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Reliability improvement in radial electrical distribution network by optimal planning of energy storage systems

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ABSTRACT

This paper provides an optimal approach to denote the location and size of ESSs (energy storage systems) with the intention of reliability improvement in radial electrical distribution networks. The proposed optimal ESSs planning is addressed as a minimization problem which aims at minimizing the cost of ENS (energy not supplied) as well as ESSs costs at the same time, subject to safe operation of the network; where, the safe operation is guaranteed through satisfying security constraints such as voltage and line-flows limits. The minimization problem is mathematically formulated as a mixed-integer nonlinear programming and solved by PSO (particle swarm optimization) algorithm. A comprehensive sensitivity analysis is carried out on the results such as ESSs numbers, ESSs cost and reliability parameters. Simulation results demonstrate the viability of the proposed method in the real networks. Results also indicate the positive impact of ESSs on the network reliability. The proposed ESSs planning significantly reduces the ENS of the network and can be employed to deal with low reliability issues in the real networks.

1. Introduction

Radial electrical distribution networks are the most conventional configuration of distribution networks. In these systems, feeders are extended from the distribution substations to the lateral feeders and all consumers are supplied through these lateral feeders. This simple configuration provides some advantages such as low cost, simplicity of the network topology and the simple protection system [1]. On the other hand, low reliability issues due to the radial structure can be stated as the worst disadvantage of these networks. In such networks, each disconnection in a feeder leads to disconnecting all loads on the feeder. Thus, such networks are exposed to the highest rates of interruption [1].

Regarding the low reliability issues of radial electrical distribution networks, several methods have been reported to improve the reliability in such networks. Network reconfiguration is one of the main methods which has been proposed to increase the network reliability [2]. The approach addressed in Ref. [2] proposes the reconfiguration problem on three radial distribution networks of 33-bus, 69-bus, and 136-bus. Where, the reconfiguration problem minimizes the network loss as well as maximizes the network reliability subject to the network constraints of performance. It is indicated that network reconfiguration can successfully improve the network reliability in the radial distribution networks. Electrical distribution network planning can also be considered as a suitable method to improve the network reliability [3]. The Methodology presented in Ref. [3] expresses the distribution network expansion planning problem as a mixed integer linear programming and solves it using pseudo-dynamic planning approach. Where, simulation results are carried out on a 54-bus distribution network and demonstrate the effectiveness of the given reliable planning on the network reliability. Energy expansion planning has also been proposed to improve the network reliability [4]. In the approach given by Ref. [4], an expansion planning for electrical and thermal energy distribution systems is presented. Where, the problem aims at minimizing the investment and operational costs as well as improving the reliability of the network based on the reliability indexes of SAIFI (system average interruption frequency index), SAIDI (system average interruption duration index), and AENS (average energy not supplied). It is demonstrated that the contributed methodology can effectively improve the network reliability. Reference [5] proposes an optimal switch allocation in

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radially operated distribution networks for reliability enhancement. Where, sectionalizing and link switches with manual or automatic control strategies are well-thought-out in the solution methodology. The approach addressed by Ref. [5] minimizes the costs of switch allocation and reliability index of energy not supplied (ENS), at the same time. It is indicated that optimal switch allocation reduces the cost and improves the network reliability through significant ENS reduction. Advanced design of distribution automation devices (e.g., automatic re-closers) has also been addressed for reliability improvement in distribution networks [6]. The method addressed by Ref. [6] suggests contingency-load-loss-index for reliability assessment and improves the reliability though optimal allocation of automatic re-closers. Simulation results on two distribution networks 54-bus and 100-bus demonstrate that the advanced design of distribution automation devices can enhance the reliability of the network based on the contingency-load-loss-index. DG (distributed generation) has also be utilized to enhance the network reliability [7]. DGs provide numerous advantages in distribution networks such as reliability improvement [7]. DGs in distribution networks are mainly classified as intermittent and dispatchable DGs. The dispatchable based DGs can operate under islanding condition and therefore improve the network reliability [7]. Optimal allocation of dispatchable based DGs for reliability enhancement has been studied by Ref. [7]. The approach presented in Ref. [7] evaluates the network reliability through a reliability index which is defined as "customers' willingness to pay" to prevent power interruptions. In Ref. [7], DG planning is carried out to minimize the DG cost and improve the network reliability, at the same time. It is demonstrated that DGs can effectively enhance the network reliability based on the defined index.

Regarding the above issues, it can be concluded that many approaches have been addressed to improve the network reliability. Furthermore, with respect to the reliability concept, it seems that ESSs (energy storage systems) can also impact on the network reliability. But, ESSs have not been adequately studied to improve the reliability in distribution networks. Therefore, this paper addresses the reliability improvement in radial electrical distribution networks by optimal planning of energy storage systems. Next subsection introduces the applications of ESSs in the electrical networks. Then, the functions and technologies of ESSs are discussed and eventually, the orientation of the paper is presented.

1.1. ESSs applications in electrical networks

ESSs mainly convert electrical energy into a more convenience storable form for converting back to the electricity when required. ESSs have been widely developed in electrical networks. Mitigating the uncertainties related to the renewable energy resources is one the main applications of ESSs [5–8]. Nowadays, wind farms are increasing their part of the energy production in electrical networks in the world. The incapability of wind farms to match demand power profiles increases the requirement for large ESSs. The ESSs are capable to balance the instability of wind farms and shifting the generated power during low demand to peak periods [5,8]. Furthermore, ESSs have been successfully utilized in cooperation with solar power plants [6,7] and photovoltaic systems [9]. The ESSs have also been widely utilized in microgrids networks. Microgrids are mainly equipped with renewable energy resources such as photovoltaic systems, solar-thermal systems, geothermal heat pump, and wind units [10,11]. In such systems, ESSs play a fundamental role in the management of the microgrids demand and produced energy by renewable energy resources. Where, ESSs collect renewable energy during day-time to release it during night-time, or store renewable energy during low demand to release it during high demand and effectively shave the peak of the demand [10,11]. The ESSs are also utilized in electricity market to mitigate the risk of the private participants [12,13]. The methodology specified in Ref. [12] addresses an optimal allocation of ESSs for risk mitigation of DISCO (distribution company) with high renewable penetrations. Where, the risk of price volatility in electricity market is mitigated through optimal sizing and siting of ESSs based on the cost-benefit analysis approach. The planning given by Ref. [13] also utilizes ESSs together with wind power plants in deregulated electricity market. The other ESSs applications in electric power systems can be summarized as frequency control [14], stability improvement [15], power quality enhancement [16,17], increasing transmission line capacity [15,18], reliability improvement in generating systems [19], peak load shaving and load leveling [20,21]. Furthermore, by installing large-scale ESSs, network planners would need to build only sufficient generating capacity to meet average electrical demand rather than peak demands [22].

1.2. Functions and technologies of ESSs

Regarding the function of ESSs, electrical energy storage technologies are usually intended for energy management or power quality-reliability issues [23]. The technologies related to the power quality issues include low energy content ESSs such as supercapacitors [24], SMES (superconducting magnetic energy storage) [25], flywheels [26], and batteries [27]. On the other hand, the energy management technologies comprise large energy content ESSs such as PHS (pumped hydroelectric storage) [28], CAES (compressed air energy storage system) [29], TES (thermal energy storage) [30], large-scale batteries [31], flow batteries [32], and fuel cells [23,33].

Additionally, electrical storage technologies are classified based on the form of storage. In this respect, subsequent technologies are utilized [23,24,33,34]; (i) Electrical energy storage techniques including electrical field storage (super capacitors), and magnetic field storage (SMES) [23]; (ii) Mechanical energy storage systems containing kinetic energy storage (flywheels), and potential energy storage (PHS and CAES) [24]; (iii) Electrochemical energy storage approaches comprising conventional batteries (e.g., lead-acid, nickel metal hydride, lithium ion), and flow batteries (e.g., zinc bromine and vanadium redox) [31]; (iv) Chemical energy storage methods consist of fuel cells, molten-carbonate fuel cells-MCFCs, and Metal–air batteries [23]; (v) Thermochemical energy storage approaches involving solar hydrogen, solar metal, solar ammonia dissociation–recombination, and solar methane dissociation–recombination [23]; (vi) Thermal energy storage systems including low temperature energy storage (e.g., aquifer cold energy storage, cryogenic energy storage), high temperature energy storage (e.g., steam or hot water accumulators, graphite, hot rocks, and concrete), and latent heat systems (e.g., phase change materials) [23,35,36].

1.3. Orientation of this paper

This paper addresses an optimal ESSs planning to denote the place and size of ESSs in radial electrical distribution networks. The proposed planning aims at improving the network reliability by minimizing ENS (energy not supplied). The problem is expressed as a mixed-integer nonlinear programming and solved by PSO (particle swarm optimization). It is shown that ESSs can successfully improve the network reliability through reducing ENS index.

It is worth remarking that ESSs planning can also be considered together with other devices expansion such as transformers and distribution lines. But, expansion of transformers and distribution lines for reliability improvement has already been investigated [37,38], while ESSs planning for reliability enhancement has not been investigated so far. As a result, this paper only focus on the reliability improvement by ESSs planning. Since, including the conventional approaches which have been widely investigated (i.e., including lines and transforms) may hide the novelty of the paper and put out of sight the main idea of the paper.

2. Energy storage systems

Fig. 1 shows a typical ESS. ESSs mainly produce a DC voltage by using an energy storage device such as battery. This DC voltage is converted to a controllable AC voltage by using DC–AC converter and AC voltage is often increased by step-up transformer and sent to the AC network. The output AC voltage of the converter (voltage on ac terminal in Fig. 1) is characterized by three parameters of magnitude, phase angle, and frequency. These three parameters can be controlled through controlling PWM (pulse width modulation) control signal of the converter [39]. By controlling magnitude and phase angle of the voltage on ac terminal of Fig. 1, active (P) and reactive (Q) powers between ac terminal and AC network can be controlled and ESS can absorb or supply P or Q [39]. In this regard, four possible cases can be derived as Table 1. Fig. 2 shows the transferred P–Q status in the ac and dc terminals of ESS. It is clear that by controlling voltage at ac terminal, P and Q can be thoroughly controlled. It should be noted that the exchanged active and reactive powers between ESS and the AC network can be controlled independently of each other. Any combination of active and reactive powers absorption or generation is achievable as shown in Fig. 2. In addition, the interface transformer is mainly molded by a reactance and absorbs reactive power.

2.1. Control scheme of ESS

ESSs can supply or absorb active and reactive powers. Therefore, ESSs can be considered as controllable loads or generators. These controllable devices can store energy for the duration of charging state and supply it to the network for the period of discharging state. Generally, charging and discharging states are specified by operators subject to the network load level. ESSs are charged when the demand is low (generated power is more than demand). Then, at the time of high demand, ESSs are discharged to supply the loads. A typical charging and discharging state based on the load levels is

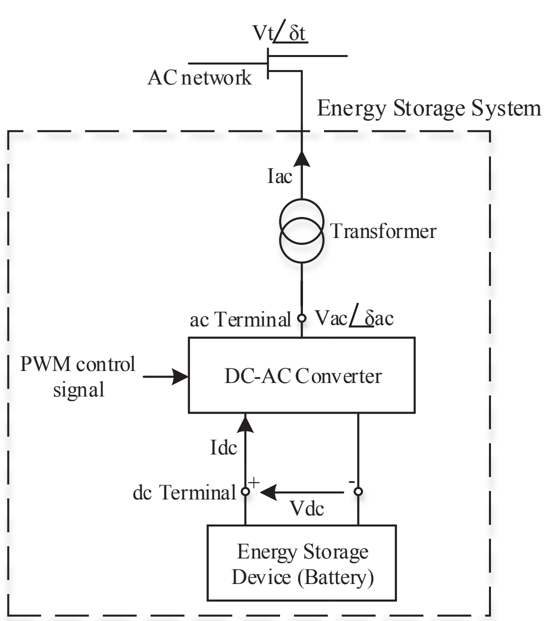

Fig. 1. Typical ESS installed to the AC system through DC–AC converter.

Table 1
Possible cases to exchange power by ESS.

$\delta_{ac} > \delta_t$	ESS supplies P
$\delta_{ac} < \delta_t$	ESS absorbs P
$V_{ac} > V_t$	ESS supplies Q
$V_{ac} < V_t$	ESS absorbs Q

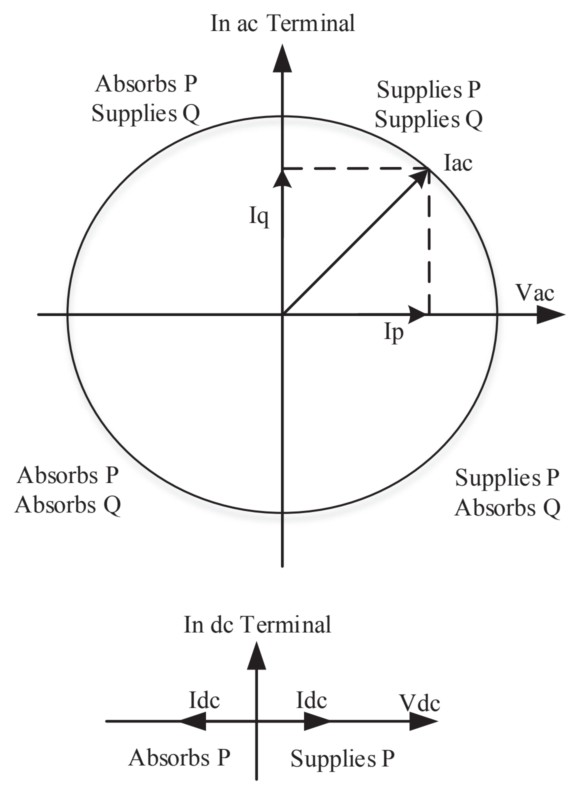

Fig. 2. Transferred P–Q status in ac and dc terminals of ESS.

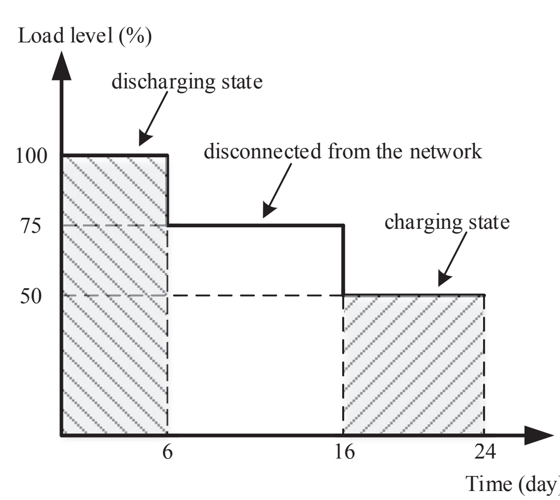

Fig. 3. Typical performance of ESSs based on the load level.

depicted in Fig. 3. For the period of mid-load levels, ESSs can be disconnected from the network to reduce the unnecessary losses.

2.2. Modeling ESS for power flow studies

In power flow or load flow studies, the network buses are classified as follows:

PQ (load) bus: the active power (P) and reactive power (Q) are specified.

PV (generator) bus: the active power (P) and the voltage magnitude (V) are specified. In these buses, the voltage magnitude is fixed on the specified value by changing the reactive power of generator. Therefore, generators on PV buses may absorb or supply reactive power in order to control the bus voltage magnitude.

Slack (swing) bus: the voltage magnitude (V) and voltage phase angle (δ) are specified.

With respect to the above classification as well as the performance of ESS, the bus where is installed by ESS can be modeled as a PV or PQ bus. Table 2 shows different possible power flow models for ESS. It is clear that at charging state, ESS absorbs active power, while it can absorb or supply reactive power. Therefore, it can be modeled as a PQ bus with positive P, and positive or negative Q. During discharging state, ESS supplies active power, while it can absorb or supply reactive power. Therefore, it can be modeled as a PQ bus with negative P (generate P), and positive or negative Q. Furthermore, during discharging state, since ESS produces active power, thus it can also be molded as PV bus with the specified P and V.

In all cases the interface transformer in Fig. 1 absorbs reactive power and this positive Q should be added to the absorbed (positive) or supplied (negative) Q of ESS.

2.3. Practical issues for power flow models

In the PV model for ESSs, the reactive power of ESS is a variable and varies to fix voltage magnitude on the specified value. In such condition, it is possible to absorb or supply a large amount of reactive power by ESS in order to support the voltage. Therefore, the capacity of ESS components such as interface transformer, converter and lines are occupied by reactive power and the capability of transferring active power between ESS and AC network is significantly decreased. While the main purpose of ESS is to charge and discharge of energy or active power. Therefore, PV model is not a suitable and practical model. The best model, is a model that does not exchange reactive power and all capacity of ESS is devoted to the active power. In such condition, ESS only produces a little amount of reactive power to supply interface transformer and exchanged reactive power between AC network and ESS is zero. Regarding Table 2, the best models for charging and discharging states are model 2 of PQ models. In these models, ESS charges and discharges active power while its reactive power is only set on a little amount to supply the interface transformer. In such condition, ESS can be molded on the AC network as a PQ bus with Q equal to zero and positive or negative P in the course of charging and discharging state respectively. Fig. 4 shows ESS on the AC network as a PQ model. It is worth mentioning that the proposed condition (setting the reactive power on a desired level and controlling active power) can be easily obtained through controlling DC–AC converter based on the PWM control concept [39].

Table 2
Power flow models for ESS.

	Charging state		Discharging state	
	PQ model	PV model	PQ model	PV model
Model 1	P > 0 Q > 0	–	P < 0 Q > 0	P > 0 Q is a variable and varies to fix V
Model 2	P > 0 Q < 0	–	P < 0 Q < 0	–

3. Problem formulation

This paper aims at minimizing the network ENS through optimal installing ESSs. The objective function of the planning comprises three terms as follows;

3.1. ENS cost

The ENS cost is mainly considered as the cost of unsupplied demands over a time period (mainly one year). This cost is calculated as the amount of unsupplied energy multiplied by the forfeit as (1). Where, ENS_t specifies the amount of unsupplied energy (kWh) at stage t and EC_t signifies the value of forfeit ($/kWh) for the unsupplied energy at stage t and T indicates set of days at one year. It is clear that of_1 indicates the annual cost in $/year.

$$of_1 = \sum_{t=1}^{T} (ENS_t \times EC_t) \quad (\$/year) \tag{1}$$

It is worth remarking that many reliability indexes are defined in the distribution networks. But, in this paper, ENS is considered. Since, the objective function of this paper (Equation (4)) comprises several terms and all terms are given in "$/year". Therefore, the reliability cost should also be given in "$/year". As a result, ENS (kWh) multiplied by the value of forfeit ($/kWh) is equal to the reliability cost (ENS cost) in "$/h" or "$/year". In case of applying the other reliability indexes that their units are not $/year, the problem has to be reformulate as a multi-objective problem that allows different units. For instances, many electric distribution company use SAIFI or SAIDI because of end-users. In such case, the problem is reformulate as a multi-objective problem, since units of SAIFI and SAIDI are not $/year.

3.2. Investment cost of ESSs

The investment cost of ESSs is given by (2). In this equation, vector EE denotes the installed ESSs, vector IEE shows the cost of ESSs ($), vector VEE indicates the capacity of ESSs (kWh), r denotes the discount rate and LT specifies ESS lifetime (year). It is worth noting that, of_1 is presented in $/year. Therefore, of_2 must also be presented in the term of annual investment cost in $/year. The equivalent annual cost is mainly defined as the cost per year over the lifetime [40]. In this regard, the last term of (2) is used to convert the total investment cost in $ to the annual investment cost in $/year. It should also be stated that EE is a vector which contains

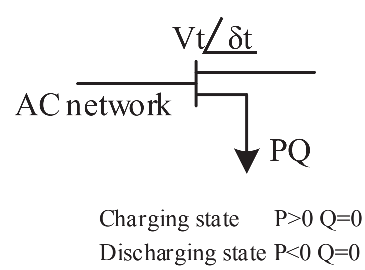

Fig. 4. ESS on AC network as PQ model.

integer elements and shows the design variable of the problem. This vector specifies that whether ESSs are installed or not.

$$of_2 = (E_E \times VE_E \times IE_E)\left(\frac{r \times (1+r)^{LT}}{(1+r)^{LT} - 1}\right) \quad (\$/year) \tag{2}$$

3.3. Operation cost of ESSs

The operation cost of ESSs is also given by (3) as $/year. Where, vector *OEt* indicates the operation cost ($/kWh) at hour *t*.

$$of_3 = \sum_{t=1}^{T} (E_t \times VE_t \times OE_t) \quad (\$/\text{year}) \tag{3}$$

3.4. Final objective function

Regarding functions (1)–(3), the final objective function can be expressed by (4), where, *ob* specifies the annual operation cost of the network in $/year.

$$ob = (of_1 + of_2 + of_3) \quad (\$/\text{year}) \tag{4}$$

3.5. Standard optimization formulation

Based on the proposed objective function, the reliability improvement problem is given as a constrained, nonlinear and mixed integer optimization problem. The mathematical formulation of the problem are as follows;

$$\text{Min} \quad ob \tag{5}$$

subject to

$$\sum P_{in}^{b} = \sum P_{out}^{b} \quad \forall b \in nb \tag{6}$$

$$\sum Q_{in}^{b} = \sum Q_{out}^{b} \quad \forall b \in nb \tag{7}$$

$$V_b^{\min} \le V_b \le V_b^{\max} \quad \forall b \in nb \tag{8}$$

$$S_l \le S_l^{\max} \quad \forall l \in nl \tag{9}$$

$$VE_E \le VE_E^{\max} \tag{10}$$

$$P_{ch} \le P_{ch}^{rate} \tag{11}$$

$$P_{disch} \le P_{disch}^{rate} \tag{12}$$

$$E_{disch} \le E_{ch} \times \eta_{ESS} \tag{13}$$

$$E_{ch}^{d} = P_{ch}^{d} \times T_{ch}^{d} + \left(E_{disch}^{d-1} - \eta_{ESS} \times E_{ch}^{d-1}\right) \quad \forall d \in nd \tag{14}$$

The problem constraints are specified by (6) to (14). Constraints (6) and (7) specify the power flow formulation. In other words, the equilibrium of active and reactive powers on all buses are satisfied through these constraints and they ensure the convergence of power flow. In these equations, *b* shows bus number and *nb* indicates set of all buses, *Pin* and *Qin* display input real and reactive powers to bus, *Pout* and *Qout* exhibit output active and reactive powers from bus. Constraint (8) limits the maximum and minimum values of voltage magnitude on all buses. Where, *Vb*, *Vbmax* and *Vbmin* give the voltage magnitude and its allowable maximum and minimum values on each bus respectively. Constraint (9) ensures the transferred apparent power through each line is less than maximum allowable capacity of line. In this constraint, *l* demonstrates line number and *nl* presents set of all lines, *Sl* and *Slmax* models the apparent power of line and maximum permissible capacity of line respectively. The maximum capacity of the installed ESSs is limited by (10) and *VEEmax* indicates the maximum capacity of installed ESSs. Constraints (11) and (12) confirm that charged and discharged powers to ESSs are less than their rated powers. In these constraints, *Pch* and *Pchrate* indicate charged power and its rate; *Pdisch* and *Pdischrate* represent the discharged power and its rate respectively. The ESS efficiency is signified by (13) and it specifies that discharged energy *Edisch* should be less than *Ech* multiplied by ESS efficiency ηESS. Constraint (14) indicates that the stored energy at each day is sum of current stored energy and remained energy from the previous day.

It is worth mentioning that most of the planning in distribution networks are carried out based on the balanced three-phase networks [41–43] and the methodology in this paper is also presented based on the balanced network. However, this methodology can also be adopted for unbalanced networks. Since, it is straightforward to convert the unbalanced networks to a balanced three-phase network, and then performing the proposed methodology. Under unbalanced networks, the planning is carried out in following phases:

First phase: Converting the unbalanced networks to a balanced network using reactive power planning.

Second phase: Performing the proposed ESS planning based on the obtained balanced network.

As a result, unbalanced networks only add one phase to the methodology and does not change the results. Converting the unbalanced networks to a balanced network using reactive power planning has been completely addressed by Ref. [44].

4. ENS calculation in radial distribution network

A radial distribution network comprises a set of series components, including lines, cables, switches, bus-bars, etc. A load connected to any point of such a network needs all components between himself and the supply point to be operating. Therefore, from the reliability standpoint, the principle of series systems can be applied to radial networks [45]. The basic reliability parameters of average failure rate, λ_s, average outage time, r_s, and average annual outage time, U_s, are given as follows [45];

$$\lambda_s = \sum_i \lambda_i \tag{15}$$

$$U_s = \sum_i \lambda_i r_i \tag{16}$$

$$r_s = \frac{U_s}{\lambda_s} = \frac{\sum_i \lambda_i r_i}{\sum_i \lambda_i} \tag{17}$$

where, *i* shows the load point number. By using the above relationships, the load and energy oriented indexes can also be calculated. One of the important parameters which is needed in the assessment of load and energy orientated indices is the average load at each load point. The average load L_a is gives by (18).

$$L_a = \frac{\text{Total energy demand in period of interest}}{\text{Period of interest}} = \frac{E_d}{t} \quad (18)$$

where, E_d and t are shown in Fig. 5 and t is mainly one year. Then, the total expected ENS (energy not supplied) and AENS (average energy not supplied) are calculated as (19) and (20);

$$ENS = \sum_i L_a(i) \times U_i \quad (19)$$

$$AENS = \frac{\sum_i L_a(i) \times U_i}{\sum_i N_i} \quad (20)$$

4.1. ENS calculation in the presence of ESS

When ESSs are installed on the network, the total energy demand in the period of interest, E_d, is reduced during discharging state of ESSs and E_d can be calculated as follows;

$$E_d = \begin{cases} E_{demand} - E_{disch} & t \in t_{disch} \\ E_{demand} & t \notin t_{disch} \end{cases} \quad (21)$$

where, E_{demand} specifies the energy of loads, E_{disch} indicates the discharged energy from ESSs and t_{disch} denotes the discharging time.

5. The proposed methodology for ESSs planning

Fig. 6 depicts the proposed methodology for ESSs planning in details. The blocks in this flowchart are discussed in the following.

Block A: As stated before, the problem is solved by using PSO algorithm. In this block, the initial population of PSO algorithm is generated based on the random procedure and the initial data of the problem (network data and etc.) are set. The population is a matrix and each row of this matrix is called a particle. The elements of the particle signify number of optimization variables (design variables). For instance, in a problem with ten design variables, population matrix contains ten columns (or the particle comprises ten elements).

Block B: In this block, one particle in the population is selected to evaluate .

Block C: As specified before, the particle is a vector with a number of elements. In this paper, the particle shows the installed ESSs on the network. Fig. 7 shows a typical particle with five ESSs as an example. In this figure, each new ESS is denoted by an integer number. Regarding this particle, ESS 1 shows two new ESSs and it means that for simulation of this particle, two new ESSs should be installed in the bus where is addressed by ESS 1. In order to simulating ESSs with zero number, ESSs should not be installed.

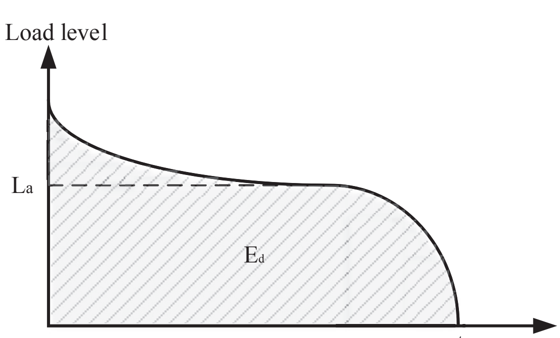

Fig. 5. Total energy demand E_d in period t and average load L_a.

Block D: At this point, daily load profile is set on the first level.

Blocks E and F: These blocks model ESSs with respect to the daily energy level. The proposed procedure replicates the practical behavior in real distribution networks indicating when energy resources are limited (e.g., maximum load level), ESSs are discharged to supply the demand, and for the periods in which there is no limitation in the energy sources (e.g., minimum load level), ESSs are charged to store the energy. If daily load level is between minimum and maximum levels, ESSs are not required and can be disconnected from the network.

Block G: After modeling ESSs, setting load levels, and also installing ESSs for current particle (in block C); power flow in carried out on the distribution network. Power flow in distribution network is a well-known problem and can be carried out by using forward-backward method [46]. In this method, power flow in the distribution network is performed in two steps as forward swept and backward swept [46]. In Backward swept, the transmitted active and reactive powers through the lines and power of each node (bus) are calculated as (22) and (23), respectively. The losses in first iteration are not regarded [46].

$$Sbranch_n^k = Snode_i^k + Sload_n + Loss_n^k \quad (22)$$

$$Snode_M^k = \sum_{n \in M} Sbranch_n^k \quad (23)$$

where, *Sbranchnk* shows the transferred power through the *nth* branch at *kth* iteration, *Snodeik* represents the power injected to the *ith* bus at *kth* iteration, $Sload_n$ demonstrates the load demand on the *nth* branch, and $Loss_n^k$ shows the losses of the n_{th} branch at *kth* iteration. Then in forward sweep, the current in the branches are calculated as (24). After calculating the current, the voltages of the buses are computed as (25) and network losses in each branch can also be obtained as (26). The forward and backward sweeps are iterated until convergence of the results. Convergence criterion is mainly defined as (27) and the sweeps are iterated until error index *e* is larger than a preferred or predefined value.

$$I_n^k = \left(\frac{Sbranch_i^k}{V_i^k}\right)^* \quad (24)$$

$$V_j^k = V_j^k - \left(Z_n \times I_n^k\right) \quad (25)$$

$$Loss_n^k = \left(V_i^k - V_j^k\right) \times \left(I_n^k\right) \quad (26)$$

$$e = \max\left|\left(V_j^k - V_j^{k-1}\right)\right| \quad (27)$$

where I_n^k represents the n_{th} branch current at *kth* iteration and shows the *Vik* of i_{th} bus voltage at k_{th} iteration, *Zn* shows the impedance of the *nth* branch. The ESSs are modeled as PQ loads with zero Q and positive P for charging state, and negative P at the time of discharging.

Block H: After carrying out power flow in the previous block, constraints (6) to (14) are calculated in this block and the violated constraints are denoted.

Block I: This block accounts the violated constraints under each load level. Eventually, the violations under all load levels are added as the final number of the violated constraints.

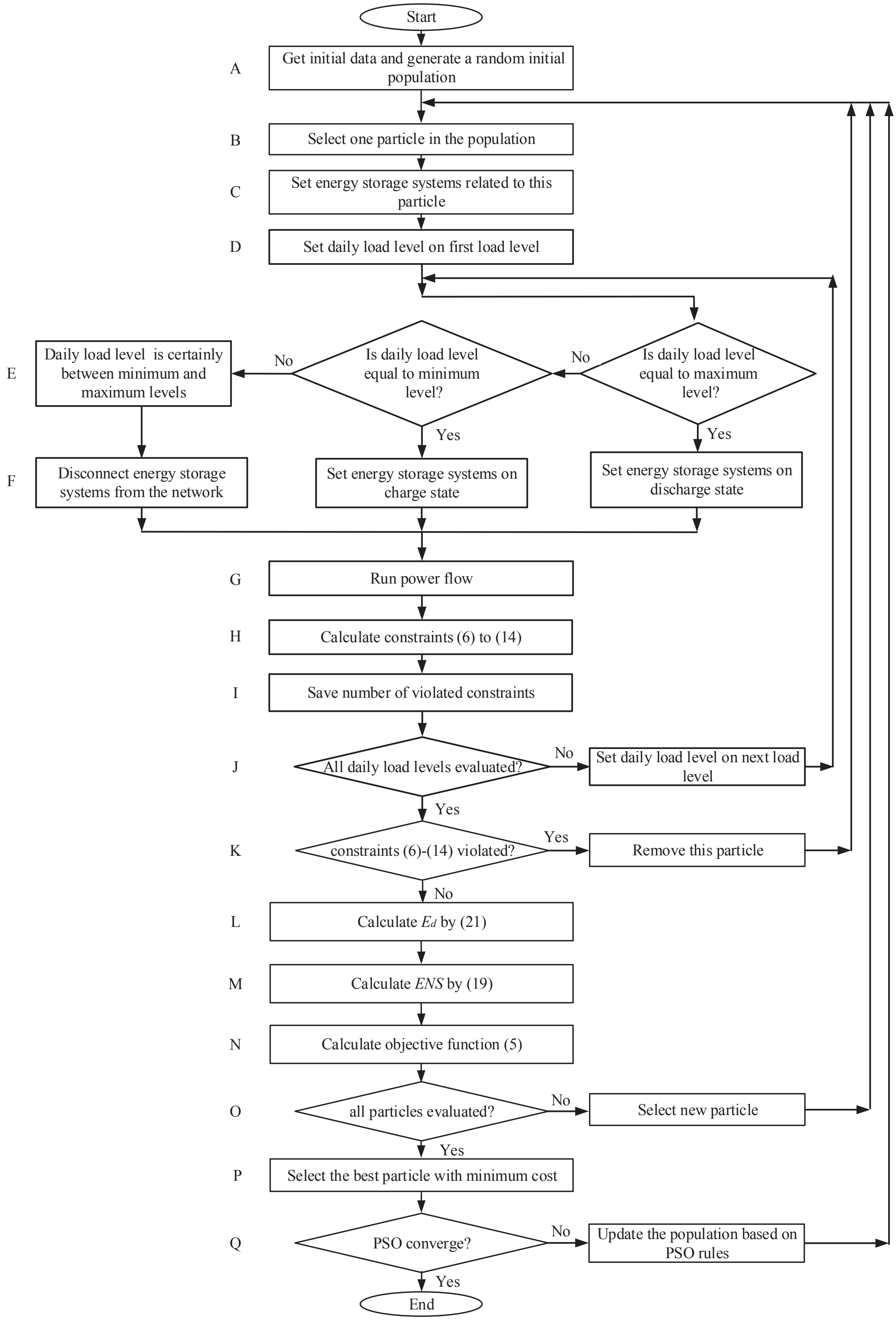

Fig. 6. Flowchart of the proposed method for optimal ESSs planning.

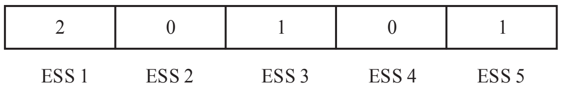

Fig. 7. Typical particle with five optimization variables.

Blocks J: This block checks to evaluate all daily load levels. The process is repeated until evaluating of all load levels.

Block K: This block checks the problem constraints. If there is at least one violated constraint, then current particle is removed and the flowchart will go to block B to select new particle.

Block L: Here, the total energy demand in the period of interest, E_d, is calculated by (21). This equation indicates that during discharging state of ESSs, the energy demand from the network is reduced, due to supplying the loads through ESSs.

Block M: After calculating E_d in the previous block, the ENS is calculated in this block by (19).

Block N: Here, the objective function (5) is calculated for the particles.

Block O: The purpose of this block is to check the program in order to evaluating all particles in the population.

Block P: In this block, the best particle in the population is selected and saved.

Block Q: Here, PSO convergence criteria is checked. If convergence is reached, the optimization process is finished and the optimal solution is obtained. Otherwise, PSO population is updated and algorithm is reiterated from block B.

5.1. PSO algorithm

PSO algorithm is a population based optimization technique which is effectively used to solve various optimization problems. This algorithm is inspired based on the social behavior of bird flocking. PSO algorithm begins with a random population matrix and each row of this matrix is known as a particle. Each particle in the population moves toward the best solution with a velocity. In PSO algorithm, each particle is defined through two values of velocity and position. In each iteration of PSO, the local and global best solutions are determined and then, the particles update their velocity and position by (28) and (29) [47].

$$v_{id}(k+1) = w(k)\cdot v_{id}(k) + c_1\cdot rand\cdot(p_{best\ \ i,d}(k) - p_{id}(k)) + c_2\cdot rand\cdot(g_{best\ \ d}(k) - x_{id}(k)) \quad (28)$$

$$p_{id}(k+1) = p_{id}(k) + v_{id}(k+1) \quad (29)$$

In the above equations, $rand$ is a random value in the range [0, 1], parameter w shows the inertial and is linearly decreased from 0.95 to 0.2, $P_{best}(t)$ and $g_{best}(t)$ are the local and global best solutions, $p_{id}(t)$ and $v_{id}(t)$ are the population and velocity matrixes in iteration k and parameter k shows number of iterations respectively [47].

Although, PSO was firstly developed for the continuous variables, but is has been widely applied to integer variables in electric power systems. It is worth remarking that most of the problems in electric power systems are mixed integer and include the integer variables. In this regard, PSO has been widely carried out to solve following mixed integer problems: transmission expansion planning [48,49], reliability–redundancy optimization applications [50], generation expansion planning [51], coordinated generation-transmission expansion planning [52], distribution network expansion planning [53], unit commitment [54], reactive power planning [48]. A survey of PSO applications in electric power systems has been addressed by Ref. [55], and it indicates that many continuous and mixed integer problems in electric power systems have been successfully solved using PSO. Details of PSO algorithm for integer programming and solving mixed integer problems can be found in Ref. [56,57]. One of the methods to deal with mixed integers is to round the continuous variables to the nearest integers. This method has already been tested to solve many mixed integers optimization problems and suitable results have been obtained [48,49]. Therefore, this method is adopted to handle integer variables in this paper.

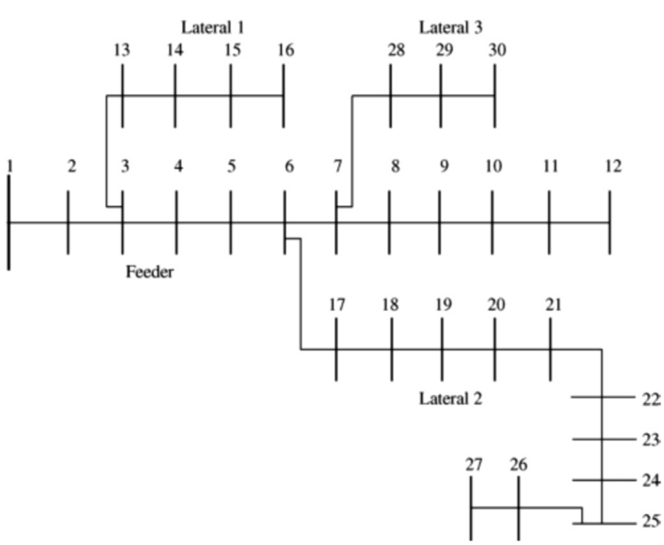

Fig. 8. Radial 30-bus and 11 kV distribution network.

Table 3
Line data of the test network.

Line No.	From bus	To bus	R (p.u.)	X (p.u.)	S_{max} (p.u.)
1	1	2	0.0967	0.0397	0.13
2	2	3	0.0967	0.0397	0.13
3	3	4	0.1359	0.0377	0.10
4	4	5	0.1359	0.0377	0.10
5	5	6	0.1359	0.0377	0.10
6	6	7	0.1515	0.0311	0.06
7	7	8	0.2598	0.0446	0.04
8	8	9	0.2598	0.0446	0.04
9	9	10	0.2598	0.0446	0.04
10	10	11	0.2598	0.0446	0.04
11	11	12	0.2598	0.0446	0.04
12	3	13	0.2598	0.0446	0.04
13	13	14	0.2598	0.0446	0.04
14	14	15	0.2598	0.0446	0.04
15	15	16	0.2598	0.0446	0.04
16	6	17	0.1515	0.0311	0.06
17	17	18	0.1515	0.0311	0.06
18	18	19	0.1515	0.0311	0.06
19	19	20	0.1515	0.0311	0.06
20	20	21	0.1515	0.0311	0.06
21	21	22	0.1515	0.0311	0.06
22	22	23	0.1515	0.0311	0.06
23	23	24	0.2598	0.0446	0.04
24	24	25	0.2598	0.0446	0.04
25	25	26	0.2598	0.0446	0.04
26	26	27	0.2598	0.0446	0.04
27	7	28	0.2598	0.0446	0.04
28	28	29	0.2598	0.0446	0.04
29	29	30	0.2598	0.0446	0.04

Table 4
Loading data and capacity of candidate ESSs.

Bus No.	P (p.u.)	Q (p.u.)	Capacity of candidate ESSs (kWh)
1	–	–	0
2	0.0042	0.0026	336
3	–	–	0
4	0.0042	0.0026	336
5	0.0042	0.0026	336
6	–	–	0
7	–	–	0
8	0.0042	0.0026	336
9	0.0042	0.0026	336
10	0.0041	0.0025	328
11	0.0042	0.0026	336
12	0.0025	0.0015	200
13	0.0010	0.0007	80
14	0.0010	0.0007	80
15	0.0010	0.0007	80
16	0.0002	0.0001	16
17	0.0044	0.0027	352
18	0.0044	0.0027	352
19	0.0044	0.0027	352
20	0.0044	0.0027	352
21	0.0044	0.0027	352
22	0.0044	0.0027	352
23	0.0044	0.0027	352
24	0.0044	0.0027	352
25	0.0022	0.0014	176
26	0.0022	0.0014	176
27	0.0013	0.0080	104
28	0.0017	0.0011	136
29	0.0017	0.0011	136
30	0.0017	0.0011	136

6. Illustrative test system

Fig. 8 depicts a 11 kV and 30-bus radial distribution network as case study [46]. The network data are summarized in Tables 3 and 4 [46]. Table 4 also indicates the capacity (kWh) and place of candidate ESSs to install on the network; where, all load buses (PQ buses) are regarded as candidate places. Furthermore, a large number of capacities are considered for each ESS. These issues (i.e., considering a large number of candidate buses a variety of capacities for ESSs) significantly increase the flexibility of the problem. It is worth remarking that the capacities in Table 4 changes from zero to the rated capacity by 8 kWh step change. Power rating of the network is 10 MVA. Table 5 shows ESSs data for a typical 8 kWh capacity. Daily load profile is regarded as Table 6. Voltage limits are assumed as 0.9 and 1.1. The failure rate and outage time for all lines are considered as 2 (fail/year) and 194.66 (hours) respectively. ESS lifetime equals 15 years and discount rate is equal to 10%.

7. Simulation results

The proposed methodology is carried out on the given test system. Table 7 indicates the location and capacity of the installed ESSs. It is clear that 15 buses are equipped with ESSs. It is worth remarking that all PQ buses (26 buses) are candidate buses to install ESSs and only 15 bus are installed by ESS. In order to provide a comparative study, two cases are simulated and compared as (i) network with ESSs and, (ii) network without ESSs. Table 8 comparisons the network installed with ESSs and the network without ESSs. It is clear that installing ESSs significantly reduces the ENS of the network by 49% which is a considerable amount in the real networks. This issues denotes that the network reliability has been extensively improved by installing ESSs. On the other hand, the cost of ESSs (operation and investment costs) in the network installed with ESSs is 44,897 ($/year) while the network without ESSs does not comprise such cost. Finally, the total operation cost of the network installed with ESSs is 20,412 ($/year) or 11.5% less than the network without ESSs. The results emphasize on the positive financial impacts of ESSs on the network. In order to more evaluation, the technical impacts of ESSs on the network can also be discussed. Fig. 9 represents the transmitted power through the network lines. It is clear that in the network installed with ESSs the occupied capacity of lines is significantly less than the network without ESSs and therefore, the network installed with ESSs provides more free capacity. This issue provides many helpful consequences on the network such as postponing the network reinforcement or expansion, increasing the network reliability-stability, safe operation of the network and etc. Furthermore, Fig. 10 shows the bus voltages for two cases of with and without ESSs. It is clear that the voltage profile in the network equipped with ESSs is considerably safer than the other network. In the network without ESSs, the voltage on some buses (e.g., bus 27) is close to the minimum permitted level (0.9 p.u.) and each change in the network topology may violate the security limits. On the other hand, the network with ESSs provides a considerable voltage stability margin and guarantees the safe and secure operation of the network. It can also be useful to evaluate the charging and discharging states of ESSs. Fig. 11 depicts the charging and discharging states of ESS on bus 9 with 320 kWh capacity and 40 kW power rate. With respect to the load levels listed in Table 6, it is clear that ESS is charged and discharged regarding the load levels, and the figure also indicates that the equilibrium between charged and discharged energies is passed.

Table 6
Daily load levels.

Load level No.	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
Duration time (hour)	4	8	12	16	20	24
Load percent (%)	50	60	70	80	90	100

7.1. Sensitivity analysis on the results

As stated before, all PQ buses (26 buses) are considered as candidate buses to install ESSs. In other words, 26 ESSs can be installed on the network. In this section a comprehensive sensitivity analysis is carried out on the number of permitted ESSs which can be installed. Table 9 summarizes the planning results for different ESSs number. When 15 or more than 15 ESSs are permitted to be installed, one unique result is obtained (as shown previously in Table 7). It means that the network needs 15 ESSs to minimize the ENS or maximize the network reliability. By reducing ESSs number on the network, the network operation cost is increased. Eventually for zero ESS, the result of the network without ESS in Table 7 is obtained. The results can be studied to

Table 5
Data of the typical ESS.

ESS No.	Charging and discharging power rate (kw)	Capacity (kWh)	Total investment cost ($)	Investment cost per capacity ($/kWh)	Total operation cost for 8 kWh ESS per day ($)
1	1	8	700	700/8	0.002

Table 7
The optimal capacity and place of the installed ESSs.

Bus No.	9	10	11	12	19	20	21	22	23	24	25	26	27	29	30
ESS capacity (kWh)	320	312	320	200	328	336	336	336	336	352	168	168	104	128	128

Table 8
Comparing the network installed with ESSs and the network without ESSs.

	Network installed with ESSs	Network without ESSs
ENS (kWh/year)	1,320,800	1,973,920
Cost of ENS ($/year)	132,080	197,392
Cost of ESSs ($/year)	44,897	–
Total operation cost ($/year)	176,980	197,392

provide a tradeoff between ESSs number and the network cost. By reducing ESSs number, the network simplicity is increased as well as a simple protection scheme may be enough. On the other hand, the reliability is reduced and the network cost is also increased. Regarding these issues, the network operator can decide on ESSs number in the network. In order to show the technical benefits that the energy storage devices could mean for the distribution grid, Fig. 12 demonstrates the voltage profile on network buses under different ESSs number (i.e., 15, 10, and 5 ESSs as specified in Table 9). It is clear that together with restricting ESSs number, voltage profile is reduced. The figure indicates that increasing ESSs numbers improve the network performance and provide technical benefits in the network. The other sensitivity analysis is carried out on the investment cost of ESSs as summarized in Table 10. It is clear that by increasing ESSs investment cost (i.e., changing ESS technology), number of installed ESSs is reduced. This issue indicates that all ESS technologies are not suitable to install on this network and appropriate ESS type should be chosen based on the investment cost. Table 11 also demonstrates the sensitivity analysis on ESSs capacities. It is clear that through increasing the capacities, the planning output does not change and the results are similar to the nominal case. On the other hand, when the capacities are reduced by 20 percent, the total planning cost is increased by 2789.3 $/year or 1.5 percent. As a result, it can be concluded that the limited capacities reduce the planning flexibility and increase the planning cost. The planner had better to provide suitable capacities for ESSs. In order to more analysis, providing an investigation on ENS index

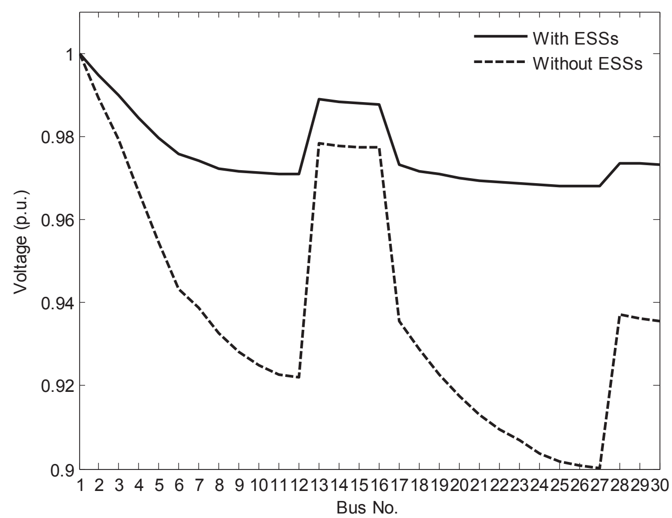

Fig. 10. Bus voltages for two cases of with and without ESSs.

during next years is valuable. In the real networks, the failure rate, λs, is mainly considered as constant. This issues is justified through maintenance of the network. In other words, after the repair, the element is expected to be restored to as good as new condition from the reliability viewpoint. Nevertheless, in practice, the risk of the

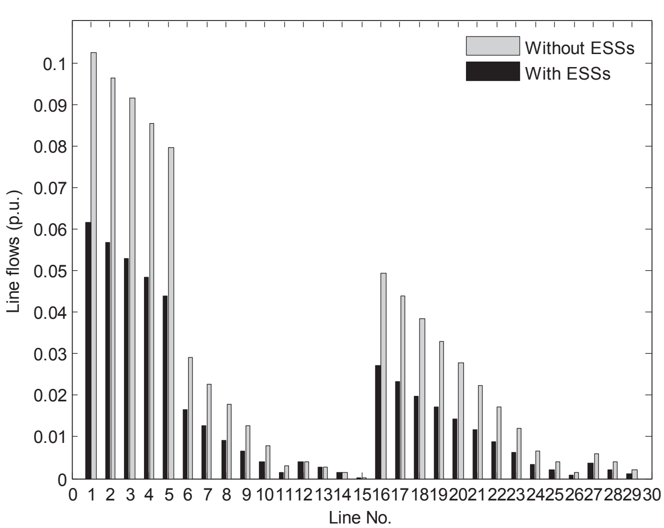

Fig. 9. Transmitted power through the network lines.

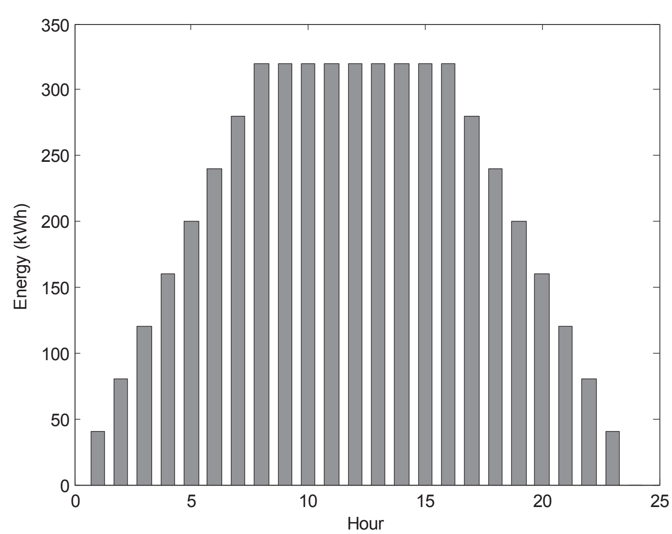

Fig. 11. Charging-discharging states of ESS on bus 9 at one day.

Table 9
Sensitivity analysis on ESSs number in the planning.

Number of permitted ESSs to be installed	Place and capacity of the installed ESSs (kWh)	Total operation cost ($/year)
15 and higher	Bus9 = 320; Bus 10 = 312; Bus 11 = 320; Bus 12 = 200; Bus 19 = 328; Bus 20 = 336; Bus 21 = 336; Bus 22 = 336; Bus 23 = 336; Bus 24 = 352; Bus 25 = 168; Bus 26 = 168; Bus 27 = 104; Bus 29 = 128; Bus 30 = 128	176,980
10	Bus 12 = 192; Bus 16 = 336; Bus 17 = 352; Bus 18 = 336; Bus 19 = 336; Bus 20 = 352; Bus 21 = 176; Bus 22 = 176; Bus 23 = 104; Bus 25 = 128;	180,920
5	Bus 22 = 336; Bus 23 = 336; Bus 24 = 336; Bus 25 = 168; Bus 26 = 168	185,580
1	Bus 24 = 336;	194,240
0	NO ESS	197,392

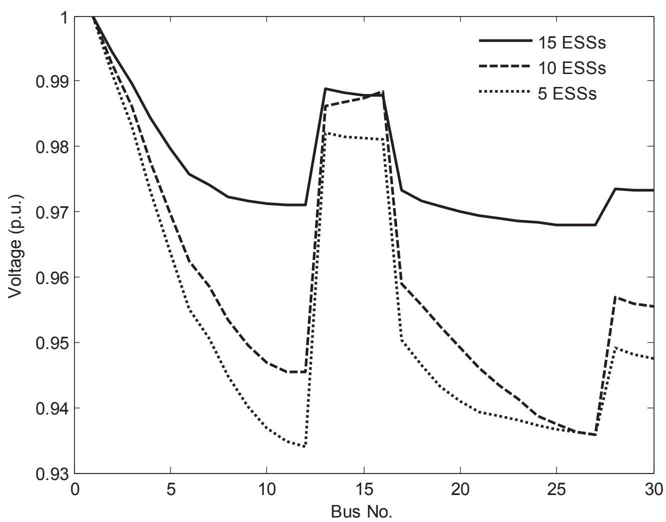

Fig. 12. Bus voltages under different ESSs number.

failure is increased due to the aging of elements. Here, the impact of aging is investigated on the reliability of the network. It is assumed that the failure rate of the network elements is annually increased by 10%. Fig. 13 shows the impact of aging on the ENS during next ten years. It is clear that by increasing the failure rate during next years, the evolution of the ENS in the network without ESSs is more than the other network. This issue indicates that in the network without ESSs, the operator has to pay more forfeit to the consumers during next years; while in the network with ESSs, the evolution of the ENS is controlled by ESSs and the network operator can reduce the forfeit cost during next years. Therefore, it is concluded that ESSs not only show the positive impacts at the current year, but also provide suitable impacts at next years.

7.2. Impact of replacement cost on the planning

Table 12 demonstrates the common applications of ESSs [27]. ESS type 2 is generally utilized in electrical distribution networks. In such ESSs, cycles per year are from 300 to 400, i.e., approximately one cycle per day. As a result, through utilizing such ESSs as one cycle per day, these ESSs can be utilized for 15 years and replacement cost is required after 15 years. In the proposed planning, ESS type 2 is used and ESSs are utilized as one cycle per day. Fig. 11 depicts the charging-discharging states of a typical ESS in the planning. It is clear that ESS is utilized as one charging-discharging cycle per day. As a result, ESSs in the planning can be utilized for 15 years and accordingly, ESSs lifetime is considered as 15 years. Therefore, the planning will not be subject to replacement cost. Apart from this issue, in order to investigate the impacts of

Table 10
Sensitivity analysis on the investment cost of ESSs.

	Place and capacity of the installed ESSs (kWh)	Total operation cost ($/year)
Nominal investment cost	Bus9 = 320; Bus 10 = 312; Bus 11 = 320; Bus 12 = 200; Bus 19 = 328; Bus 20 = 336; Bus 21 = 336; Bus 22 = 336; Bus 23 = 336; Bus 24 = 352; Bus 25 = 168; Bus 26 = 168; Bus 27 = 104; Bus 29 = 128; Bus 30 = 128	176,980
50% increasing the investment cost	Bus 23 = 328; Bus 24 = 328; Bus 25 = 168; Bus 26 = 168; Bus 27 = 104;	180,920
100% increasing the investment cost	Bus 26 = 160; Bus 27 = 96;	196,920
150% increasing the investment cost	NO ESS	197,392

Table 11
Sensitivity analysis on ESSs capacities.

	Place and capacity of the installed ESSs (kWh)	Total cost ($/year)
20% decreasing all capacities	Bus9 = 269; Bus 10 = 262; Bus 11 = 269; Bus 12 = 160; Bus 19 = 282; Bus 20 = 282; Bus 21 = 282; Bus 22 = 282; Bus 23 = 282; Bus 24 = 282; Bus 25 = 141; Bus 26 = 141; Bus 27 = 83; Bus 29 = 109; Bus 30 = 109;	179,770
Nominal capacities	Bus9 = 320; Bus 10 = 312; Bus 11 = 320; Bus 12 = 200; Bus 19 = 328; Bus 20 = 336; Bus 21 = 336; Bus 22 = 336; Bus 23 = 336; Bus 24 = 352; Bus 25 = 168; Bus 26 = 168; Bus 27 = 104; Bus 29 = 128; Bus 30 = 128;	176,980
20% increasing all capacities	Similar to the nominal capacities	176,980

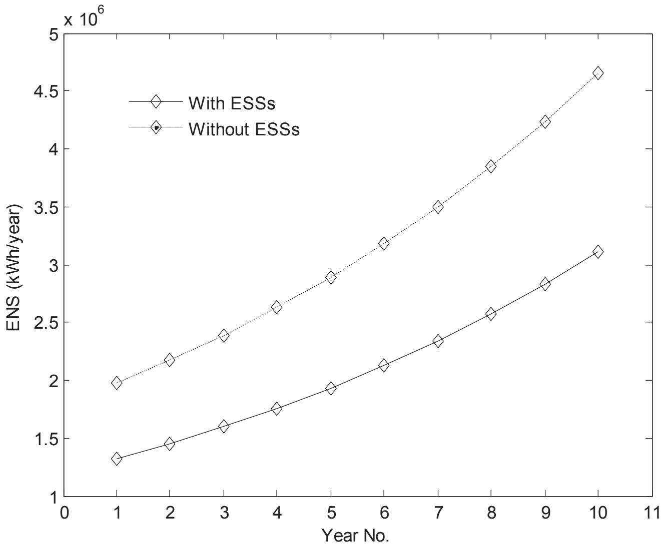

Fig. 13. Impact of aging on the reliability of the network.

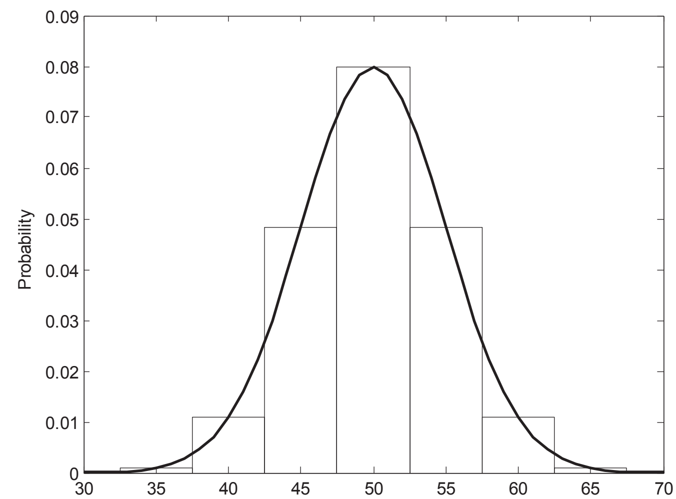

Fig. 14. Relationship between the binomial distribution and the normal distribution.

replacement cost on the planning, the planning is carried out incorporating the replacement cost for ESSs. Where, the planning lifetime is regarded as 30 years and ESSs are subject to the replacement cost after their lifetime (15 years). Table 13 specifies the planning output under such consideration. It is clear that considering replacement cost increases the planning cost and also reduces the installed ESSs capacities. The result demonstrates that it is necessary to select appropriate ESS technology for each planning. The suitable ESS technology should be denoted with respect to ESS data such as lifetime per years as well as lifetime per charging-discharging cycles.

7.3. Impact of load uncertainty on the planning

In real distribution networks, the future load level is uncertain. Therefore, it is valuable to evaluate the impacts of such uncertainty on the planning. In order to model load uncertainty, all network loads are assumed as Gaussian probability distribution function (PDF) and Monte-Carlo simulation is used to deal with the uncertainty. The details for considering uncertainty in the planning based on the Monte-Carlo simulation can be found in Refs. [37,48]. Then, Gaussian PDF is approximated based on the Binomial probability mass function as shown in Fig. 14. Where, Gaussian distribution is approximated as several discrete histograms (e.g., seven discrete histograms in Fig. 14). Then, the proposed methodology is simulated under each set of load levels (load scenario) and the planning cost is denoted for each individual load scenario. Eventually, the final planning cost for each particle in PSO population is calculated as the expected value of all individual costs. Table 14 specifies the planning output with and without load uncertainty. It is clear that considering load uncertainty thoroughly changes the planning output as well as increases the planning cost. Although considering uncertainty increases the planning cost, but it also increases the network flexibility under load fluctuations. The planning including load uncertainty is turn out to be more robust under load variations.

8. Conclusions

This paper addressed an optimal and practical methodology to denote the place and size of energy storage systems in radial electrical distribution networks. The proposed planning aimed at maximizing the network reliability subject to safe and secure operation of the network. The problem was formulated as a mixed-integer nonlinear programming and solved by PSO algorithm. It was demonstrated that the installed ESSs provided positive financial-technical impact on the network at the current year as well as the future years. An appropriate and comprehensive

Table 12
Three common applications of ESSs [27].

Type No.	Application type (usage frequency)	Cycles per year	Application lifetime	EES technology
Type 1	Long-duration, frequent	250–300	20	PHS, CAES, lead–acid, NaS, Ni–Cd, VRFB, Fe–Cr
Type 2	Medium duration, fast response	300–400	15	CAES (aboveground), lead–acid, NaS, ZEBRA, Li-ion,
Type 3	Short duration, highly frequent	+1000	10	VRFB, Zn–Br, Fe–Cr, Ni–Cd, hydrogen, Flywheel, lead–acid, Li-ion

Table 13
Impact of replacement cost for ESSs on the planning output.

	Place and capacity of the installed ESSs (kWh)	Total planning cost ($/year)
ESSs without replacement cost	Bus9 = 320; Bus 10 = 312; Bus 11 = 320; Bus 12 = 200; Bus 19 = 328; Bus 20 = 336; Bus 21 = 336; Bus 22 = 336; Bus 23 = 336; Bus 24 = 352; Bus 25 = 168; Bus 26 = 168; Bus 27 = 104; Bus 29 = 128; Bus 30 = 128;	176,980
ESSs with replacement cost	Bus 23 = 328; Bus 24 = 328; Bus 25 = 168; Bus 26 = 168; Bus 27 = 96;	194,030

Table 14
Planning output with and without load uncertainty.

	Place and capacity of the installed ESSs (kWh)	Total planning cost ($/year)
planning without load uncertainty	Bus9 = 320; Bus 10 = 312; Bus 11 = 320; Bus 12 = 200; Bus 19 = 328; Bus 20 = 336; Bus 21 = 336; Bus 22 = 336; Bus 23 = 336; Bus 24 = 352; Bus 25 = 168; Bus 26 = 168; Bus 27 = 104; Bus 29 = 128; Bus 30 = 128;	176,980
ESSs with load uncertainty	Bus9 = 272; Bus 10 = 280; Bus 11 = 280; Bus 12 = 184; Bus 19 = 272; Bus 20 = 304; Bus 21 = 312; Bus 22 = 352; Bus 23 = 352; Bus 24 = 352; Bus 25 = 176; Bus 26 = 176; Bus 27 = 104; Bus 29 = 96; Bus 30 = 112;	179,920

sensitivity analysis was carried out on the results. It was proven that ESSs can successfully improve the network reliability and reduce the operation cost of the network.

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