Security-constrained Economic Dispatch with Linear/Nonlinear Energy Sources during Short-Term Emergency Period

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Received: 04.06.2017 Accepted:25.07.2017

Abstract- In the last decade, renewable energy resources and energy storage systems (ESSs) played a pivotal role in the enhancement of the security of power systems. They exhibit great potential in power system operations: maintaining the load balance and improving power system security. This paper investigates the impact of linear and nonlinear energy resources on security-constrained economic dispatch (SCED) solution with different contingencies as a time-varying optimization problem. Linear ESSs are prominent in the literature on SCED. However, most of the previous studies do not take into account the impact of ESSs' nonlinear characteristic as highlighted in this paper. Therefore, the SCED problem should be discussed as a time-varying optimization problem. A new procedure is presented to handle time-varying optimization problems by finding the switching points and generator response equations. Not only this paper highlights the limitations of linear ESS characteristic and the effectiveness of using nonlinear characteristic of ESS in SCED solutions; illustrated on modified IEEE 6-bus and 14-bus systems, but also different optimization methods are used to validate the proposed procedure.

Keywords Energy storage systems, Nonlinear energy resources, Optimization, Renewable energy sources, Security-constrained economic dispatch (SCED), Security constrained optimal power flow (SCOPF).

1. Introduction

Considerable attention has been paid to the rapidly growing need of incorporating renewable energy in power system operation. Due to the uncertainty and intermittency of renewable energy sources and the fast response of the ESS that allows their use as controlled variables in power system operations, ESS has been used as a complimentary and an integral part to renewable resources. Power system security is defined as the ability of the power system to operate in secure and safe conditions with no violations when a contingency occurs until the system operator takes a proper action [1]. The installation of ESSs to the power system is to put them of use in different applications such as peak shaving, load leveling, and frequency control [2], [3]. In [4], ESS with linear response (characteristic) was adapted to enhance the security-constrained optimal power flow (ESCOPF) and to maintain line flows during short-term period until generators take their corrective actions, when a contingency -loss of line- occurs. Moreover, the generation outage was not part of [4]. The short-term emergency period is typically 15 minutes. The short-term ratings are more relaxed than long-term ratings and any violation over the relaxed constraints might be harmful to the power system. On the other hand, considering that generators ramp slowly until reaching their rescheduled values, ESS was used in [5] to provide a primary frequency reserve to maintain load balance and to cover the generation mismatch at any instant to satisfy the primary frequency control.

If any insecurity is detected, it must be eliminated by adding at least one constraint to the original optimization problem in addressing of it to attain a new optimal operating point. This preventive action will add an additional cost compared to the previous optimal solution. This is called preventive security-constrained optimal power flow (PSCOPF). However, instead of adding preventive actions to eliminate the violations, the corrective actions (i.e., generation rescheduling, tap changers rescheduling, area inter-exchange control, etc.) can help restore the power system to a secure operating point after the occurrence of the contingency. With this in mind, from the economical point of view, allowing some corrective actions will reduce the cost at the normal case (pre-contingency) [6]. This is called corrective security-constrained optimal power flow (CSCOPF). In general, CSCOPF is more economical but less secure than PSCOPF.

It is important to study SCED during pre-contingency, short-term emergency post-contingency, and long-term post contingency [7], [8]. Introducing ESS with general linear/nonlinear characteristic in SCED problem will present time varying generator(s)/load(s) to the optimization problem. With linear ESS characteristics, starting and ending points are sufficient to check the system security. However, in nonelectrical ESS [9] (i.e., pumped hydroelectric storage, compressed air energy storage, flywheel energy storage, etc.) most of the stored energy is related to the kinetic energy that can be modeled as quadratic function [10]. On the other hand, the batteries as electrical ESSs are usually working under either constant voltage or constant current (charging/discharging) mode. Therefore, if the battery is charging under constant current mode, the power characteristic will follow the voltage state-of-charge (SOC) profile that is best to be described as exponential characteristic. The same thing is also applicable when the battery is working at constant voltage mode of control [11]. Therefore, from a practical point of view, it is desirable to consider the impact of nonlinear ESSs characteristic on the SCED and this is the first objective of this paper.

Toward that end, solving time-varying and nonlinear optimization problem can either be addressed using available deterministic or stochastic optimization algorithms. Sequential algorithms such as linear programming (LP) or quadratic programming (QP) [12] are deterministic optimizations that give global optimal solutions when linear or quadratic convex optimization problems is considered, respectively. A cutting-plane algorithm was presented in [13] to solve the SCED problem using a homogeneous interior-point (HIP) method. In [14], convex transformation techniques and Taylor series have been discussed to solve SCOPF problems and the sequential linear programming has been used in [15]. On the other hand, intelligent search algorithms are iterative techniques that use randomness in their search for the optimal solution that are extensively used in power system optimization problems. These algorithms are stochastic optimizations and proved their effectiveness in non-convex optimization problems [16], [17]. They give the global or near-global optimal solution. Different optimization algorithms can be derived from stochastic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), and teaching learning-based optimization (TLBO), etc. [18]. multiobjective GA has been applied to hybrid renewable energy system design in [19]. PSO has been applied to the power system for solving OPF in [20] while for the SCOPF in [21], [22] and for reserve constrained economic dispatch in [23]. Gravitational search algorithm (GSA) was applied to solve SCED in [24], [25]. TLBO was used with fuzzy-based multi-objective to solve security-constrained unit commitment within [26] and using Artificial Bee Colony (ABC) algorithm in [27].

Linearizing the non-convex or the nonlinear optimization problem is one notable way to take over the problem and to use the available deterministic tools. For convex problem, piece-wise linearization is usually adopted. However, selecting the sufficient number of linear periods accurately is a challenging task. Linearizing non-convex problems will introduce integer variables that will increase the complexity of the optimization problem, as it will convert the problem into a mixed integer optimization problem. As a second objective of this paper, a new procedure is proposed to solve convex and non-convex SCED based on finding the switching (critical) points and the generation response equations (GRE). The switching points will divide the problem into sufficient number of sub-problems needed to solve the optimization without linearizing it or converting the problem into a mixed integer problem. The proposed procedure is considered as alternative algorithm to solve the nonlinear optimization problems with more accuracy and less complexity.

Integrating ESSs in power system as corrective control systems [3], [9] or as parts of the renewable energy sources [28,29] is becoming a rapidly growing necessity. In power system operation, electrical ESS can be modelled as exponential power source [29-31]. Several studies were executed to investigate the OPF with the existence of ESS. In [32], the authors presented a multi-period OPF algorithm to process the computational efforts. Moreover, the complexity of the mathematical formulation increases when mixed-integer optimization problem was adopted while considering renewable energy resources and ESS. Utilizing hybrid combinations between interior-point and differential evolution (DE) methods [33], ESS as a corrective action in short- and long-term CSCOPF considering SOC and linear capacity of ESS was modelled and solved. The dynamic characteristic of ESS was considered in [34] in terms of SOC and time-of-use as cost coefficients in the economic dispatch problem without taking in consideration the network security. In [35], the coupling between decision and stochastic variables in centralized dispatch formulation with multiple ESSs was solved through a distributed economic dispatch strategy. An arrangement of the bacterial foraging algorithm (BFA) and PSO was used in [36] to propose ED model for a wind-storage combined system to enhance the wind power utilization including the cost of all generation systems and environmental and operating constraints. An economical assessment for employing ESSs in isolated and centralized power systems as reserve and peak shaving controlled systems was performed in [37]. In [38], DC power flow (DCPF) was adopted to study the linear ESSs and the network security considering the line outage as contingency and SOC as a state in CSCOPF problems. From the aforementioned state-of-research works, the impact of nonlinear characteristic of ESS on SCED while considering line and generation outages has not attracted much attention so far.

The main contribution of this paper is to establish a new optimization procedure that can handle the nonlinearities of the energy resources in SCED. Without losing generality, the following parts of this paper will focus on electrical ESS, the same procedure can be used for any energy source system nevertheless. Moreover, this paper highlights the impact of the nonlinear characteristic of ESS on the power system security. Two important types of optimizations are considered; the sequential algorithms and intelligent search algorithms. The use of deterministic algorithms validates the proposed work and verifies the results obtained from sequential algorithms. Moreover, comparing the results obtained from the proposed algorithm with the state-of-art research in [4] shows the generality of this work and the importance of considering nonlinear ESSs response in SCED.

The remainder of this paper is organized as follows: formulation of the proposed algorithm for solving the time-varying optimization problem using switching points and generator response equations is done in section 2. Section 3 examines the linear/nonlinear ESSs implementation on security-constrained economic dispatch for different contingencies. Case studies using the modified IEEE 6-bus and 14-bus systems are done in section 4. Finally, conclusions are drawn in the final section. A nomenclature can be found at the end of this paper.

2. Problem formulation, Switching Points, and Generator Response Equations

The charging and discharging characteristics of ESS are discussed as time-varying linear/nonlinear functions (i.e., linear, quadratic and exponential). Fig. 1 shows the discharging characteristic.

Within the time interval $[0, T]$, the area under the curve is equal to the energy extracted from the ESS [10]

$$E = \int_0^T P(t)dt \qquad (1)$$

The power equation $P(t)$ of different ESS characteristics can be written as :

$$P(t) = \begin{cases} P_{b,\max}\left(1 - t/T\right) & (2.a) \\ \left(P_{b,\max}/T^2\right)\cdot t^2 - \left(2\cdot P_{b,\max}/T\right)\cdot t + P_{b,\max} & (2.b) \\ P_{b,\max}e^{-5t/T} & (2.c) \end{cases}$$

Equation (2.a) is for linear ESS, Eq. (2.b) is for quadratic ESS, while Eq. (2.c) is for exponential ESS.

$P_{b,\max}$ can be selected from the solution of OPF or it must be predefined by the current situation of the energy stored in the ESS. Moreover, to have feasible solution for the OPF, $P_{b,\max}$ must be sufficient to supply the needed energy during this interval. Evaluating Eq.(1) and making use of Eq.(2), the energy equations ΔE will be:

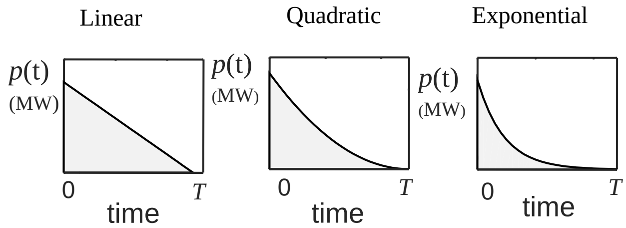

Fig. 1. Different battery discharging characteristics as functions of time

$$\Delta E = \begin{cases} (T/2)P_{b,\max} & \text{Linear ESS} & (3.a) \\ (T/3)P_{b,\max} & \text{Quadratic ESS} & (3.b) \\ (T/5)\,P_{b,\max} & \text{Exponential ESS} & (3.c) \end{cases}$$

The same lines are applicable for the charging characteristic of the ESS.

2.1. Time-Varying Optimization Problem

When ESS participates in power system operation, DCPF problem formulation can be represented as follows [38]:

$$Min \sum_{i\in NG} F_i(P_i) \qquad (4.a)$$

s.t

$$P_{i,\min} \le P_i \le P_{i,\max} \qquad (4.b)$$

$$\left|SF \times P_{inj,t}\right| \le P_{L,\max} \qquad (4.c)$$

$$\begin{aligned} P_{inj,t} &= [Kp][P] + [K_{batt}][P_D(t)] \\ &\quad -[KD][D] - [K_{batt}][P_C(t)] \\ 0 &\le P_{D,k} \le P_{D,k}(t) \\ 0 &\le P_{C,k} \le P_{C,k}(t) \end{aligned} \qquad (4.d)$$

$$\sum_{i\in NG} P_i + \sum_{K\in Nbatt} P_{D,k}(t) = \sum_{j\in Nload} D_j + \sum_{K\in Nbatt} P_{C,k}(t) \qquad (4.e)$$

If ESS is considered as a time independent power source, this may cause a thermal overload on transmission lines during the short-term period. In addition, some hidden violations may happen while the results at the edges will not show any, in the case of studying the edges of this interval without knowing what is inside. Therefore, the optimization problem must be studied during the interval as a time-varying problem. In the counterpart, it is also applicable if the problem was linearized. The linearization step must be accurately selected for convex problems. Moreover, the linearized problem will be converted into mixed integer problem if the problem is non-convex. However, when the proposed algorithm is adopted, this complexity is avoided. The heart of the proposed procedure is the generator(s) response equation and the switching point(s) concepts that are discussed in the next sub-sections.

2.2. Generator response equations

From the load balance equation Eq. (4.e), the characteristics of the ESS determine the GRE. For example, if the ESS is discharging exponentially, to maintain the load balance within the generators ramping capabilities, the power of the generators increases exponentially during the same time interval. For linear, exponential and quadratic characteristics, it is important to select two/three optimization points at the beginning of the interval to insure that the power system operating points are close and no major changes occur. For example, the optimization problem is needed to be solved at $t=\{0,t_1\}$ for linear and exponential ESS characteristics, or at $t=\{0,t_1,t_2\}$ for quadratic ESS characteristics, where time "t" is in hours.

Each generator will deliver its selected power by its GRE until reaching a switching point. The switching point can be defined as the moment when any generator changes its output power characteristic. Generally, and without restricting the following discussions are for linear charging characteristics the same lines are applicable for linear/nonlinear ESS charging/discharging characteristics. Switching points occur in the following cases:

A) When maximum allowance power change of a generator is reached.
B) When the maximum or minimum limit of a generator is reached.
C) When the order of ICs is changed.
D) When any constraint is violated.

Some of the expected but not limited scenarios of generators in case of discharging ESS (as seen in Fig. 2) are:

1- A generator operates over the whole period without changing its characteristic.
2- A generator operates with its characteristic until reaches its maximum at T_{SW} and in the remaining time will deliver a constant power ($P_{i,\max}$) until T.
3- A generator delivers constant power until T_{SW}. After that, it will deliver power with a new characteristic until T.
4- A generator delivers constant power until $T_{SW,1}$, then it will deliver power with its new characteristic until reaches its maximum at $T_{SW,2}$, and in the remaining time, it will deliver $P_{i,\max}$ until T.

2.3. Determination of the Switching Points

This process can be divided as shown in Fig.3 into three main steps. The first one is to solve the classical ED problem as in Eq. (4). For linear and exponential ESS, it is sufficient to solve the problem at $t=0$ and at $t=t_1$ to find the two unknowns *a* and *b*. However, for quadratic ESS, three unknowns are needed to be found and hence ED is solved for three points ($0,t_1,t_2$). The next step is to find the switching points for the predefined characteristic of the used ESS. The possible switching points are listed in subsection 2.2 and summarised in the flow chart. The purpose of this step is to find the generation based switching points. Finally, network security check is needed to search for network based switching points if existed.

2.3.1. ESS as a linear function of time

To find the GRE, the optimization can be solved for two points ($0,t_1$). From the solutions, the GRE of each generator can be found as follows:

$$P(0\le t\le T_{sw})=a+b\cdot t$$
$$a=P(0);\ b=\left(P(t_1)-P(0)\right)/t_1 \tag{5.a}$$

Following the flow chart shown in Fig. 3, the GRE for $t\ge T_{sw}$ can be found:

$$P(T_{sw}\le t\le T)=a+b\cdot(t-T_{sw})$$
$$a=P(T_{sw});\ b=\left(P(T_{sw}+t_1)-P(T_{sw})\right)/t_1 \tag{5.b}$$

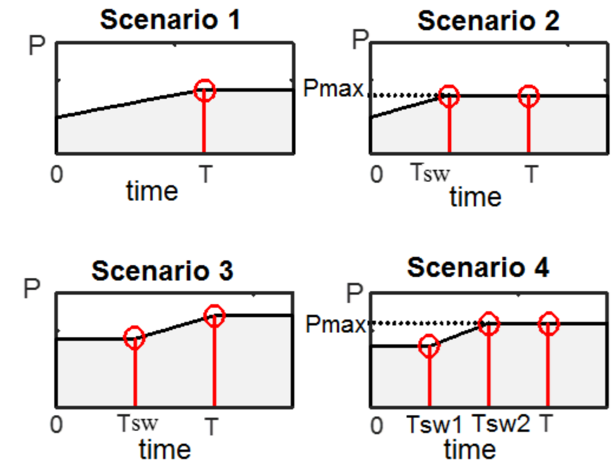

Fig. 2. Some of the expected generator scenarios for linear ESS.

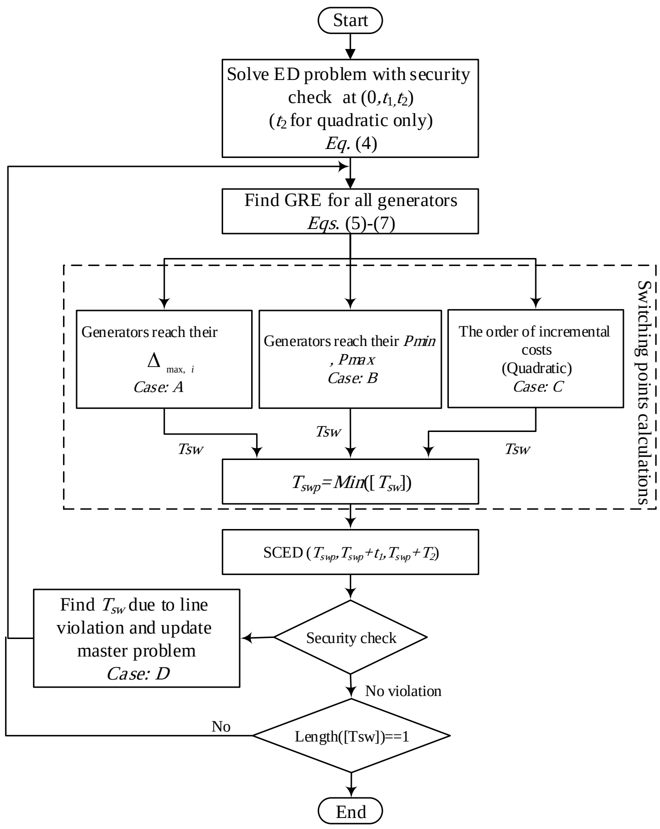

Fig. 3. Flow chart for finding GREs and switching points within short-term period.

2.3.2 ESS as a quadratic function of time:

To find the GRE, the optimization can be solved for three points (0 ,t_1, t_2). Following the flow chart in Fig.3, the quadratic GRE can be described as:

$$P(0 \le t \le T_{sw}) = c \cdot t^2 + b \cdot t + a \, ; \, a = P(0)$$

$$\begin{bmatrix} (t_1)^2 & t_1 \\ (t_2)^2 & t_2 \end{bmatrix} \begin{bmatrix} c \\ b \end{bmatrix} = \begin{bmatrix} P(t_1) - P(0) \\ P(t_2) - P(0) \end{bmatrix} \tag{6.a}$$

$$P(T_{sw} \le t \le T) = c \cdot (t - T_{sw})^2 + b \cdot (t - T_{sw}) + a;$$
$$a = P(T_{sw}) \tag{6.b}$$
$$\begin{bmatrix} (t_1)^2 & t_1 \\ (t_2)^2 & t_2 \end{bmatrix} \begin{bmatrix} c \\ b \end{bmatrix} = \begin{bmatrix} P(T_{sw} + t_1) - P(T_{sw}) \\ P(T_{sw} + t_2) - P(T_{sw}) \end{bmatrix}$$

2.3.3. ESS as an exponential function of time

In this case, solving the optimization for two points is needed to find the GRE at ($0, t_1$). Then as in Fig.3, the exponential GRE can be described as:

$$P(0 \le t \le T_{sw}) = a + b \cdot e^{-5t/T}$$
$$b = \frac{P(t_1) - P(0)}{\left(e^{-t_1/T} - 1\right)}; a = P(0) - b \tag{7.a}$$

$$P(T_{sw} \le t \le T) = a + b \cdot e^{-5(t - T_{sw})/T}$$
$$b = \frac{P(t_1 + T_{sw}) - P(T_{sw})}{\left(e^{-t_1/T} - 1\right)}; a = P(T_{sw}) - b \tag{7.b}$$

To this end, following the flow chart of Fig.3, the number of switching points is not necessarily one and the interval can be divided into more than two subintervals. In addition, the switching point at any time T_x cannot be found without studying all proceeding subintervals. Updating of the proceeding GREs can affect the coming switching point(s). Moreover, the proposed procedure illustrated in Fig.3 will find the sufficient switching point needed to solve the optimization.

3. Implementation of Proposed Algorithm on SCED

Linear/nonlinear characteristics of ESS can affect the solution of SCED in two ways. The first one is the selection of $P_{b,\max}$ which is selected to handle the contingency period. This is necessary to avoid the thermal overload on violated lines, and cover the loss of generation(s) or load restoration. From Eq. (3), the ratio between the power of ESS with exponential and linear characteristic is

$$\frac{P_{b,\exp}}{P_{b,lin}} = \frac{\Delta E / 0.2T}{2\Delta E / T} = 2.5 \tag{8}$$

Based on Eq. (8), $P_{b,\max}$ for exponential ESS is almost 2.5 times higher than $P_{b,\max}$ for linear ESS characteristic. This means, for the same amount of energy, the possible ESS initial injected power can be magnified if the response of the ESS is considered to be exponential.

The second one is the dependency of the probability of obtaining infeasible SCED solution on the starting power of the ESS as discussed in the case studies part. This dependency shows the importance of studying the nonlinear characteristic of the ESS in power system operation as illustrated in the following contingencies:

3.1. Loss of Line

The security of the power system during the loss of line has to be taken into consideration within the short-term period, the violations during this period may initiate the protection devices. The formulation of the SCED problem with ESS for this case can be divided into three stages:

Stage 1: Pre-contingency (base case formulations)

The objective function Eq. (4.a) and the constraints Eqs. (4.b-c) are used to solve the base case (before the ESS starts its corrective action). The load balance equation will be:

$$\sum_{i \in NG} P_i = \sum_{j \in Nload} D_j$$
$$P_{inj,t} = [Kp][P] - [KD][D] \tag{9}$$

Using linear sensitivity factor (LSF) method [39], the solution of the base case, will be the input to stage 2 ($P_{i0} = P_i$).

Stage 2: Short-term contingency

Before the generators ramp up/down ($t = 0$), ESSs will charge/discharge the maximum selected power to mitigate the short-term violations. By solving the optimization problem, the values of the starting power of ESS $P_{b,\max}$ can be found and the obtained solution will be the input to the next step.

$$Min \sum_{k \in Nbatt} (P_{D,k}^{c'} + P_{C,k}^{c'}) \;\; ,\forall c' \in Nc' \tag{10.a}$$

s.t.

$$\sum_{k \in Nbatt} P_{D,k}^{c'} = \sum_{k \in Nbatt} P_{C,k}^{c'} \;\; ,\forall c' \in Nc' \tag{10.b}$$

$$\left.\begin{aligned} 0 \le P_{D,k}^{c'} \le P_{D,k,\max} \\ 0 \le P_{C,k}^{c'} \le P_{C,k,\max} \end{aligned}\right\} ,\forall c' \in Nc' \tag{10.c}$$

$$\left| SF \times P_{inj}^{c'} \right| \le \gamma \cdot P_{L,\max}^{c}$$
$$P_{inj}^{c'} = [Kp][P] + [K_{batt}]\left[P_D^{c'}(t)\right] \tag{10.d}$$
$$- [KD^c][D^c] - [K_{batt}]\left[P_C^{c'}(t)\right]$$

Similar to LSF method, the constraint Eq. (10.d) will be added when the contribution of ESS is needed (when short-term violations occurred), it allows the ESSs to contribute to the handling of contingency by substituting P from stage 1, then the constraint will be in terms of P_C and P_D in stage 2.

The solution of the optimization problem in Eq. (10) is used as the maximum starting power for charging and discharging ESS characteristics. Then, the equations of ESSs are found using Eq. (1).

The switching points and the security check are done to update the master problem when needed. Formulation of the problem within the short-term period will be:

$$Min \sum_{i\in NG} F_i(P_i(t)) \tag{11.a}$$

s.t.

$$\begin{aligned} &0 \le P_{D,k} \le P_{D,k}(t) \\ &0 \le P_{C,k} \le P_{C,k}(t) \end{aligned} \tag{11.b}$$

$$\begin{aligned} P_{inj} &= [Kp][P] + [K_{batt}][P_D(t)] \\ &\quad - [KD][D] - [K_{batt}][P_C(t)] \end{aligned} \tag{11.c}$$

$$\left| SF \times P_{inj} \right| \le \gamma \cdot P_{L,\max}$$

$$\sum_{i\in NG} P_i(t) + \sum_{K\in Nbatt} P_{D,k}(t) = \sum_{j\in Nload} D_j + \sum_{K\in Nbatt} P_{C,k}(t) \tag{11.d}$$

$$\begin{aligned} &\max\left(P_{i,\min}, P_{i0} - \Delta_{\max,i}\right) \ge P_i \\ &\min\left(P_{i,\max}, P_{i0} + \Delta_{\max,i}\right) \le P_i \end{aligned} \tag{11.e}$$

This optimization problem is a time dependent problem and it should be solved as discussed in section 2.3.

Stage 3: Long term contingency

The updated constraints in the long-term period can restrict the optimization problem to a new operating point. At this period, the outputs of ESSs are zeros and the generators reached to their new redispatched value.

To this end, there are two main options that can be discussed:

Option 1: Minimizing the long-term corrective actions:

Problem formulation is as follows:

$$Min \sum_{i\in NG} \Delta P_i^{c+} + \sum_{i\in NG} \Delta P_i^{c-} \ ,\forall c \in Nc \tag{12.a}$$

s.t.

$$\left.\sum_{i\in NG} \Delta P_i^{c+} = \sum_{i\in NG} \Delta P_i^{c-} \right\} ,\forall c \in Nc \tag{12.b}$$

$$\left.\begin{aligned} &0 \le \Delta P_i^{c+} \le \Delta P_{i,\max} \\ &0 \le \Delta P_i^{c-} \le \Delta P_{i,\max} \\ &P_{i,\min} \le P_i^c \le P_{i,\max} \\ &P_i^c = P_i^0 + \Delta P_i^{c+} - \Delta P_i^{c-} \end{aligned}\right\} ,\forall c \in Nc \tag{12.c}$$

$$\left.\begin{aligned} &\left| SF \times P_{inj}^c \right| \le P_{L,\max}^c \\ &P_{inj}^{c'} = [Kp^c][P^c] - [KD^c][D^c] \end{aligned}\right\} ,\forall c \in Nc \tag{12.d}$$

$$\sum_{i\in NG} P_i^c = \sum_{j\in Nload} D_j^c \tag{12.e}$$

Since the load balance condition is satisfied, the default corrective actions are zeros. The constraint Eq. (12.d) will be included for the violated line(s) when the corrective actions are needed. By substituting P from stage 1, the load balance condition will be in terms of ΔP_i^{c-}, ΔP_i^{c+} then it will be added to stage 3.

If $\Delta_{\max,i}$ is not enough to eliminate the violation within this long term-period, the solution of stage 3 is infeasible. Therefore, a preventive action is required, using Eq. (12.d) for the violated line, by substituting $P_i^c = P_i^0 + \Delta P_i^{c+} - \Delta P_i^{c-}$. The constraint Eq. (12.d) will be modified to:

$$\left.\begin{aligned} &\left| SF \times P_{inj}^c \right| \le P_{L,\max}^c \\ &P_{inj}^{c'} = [Kp^c][P_i^0 + \Delta P_i^{c+} - \Delta P_i^{c-}] - [KD^c][D^c] \end{aligned}\right\} ,\forall c \in Nc$$

Such that $\Delta P_i^{c+} = \Delta P_{i,\max}$, $\Delta P_i^{c-} = 0$ if the generator is ramping up and $\Delta P_i^{c-} = \Delta P_{i,\max}$, $\Delta P_i^{c+} = 0$ if the generator is ramping down. This constraint will be in terms of P and it will be added to stage 1.

Option 2: Minimizing the generation cost of long-term period:

Problem formulation follows the same lines of option 1. However, the objective function will be modified as in Eq. (13) while the constraints are Eqs. (12.b-e):

$$Min \sum_{i\in NG} F_i(P_i^c) \tag{13}$$

3.2. Restoring loads

If load shedding is present and it is desired to restore the load, ESS can contribute (discharge) to the grid during the generators ramping period. The formulation is similar to the loss of line case with the following three stages:

Stage 1: Pre-contingency (base case)

Similar to the loss of line case.

Stage 2: Short-term contingency

ESSs need to participate during this contingency to cover the load while the generators are ramping to their new redispatched values.

The formulation needed to determine the starting point of ESS would be similar to contingency loss of line taking the objective function as in Eqs. (10.a) and the constraints as in Eq. (10.c) and Eqs. (14.a-b):

$$\sum_{k\in Nbatt} P_{D,k}^{c'} - \sum_{k\in Nbatt} P_{C,k}^{c'} = \sum_{j\in Nload} D_{new,j} - \sum_{j\in Nload} D_{old,j} \tag{14.a}$$

$$\left.\begin{aligned} &\left| SF \times P_{inj}^{c'} \right| \le \gamma \cdot P_{L,\max}^c \\ &P_{inj}^{c'} = [Kp][P] + [K_{batt}][P_D^{c'}(t)] - [KD^c][D_{new}^c] \\ &\quad - [K_{batt}][P_C^{c'}(t)] \end{aligned}\right\} \tag{14.b}$$

The ESSs are discharging within the short-term period. If line violations occurred, the ESSs can be used to eliminate these violations by allowing the charging and discharging of ESSs using constraint Eq. (14.b).

The formulation to check the security and find the switching points of the problem within the short-term period and the solution procedure follows loss of line contingency. Its objective function is Eq. (11.a) and the constraints are Eqs. (11.b), (11.e) and (15.a-b).

$$\begin{aligned} P_{inj} &= [Kp][P] + [K_{batt}][P_D(t)] - [KD][D_{new}] \\ &\quad - [K_{batt}][P_C(t)] \end{aligned} \tag{15.a}$$

$$\left| SF \times P_{inj} \right| \le \gamma \cdot P_{L,\max}$$

$$\sum_{i\in NG} P_i(t) + \sum_{K\in Nbatt} P_{D,k}(t) = \sum_{j\in Nload} D_{j,new} + \sum_{K\in Nbatt} P_{C,k}(t) \tag{15.b}$$

Stage 3: Long term contingency

At this period, the outputs of ESSs are zeros and the generators reached their new redispatched value. The procedures are similar to loss of line contingency. However, the constraint Eq. (12.b) should be modified to:

$$\sum_{i\in NG}\Delta P_i^{c+} - \sum_{i\in NG}\Delta P_i^{c-} = \sum_{j\in Nload} D_{new,j} - \sum_{j\in Nload} D_{old,j} \quad (16)$$

3.3. Loss of Generator

ESS will discharge to cover the power imbalance or help the generation units to ramp up without affecting the security of the power system. The formulation of the SCED problem with ESS for this case can be divided into three stages.

Stage 1: Pre-contingency (base case formulations)

Similar to the previous cases.

Stage 2: Short-term contingency

To determine the starting point of ESS, similar formulation of contingency loss of line, with objective function Eq. (10.a) and the constraints are Eqs. (10.c-d) and (17):

$$\sum_{k\in Nbatt} P_{D,k}^{c'} - \sum_{k\in Nbatt} P_{C,k}^{c'} = P_{gen\_lost}, \forall c' \in Nc' \quad (17)$$

If there is a line violation during the short-term period, ESSs can be used to eliminate this violation by using the constraint Eq. (10.d).

The formulation of the problem within the short-term period will be as mentioned in the loss of line, its objective function is Eq. (11.a) and the constraints are Eqs. (11.b-e) and (18):

$$P_{gen\_lost}^{c} = 0 \quad (18)$$

Stage 3: Long-term contingency

The same two options of contingency loss of line are applicable here with additional constraints Eqs. (19.a-b):

$$\left.\sum_{i\in NG}\Delta P_i^{c+} - \sum_{i\in NG}\Delta P_i^{c-} = P_{gen\_lost}^{0}\right\}, \forall c \in Nc \quad (19.a)$$

$$\Delta P_{gen\_lost}^{c+} = 0$$

$$\Delta P_{gen\_lost}^{c-} = P_{gen\_lost} \quad (19.b)$$

$$P_{gen\_lost}^{c} = 0$$

4. Case Studies

The proposed algorithm is verified using modified IEEE 6-bus and modified IEEE 14-bus systems. The modified IEEE 6-bus system is selected in order to compare the proposed work with the state of art publication [4] and to clarify the proposed procedure. On the other hand, to demonstrate the applicability of the proposed work the modified IEEE 14-bus is selected. The two systems are acceptable benchmark in the literature to verify and demonstrate new procedures and algorithms [40],[41]. All cases have been simulated on a personal computer (Intel(R) Core(TM) i3 CPU M350 (2.27 GHz) with 2 GB of memory). The short term (T) period is assumed to be 15 minutes, the short-term emergency factor (γ) is 1.2, $t_1 = 0.01$ h and $t_2 = 0.02$ h.

4.1 Modified IEEE 6-Bus System

A 6-bus, three generators, and three ESS system as in Fig. 4 is taken as example. The total load is 199.5 MW. The maximum allowable energy of ESSs is 10 MWh. For this system, a loss of line 9 is studied. The results of [4] which is labeled as ESCOPF for different characteristics of ESS (linear, quadratic and exponential) are shown in table 1 with ΔE=0.6 MWh. The (*) cases indicate that the energy is not sufficient to eliminate the violations. Hence, preventive actions are added. Therefore, the base case generations are maintained. From the results, it can be seen that in linear ESS characteristic a preventive action is used while in nonlinear ESS characteristics there is no need for the preventive action. ESS1 is in charging mode, ESS5 is in generation mode and ESS6 is not contributing in this contingency.

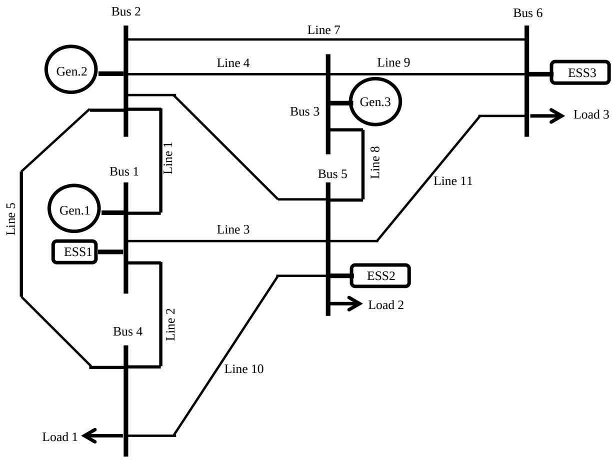

Fig.4. Modified IEEE 6-bus system

Table 1. Results for contingency loss of line 9

	ESCOPF*	Linear ESS*	Quadratic ESS	Exponential ESS
P1(MW)	50	50	50	50
P2(MW)	83.7039	83.7039	83.3003	83.3003
P3(MW)	65.7961	65.7961	66.1997	66.1997
Cost ($)	2931	2931	2922	2922
ESS1 MWh	0.6	0.6	0.5201	0.3098
ESS5 MWh	-0.6	-0.6	-0.5201	-0.3098
ESS6 MWh	0	0	0	0
$P1^C$ (MW)	66.249	66.249	66.6014	66.6014
$P2^C$ (MW)	83.7035	83.7035	83.3003	83.3003
$P3^C$ (MW)	49.5475	49.5475	49.598	49.598

Next, a contingency, loss of generator 1, is studied with ΔE=10 MWh, the results are shown in table2. From the results of table2, the energy contributed by ESS is related to the ESS characteristic. In nonlinear characteristics, the energy from ESS is less than in linear characteristic. For example, if the maximum allowable exchange energy in battery 1 and 5 is only 0.5 MWh, then in this case, both linear and quadratic characteristics will give infeasible solution, while the exponential characteristic will manage to give a feasible one.

From table 2, all ESS characteristics are in discharging mode to cover the loss in generation. It can be noticed that the exponential ESS supplied the least amount of energy $\Delta E_{\exp} = 0.4\,\Delta E_{lin}$, while for quadratic ESS $\Delta E_{quad} = (2/3)\Delta E_{lin}$. For different ESS characteristics, the base case and the long-term post-contingencies have the same values. That is because there are no preventive actions in this kind of contingency.

Table 2. Results for contingency loss of generator 1

	Linear ESS	Quadratic ESS	Exponential ESS
P1(MW)	50	50	50
P2(MW)	83.3003	83.3003	83.3003
P3(MW)	66.1997	66.1997	66.1997
Cost ($)	2922	2922	2922
ESS1(MWh)	-2.0833	-1.3887	-0.8275
ESS5(MWh)	-2.0833	-1.3887	-0.8275
ESS6(MWh)	-2.0833	-1.3887	-0.8275
$P2^C$(MW)	106.081	106.081	106.081
$P3^C$(MW)	93.419	93.419	93.419

The results for linear ESS characteristics in contingency loss of generator 1 are shown in table 3 and for exponential ESS characteristics are shown in table 4. In PSO and TLBO, the maximum number of iterations was 350 and the population size equals 20. The acceleration factor of PSO method was selected to be 1 and the initial inertia weight factor was 0.9.

Table 3. Contingency loss of generator 1 for linear ESS under different optimization methods

	Quadprog	GA	TLBO	PSO
P1(MW)	50	50.0418	50	53.3002
P2(MW)	83.3003	83.111	83.3003	75.5402
P3(MW)	66.1997	66.3463	66.1997	70.6588
Cost ($)	2818.3	2819	2818.3	2822.5
ESS1(MWh)	-2.0833	-2.0851	-2.0833	-2.2208
ESS5(MWh)	-2.0833	-2.0851	-2.0833	-2.2208
ESS6(MWh)	-2.0833	-2.0851	-2.0833	-2.2208
$P2^C$(MW)	106.081	112.802	106.081	101.118
$P3_C$(MW)	93.419	86.698	93.419	98.382
Computational Time (s)	0.1630	1.9559	0.6257	0.7527

Table 4. Contingency loss of generator 1 for exponential ESS under different optimization methods

	Quadprog	GA	TLBO	PSO
P1(MW)	50	50.0123	50	51.8513
P2(MW)	83.3003	83.2028	83.3003	75.575
P3(MW)	66.1997	66.2839	66.1997	72.0728
Cost ($)	2818.3	2818.9	2818.3	2821.3
ESS1(MWh)	-0.8275	-0.8277	-0.8275	-0.8581
ESS5(MWh)	-0.8275	-0.8277	-0.8275	-0. 8581
ESS6(MWh)	-0.8275	-0.8277	-0.8275	-0. 8581
$P2^C$(MW)	106.081	106.063	106.081	100.192
$P3^C$(MW)	93.419	93.437	93.419	99.308
Computational Time (s)	0.1760	1.9705	0.6197	0.7343

From the results in tables 3and 4, Quadprog and TLBO are giving the best results. Moreover, the results of TLBO are better than of other stochastic algorithms with less computational time. For different optimization methods, the computational times are listed in tables 3 and 4. The power generations results of the base case and the energy delivered by ESS shows the effectiveness of using TLBO in SCED problems.

4.2 Modified IEEE 14-Bus System

A 14-bus system with three ESSs has been discussed as in Fig.5. The total load is 259.5 MW. The maximum allowable energy of ESSs is 2 MWh. A contingency loss of line 3 and loss of generator 6 have been studied. The results are as shown in table 5and table 6, respectively.

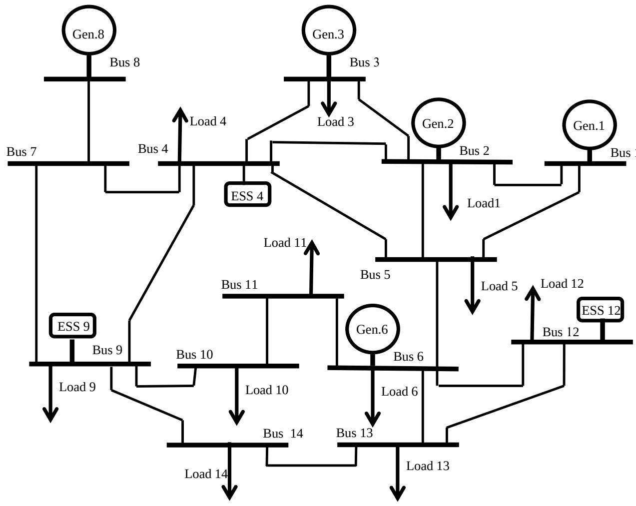

Fig. 5. Modified IEEE 14-bus system.

In (*) cases, a preventive action was added. It can be seen from table 5, ESS characteristic will be used when it is needed; ESS 4 and 12 can participate in the power system to eliminate the violations, while ESS 9 will not participate.

For different ESS characteristics, the base case and the long-term post-contingencies have the same values as shown in the results of table 6, because there are no preventive actions in this type of contingencies.

Table 5. Results for contingency loss of line 3

	ESCOPF*	Linear ESS*	Quadratic ESS	Exponential ESS
P1(MW)	65.9674	65.9674	67.7784	67.7784
P2(MW)	64.6954	64.6954	66.5285	66.5285
P3(MW)	45.0921	45.0921	42.2233	42.2233
P6(MW)	40	40	40	40
P8(MW)	43.2451	43.2451	42.4698	42.4698
Cost ($)	4107.8	4107.8	4107.3	4107.3
ESS4(MWh)	-2	-2	-1.63	-0.9712
ESS9 (MWh)	0	0	0	0
ESS12(MWh)	2	2	1.63	0.9712
$P1^C$(MW)	35.3499	35.3499	33.7965	33.7965
$P2^C$(MW)	64.6954	64.6954	66.5285	66.5285
$P3^C$(MW)	60	60	60	60
$P6^C$(MW)	40	40	40	40
$P8^C$(MW)	58.9547	58.9547	58.675	58.675

Different optimization algorithms have been applied for linear ESS characteristics in contingency loss of generator 6, the results are shown in table 7, for exponential ESS results are shown in table 8, respectively. From the result of tables7 and 8, Quadprog and TLBO are giving the best results. Moreover, TLBO is considered the best between stochastic algorithms with the least computational time.

Table 6. Contingency loss of generator 6 solutions for different linear/nonlinear ESS

	Linear ESS	Quadratic ESS	Exponential ESS
P1(MW)	67.7784	67.7784	67.7784
P2(MW)	66.5285	66.5285	66.5285
P3(MW)	42.2233	42.2233	42.2233
P6(MW)	40	40	40
P8(MW)	42.4698	42.4698	42.4698
Cost ($)	4107.3	4107.3	4107.3
ESS_4 (MWh)	-1.6667	-1.111	-0.6620
ESS9 (MWh)	-1.6667	-1.111	-0.6620
ESS12(MWh)	-1.6667	-1.111	-0.6620
$P1^C$(MW)	86.7196	86.7196	86.7196
$P2^C$(MW)	68.2656	68.2656	68.2656
$P3^C$(MW)	49.6043	49.6043	49.6043
$P8^C$(MW)	54.4105	54.4105	54.4105

Table7. Contingency loss of generator 6 for linear ESS and different optimization methods

	Quadprog	GA	TLBO	PSO
P1(MW)	67.7784	69.2304	67.7784	78.5327
P2(MW)	66.5285	54.5177	66.5285	58.1125
P3(MW)	42.2233	46.6954	42.2233	40.3422
P6(MW)	40	39.9732	40	34.1590
P8(MW)	42.4698	48.5823	42.4698	47.8528
Cost ($)	4107.3	4113.9	4107.3	4136.9
ESS4(MWh)	-1.6667	-1.6656	-1.6667	-1.4233
ESS9 MWh)	-1.6667	-1.6656	-1.6667	-1.4233
ESS12(MWh)	-1.6667	-1.6656	-1.6667	-1.4233
P1C(MW)	86.7196	87.1713	86.7196	91.6390
P2C(MW)	68.2656	60.5579	68.2656	62.5256
P3C(MW)	49.6043	52.4916	49.6043	47.5597
P6C(MW)	0	0	0	0
Computational Time (s)	0.2539	3.1858	0.6926	0.7608

Table 8. Contingency loss of generator 6 for exponential ESS and different optimization methods

	Quadprog	GA	TLBO	PSO
P1(MW)	67.7784	69.2304	67.7784	78.5327
P2(MW)	66.5285	54.5177	66.5285	58.1125
P3(MW)	42.2233	46.6954	42.2233	40.3422
P6(MW)	40	39.9732	40	34.1590
P8(MW)	42.4698	48.5823	42.4698	47.8528
Cost ($)	4107.3	4113.9	4107.3	4136.9
ESS4(MWh)	-0.6620	-0.6615	-0.6620	-0.5653
ESS9(MWh)	-0.6620	-0.6615	-0.6620	-0.5653
ESS12(MWh)	-0.6620	-0.6615	-0.6620	-0.5653
$P1^C$(MW)	86.7196	87.1713	86.7196	91.6390
$P2^C$(MW)	68.2656	60.5579	68.2656	62.5256
$P3^C$(MW)	49.6043	52.4916	49.6043	47.5597
$P8^C$(MW)	0	0	0	0
Computational Time (s)	0.2628	3.0363	0.6850	0.7670

5. Conclusion

The work presented in the paper analysed the impact of both linear and nonlinear characteristics of ESSs on SCED under comprehensive contingency analysis. Different contingencies were studied; loss of line, loss of generator, and restoring loads. This paper stressed the importance of studying SCED during the short-term period as a time varying optimization problem. The impact of linear/nonlinear characteristic of ESSs on OPF solution was clarified for planning and operation purposes. To avoid the complexity associated with the time varying nature of the problem, a new procedure was presented to handle the time varying SCED problems based on finding the GREs and the switching points. Adapting the proposed procedure did avoid linearizing the problem or converting the problem into mixed integer problem if the problem is non- convex. Therefore, this algorithm was straightforward, less time-consuming, and less exhaustive. To validate the proposed algorithm, different deterministic and stochastic algorithms were used to obtain the solution under extensive case studies using 6-bus and 14-bus power systems. The powerful of using the new stochastic TLBO algorithm was shown in this paper over the other stochastic algorithms. Moreover, the presented work was compared with the previous work to validate and show the generality of this work and the importance of considering nonlinear ESSs response in SCED.

Acknowledgements

This work was supported, under grant number 20150268, by the deanship of research at Jordan University of Science and Technology (JUST).

Nomenclature

Indices and Sets

t`	Index for time
i	Index for generators
j	Index for loads
k	Index for ESS
c'	Contingency in short term limits
c	Contingency in long term limits
NG	Number of generators
Nt	Number of hours
Nc	Number of contingencies for long term
Nc'	Number of contingencies for short term
$Nload$	Number of Loads
$Nbatt$	Number of ESS

Parameters

T_{sw}	Switching time
T	Final time of the period
$P_{L,\max}$	Maximum power limits of the transmission line
$P_{i,\max}$	Maximum power generation of unit i

$P_{i,\min}$ Minimum power generation of unit i

$\Delta_{\max,i}$ Maximum allowance power change of generator i

γ Vector of factors relating the short- and long-term ratings of the branches

Variables

E Energy stored in battery

$P(t)$ Power characteristic as a function of time

$P_{b,\max}$ Maximum power delivered or absorbed by battery

P_i Power generation of unit i

P_i^c Power generation of unit i in contingency c

P_i^0 Power generation of unit i in base case

P_{gen_lost} Power generation of the lost generator in base case

$P_{D,k}(t)$ Discharging power characteristic of ESS number k

$P_{C,k}(t)$ Charging power characteristic of ESS number k

$P_{C,K}^{c'}$ Charging power of ESS number k

$P_{D,K}^{c'}$ Discharging power of ESS number k

ΔP_i^{c+} Long-term increase in the output power of generator i following contingency c

ΔP_i^{c-} Long-term decrease in the output power of generator i following contingency c

$D_{new,j}$ New load at bus i (after adding restoring the load)

$D_{old,j}$ Old load at bus i (before adding restoring the load)

D_j Load at bus j

$F_i(P_i)$ Cost function of generator i

IC Incremental cost

Matrices and Vectors

SF Sensitivity factor matrix

P_{inj} Injected power vector of the power system i

$[Kp]$ Bus generator incidence matrix

$[K_{batt}]$ Bus ESS incidence matrix

$[KD]$ Bus Load incidence matrix

$[P]$ Power generation Vector

$[P_D(t)]$ Power of ESS discharging Vector

$[P_C(t)]$ Power of ESS charging Vector

$[D]$ Demand Vector

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