SOC_i^h = SOC^{Min} \text{ or } I_G^h \leq 0 \\ P_B^{Min}; & SOC_i^{h-1} - \frac{P_B^{Min}}{\eta_d W_B^R}\Delta t > SOC^{Min} \;\&\; I_G^h > 0 \\ (SOC_i^{h-1} - SOC^{Min})\frac{W_B^R}{\Delta t}; & SOC_i^{h-1} - SOC^{Min} < \frac{P_B^{Min}}{\eta_d W_B^R}\Delta t \;\&\; I_G^h > 0 \end{cases} \quad ,\forall i \in \Omega, h \in T \tag{2}$$

rated energy storage capacity of BESS, current magnitude in secondary winding of grid substation transformer, set of system nodes and set of system states respectively.

2.2. *Solar Photovoltaic (SPV) Power Generation*

The power output of SPV unit is uncertain because of the intermittency and variability of illumination intensity. The electricity generation can be represented as a linear function of illumination intensity [36], expressed mathematically as given in equation (3). The electricity generated is equal to the rated output power of SPV, if the illumination intensity is greater than the rated intensity.

$$P_{DG_i}(h) = f(\chi);$$
$$P_{DG_i}(h) = \begin{cases} P^{SPV-Rated}; \chi_i^h \geq \chi_r \\ P^{SPV-Rated}\frac{\chi_i^h}{\chi_r}; 0 < \chi_i^h < \chi_r \end{cases} ,\forall i \in \Omega, h \in T \tag{3}$$

In equation (3), P_{DG_i}, $P^{SPV-Rated}$, χ_i^h, χ_r represent output power of *SPV* unit, rated output power of *SPV* unit, illumination intensity at i^{th} node in h^{th} hour and rated illumination intensity respectively.

2.2.1. *Proposed Synthetic Data Generation Model*

In the existing literature, many authors [5-6, 9-10] have taken deterministic nature of renewable generation and load data into the consideration to solve DER allocation problem. As a matter of fact, load demand and generation from RESs are highly variable and intermittent in nature. The intermittency in power generation from DG units and the stochastic nature of load demand should be taken into consideration to obtain practical solutions. Various stochastic programming methods like point estimation method (PEM) [37], Monte Carlo simulation (MCS) [38], and others [39, 40] have been employed for this purpose but require vast information, large number of system states, and are computationally demanding. Reference [41] proposed simple deterministic approach which quickly handles uncertain data, however, needs trade-off between robustness and conservativeness of the solution. This limitation is overcome in [42] by introducing self-adaptivity in polyhedral uncertainty sets. However, the method considers annual mean day while generating polyhedral uncertainty sets and therefore may not be very accurate.

In [42], data spread (DS) is determined using monthly historical data used to generate synthetic data which is further constrained by budget of uncertainty (BOU). The data spread varies hourly while considering a month whereas BOU remains constant throughout the year. More explanation is given in [42]. In the proposed uncertainty model, DS is taken same as that in [42], however, BOU is modified. The proposed modelling can be mathematically expressed as below:

$$W_{m,h}^{SPV} = \chi_{i,m,h}^{SPV} \in R^{SPV} : \underline{\omega}_{i,m,h}^{SPV} \leq \chi_{i,m,h}^{SPV} \leq \overline{\omega}_{i,m,h}^{SPV} \;; \forall i \in \Omega, \forall h \in T \tag{4}$$

$$\underline{\omega}_{i,m,h}^{SPV} = \omega_{i,m,h}^{SPV} - \sigma_{i,m,h}^{SPV} \;\&\; \overline{\omega}_{i,m,h}^{SPV} = \omega_{i,m,h}^{SPV} + \sigma_{i,m,h}^{SPV}; \forall i \in \Omega, \forall h \in T \tag{5}$$

$$\underline{\mu}_{i,m}^{SPV} \leq \hat{\chi}_{i,m}^{SPV} \leq \overline{\mu}_{i,m}^{SPV} \;; \underline{\mu}_{i,m}^{SPV} = \mu_{i,m}^{SPV} - \hat{\sigma}_{i,m}^{SPV} \;, \overline{\mu}_{i,m}^{SPV} = \mu_{i,m}^{SPV} + \hat{\sigma}_{i,m}^{SPV} \;, \forall i \in \Omega \tag{6}$$

Equation (4) describes polyhedral uncertainty set for SPV, DS is given by equation (5) and proposed BOU is given by equation (6). Where, the ω-terms represent in hand available data and χ-terms represent uncertain data being synthesized. The lower and upper bounds of DS are represented by [$\underline{\omega}_{i,m,h}^{SPV}$, $\overline{\omega}_{i,m,h}^{SPV}$] and that of proposed BOU are shown by [$\underline{\mu}_{i,m}^{SPV}$, $\overline{\mu}_{i,m}^{SPV}$]. $\sigma_{i,m,h}^{SPV}$ represents SD of historical data for the hour h taken during the month m and $\hat{\sigma}_{i,m}^{SPV}$ denotes SD of the daily solar power generation while considering month m. The BOU proposed constrained the data being synthesized using DS while considering mean generation from a monthly mean day rather the mean generation from an annual mean day, as in [42]. Such modification in BOU mitigates under or over constrained problem that may arise while dealing with system operation problem. Similarly, DS and BOU can be defined for load demand data. Fig. 1 shows the flow chart for generating synthetic data from intermittent RESs and stochastic load demand. Also, seasonal variations in RESs and stochastic load demand are inherently considered by modified polyhedral uncertainty sets. With these smaller modifications, the proposed uncertainty sets become self-adaptive and dynamic in nature.

2.3. *Mathematical Formulation of the Problem*

The mathematical modeling for bi-layer optimization for optimum SPV and BESS allocation is expressed as under.

2.3.1. Inner-layer Optimization

Following objectives are considered for inner level optimization:

A. Minimization of Feeder Power Loss

$$\text{Min } F_{1in}(\text{h}) = \sum_i \sum_j \alpha_{ij}^h (P_i^{\text{h}} P_j^h + Q_i^h Q_j^h) + \beta_{ij}^h (Q_i^h P_j^h - P_i^h Q_j^h);$$

$$\alpha_{ij}^h = \frac{r_{ij} \cos(\delta_i^h - \delta_j^h)}{V_i^h V_j^h} \text{ and } \beta_{ij}^h = \frac{r_{ij} \sin(\delta_i^h - \delta_j^h)}{V_i^h V_j^h}; \forall i, j \in \Omega,$$

$$i \neq j, \forall h \in T \tag{7}$$

In equation (7), P_i^h & Q_i^h, V_i^h & δ_i^h, r_{ij} are representing, real and reactive power injection, voltage magnitude and angle at i^{th} node in h^{th} hour and resistance of branch connecting nodes *i* and *j* respectively.

B. Minimization of Reverse Power Flow

$$\text{Min } F_{2in}(\text{h}) = P_{\text{rev}}^h;\ P_{\text{rev}}^h = \begin{cases} \text{Real}(V_G^h I_G^{h*}); & I_G^h < 0 \\ 0; & I_G^h \geq 0 \end{cases}, \forall h \in T \tag{8}$$

In equation (8), I_G^h, V_G^h are representing current and voltage magnitude respectively in secondary winding of grid substation transformer.

C. Minimization of Node Voltage Deviation

$$\text{Min } F_{3in}(\text{h}) = 1 + \sum_i \left| (V^{\text{target}} - V_i^h) \right|; \forall i \in \Omega, \forall h \in \text{T} \tag{9}$$

In equation (9), V^{target} is the p. u. substation voltage.

Subjected to the following constraints

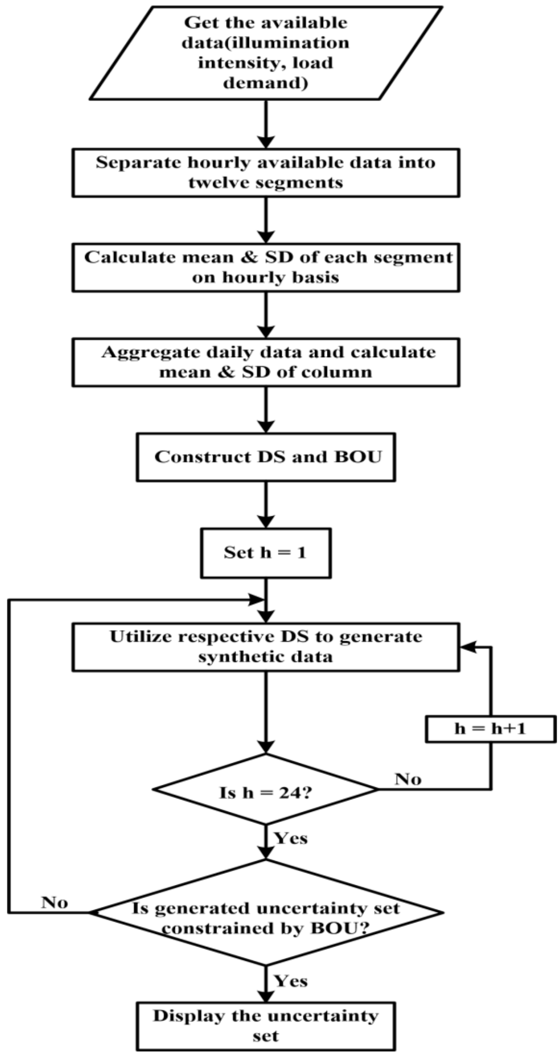

Fig. 1 Flow chart to generate synthetic data

$$P_{DG_i}^h \pm P_{dis_i}^h / P_{ch_i}^h - P_{D_i}^h = V_i^h \sum_{j=1}^{N} V_j^h Y_{ij} \cos\ \theta_{ij} + \delta_j^h - \delta_i^h\ ;$$
$$\forall i, j \in \Omega, i \neq j \tag{10}$$

$$0 - Q_{D_i}^h = -V_i^h \sum_{j=1}^{N} V_j^h Y_{ij} \sin\ \theta_{ij} + \delta_j^h - \delta_i^h\ ; \forall i, j \in \Omega, i \neq j \tag{11}$$

$$I_{ij}^h \leq I_{ij}^{Max}; \forall i, j \in \Omega, h \in T \tag{12}$$

$$0 \leq P_{DG_i} \leq P_{DG}^{Max}; \forall\, i \in \Omega \tag{13}$$

$$0 \leq W_{B_i} \leq W_B^{Max}; \forall\, i \in \Omega \tag{14}$$

$$P_B^{Min} \leq P_{ch_i / dis_i}^h \leq P_B^{Max}; \forall\, i \in \Omega, h \in T \tag{15}$$

$$SOC^{Min} \leq SOC_i^h \leq SOC^{Max}; \forall\, i \in \Omega, h \in T \tag{16}$$

$$SOC_i^h = SOC_i^{h-1} + \left(\frac{\eta_c P_{ch}^h}{W_B^R} - \frac{P_{dis}^h}{\eta_d W_B^R} \right) \Delta t; \forall i \in \Omega, h \in T \quad (17)$$

Equations (10)-(12) represent nodal power balance and feeder thermal limit respectively, equations (13) and (14) represent DG and BESS generation limit. BESS charging/discharging is represented by equations (1), (2), and (15), whereas the SOC limits are denoted in equations (16) and (17). The notations used to represent active and reactive demand of system, active power generation from DGs, charging dispatch and discharging dispatch of BESS at i^{th} node in h^{th} hour are $P_{D_i}^h$, $Q_{D_i}^h$, $P_{DG_i}^h$, $P_{ch_i}^h$ and $P_{dis_i}^h$ respectively [refer equations (10) and (11)]. Likewise, Y_{ij} , θ_{ij} , I_{ij}^h and I_{ij}^{Max} are representing the elements of Y-bus matrix, impedance angle, current flow in h^{th} hour and maximum line thermal limit, respectively. In particular, these elements are connected between i^{th} and j^{th} bus. In equations (13) and (14), W_{B_i} , P_{DG}^{Max} , W_B^{Max} are denoting energy dispatch of BESS, maximum power generation limit of DG and maximum energy generation limit of BESS at node *i*, respectively.

2.3.2. Outer-layer Optimization

Following objectives are considered for the outer-layer optimization:

A. *Minimization of Annual Energy Losses*

$$\text{Min}\, F_{1out} = 365 \sum_{h=1}^{24} F_{1in}(\text{h}); \forall i \in \Omega \quad (18)$$

In equation (18), F_{1in} is the feeder power loss defined in equation (7).

B. *Minimization of Load Deviation Index (LDI)*

$$\text{Min}\, F_{2out} = \left(\sqrt{\frac{1}{24} \sum_{h=1}^{24} \left(\overline{P_D} - P_D^h \right)^2} \right) \quad (19)$$

In equation (19), $\overline{P_D}$ is the mean demand and P_D^h is the demand at h^{th} hour of the system.

C. *Maximization of BESS Utilization*

$$\text{Min}\, F_{3out} = \left| \sum_{h=1}^{24} P_{ch_i}^h - \sum_{h=1}^{24} P_{dis_i}^h \right|; \forall i \in \Omega \quad (20)$$

Subjected to the constraints defined in equations (1), (2), and (10)-(17).

2.3.3. Multi-objective Formulation in Fuzzy Framework

In the literature, the multiobjective optimization problems have been framed using various approaches [6, 37, 43-46]. Among these, some are having limitations in terms of dependency on selected weights, pre-defined goal requirement, classification of various objectives into master and slave categories, etc. However, techniques like fuzzification [5, 44] and max-min approach [45] may be supportive in overcoming these limitations by scaling all the multiple objectives in one frame [6]. Therefore, the multiobjective problem for simultaneous placement of DGs and BESSs is formulated in fuzzy framework and is solved as single objective problem. Each of the objectives is first transformed into fuzzy membership function using the truncated cosine function as shown in Fig. 2. The fuzzy membership of truncated function (F_{in}) is given by the expression.

$$\mu_{in} = \begin{cases} 0; & F_{in} \le F_{in,\min} \\ \cos\left[\frac{\pi}{2} * \frac{(F_{in} - F_{in,\min})}{F_{in,\max} - F_{in,\min}} \right]; & F_{in,\min} < F_{in} < F_{in,\max} \\ 1; & F_{in} \ge F_{in,\max} \end{cases} \quad (21)$$

In equation (21), $F_{in,\max}$, $F_{in,\min}$ are the upper and lower bounds of the function F_{in}. These bounds are vital in deciding the fuzzy membership functions. In the present work, these bounds are determined by separately running GA for each of the objectives while maximizing and minimizing the objective function.

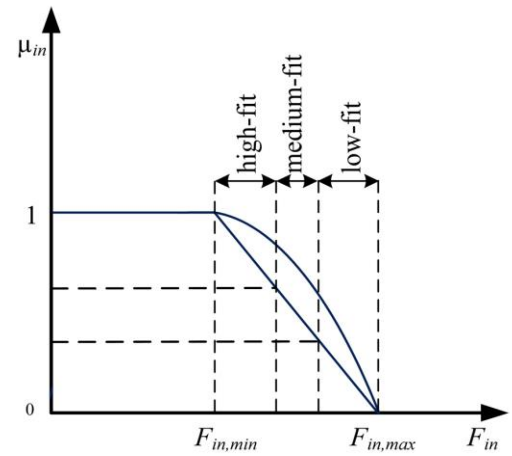

Fig. 2 Truncated cosine fuzzy membership function

The comparison of truncated cosine function with the conventional trapezoidal function in Fig. 2 reveals that the slope of the former function varies at faster rate with decrease in the value of the objective function whereas it remains constant for the latter function. The truncated function, therefore, provides increased discrimination consistently as the objective function is going through low-fit to medium-fit and then to high-fit values. The sensitivity of the membership function becomes higher during high-fit region which in turn significantly affects the value of multiobjective function being optimized. The phenomenon becomes intense in case the objectives are combined using max geometric mean approach, as suggested by the same authors [44]. Therefore, the objective functions for inner layer and outer layer of the proposed bi-layer optimization strategy are presented as below:

$$Max \mu_{in} = \left(\mu_{1in} \mu_{2in} \mu_{3in} \right)^{1/3} \quad (22)$$

$$Max\mu_{out} = \left(\mu_{1out}\mu_{2out}\mu_{3out}\right)^{1/3} \quad (23)$$

In equation (22), μ_{1in}, μ_{2in}, and μ_{3in} denote the fuzzy membership values for the objectives in equations (7), (8) and (9) respectively. Similarly, in equation (23), μ_{1out}, μ_{2out}, and μ_{3out} represent the values of fuzzy membership for the objectives defined by equations (18), (19) and (20) respectively.

3. Solution Technique for Proposed Methodology

Simultaneous allocation of BESSs and SPVs is non-linear, multi-constraint, non-convex optimization problem that cannot be solved by utilizing conventional optimization techniques. Such complex combinatorial optimization problems can be solved by using meta-heuristic or evolutionary techniques. The genetic algorithm (GA) is a population based metaheuristic optimization technique inspired by the concept of natural selection and evolutionary process [47]. It can search for a global or near-global solution for complex power system optimization problems [44]. In the proposed approach GA is used as an optimization technique for each layer while satisfying system and BESS operational constraints. The basic steps of the algorithm can be referred from [44]. The generalised structure of an individual used in the current work is presented in Fig. 3. The figure shows genetic information in terms of siting and sizing of SPVs and BESSs. The complete structure of the proposed strategy, utilizing GA in both the layers, is presented in the flow chart as shown in Fig. 4.

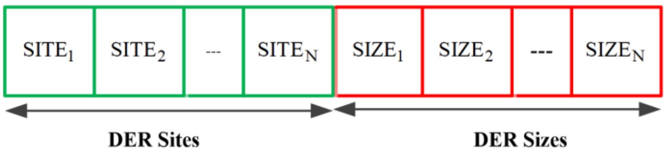

Fig. 3 Generalised structure of an individual employed in GA.

4. Simulation Results and Discussion

In this section, the proposed optimization strategy is validated by implementing on 12.66 kV, 33-bus test distribution system [48]. For this system, the active and reactive nominal demand is 3.715 MW and 2.300 MVAr respectively. With this system loading the nominal power losses and minimum node voltage are 202.67 kW and 0.9131p.u, respectively. The detailed information about the bus and line data of the concerned system may be referred from [48]. The basic schematic representation of the 33-bus test system is shown in Fig. 5. Further, several technical parameters utilized for simulation purposes in the current study are presented in Table 1. In this system, it is assumed that three SPVs and three BESSs are found to be optimal for placement [49]. Due to techno economic feasibility the upper limits of each SPV and BESS are assumed to be 2MWp and 5MWh, respectively. The dispatch cycle of 1 day is considered and is divided into 24 periods; each period is of one hour. The synthetic data for load demand and illumination intensity of solar insolation are generated using equations (4), (5) and (6) as shown in Fig. 6. From this figure it can be observed that power generation and demand show different peaking time. The proposed methodology is applied to optimize the objective functions defined by equations (22) and (23). For both levels, the population size of GA is taken as 200, the maximum number of generations is taken 100, the crossover rate is assumed to be 0.95 and the mutation probability is taken 0.05. Backward/Forward load flow method is employed.

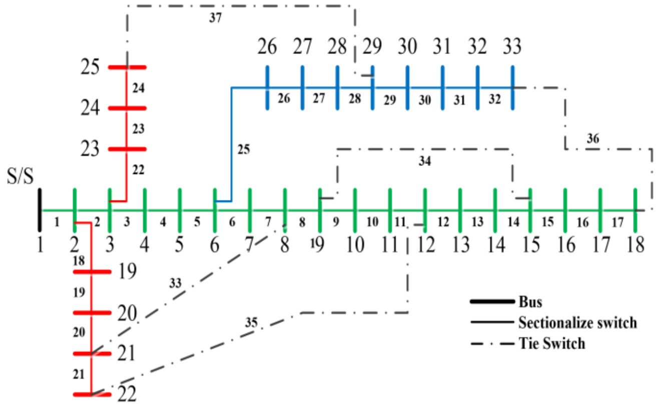

Fig. 5 Schematic representation of 33-Bus test distribution system [48]

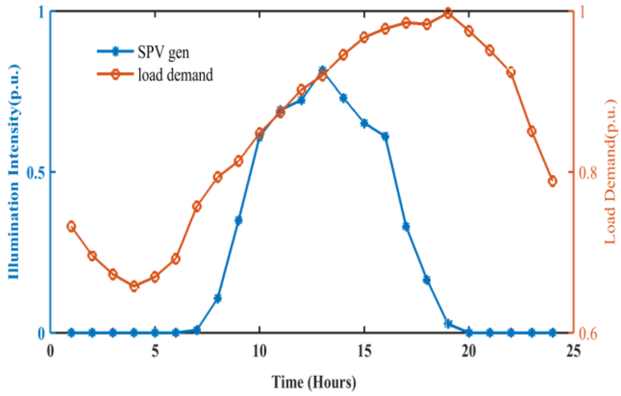

Fig. 6 Synthetic data generated for load demand and illumination intensity of solar insolation

For optimal sizing and siting of SPVs and BESSs the application results of the proposed methodology are shown in Table 2. It may be observed from the Table 2, that the optimal total sizing of SPV and BESS obtained are 3610 kWp and 7300 kWh, respectively. Also, the SPV penetration is found to be 60.73%, calculated as the fraction of system's peak demand which is assumed to be 1.6 times the nominal demand. Interestingly, the optimal locations are found to be identical for SPVs and BESSs. This may be due to the fact that identical locations avoid additional losses incurred on charging of BESSs from other locations.

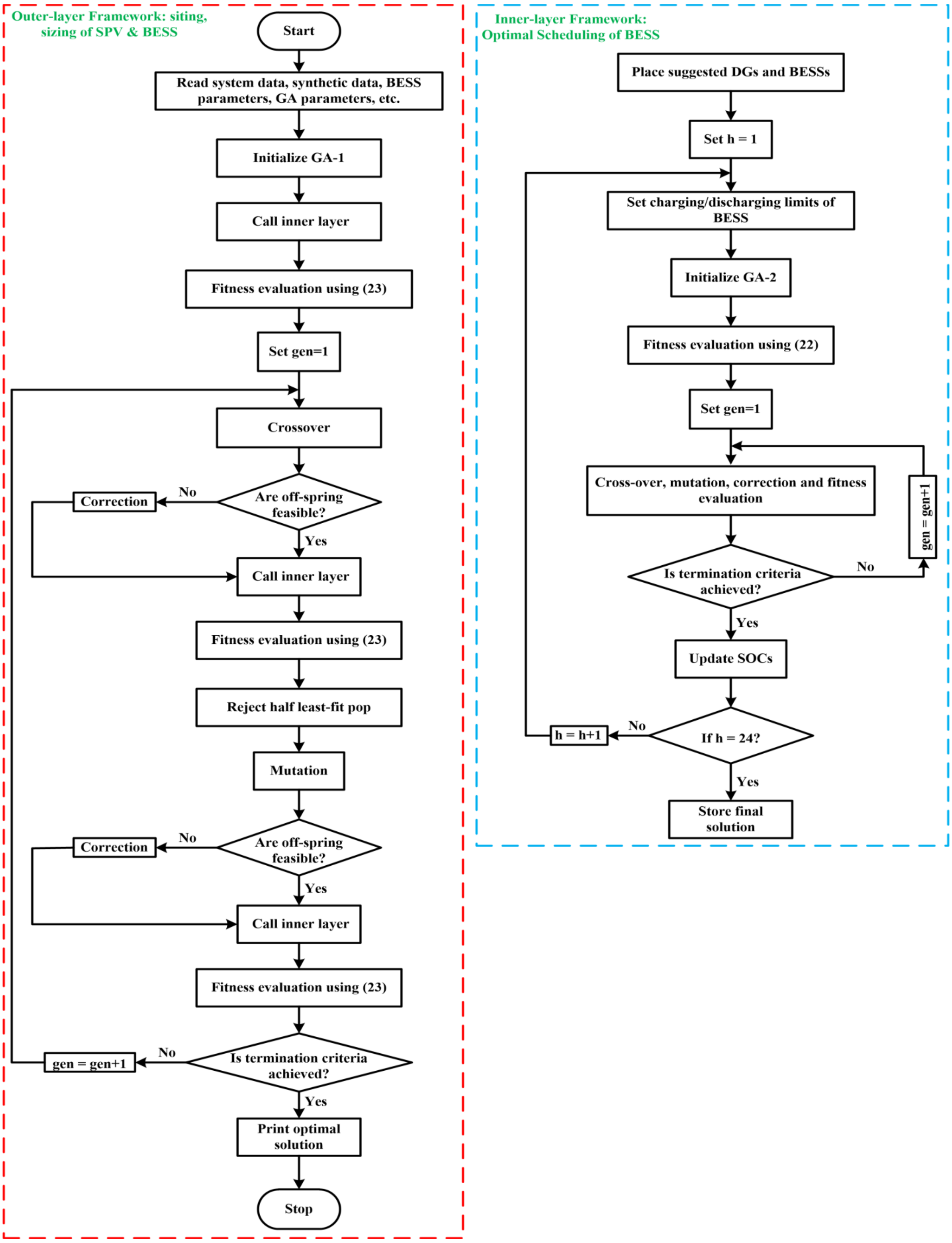

Fig. 4 Flow chart of the proposed methodology

Table 1 Technical parameters considered for simulation purpose

Parameter	Value	Parameter	Value	Parameter	Value
T	24 h	P_B^{Min} / P_B^{Max}	1MW/1MW	P_{DG}^{Max} / W_B^{Max}	2MW/5MWh
$\eta_{c/d}$	85%	SOC^{Min} / SOC^{Max}	0.1/ 1.0	χ_r	1000 W/m^2

Table 2 Optimal solution obtained for sizing and siting of DERs

Node	SPV (kWp)	BESS (kWh)
08	1820	4500
14	540	300
31	1250	2500

The optimal charging and discharging of individual BESSs obtained over a dispatch cycle are presented in Fig. 7. It can be observed that the BESS charging pattern falls in line with generation pattern of SPVs and is completed by 17:00 Hrs. In a way the intermittencies of SPV generations are completely absorbed by BESSs. From the figures it may also be observed that discharging of BESSs takes place during on-peak hours which results in peak shaving in the demand from the grid. Such charging and discharging of BESSs are quite desirable as the power being tapped from SPVs is delivered to the network during most desirable conditions besides absorbing intermittency. The SOC status of individual BESSs are shown in Fig. 8. The figure shows that all BESSs are fully utilized as the SOC status of each BESS varies from pre-defined lower limit to pre-defined higher limit and again reaches to the pre-defined lower limit at the end of dispatch cycle. Thus optimum utilization of all the BESSs takes place over a cycle.

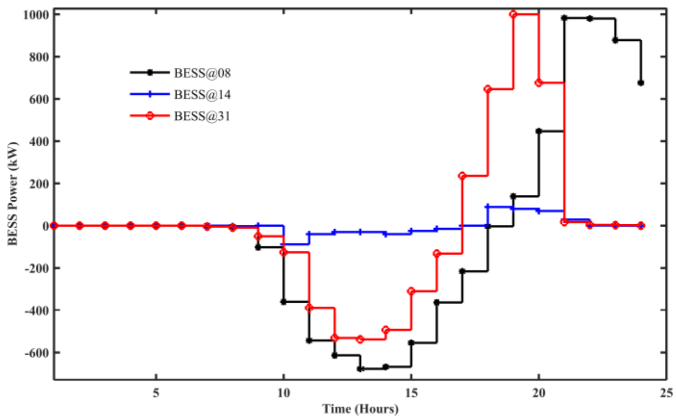

Fig. 7 Optimal charging and discharging of BESSs over one dispatch cycle

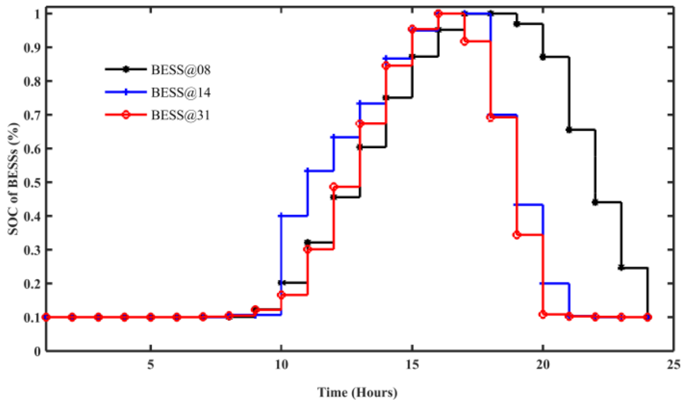

Fig. 8 SOC status of BESSs over one dispatch cycle

Figure 9 shows overall generation profile of SPVs, overall charging and discharging profile of BESSs and net generation profile from these DERs, obtained over a day. The power generation is taken as negative whereas power demand is taken as positive. It can be observed from the net generation profile that local generation remains zero, most of the times, during off-peak hours, but is found to be adequate for rest of the day. In addition, the profile never becomes positive which ensures charging of BESSs exclusively from the SPV units. In order to show the effectiveness of BESS, a comparison of grid demand profile without DERs, with SPVs alone and with both SPVs and BESSs is presented in Fig. 10. It can be observed from the figure that SPV causes an insignificant peak shaving. However, it severely deteriorates load profile flatness. The calculation shows that the SPV deteriorates the load deviation index from 467.30 kW to 936.26 kW. However, the index is improved significantly from 936.26 kW to 152.84 kW, i.e. about 67% with an optimal placement of SPVs and BESSs and optimal operational management of BESSs simultaneously. As a consequence, the difference between peak demand and valley point is reduced from 1380.80 kW to 603.78 kW, i.e. about 56%. Moreover, a peak shaving of about 25% is achieved using this optimal solution. This certainly facilitates system to cope against stressed conditions and also enhances system efficiency, reliability and self-adequacy. The grid demand profile with SPVs and BESSs remains positive which ensures no reverse power flow. The proposed methodology, therefore, replicates the most desired charging and

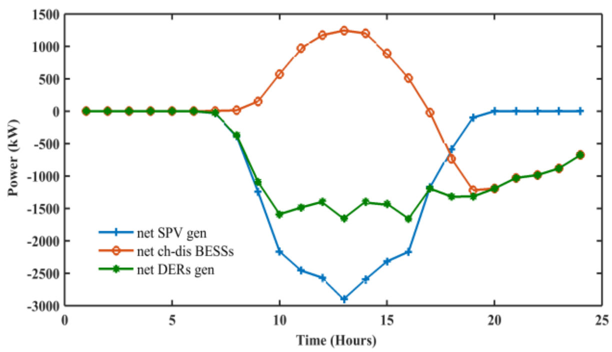

Fig. 9 Overall generation profile of SPVs, overall charging and discharging of BESSs and net generation profile of SPVs and BESSs

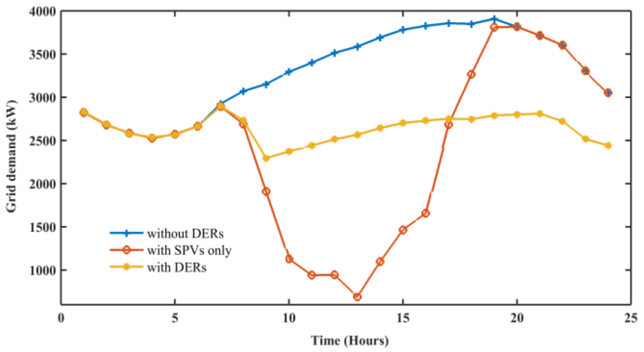

Fig. 10 Impact of integrating SPVs alone and SPVs with BESSs on grid demand profile

discharging profiles of BESSs in order to optimally tap RESs, peak load shaving without using grid energy to charge energy storage components.

The optimal solution provides better management of BESSs via optimal power flow among distribution feeders while absorbing intermittency and variability in power generation from SPV units and load demand. This eventually results in loss reduction and node voltage profile enhancement. It can be observed from Fig. 11, that hourly feeder power losses are reduced by about 30% during the utilization period of BESSs and SPVs. Since the load demand remains fairly good during these hours, the loss reduction is significant. The calculation shows that the figure for this loss reduction is around 330 MWh per annum. A substantial enhancement in node voltage profile using the optimal solution can be observed from Fig. 12, where all node voltages remain within predefined limits of ± 6% during peak load hour. The optimal solution obtained using the proposed methodology thus faithfully follows the operating strategy of BESSs with SPVs as mentioned in Subsection 2.1 and completely restricts reverse power flow besides enhancement in network performance.

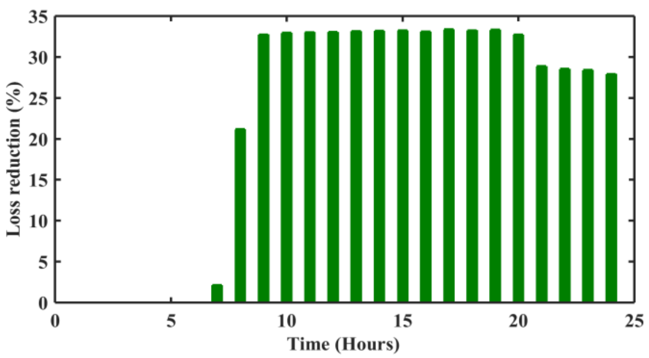

Fig. 11 Percentage power loss reduction using optimal DERs

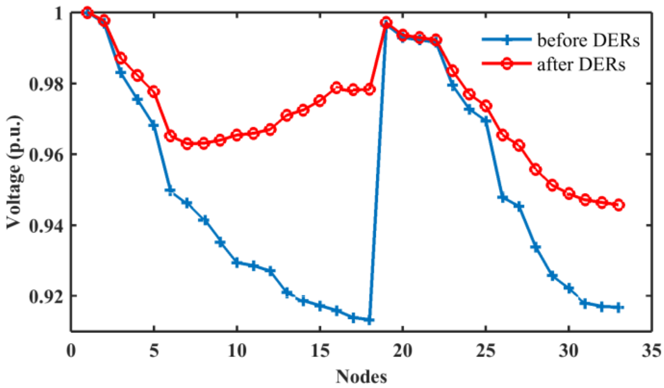

Fig. 12 Node voltage profile before and after optimal DERs during peak load

5. Conclusions

In this paper, a comprehensive methodology is proposed for simultaneous optimal siting and sizing of SPVs and BESSs in the distribution system which optimizes various performance objectives of distribution systems. The application results show that the proposed methodology results in optimum utilization of BESSs and SPVs and also ensures high penetration of SPVs while satisfying several operational constraints. The methodology successfully manages BESSs by coordinating charging and discharging cycles of BESSs with renewable generations and load demand. Moreover, the optimum management of charging and discharging cycles of BESSs absorbs the variability of SPVs generation and helps to make it a dispatchable source. The overall methodology results in significant improvement in load deviation index, improvement in node voltage profile, reduction in feeder power loss with no reverse power flow. Further, in order to competently and effectively deal with the uncertainty of load and generation data an existing self-adaptive polyhedral uncertainty sets is modified. The economic analysis of DERs allocation is not considered in this paper. This may be the future extension of the present work. However, the methodology for optimal sizing, siting, and management of DERs can be faithfully employed to investigate the economic benefits of DERs. In the future, Electric vehicles (EVs) may become integral components of distribution systems. The proposed method may be extended to investigate the impact of EVs on distribution systems' performance.

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