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Efficient Allocation Strategy of Energy Storage Systems in Power Grids Considering Contingencies

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ABSTRACT This paper addresses the allocation of Energy Storage Systems (ESSs) in power grids by finding the optimal number of ESSs and their locations and sizes with the goal of improving reliability in contingency states. We propose a contingency-sensitivity-based heuristic to decide the optimal number of ESSs and the most effective locations for ESSs support, while circumventing the combinatorial nature of the siting problem. A contingency sensitivity index (CSI) is proposed which represents the impacts of contingencies on the network buses. The CSI ranks the buses, such that those with higher impacts have the privilege for installing ESSs. For the ESSs being fixed, the sizing is formulated as a multi-period AC optimal power flow (OPF) problem and solved by Self-Organizing Hierarchical Particle Swarm Optimization with Time Varying Acceleration Coefficients (HPSO TVAC). The optimal ESSs sizes are selected by minimizing a total cost, which includes investment cost of storage devices, bus voltage deviation cost and average network losses cost. Uncertainties of the renewable generation are accounted by considering different realizations of the generation profiles, then, ESSs sizes are selected by taking the worst case approach. The proposed methodology has been demonstrated on the modified IEEE 30-bus system and Tunisian Grid. The obtained results show the effectiveness of the proposed methodology and the related reliability merits.

INDEX TERMS Contingency sensitivity matrix, energy storage systems, multi-period OPF, power grid, siting and sizing.

NOMENCLATURE

P_{Gi}^t	Real power generation at bus i and time t.
Q_{Gi}^t	Reactive power generation at bus i and time t.
P_{Di}^t	Real power demand at bus i and time t.
Q_{Di}^t	Reactive power demand at bus i and time t.
P_{Si}^t	Real power exchanged from ESS at bus i and time t.
Q_{Si}^t	Reactive power exchanged from ESS at bus i and time t.
$\underline{P}_{Si}$	Minimum real power exchanged from ESS at bus i.
$\overline{P}_{Si}$	Maximum real power exchanged from ESS at bus i.
$\underline{Q}_{Si}$	Minimum reactive power exchanged from ESS at bus i.
$\overline{Q}_{Si}$	Maximum reactive power exchanged from ESS at bus i.
E_i^t	Energy stored of ESS at bus i and time t.
$\underline{E}_i$	Minimum allowed energy stored at ESS and bus i.
$\overline{E}_i$	Maximum allowed energy stored at ESS and bus i.
C^L	Cost of energy loss.
C^V	Cost of bus voltage deviation.
$C^I(n_s)$	Investment cost for building ESS.
V_i^t	Voltage magnitude at bus i and time t.
$\overline{V}_i$	Upper limit of voltage magnitude at bus i.
$\underline{V}_i$	Lower limit of voltage magnitude at bus i.
V_D^t	Bus voltage deviation index at time t.
I_{ij}^t	Magnitude of the current flowing from buses i to j at time t.
$\overline{I}_{ij}$	Branch current limit from buses i to j.
P_L^t	System power losses at time t.
$\vec{S}$	Vector of ESS sizes.
$\vec{S}^{opt}$	Vector of ESS optimal sizes.
n	Number of buses.

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n_g Number of generating units.
n_r Number of renewable generating units.
n_s Number of ESSs.
n_l Number of transmission lines.
n_c Number of contingencies.
n_d Number of power demands.
$\overline{B}$ Budget limit for investment.
T Planning horizon.

I. INTRODUCTION

The penetration of renewable energy sources (RES) is rapidly increasing in recent years to achieve a sustainable power system. However, when the RES penetration reaches a sufficiently high level of the total power generation, the intermittent nature of renewable generation can have negative impacts on the reliability of the power system [1]–[3]. Due to the stochastic nature of renewable distributed generation (DG) and peaks of load demands, system contingencies may regularly show up; involving deviation of typical power flows in the transmission network. Maintaining the system in an acceptable state, is one of the main challenges faced by transmission system operators [4], [5]. In order to overcome these problems, several actions can be taken. Generally, frequency control strategies are used to maintain the system in an acceptable state [6]–[8]. The vast majority of these strategies is based on the management of power reserves for smoothing possible power deviations [9]. These methods, however, may lose their effectiveness when power demand exceeds power reserve capacity. In this case, similar to production scheduling [10]–[14], load shedding has to be employed as a last resort [15]. Grid reinforcement is a feasible solution, but it involves investments in infrastructures of a transmission network. Thus, effective and cheap solutions should be looked for. Recently, energy storage systems (ESSs) can be an appropriate alternative for the aforementioned methods. Furthermore, ESSs can maintain power supply for a short time which can avoid load shedding [16]. However, ESSs should have a proper configuration to support the power system which triggers the problem of ESS allocation in power grids. Thus, an efficient integration lies in the support of ESSs in contingency states, such that, operations of a power system can be restored in a proper way without violating system constraints such as frequency and voltage constraints.

The main objective behind the ESSs allocation is to find an integrated solution in a power system by selecting the optimal number of ESSs and determining their locations and sizes. Optimal siting and sizing of ESSs have been addressed in the literature from different perspectives of grid operators [17]. The commonest approach is the optimal power flow (OPF) formulation [18], where optimization variables are ESS locations and sizes. The optimized cost function may include operation costs, storage investment costs and power losses [19].

The optimal ESSs allocation problem can be divided into three sub-problems: siting, sizing and the number of ESSs. However, integer variables involved in the problem formulation to describe the locations of storage devices and non-convex power flow constraints make the problem NP-hard. Different approaches have been investigated to find an approximate solution so as to reduce the computational burden. A direct current (DC) approximation is adopted when dealing with transmission networks [20]–[22]. The authors in [23] determine optimal ESS locations and parameters by solving a unit commitment (UC) problem over one year, which is still computationally inefficient. Convex relaxations are often adopted to the full alternating current optimal power flow (AC OPF), such as the second-order cone programming OPF approach in [24] and semidefinite programming (SDP) in [25], [26]. The work in [26] proposes a mixed integer programming formulation for the placement problem. Till now, the problem has not been solved efficiently [17]. Furthermore, the existing studies in the literature consider the ESS allocation as an optimization problem where researchers optimize an objective function that includes several terms like power loss, investment cost, maintenance cost [19]... etc.

These studies are interesting, but they may obtain biased solutions sometimes [27]–[29]. In addition, none of these studies considers potential risks of system contingencies such as peak loads or system faults that cause voltage or frequency deviation. The siting of an ESS has a great impact on contingency states where an ESS can optimize power balance, smooth voltage deviation and regulate frequency variation. In addition, the efficiency of the existing methods in literature in terms of computation time and optimality is not well investigated yet.

For this purpose, we propose a technically solid and computationally efficient methodology to solve the ESS allocation problem. The contributions of this paper are:

- For the optimal ESS siting, we propose a contingency-sensitivity-based heuristic to select the optimal locations of ESSs. The heuristic is based on contingency analysis to calculate a contingency sensitivity index (CSI). The CSI evaluates the impacts of system contingencies on network buses. The impacts of contingencies on network buses are the deviation of bus voltage, the alteration in power generation and change in typical power flows. Buses with high impacts are expected to be the most effective locations for ESS support.
- For the optimal number of ESSs, we use the proposed contingency-sensitivity-based heuristic to determine the optimal number. After calculating the contingency sensitivity index (CSI) for each bus in network, if the CSI exceeds a given sensitivity threshold, then, the number of ESSs is incremented. Furthermore, the proposed heuristic circumvents the combinatorial nature of the siting problem, leading to the improvement of computation time.

- For the optimal ESS sizing, we determine the sizes of ESSs by combining a multi-period AC-OPF and Self-Organizing Hierarchical Particle Swarm Optimization with Time Varying Acceleration Coefficients (HPSO TVAC), which outperforms other PSO types in the studied optimization problem. The optimal ESS sizes are obtained by minimizing the total cost, which includes investment cost, voltage deviation cost and average network loss cost.

The originality of this paper is the definition of a new index (CSI) to decide the optimal locations and the required number of ESSs in a network. This index exploits the network topology and the results of contingency analysis to find the vulnerable locations of the network that needs an ESS support. In addition, the complexity of the siting problem is controlled, which facilitates the resolution of the sizing problem. The advantages of the proposed methodology are:

- The preservation of system constraints such as voltage and line flow limits in an acceptable interval in contingency states.
- The support of power supply in contingency states for a short time until the power reserves turn on.
- The reduction of computational burden of the siting problem. In addition, the methodology for this problem is especially designed to facilitate the solution of the following sizing problem by privileging locations with highest sensitivity to system contingencies.

The proposed methodology is really applied to a Tunisian grid where satisfactory performance is achieved. The performance is in terms of ESS support in contingency states and reliability improvement (voltage deviation, frequency control) thanks to the proposed siting approach that prefers the vulnerable locations for ESS support and in terms of computation time, thanks to the proposed heuristic that reduces the complexity of the ESS allocation problem. Overall, the objective of the proposed methodology is to find a cost-effective ESS allocation strategy, to improve stability and reliability of the power grid and to minimize network losses and voltage deviation, while reducing the computational burden.

This paper is organized as follows: Section III gives the formulation of the problem. Section II highlights the related works in literature. Section IV defines the proposed methodology to find the number, locations and sizes of ESSs. Section V presents the results for the IEEE-30 bus system and Tunisian grid and compares the obtained results with the existing methods. Finally, Section VI concludes this paper.

II. RELATED WORKS

Recently, the potential of energy storage systems (ESSs) has been investigated to overcome power system problems [30], [31], such as voltage problems [32]–[34], wind farm fluctuation [35], [36], load balancing and transmission congestion [37], [38]. Furthermore, the effectiveness of Large-scale ESSs in providing ancillary services and increasing grid reliability is proved in [39]. In addition, ESSs are used in different fields today such as electric vehicles (EV) [40], wireless sensor networks [41]–[43] and real time systems [44]. This paper addresses the allocation of ESSs for improving reliability of a power system. The motivation of our research to address the ESSs allocation in power systems is that they can provide a local solution of the problem such that its impact on the transmission network is limited. Also, a curtailment of renewable generation is not required, thanks to the flexible charging and discharing of ESSs. Various methodologies have been proposed to solve the problem of ESSs allocation by searching the optimal siting and sizing of ESSs, such as optimization of economic profits of the operators [24], [45], [46] and the optimization of the system power balance in [27]–[29]. The work in [27] deals with the optimal siting and sizing of battery banks based on a multi-objective planning considering temporary interruptions to improve the momentary average interruption frequency index. Integration methods for ESSs are proposed to minimize system losses with the advantage of an adjustment benefit [28], and reduce system losses using loss sensitivity and particle swarm optimization [29].

Tab. 1 shows a comparison between the existing studies and the proposed methodology. The proposed methodology deals with many optimization issues relevant to the addressed problem, thus, the integration is optimized in terms of investment and operation cost, the effects of integration are also minimized such as the network losses and bus voltage deviation. Power system reliability is optimized by considering the effects of contingencies on stability of the power system. The state-of-the-art methods cited in Tab. 1, do not regroup all these optimization fields, hence, their solution can be biased.

TABLE 1. Qualitative comparison between the proposed methodology and related work.

Methodology	Economy	Loss Reduction	Voltage regulation	Stability	Reliability
[47]	✗	✗	✓	✗	✗
[29]	✗	✓	✗	✗	✓
[48]	✗	✗	✗	✓	✗
[46] [27]	✗	✗	✗	✗	✓
[49]	✗	✗	✓	✗	✓
The proposed methodology	✓	✓	✓	✓	✓

Moreover, the proposed methodology is computationally efficient. The main problem is divided into three sub-problems where each sub-problem is tackled separately in order to have an optimal solution. The complexity of the siting problem is reduced by the proposed heuristic. The solution for deciding the number of ESSs is derived from this heuristic. Thus, the solution of the sizing problem is facilitated.

III. PROBLEM FORMULATION

This section describes the power grid model with equations and constraints characterizing the system, distributed generators and ESS units.

A. SYSTEM OVERVIEW

A power grid is modeled as a connected graph $G = (N, L)$ composed of a set of buses $N = \{1, 2, ..., n\}$ connected by a set of transmission lines $L = \{1, 2, \ldots, n_l\}$. We consider a set of energy resources denoted by $G_{ER} = (G_C, G_R, G_S)$, where $G_C = \{1, 2, ..., n_g\}$ denotes the subset of conventional power plants, $G_R = \{1, 2, \ldots, n_r\}$ denotes the subset of renewable power plants and $G_S = \{1, 2, ..., n_s\}$ denotes the subset of energy storage systems. We also assume that there is a set of demands denoted by $D = \{1, 2, \ldots, n_d\}$. The power balance equations at bus i and time t are given by

$$P^t_{Gi} + P^t_{Si} - P^t_{Di} = 0 \quad (1)$$

$$Q^t_{Gi} + Q^t_{Si} - Q^t_{Di} = 0 \quad (2)$$

Bus 1 is supposed to be the slack one characterized by fixed voltage magnitude and phase, while complex voltages on buses $i = 2, \ldots, n$ are characterized by a variable voltage magnitude V^t_i, which is maintained within allowable limits to ensure the required quality of service of the transmission system, i.e.,

$$\underline{V}_i \leq V^t_i \leq \overline{V}_i \quad (3)$$

In transmission line l between buses i and j, the limitation on the line current is also imposed as follows:

$$I^t_{ij} \leq \overline{I}_{ij} \quad (4)$$

The dynamics of the energy storage level is modeled by the following equation and constraints

$$E^{t+1}_i = E^t_i + P^t_{Si} \quad (5)$$

Note that P^t_{Si} is positive in the case of charging and negative in the case of discharging. Energy stored at an ESS is bounded as follows:

$$\underline{E}_i \leq E^t_i \leq \overline{E}_i \quad (6)$$

Similarly to Eq. 6, active and reactive power exchanged with an ESS are given by

$$\underline{P}_{Si} \leq P^t_{Si} \leq \overline{P}_{Si} \quad (7)$$

$$\underline{Q}_{Si} \leq Q^t_{Si} \leq \overline{Q}_{Si} \quad (8)$$

We consider two types of generation in the system: (i) renewable generation (e.g., a wind turbine) which is a non-dispatchable unit, where its power output is dependent on the availability of primary sources, i.e, wind, and (ii) conventional power generation (e.g., thermal power plant) which is a dispatchable unit, where its power output at a particular time t is controllable.

B. OBJECTIVE FUNCTION

The effectiveness of a given ESS in providing stability and reliability to the power grid varies significantly, depending on the bus where it is located. In addition, the investment cost of ESSs in the power grid (e.g., installation and maintenance cost) depends on the total ESSs capacity installed. Thus, the ESSs allocation problem should be tackled at the planning stage by finding the optimal siting and sizing.

Consider that we have a set fo buses $N = 1, ..., n$. These buses are candidate locations for the ESSs siting. The problem of ESSs siting consists of finding the n_s buses from the set of N buses to have en ESS support. An exhaustive search of the solution consists of checking C^{ns}_n combinations which is computationally hard. Thus, an efficient solution should be looked for to tackle both of the technical and computational issues of the problem. Considering the vector of ESS locations $\vec{L}$ as a control variable, the objective function of the siting problem aims to improve reliability of the power grid under system contingencies, i.e.,

$$\begin{aligned} &\textit{Select } \vec{L} \textit{ to optimize } (Reliability) \\ &\textit{subject to } (1) - (8) \end{aligned} \quad (9)$$

Considering the vector of ESS sizes $\vec{S}$ as a control variable, the objective function of the sizing problem aims to minimize the total cost which includes investment cost, bus voltage deviation cost, and power loss cost given by

$$\begin{aligned} &\textit{Select } \vec{S} \textit{ to minimize}(Total\ Cost) \\ &\textit{subject to } (1) - (8) \end{aligned} \quad (10)$$

where total cost is the sum of the investment cost, bus voltage deviation cost and average network losses cost.

In other words, the cardinality of ESSs and the composition of the ESS locations and sizes should be determined. Solving the optimal ESSs allocation problem involves a multi-period OPF with integer and continuous optimization variables, which makes the problem NP-hard to solve. To circumvent the combinatorial nature of the ESS allocation problem and reduce its computational burden, a three stage procedure is proposed. A contingency-sensitivity-based heuristic is designed, which takes into account the effects of contingencies on network buses. The heuristic selects the most effected buses by contingencies as the most effective buses for ESS support. In addition, the heuristic allows to find a suitable number of ESS devices. Finally, the sizing of the ESS devices is calculated by solving a multi-period OPF and minimizing a total cost which includes investment cost, bus voltage deviation cost and power loss. Each step of the proposed methodology is illustrated separately in the following section.

C. PRELIMINARIES

For the siting problem, contingency sensitivity analysis is performed, which is based on three impacts. First, the impact on voltage deviation IVD^j, which is calculated using the voltage at bus j under contingency and the base case (V^{cont}_j and V^{base}_j), respectively. Second, the impact on line current flow ILF^{ij}_l, which is calculated using the line current flow of line l located between buses i and j, under contingency and base case (LF^{cont}_l and LF^{base}_l), respectively. Third, the impact on power generation IPG^j_g on bus j, which is calculated using the power output of generator g located at bus j under contingency and the base case (PG_g^{cont} and PG_g^{base}), respectively.

IV. METHODOLOGY

This section gives a detailed description of the proposed methodology, the siting part in first, followed by the sizing part in second.

A. ESS SITING

We propose a contingency sensitivity index (CSI) for each bus that combines the ratio between bus voltage deviation IVD^j, line current flow variation ILF_l^{ij}, and generator power output variation IPG_g^j caused by the considered contingencies. CSI is calculated through a contingency sensitivity matrix (CSM) generated with contingency analysis. The input of this stage is the contingency analysis data. The results of this analysis identify vulnerable buses in the power grid representing the most effective locations for ESS support, and the number of ESSs that should be installed.

The impact factors caused by a contingency can be measured by IVD^j, ILF_l^{ij}, and IPG_g^j evaluated by

$$IVD^j = \begin{cases} 1, & \text{if } |V_j^{cont} - V_j^{base}| > t_b, \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

$$ILF_l^{ij} = \begin{cases} 1, & \text{if } |LF_l^{cont} - LF_l^{base}| > t_l, \\ 0, & \text{otherwise} \end{cases} \tag{12}$$

$$IPG_g^j = \begin{cases} 1, & \text{if } |PG_g^{cont} - PG_g^{base}| > t_g, \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

where

- IVD^j is *true* if an impact for bus voltage deviation at bus j is engendered by a contingency,
- ILF_l^{ij} is *true* if an impact for line current flow variation (in line l between buses i and j) is engendered by a contingency and
- IPG_g^j is *true* if an impact for generator power output variation (in generator g at bus j) is engendered by a contingency.

t_b, t_l and t_g are thresholds for IVD^j, ILF_l^{ij} and IPG_g^j, respectively. For these impact factors, "1" and "0" define that it has impact and it has no impact, respectively.

A contingency sensitivity matrix (CSM) is generated, which represents the impacts of contingencies on the network buses. The $[n_c \times n]$ matrix is given by

$$\mathbf{CSM} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{n_c1} & a_{n_c2} & a_{n_c3} & \dots & a_{n_cn} \end{bmatrix} \tag{14}$$

where

$$a_{ij} = \begin{cases} 1, & \text{if } IVD_j = 1 \\ 1, & \text{if } ILF_l^{ij} \text{or } ILF_l^{ji} = 1 \\ 1, & \text{if } IPG_g^j = 1 \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

n_c is the number of contingencies and n is the number of network buses. For example, if a contingency c causes an impact on generator g located at bus j, and an impact on line l located between buses m to n, then buses j, m and n have a "1" in row c of the CSM matrix. Hence, the row is given by

$$\mathbf{CSM_c} = \begin{array}{c} \begin{array}{ccccc} bus & j & m & n & \end{array} \\ \begin{bmatrix} \dots & 1 & 1 & 1 & \dots \end{bmatrix} \end{array} \tag{16}$$

By taking these impact factors into account, the value of CSI of each bus is calculated by the summation of each column of the CSM matrix. The CSI value for each bus j is given by

$$CSI_j = \sum_{i=1}^{n_c} CSM_{ij} \tag{17}$$

After the CSI analysis, the buses are arranged in a decreasing order. Their ranking is considered as the criterion for ESS siting selection.

B. ESS NUMBER

The number of ESSs is chosen through the CSI index with a sensitivity threshold, i.e., for a sensitivity threshold t_s, the number of ESS is equal to the cardinality of buses which exceeds t_s, i.e.,

$$n_s = \mathbf{card}(\underset{j=1,\dots,n}{CSI_j} \geq t_s) \tag{18}$$

C. ESS SIZING

The minimization of power losses and bus voltage deviation for the sizing problem constitutes a complex nonlinear optimization problem. To solve this problem, we use the HPSO TVAC [50] which is a relatively new and powerful optimization method that is well suited to solve continuous nonlinear problems. A brief description of PSO and HPSO TVAC techniques is given in Appendices A and B. The problem is formulated as an AC OPF and solved with the HPSO TVAC algorithm to determine the size of ESSs that are placed at the selected buses. The size intervals of ESSs are chosen such that the sum of their maximum is between (15-25)% of the rated renewable capacity which is a correct ESS size [51]. The objective function is given by

$$\min f(\vec{S}) = \left[\sum_{t=1}^{T} [C^L.P_L^t] + \sum_{t=1}^{T} [C^V.V_D^t] + C^I(n_s) \right]$$
$$s.t. \quad (1) - (8) \tag{19}$$

The objective function of the sizing problem minimizes the investment cost, average network losses and bus voltage deviation. The total investment cost is calculated by

$$C^I(n_s) = \sum_{i=1}^{n_s} [c_f + c_s.S_i] \tag{20}$$

where S_i is the size of the *ith* ESS, c_f is the fixed cost related to a single ESS installation and c_s is the unitary cost associated

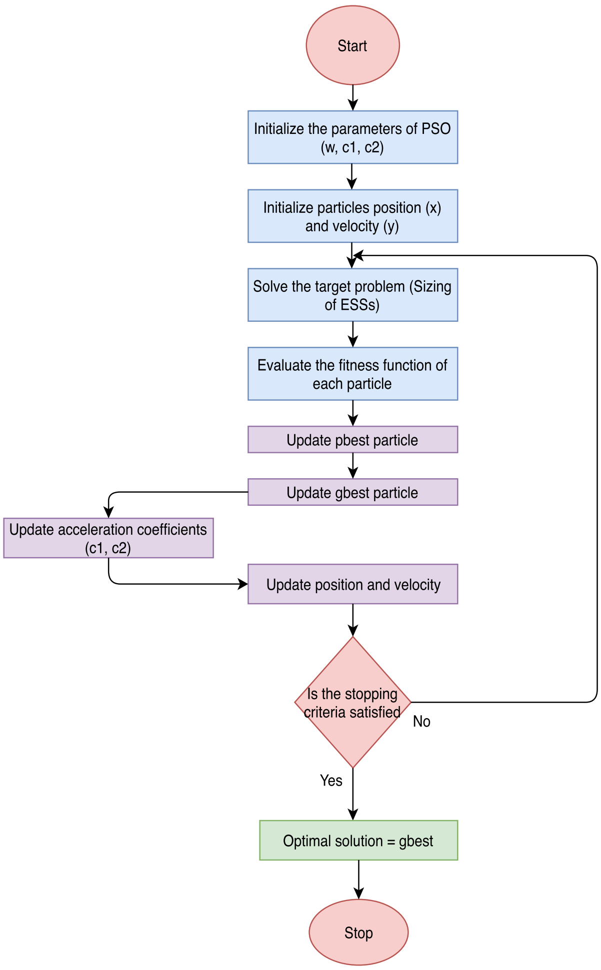


FIGURE 1. HPSO TVAC.

with S_i. The investment cost function is limited by

$$C^I(n_s) \leq \overline{B} \tag{21}$$

Fig. 1 gives the flow chart of the HPSO TVAC used to solve the sizing problem of ESSs.

The HPSO TVAC is a modified version of particle swarm optimization.

- The metaheuristic starts with the initialization PSO parameters, then, the particle's velocity and position are initialized by Eq.s 30 and 29, respectively, given in Appendix.
- After that, each particle solves the optimization problem, i.e., ESS sizing and evaluates its fitness function. Each particle updates its personal best fitness and the global best fitness is updated.
- The accelerations coefficients are updated, then, the particle's velocity and position are updated and so on.
- If the stopping criteria, i.e., number of iterations, is reached, then, the solution of the optimization problem is given by the global best particle, else, particles continue to solve the optimization problem and updates their parameters and fitness until the stopping criteria is reached.

D. IMPLEMENTATION

Overall, after ranking the buses with CSI analysis, the optimal locations of ESSs $\vec{L}^{opt}$ are determined, then, optimal sizes of ESSs $\vec{S}^{opt}$ are calculated with the following equations:

$$\vec{L}^{opt} = \underset{j=1,\ldots,n}{\arg\max}\ CSI_j \tag{22}$$

$$\vec{S}^{opt} = \arg\min f(\vec{S}) \tag{23}$$

Fig. 2 gives the detailed concept of the proposed methodology. The ESS siting starts with the contingency analysis process that evaluates the impacts of contingencies on the network buses. The CSI is calculated for each bus in the network. After that, a ranking process is launched where the

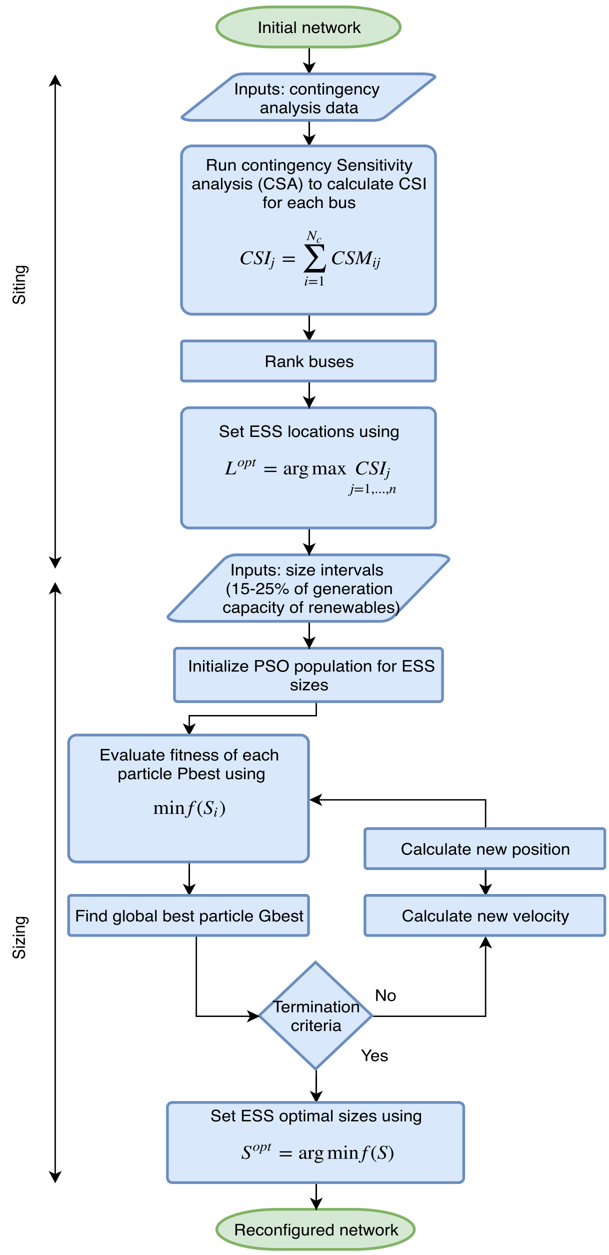


FIGURE 2. Flowchart of the proposed methodology.

buses are arranged in a decreasing order. The number of ESSs is determined through a contingency sensitivity threshold. If the CSI exceeds this threshold, then, the number of ESSs is incremented. After determining the number of ESSs, i.e., n_s, the locations of ESSs are selected by choosing the first n_s locations from the ranked buses.

After that, ESSs sizing starts with the inputs that are the size intervals of ESSs. These intervals are chosen such that their capacity is between 15-25% of the capacity of renewables that seems a correct size according to [51]. The HPSO TVAC starts with the initialization of PSO parameters where each particle updates its position according to the size interval of an ESS. After that, each particle evaluates its fitness according to Eq. 19 and updates its personal best fitness. The global best fitness is selected. If the stopping criteria is reached, then, the solution of the problem is given in the global best fitness, else, particles update their velocity and position and evaluates their fitness and so on.

In order to guarantee feasibility of the sizing problem in Eq. (19), the ESS sizes should be selected by considering all possible realizations of generation profiles. In this respect, the problem should be solved for each profile sample. So, the ESS sizes are selected with the largest size found. Formally, let $\underset{p=1,\ldots,P}{\vec{S}^{opt}}$ denote the set of optimal sizes of ESSs for the set of generation profiles $p = 1, \ldots, P$. The selected optimal sizes are:

$$\vec{S}^{*opt} = \max_{p=1,\ldots,P} \vec{S}^{opt} \tag{24}$$

V. EXPERIMENTATION

This section gives the numerical results of the proposed methodoloy. The simulation is performed on Matlab with Matpower package [52] with the AC OPF.

A. CASE STUDY

We have applied the proposed methodology for both IEEE 30 bus system and a real grid in the northwest of Tunisia.

1) IEEE 30 BUS SYSTEM

The application of the proposed methodology considers an MV network (IEEE 30 bus system, see Fig. 4). The network consists of 30 buses, hosting six conventional generators, 20 loads and two wind farms at Buses 21 and 23 with capacity of 35 MW and 25 MW, respectively. The problem here is to find an optimal configuration (the number, locations and sizes) of ESSs. For all loads, generators and transmission lines, their profiles are perturbed to originate contingencies. This means that, in the absence of ESSs in the network, typical power flows are violated at certain buses.

Fig. 3 gives the results of contingency sensitivity analysis for all buses. Figs. 3a, 3b and 3c show the impact factors for line current flow variation, power output variation and bus voltage deviation, respectively. For this 30-bus system, the contingency sensitivity matrix CSM defined in Eq. (16), is computed numerically with Equations (11)-(15). A colormap plot is shown in Figs. 3a, 3b, and 3c. This form of representation is useful to visualize the effect that a contingency has on the line flow variation, generator output variation and voltage deviation. The bar graph in Fig. 3d gives the CSI values which are calculated by Eq. (17) considering these impact factors. Here in our case, the number of ESSs to be installed is found using:

$$n_s = \mathbf{card}(\underset{j=1,\ldots,30}{CSI_j} \geq 25) \tag{25}$$

In this case, $n_s = 3$. Buses numbered as 2, 13 and 23 are those with high priorities for energy storage system installation. These locations determine the vulnerable buses in the system which are more affected by the contingencies. These buses can be considered as the most effective locations for ESS support.

Fig. 4 shows the network before the integration and Fig. 5 after the integration of ESSs. The three ESSs installed at Buses 2, 13 and 23, have the capacity of 15.7 MWh, 16.6 MWh and 17.9 MWh, respectively.

Contingency analysis is performed by direct calculation of the power flows resulting in contingency states. The performance evaluation is done by comparison of the post contingency ESS outputs. The best siting methodology gives more energy support in contingency states. In the comparison, the sizing is assumed to be equal for the three siting approach to show the advantage of the proposed siting methodology. In this comparison, we consider five contingencies in table 2:

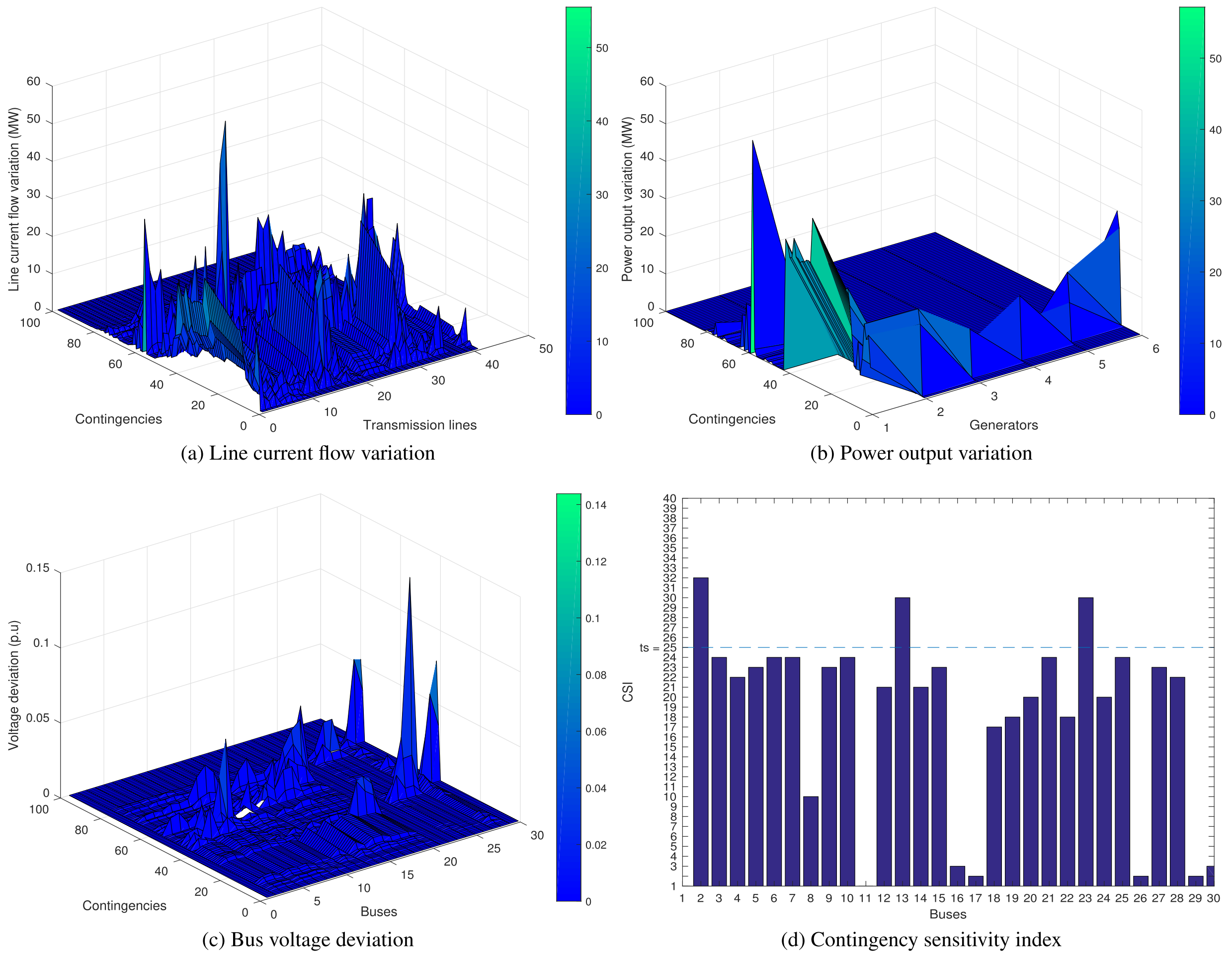
TABLE 2. Contingencies.

Symbol	$C1$	$C2$	$C3$	$C4$	$C5$
Contingency	peak load at Bus 2	renewable fluctuation	Generator 2 outage	Line 4 outage	peak load at Bus 8

Fig. 6 shows the total energy exchanged from ESSs in (MWh) in post contingency states, for the Weak bus method [47] which is based on voltage sensitivity, LSF method [29] based on loss sensitivity, the work given in [49] which is based on voltage control and the proposed method based on the contingency sensitivity. Based on the results, the power provided from ESS is larger than the other methods (in Contingency 1, 2, 3, 4), thanks to the existence of ESSs in vulnerable locations provided by the proposed siting methodology Eq. (22). The ESSs installed in these locations work as a spinning reserves in contingency states, which improve the reliability of the system under contingencies. In contrast, the ESS output in Contingency 5 is less than the other siting approaches, due to the location of the contingency which is far from the installed ESS. We conclude that the energy exchanged from ESS depends on the relative location with respect to the system contingencies.

Fig. 7 shows the the voltage profile and power loss.

These results confirm the effectiveness of the proposed methodology in terms of power loss and voltage control. The voltage profile of the proposed method in Fig. 7a does not exceed the acceptable range [0.97 1] p.u. The voltage



(a) Line current flow variation (b) Power output variation

(c) Bus voltage deviation (d) Contingency sensitivity index

FIGURE 3. Contingency sensitivity analysis.

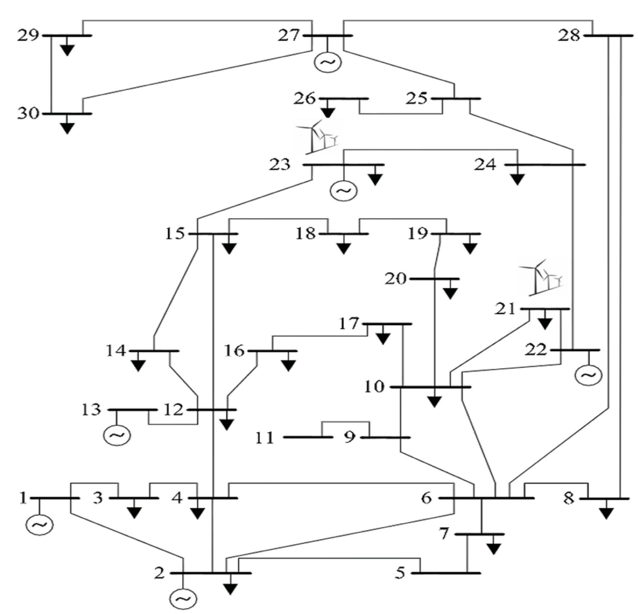


FIGURE 4. Network before integration.

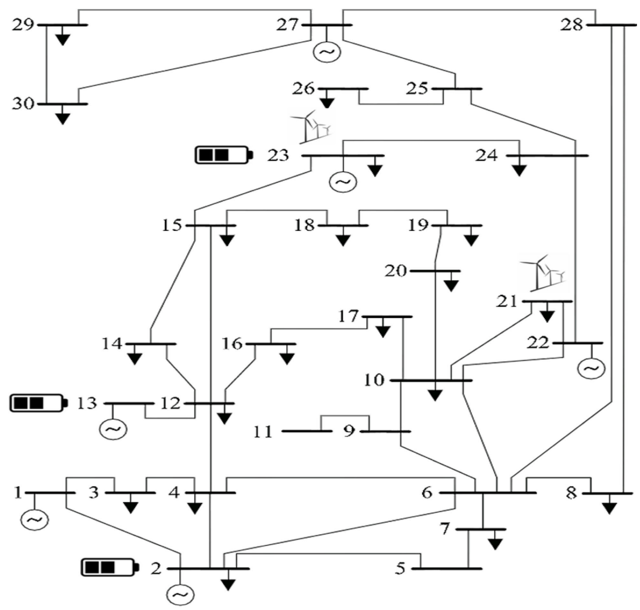


FIGURE 5. Network after integration.

profile of the weak bus, loss sensitivity and Voltage control vary in [0.963 1], [0.957 1] and [0.955 1] p.u, respectively. The deviation of the proposed methodology is smoother than other methods. The reduction rate is 12% compared with Weak bus method, 22 % compared with LSF method and 10% compared with voltage control method. The power

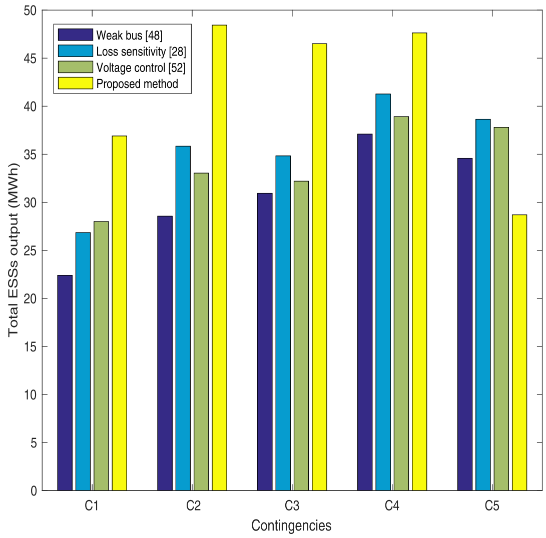
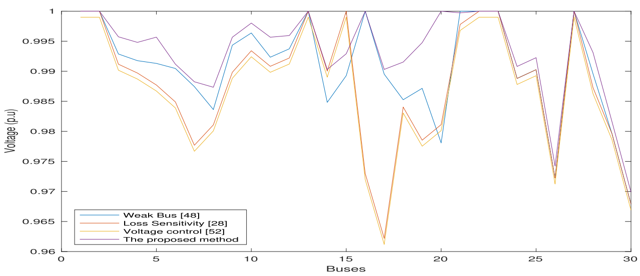
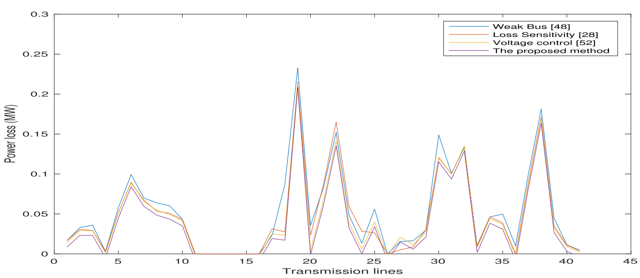


FIGURE 6. Contingency analysis.



(a) Voltage profile in Contingency 3 (C3).



(b) Power losses in Contingency 3 (C3).

FIGURE 7. Voltage profile and power losses.

losses of the proposed method in Fig. 7b are quite less than the weak bus method (about 21%), a little less than the LSF method (about 6%) and quite less than voltage control method 13%, thanks to the proposed sizing methodology that minimizes the network power losses and voltage deviation. The gain is fairly larger than Weak bus, LSF and voltage control methods especially in contingency states in terms of reliability improvement.

2) IEEE 30 BUS SYSTEM WITHOUT WIND FARMS

Here, we evaluate results of the proposed methodology in case with no renewable energy in the network. Fig. 8 shows the results of the proposed contingency sensitivity analysis.

Here the results differ from the case with renewable energy, due to the intermittent generation which causes power system instability. Now, the optimal ESS siting is in buses 22 and

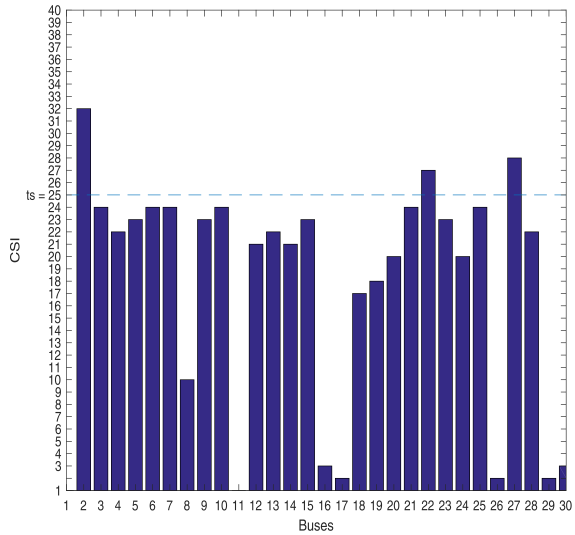


FIGURE 8. Contingency sensitivity analysis results.

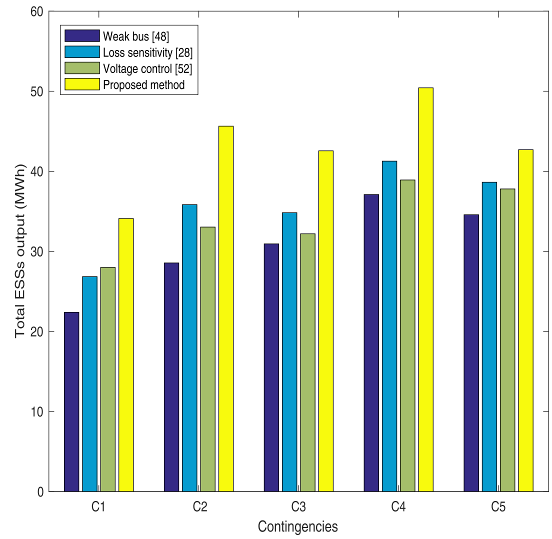


FIGURE 9. Contingency analysis.

27, this is because the variation is more in these buses that supply another buses in the network in contingency states. The optimal ESS sizes for the buses 2, 22 and 27 are 15.2, 16.3 and 17.1 MW/h respectively, which is quite equivalent to the case without ESSs. This is because optimal ESS sizes depends on the network capacity and not on renewable energy. Fig. 9 shows the total energy exchanged from ESSs in (MWh) in post contingency states for the considered methodologies.

Based on the presented results, we confirm the efficiency of the proposed ESS allocation methodology in term of power delivery. In fact, the power provided from ESS is larger than with methods (in Contingency 1, 2, 3, 4, 5), thanks to the location of ESSs in vulnerable locations provided by the proposed siting methodology. The ESSs installed in these locations run as a spinning reserves in contingency states, which improves system reliability under contingencies. In contrast with the first scenario (with wind farms), the ESS output in

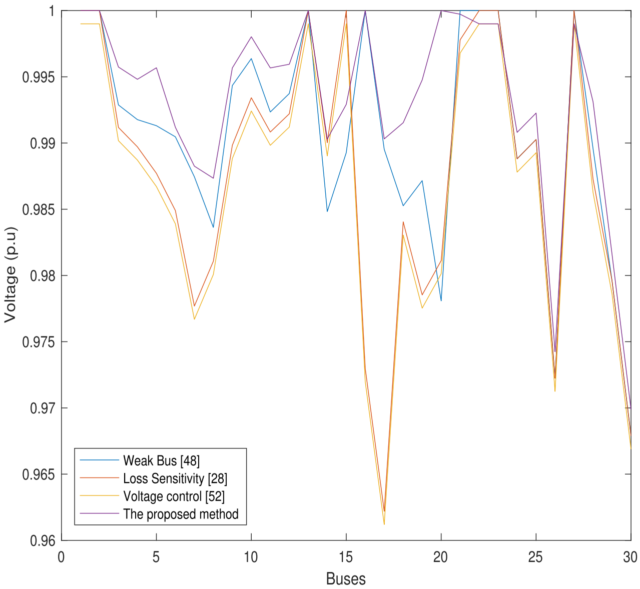


FIGURE 10. Voltage profile.

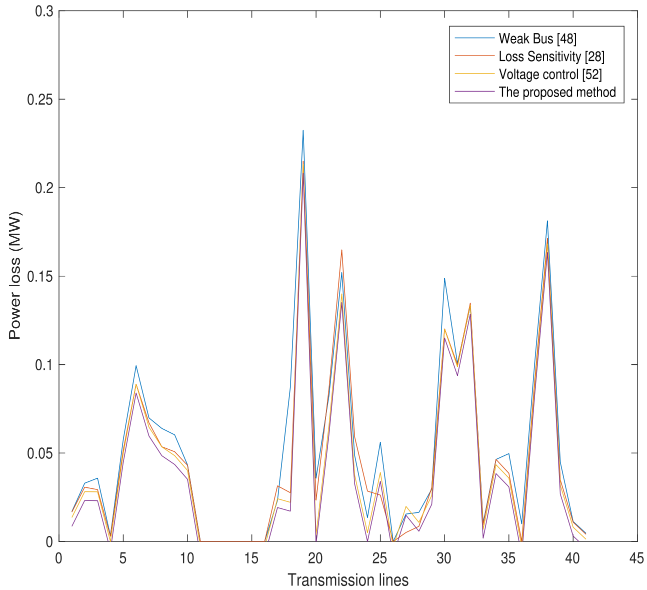


FIGURE 11. Power loss.

Contingency 5 is more than other siting approaches, thanks to the location of the ESS which is near to the contingency. Thus, we confirm our theory which argue that energy exchanged from ESS depends on the relative location with respect to the system contingencies.

Fig. 10 and 11 show the results of voltage deviation and power loss. These results confirm also the effectiveness of the proposed methodology in terms of power loss and voltage control. The voltage profile of the proposed method here also does not exceed the acceptable range [0.97 1] p.u. However, the voltage profile of the weak bus, loss sensitivity and Voltage control vary in [0.963 1], [0.957 1] and [0.955 1] p.u, respectively. The deviation of the proposed methodology is smoother than other methods. The reduction rate is 12% compared with the Weak bus method, 22% compared with the LSF method and 10% compared with the voltage control method.

The power losses of the proposed method are quite less than the weak bus method (about 21%), a little less than the LSF method (about 6%) and quite less than voltage control method 13%, thanks to the proposed sizing methodology that minimizes the network power losses and voltage deviation. The gain is fairly larger than Weak bus, LSF and voltage control methods especially in contingency states in terms of reliability improvement.

3) TUNISIAN GRID

The proposed methodology has been applied to a real Tunisian grid in the northwest of Tunisia. The Tunisian grid is composed of 18 buses consisting of four conventional generators, two wind farms and 18 loads. The architecture of the network is given in Fig. 12 and data are given in tables. 3, 4, 5. The Tunisian grid is composed of 18 buses consisting of four conventional generators, two wind farms and 18 loads. The network total power demand is 100 MW while the network generation capacity is 150 MW.

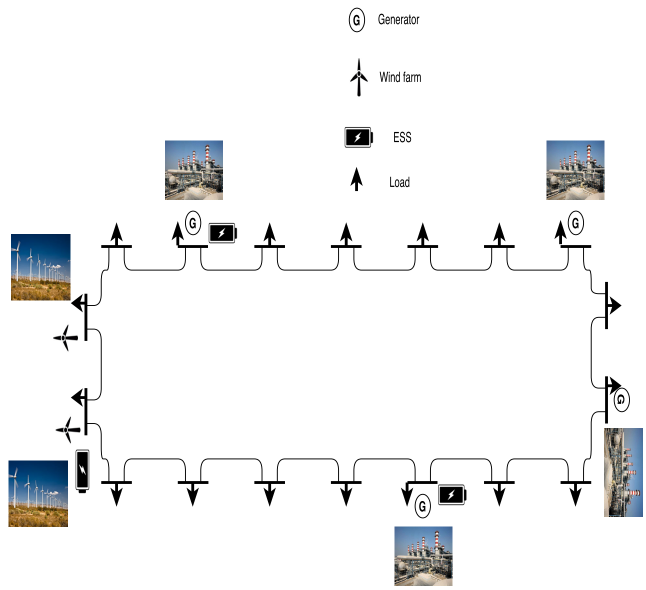


FIGURE 12. Tunisian grid.

For the energy storage system, Li-ion batteries are selected for their long lifetime and high energy capacity. Each battery rack consists of 16 modules with total energy capacity of 105.5kWh. The number of racks with the battery energy storage system BESS unit is calculated after finding the sizing of the ESSs. Fig. 13 shows the BESS model used in this case study. The BESS is capable to deliver active power during contingency states in order to improve the system reliability, i.e., limiting the voltage and frequency variation. In contingency states, the ESSs will provide a peak generation, for an additional time interval of seven seconds. This procedure can be repeated up to 20 times, until the stability is

TABLE 3. Bus data.

Bus	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Power Demand (MW)	0	9	7	6	6	5	8	7	8	8	2	5	4	6	4	5	3	3
Voltage magnitude (p.u)	1.05	1.4	1.02	1.04	1.4	1.05	1.4	1.05	1.05	1.05	1.04	1.02	1.02	1.02	1.04	1.04	1.04	1.04
Vmin	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
Vmax	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05	1.05

TABLE 4. Line parameters.

Line number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
From bus	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	17	18
To bus	1	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	18	1
Resistance (p.u)	0.020	0.06	0.04	0.06	0.05	0.06	0.02	0.08	0.23	0.18	0.10	0.13	0.07	0.03	0.13	0.19	0.17	0.19	0.18
Reactance (p.u)	0.06	0.22	0.16	0.17	0.18	0.04	0.21	0.56	0.25	0.20	0.25	0.13	0.17	0.11	0.08	0.27	0.19	0.19	0.22
Rating (kv)	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24

TABLE 5. Generator data.

Generator	1	2	3
Power generation (MW)	50	40	20
Pmin	20	10	5
Pmax	70	60	30

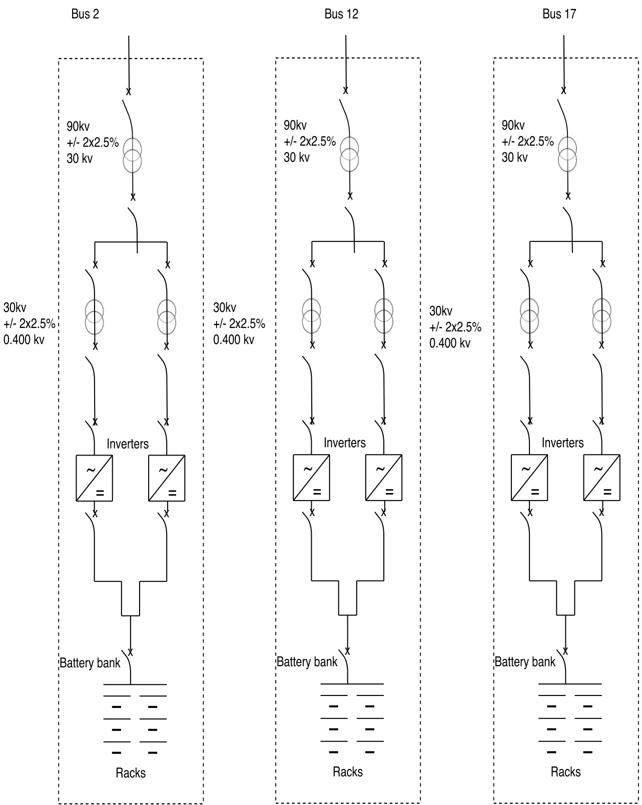


FIGURE 13. Single line diagram of BESS.

reached. After running the CSI analysis, the buses numbered as 2, 12 and 17 are selected as the optimal locations of ESSs with sizes of 7.3, 5.7 and 8.5 MWh, respectively.

Fig. 14 shows the voltage and grid frequency regulation after a peak load.

The load increase causes a transient drop of frequency as well as voltage. ESSs mitigate this droop by their power generation. Within 3 seconds, voltage and grid frequency are stabilized. The load is decreased in second 4 resulting in a transient increase of voltage and grid frequency until the combination of ESS's power and generator power reserves stabilizes the voltage at 1 p.u and grid frequency at 60 Hz. In case of the absence of ESSs, load shedding occurs almost immediately, leading to grid frequency collapsing.

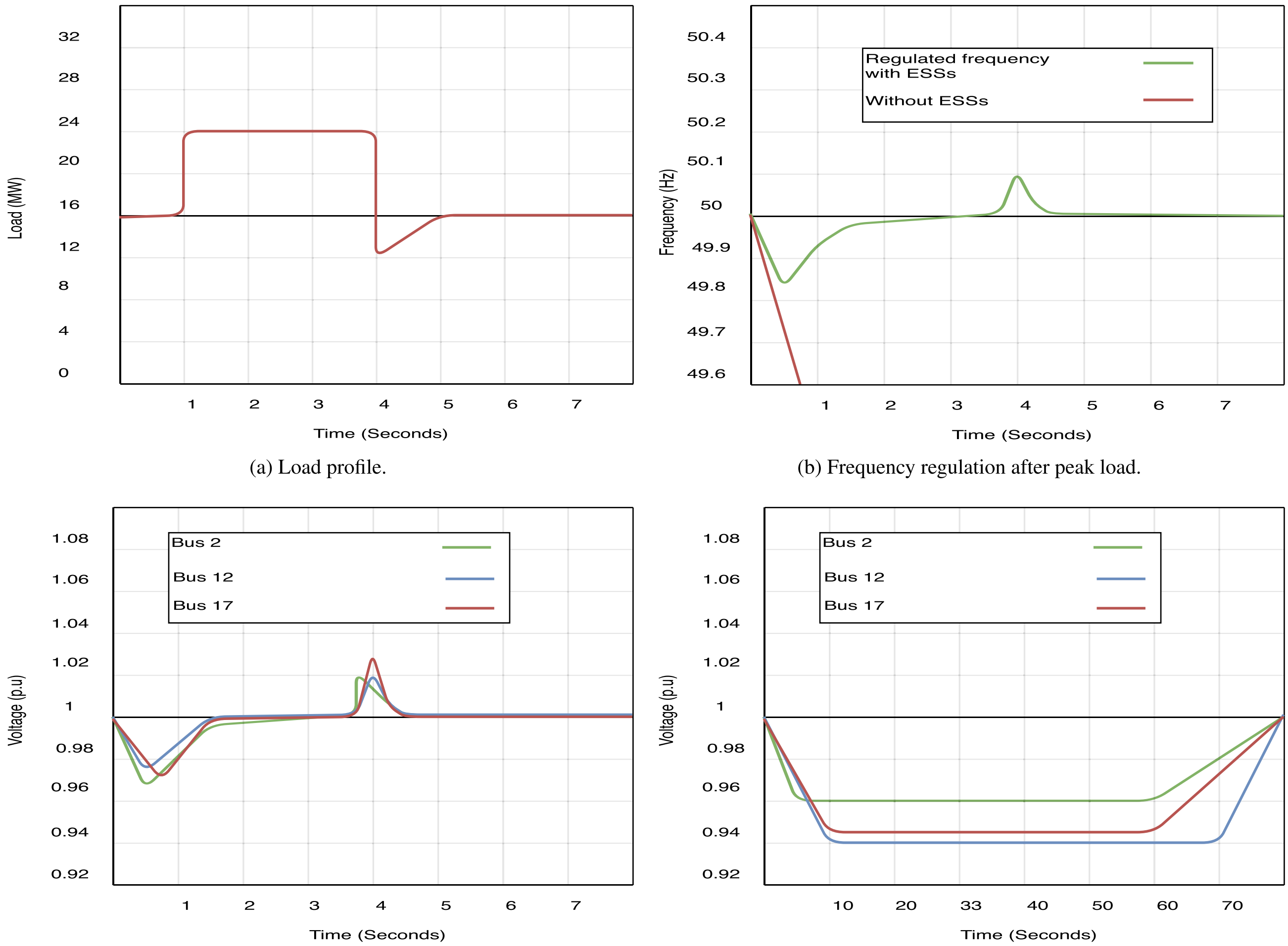
Figs. 14c and 14d show that, by using ESSs, voltage deviation is rapidly regulated in few seconds. On the contrary, without ESSs, the voltage deviation is regulated in few minutes. This is because the slow response of the system power reserves. The violation of system constraints can cause a major damage to the system operation such as faults and blackouts. Consequently, the integration of ESSs to the power system operation becomes inevitable.

B. COMPUTATIONAL PERFORMANCES

The proposed siting methodology is quite inexpensive in terms of computational burden, its heaviest task is to calculate load flow, which is executed in few seconds even for large networks. The overall computational burden of the proposed methodology is caused by the sizing procedure. Due to the presence of ESSs, which are time correlated, a multi-period AC OPF is required to solve the problem. In this respect, HPSO TVAC is adopted to solve the sizing problem.

As expected, the execution time taken by the proposed siting methodology is of the order of seconds regardless of the number of network buses. However, the exhaustive search needed for the optimal siting problem requires solving a huge number ($C_n^{n_s}$) of problems of the form Eq. (19), involving an unacceptable execution time. For this reason, the computation of the sizing of ESSs is restricted to the set of the selected buses in the siting stage, which is expected to be most effective for ESSs support.

Tab. 6 presents a comparison between the results of different metaheuristics that are Genetic Algorithms (GA) [53], Non Sorting Genetic Algorithm (NSGA-II) [54], Cuckoo Search (CS) [55] and four PSO types that are [50], [56]: Basic PSO, Time-Varying Acceleration Coefficients (TVAC PSO), Time Varying Inertia Weight (TVIW PSO) and Self-Organizing Hierarchical PSO with Time-Varying Acceleration Coefficients (HPSO TVAC) used by the proposed methodology.



(a) Load profile.

(b) Frequency regulation after peak load.

(c) Voltage profile with ESSs.

(d) Voltage profile without ESSs.

FIGURE 14. Voltage and frequency regulation.

TABLE 6. Computational performances evaluation.

Metaheuristic	ESS 1 Size (MWh)	ESS 2Size (MWh)	ESS 3Size (MWh)	Nř of iterations	Time taken in 200 iterations
GA	15.1	15.2	16.5	156	223
NSGA-II	15.3	15.5	16.8	132	202
Cuckoo search	15.4	16.1	17.2	167	234
Basic PSO	15.7	16.6	17.9	122	192
TVAC PSO	15.7	16.6	17.9	178	287
TVIW PSO	15.7	16.6	17.9	146	243
HPSO TVAC	15.7	16.6	17.9	75	161

From the above results in Tab. 6, it is seen that different types of PSO give the same optimum values for the ESSs sizes. Therefore, different techniques are able to find the global solution effectively. But compared with other PSO techniques, HPSO TVAC is the best in terms of the number of iterations as well as execution time.

C. DISCUSSION ON ECONOMY AND FEASIBILITY OF ESS

An economic analysis of ESS feasibility is performed by calculating annual cost of ESS deployment (ACD) and annual net benefits (TANB). The annual cost of ESS deployment is calculated by multiplying the cost of conventional electric service (CCES) by the total ESS capacity installed (TCI) and a fixed charge rate (FCR) as follows:

$$ACD = CCES\ (\$/kwh) \cdot TCI\ (kw/h) \cdot FCR\ (\%) \tag{26}$$

The total annual net benefits (TANB) are calculated by multiplying the total energy discharged (TED) by the average on-peak price of electricity (AONPE) minus the average off-peak price of electricity (AOFPE) divided by the storage system round (SSR) minus trip efficiency (TE) as follows:

$$\begin{aligned} TANB = TED\ (MWh) \cdot AONPE(\$ = MWh) \\ -AOFPE\ (\$ = MWh)/SSR - TR(\%) \end{aligned} \tag{27}$$

Tab. 7 illustrates the annual economic benefits and losses of implementing the most feasible ESS type which is Lithium-ion battery. The most viable ESS is Lithium-ion battery, with the annual benefit of 6000 \$/kW, the capital cost for ESS deployment is 3200-4000 \$/kW, and cumulative yearly losses and maintenance cost are 500 \$/kW. Therefore, we can estimate that approximately 2000 \$/kW is gained by employing this ESS. The number of payback years for the Lithium-ion battery is 9-10 years. It is reasonable compared with their life cycle which can attain 15 years [57].

VI. CONCLUSION

Energy storage systems play a key role to improve the reliability of power system in contingency states. ESS's performance

TABLE 7. Economic analysis of ESSs based on cumulative benefits and costs.

Type of ESS	Annual benefits of ESSs ($/kw)	Total cost for new ESSs and replacement parts ($/kw)	cumulative annual losses and maintenance costs ($/kw)	Expected payback time (years)
Lithium-ion batteries	6000	3200-4000	500	9-10

can be enhanced by selecting the best siting according to the impacts of contingencies. Therefore, statistical information on potential contingency locations seems to be decisive for the optimal siting of ESSs, to increase the probability of supporting the power grid against faults. Unlike the existing research studies that investigate the problem of siting and sizing together, in this work, we explore the problem separately. Energy storage system siting, sizing and deciding the number of ESSs are inspected based on contingency analysis, which provides more stability to power system for improving its reliability and minimizing power losses and voltage deviation. Other objectives for determining the optimal siting and sizing of ESSs will be explored in future work, such as searching for other sensitivity indexes that have a significant impact on the power system operation in terms of economy and reliability. In the future work, we will explore the considered problems in the framework of reconfiguable software [58]–[60] and also in the framework of discrete-event systems using automata and Petri nets [61]–[64].

APPENDIX

A. PARTICLE SWARM OPTIMIZATION (PSO)

The PSO algorithm [56] is inspired from social behavior of some animals such as bird flocking. The potential set of solutions is represented by the population and each solution is represented by a particle. Each particle moves in the search space according to its personal best experience (p_{best}), but is also guided toward the best experience of neighboring particles (g_{best}). To resolve the sizing problem, the candidate solutions are the elements of size intervals of an ESS's capacity. Particles are moving around these intervals according to Eq. (19). The velocity of each particle is limited by a predefined maximum value v^{max}. New positions are calculated by adding velocity coordinates (v_k) to position coordinates (x_k) and the algorithm iterates by adjusting velocities and positions. The velocity and position of each particle are given by [56]:

$$v_{k+1} = w * v_k + c_1 * r_1 * (p_{best} - x_k) + c_2 * r_2 * (g_{best} - x_k) \tag{28}$$

$$x_{k+1} = x_k + v_{k+1} \tag{29}$$

Parameters c_1 and c_2 in Eq. (28) are often called acceleration coefficients which denote the cognition and the social parameters, respectively. r_1 and r_2 are random variables and w is the inertia weight.

B. SELF-ORGANIZING HIERARCHICAL PARTICLE SWARM OPTIMIZATION WITH TIME-VARYING ACCELERATION COEFFICIENTS (HPSO TVAC)

This technique proposes to update the velocity formula without addition of previous velocity, i.e., the exclusion of the inertia term. Also, the acceleration coefficients are varied with respect to time or iteration. Instead of moving toward the g_{best} particle, particles try to converge to the global optima at the end of optimization. Therefore, the new velocity formula becomes as follows [50]:

$$v_{k+1} = c_1 * r_1 * (p_{best} - x_k) + c_2 * r_2 * (g_{best} - x_k) \tag{30}$$

Consequently, particles rapidly stagnate in a local optimum solution. To solve this problem, during particle's velocity calculation, if the new velocity becomes zero, then, velocity is reinitialized to some value according to the predefined maximum value v^{max}. Finally, the reinitialization of velocity is linearly decreased from v^{max} to $(0.1.v^{max})$.

REFERENCES

[1] D. Wu, G. Li, M. Javadi, A. M. Malyscheff, M. Hong, and J. N. Jiang, "Assessing impact of renewable energy integration on system strength using site-dependent short circuit ratio," *IEEE Trans. Sustain. Energy*, vol. 9, no. 3, pp. 1072–1080, Jul. 2018.

[2] M. Fan, K. Sun, D. Lane, W. Gu, Z. Li, and F. Zhang, "A novel generation rescheduling algorithm to improve power system reliability with high renewable energy penetration," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3349–3357, May 2018.

[3] W. Liu, Z. Li, B. Zeng, M. Yang, H. Qin, X. Zheng, and D. Zhao, "Collaborative planning of DERs and intentional islands in distribution network considering loss-of-load risk," *IEEE Access*, vol. 6, pp. 45961–45973, 2018.

[4] S. Ben Meskina, N. Doggaz, M. Khalgui, and Z. W. Li, "Multiagent framework for smart grids recovery," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 7, pp. 1284–1300, 2017.

[5] I. Naidji, O. Mosbahi, M. Khalgui, and A. Bachir, "Cooperative energy management software for networked microgrids," in *Proc. 14th Int. Conf. Softw. Technol. (ICSOFT)*, vol. 1, 2019, pp. 428–438.

[6] S. Yang, C. Huang, Y. Yu, D. Yue, and J. Xie, "Load frequency control of interconnected power system via multi-agent system method," *Electr. Power Compon. Syst.*, vol. 45, no. 8, pp. 839–851, 2017.

[7] R. Khezri, S. Golshannavaz, S. Shokoohi, and H. Bevrani, "Fuzzy logic based fine-tuning approach for robust load frequency control in a multi-area power system," *Electr. Power Compon. Syst.*, vol. 44, no. 18, pp. 2073–2083, 2016.

[8] S. Padhan, R. K. Sahu, and S. Panda, "Application of firefly algorithm for load frequency control of multi-area interconnected power system," *Electr. Power Compon. Syst.*, vol. 42, no. 13, pp. 1419–1430, 2014.

[9] W. Yang, J. Yang, W. Guo, and P. Norrlund, "Frequency stability of isolated hydropower plant with surge tank under different turbine control modes," *Electr. Power Compon. Syst.*, vol. 43, no. 15, pp. 1707–1716, 2015.

[10] N. Wu, M. Zhou, L. Bai, and Z. Li, "Short-term scheduling of crude oil operations in refinery with high-fusion-point oil and two transportation pipelines," *Enterprise Inf. Syst.*, vol. 10, no. 6, pp. 581–610, 2016.

[11] Y. Hou, N. Wu, M. Zhou, and Z. Li, "Pareto-optimization for scheduling of crude oil operations in refinery via genetic algorithm," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 3, pp. 517–530, Mar. 2017.

[12] S. Zhang, N. Wu, Z. Li, T. Qu, and C. Li, "Petri net-based approach to short-term scheduling of crude oil operations with less tank requirement," *Inf. Sci.*, vol. 417, pp. 247–261, Nov. 2017.

[13] N. Wu, Z. Li, and T. Qu, "Energy efficiency optimization in scheduling crude oil operations of refinery based on linear programming," *J. Cleaner Prod.*, vol. 166, pp. 49–57, Nov. 2017.

[14] X. Wang, Z. Li, and W. Wonham, "Dynamic multiple-period reconfiguration of real-time scheduling based on timed DES supervisory control," *IEEE Trans. Ind. Informat.*, vol. 12, no. 1, pp. 101–111, Feb. 2016.

[15] I. Naidji, M. B. Smida, M. Khalgui, and A. Bachir, "Non cooperative game theoretic approach for residential energy management in smart grid," in *Proc. 32nd Annu. Eur. Simulation Modeling Conf.*, 2018, pp. 164–170.
[16] A. Nayak, S. Lee, and J. W. Sutherland, "Storage trade-offs and optimal load scheduling for cooperative consumers in a microgrid with different load types," *IISE Trans.*, vol. 51, no. 4, pp. 397–405, 2019.
[17] M. Zidar, P. S. Georgilakis, N. D. Hatziargyriou, T. Capuder, and D. Škrlec, "Review of energy storage allocation in power distribution networks: Applications, methods and future research," *IET Generat., Transmiss. Distrib.*, vol. 10, no. 3, pp. 645–652, Mar. 2016.
[18] S. Frank and S. Rebennack, "An introduction to optimal power flow: Theory, formulation, and examples," *IIE Trans.*, vol. 48, no. 12, pp. 1172–1197, Aug. 2016.
[19] A. Fathy and A. Y. Abdelaziz, "Grey wolf optimizer for optimal sizing and siting of energy storage system in electric distribution network," *Electr. Power Compon. Syst.*, vol. 45, no. 6, pp. 601–614, Mar. 2017.
[20] H. Zhao, Q. Wu, S. Huang, Q. Guo, H. Sun, and Y. Xue, "Optimal siting and sizing of energy storage system for power systems with large-scale wind power integration," in *Proc. IEEE Eindhoven PowerTech*, Jun./Jul. 2015, pp. 1–6.
[21] C. Thrampoulidis, S. Bose, and B. Hassibi, "Optimal placement of distributed energy storage in power networks," *IEEE Trans. Autom. Control*, vol. 61, no. 2, pp. 416–429, Feb. 2015.
[22] S. Wogrin and D. F. Gayme, "Optimizing storage siting, sizing, and technology portfolios in transmission-constrained networks," *IEEE Trans. Power Syst.*, vol. 30, no. 6, pp. 3304–3313, Nov. 2015.
[23] H. Pandžić, Y. Wang, T. Qiu, Y. Dvorkin, and D. S. Kirschen, "Near-optimal method for siting and sizing of distributed storage in a transmission network," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2288–2300, Sep. 2015.
[24] M. Nick, R. Cherkaoui, and M. Paolone, "Optimal allocation of dispersed energy storage systems in active distribution networks for energy balance and grid support," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2300–2310, Sep. 2014.
[25] D. Gayme and U. Topcu, "Optimal power flow with large-scale storage integration," *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 709–717, May 2013.
[26] M. Torchio, L. Magni, and D. M. Raimondo, "A mixed integer SDP approach for the optimal placement of energy storage devices in power grids with renewable penetration," in *Proc. Amer. Control Conf. (ACC)*, Jul. 2015, pp. 3892–3897.
[27] A. V. Pombo, J. Murta-Pina, and V. F. Pires, "Multiobjective formulation of the integration of storage systems within distribution networks for improving reliability," *Electr. Power Syst. Res.*, vol. 148, pp. 87–96, Jul. 2017.
[28] A. S. A. Awad, T. H. M. El-Fouly, and M. M. A. Salama, "Optimal ESS allocation for load management application," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 327–336, Jan. 2015.
[29] S. B. Karanki and D. Xu, "Optimal capacity and placement of battery energy storage systems for integrating renewable energy sources in distribution system," in *Proc. Nat. Power Syst. Conf. (NPSC)*, Dec. 2016, pp. 1–6.
[30] K. Mansiri, S. Sukchai, and C. Sirisamphanwong, "Fuzzy control algorithm for battery storage and demand side power management for economic operation of the smart grid system at Naresuan University, Thailand," *IEEE Access*, vol. 6, pp. 32440–32449, 2018.
[31] S. Moazeni and B. Defourny, "Optimal control of energy storage under random operation permissions," *IISE Trans.*, vol. 50, no. 8, pp. 668–682, 2018.
[32] L. Wang, D. H. Liang, A. F. Crossland, P. C. Taylor, D. Jones, and N. S. Wade, "Coordination of multiple energy storage units in a low-voltage distribution network," *IEEE Trans. Smart Grid*, vol. 6, no. 6, pp. 2906–2918, Oct. 2015.
[33] H. Nazaripouya, Y. Wang, P. Chu, H. R. Pota, and R. Gadh, "Optimal sizing and placement of battery energy storage in distribution system based on solar size for voltage regulation," in *Proc. Power Energy Soc. Gen. Meeting*, Jul. 2015, pp. 1–5.
[34] M. Nick, R. Cherkaoui, and M. Paolone, "Optimal siting and sizing of distributed energy storage systems via alternating direction method of multipliers," *Int. J. Elect. Power Energy Syst.*, vol. 72, pp. 33–39, Nov. 2015.
[35] G. N. Sudha and N. Senroy, "A unified approach to the sizing and control of energy storage systems," *Electr. Power Compon. Syst.*, vol. 45, no. 7, pp. 693–704, 2017.
[36] G. Delille, B. Francois, and G. Malarange, "Dynamic frequency control support by energy storage to reduce the impact of wind and solar generation on isolated power system's inertia," *IEEE Trans. Sustain. Energy*, vol. 3, no. 4, pp. 931–939, Oct. 2012.
[37] A. D. Del Rosso and S. W. Eckroad, "Energy storage for relief of transmission congestion," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1138–1146, Mar. 2013.
[38] K. Mahmud, M. J. Hossain, and G. E. Town, "Peak-load reduction by coordinated response of photovoltaics, battery storage, and electric vehicles," *IEEE Access*, vol. 6, pp. 29353–29365, 2018.
[39] P. Stenzel, J. C. Koj, A. Schreiber, W. Hennings, and P. Zapp, "Primary control provided by large-scale battery energy storage systems or fossil power plants in Germany and related environmental impacts," *J. Energy Storage*, vol. 8, pp. 300–310, Nov. 2016.
[40] M. M. Nejad, L. Mashayekhy, R. B. Chinnam, and D. Grosu, "Online scheduling and pricing for electric vehicle charging," *IISE Trans.*, vol. 49, no. 2, pp. 178–193, 2017.
[41] H. Grichi, O. Mosbahi, M. Khalgui, and Z. W. Li, "New power-oriented methodology for dynamic resizing and mobility of reconfigurable wireless sensor networks," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 7, pp. 1120–1130, 2018.
[42] H. Grichi, O. Mosbahi, M. Khalgui, and Z. Li, "RWiN: New methodology for the development of reconfigurable WSN," *IEEE Trans. Autom. Sci. Eng.*, vol. 14, no. 1, pp. 109–125, Jan. 2017.
[43] M. Gasmi, O. Mosbahi, M. Khalgui, L. Gomes, and Z. W. Li, "R-node: New pipelined approach for an effective reconfigurable wireless sensor node," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 6, pp. 892–905, Jun. 2018.
[44] W. Lakhdhar, R. Mzid, M. Khalgui, Z. Li, G. Frey, and A. Al-Ahmari, "Multiobjective optimization approach for a portable development of reconfigurable real-time systems: From specification to implementation," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 3, pp. 623–637, Mar. 2019.
[45] S. Wen, H. Lan, Q. Fu, D. C. Yu, and L. Zhang, "Economic allocation for energy storage system considering wind power distribution," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 644–652, Mar. 2015.
[46] A. S. A. Awad, T. H. M. El-Fouly, and M. M. A. Salama, "Optimal ESS allocation and load shedding for improving distribution system reliability," *IEEE Trans. Smart Grid*, vol. 5, no. 5, pp. 2339–2349, Sep. 2014.
[47] P. Wang, D. H. Liang, J. Yi, P. F. Lyons, P. J. Davison, and P. C. Taylor, "Integrating electrical energy storage into coordinated voltage control schemes for distribution networks," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 1018–1032, Mar. 2014.
[48] C. Bussar, M. Moos, R. Alvarez, P. Wolf, T. Thien, H. Chen, Z. Cai, M. Leuthold, D. U. Sauer, and A. Moser, "Optimal allocation and capacity of energy storage systems in a future European power system with 100% renewable energy generation," *Energy Procedia*, vol. 46, pp. 40–47, Jan. 2014.
[49] A. Giannitrapani, S. Paoletti, A. Vicino, and D. Zarrilli, "Optimal allocation of energy storage systems for voltage control in LV distribution networks," *IEEE Trans. Smart Grid*, vol. 8, no. 6, pp. 2859–2870, Nov. 2017.
[50] A. Ratnaweera, S. K. Halgamuge, and H. C. Watson, "Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients," *IEEE Trans. Evol. Comput.*, vol. 8, no. 3, pp. 240–255, Jun. 2004.
[51] H. Zhao, Q. Wu, S. Hu, H. Xu, and C. N. Rasmussen, "Review of energy storage system for wind power integration support," *Appl. Energy*, vol. 137, pp. 545–553, Jan. 2015.
[52] R. D. Zimmerman, C. E. Murillo-Sánchez, and R. J. Thomas, "MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 12–19, Feb. 2011.
[53] L. D. Davis, *Handbook of Genetic Algorithms*. New York, NY, USA: Van Nostrand Reinhold, 1991.
[54] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.
[55] X.-S. Yang and S. Deb, "Cuckoo search via lévy flights," in *Proc. World Congr. Nature Biol. Inspired Comput. (NaBIC)*, Dec. 2009, pp. 210–214.
[56] J. Kennedy, "Particle swarm optimization," in *Encyclopedia Machine Learning*. Boston, MA, USA: Springer, 2011, pp. 760–766.
[57] M. Hiremath, K. Derendorf, and T. Vogt, "Comparative life cycle assessment of battery storage systems for stationary applications," *Environ. Sci. Technol.*, vol. 49, pp. 4825–4833, Apr. 2015.
[58] O. Karoui, M. Khalgui, A. Koubâa, E. Guerfala, Z. Li, and E. Tovar, "Dual mode for vehicular platoon safety: Simulation and formal verification," *Inf. Sci.*, vol. 402, pp. 216–232, 2017.

[59] M. Khalgui and O. Mosbahi, "Intelligent distributed control systems," *Inf. Softw. Technol.*, vol. 52, no. 12, pp. 1259–1271, 2010.
[60] H. Gharsellaoui, A. Gharbi, M. Khalgui, and S. Ben Ahmed, "Feasible automatic reconfigurations of real-time OS tasks," in *Handbook of Research on Industrial Informatics and Manufacturing Intelligence: Innovations and Solutions*. Hershey, PA, USA: IGI Global, 2012, pp. 390–414, doi: 10.4018/978-1-4666-0294-6.ch017.
[61] Y. Liu, K. Cai, and Z. Li, "On scalable supervisory control of multi-agent discrete-event systems," *Automatica*, to be published, doi: 10.1016/j.automatica.2019.06.012.
[62] Q. Chen, L. Yin, N. Wu, M. El-Meligy, M. Sharaf, and Z. Li, "Diagnosability of vector discrete-event systems using predicates," *IEEE Access*, vol. 7, pp. 147143–147155, 2019.
[63] D. Wang, X. Wang, and Z. Li, "Nonblocking supervisory control of state-tree structures with conditional-preemption matrices," *IEEE Trans. Ind. Informat.*, to be published, doi: 10.1109/TII.2019.2939628.
[64] D. Sun, Y. Chen, M. Chen, M. El-Meligy, M. Sharaf, N. Wu, and Z. Li, "On algebraic identification of critical states for deadlock control in automated manufacturing systems modeled with Petri nets," *IEEE Access*, vol. 7, pp. 121332–121349, 2019.

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