Resilience-Constrained Economic Dispatch for Blackout Prevention

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Abstract: The resilience of power systems under high-impact low-probability events, such as extreme weather conditions is getting a growing concern. However, the operational resilience enhancement strategy based on the generation resource dispatch needs further research. Traditional generation resource dispatch, i.e. security-constrained economic dispatch (SCED), aims at minimizing the generation cost while paying little attention to the resilience under extreme events. This paper proposes a proactive resilience-constrained economic dispatch (RCED) model to enhance operational resilience during extreme weather condition. Weather forecast information from the local meteorological agency is used to divide the whole power system area into normal state area and the extreme weather affected area. Two penalty terms are established in the proposed RCED objective function. One represents the transmission lines load rate in the extreme weather affected area and the other denotes the inhomogeneity of power flow of all lines. The penalty terms are introduced to reduce the power flow entropy and prevent power system evolving into self-organized criticality. Thus, the possibility of blackouts is reduced and the system resilience is enhanced. Case studies demonstrate the effectiveness of the proposed model.

Keywords: Resilience-constrained economic dispatch, extreme weather, power flow distribution, load rate.

1. INTRODUCTION

Blackouts and cascading failures caused by major events, especially extreme weather, are occurring with increasing frequency in these years. Between 2003 and 2012, about 679 power outages, each affecting at least 50000 customers, occurred due to weather events in the U.S. (Wang et al., 2016). In general, the power system is designed to have high reliability in response to common contingencies, but not strong enough to defense extreme weather influence due to the expensive construction cost. Though the frequency of extreme weather may be relatively low, their impact may be extremely high (Panteli et al., 2017).

To assess the ability of a power system to withstand these high-impact low-probability events, the research on power system resilience has recently received growing concern. Generally, compared with additional infrastructure investment, operation strategies are more specific and cost-effective in resilience enhancement. Several resilience-oriented restoration strategies have been discussed (Wang et al., 2016). Panteli et al. (2016) presented an approach for boosting the resilience of power grids to extreme weather events using defensive islanding strategies. Gao et al. (2016) proposed a resilience-oriented service restoration method using microgrids to restore critical load after natural disasters. Comparing with restorative strategy, preventive operation strategy could enhance power system resilience more effectively (Bie et al., 2017). Gao et al. (2017) proposed a pre-hurricane resource allocation method by considering generation fuel, batteries, and electric buses. The allocation problem was formulated into a mixed-integer stochastic nonlinear program and solved by a proposed heuristic method. A proactive SCUC framework presented by Wang et al. (2017) introduced a Markov process to model power system state transitions in extreme events and was sequentially solved within each system state. This paper focuses on the preventive resilience-oriented economic dispatch to enhancement the resilience of a power system under extreme weather conditions.

The SCED models to improve power system reliability are widely discussed in the literature (Álvaro Lorca et al., 2015) (Shi et al., 2011). However, the detailed mathematical models are limited. An event-driven security-constrained unit commitment was developed to consider the simultaneous outages of several system components (Eskandarpour et al., 2016). Ortega-Vazquez et al., (2016) established a security-constrained optimal power flow solution considering generation and transmission contingencies. Although these works have studied the preventive strategy under extreme weather conditions, they are all formulated with the stochastic method and the selected contingency set poses a great impact on final operation decision. A simple contingency set may not be able to cover all possible cascading failures, especially under extreme weather conditions. The SCED under extreme weather conditions needs further research for blackout prevention.

Dobson et al. (2007) verified that self-organized criticality is an essential characteristic of big blackout. Bao et al. (2009) showed the relationship between self-organized criticality and power flow entropy. Power flow entropy is an index to evaluate the homogeneity of power flow distribution. The bigger power flow entropy, the more easily for a system to enter self-organized criticality. Moreover, heavy load rate tends to increase the risk of transmission outage. Therefore, not only the economic consideration but also the homogeneity of power flow and transmission lines load rate should be considered in an effective and resilient dispatch strategy under extreme weather.

This paper proposes a resilience-oriented security-constrained economic dispatch (RCED) model for better prevention of blackout. Two type of penalty terms is constructed in the RCED objective function to improve the power flow distribution homogeneity. The effect of weather conditions and line load rate on the transmission lines forced outages are addressed simultaneously. Based on the cascading outages simulation process, a resilience assessment framework is established to illustrate the effectiveness of the proposed RCED model and methodology. The purpose of this paper is to develop a generalized resource dispatch model for better prevention of power system blackout. Local measurement data is needed for the introduced cascading outage model in practical applications

2. MODEL DESCRIPTION

The proposed economic dispatch model aims at enhancing the resilience of a power system in terms of cascading outages prevention. In this section, power flow entropy is introduced and two type of penalty terms are constructed in the proposed RCED objective function to improve the power flow distribution of power system under extreme weather condition.

2.1 Power Flow Entropy and Resilience Penalty Terms

Power flow entropy is proposed as a measurement of the global heterogeneity for the power flow distribution in an electricity grid (Bao et al., 2009), defined as

$$H = -\sum_{m=1}^{M} \frac{n_m}{NL} \log_2 \frac{n_m}{NL} \tag{1}$$

where M is the total number of successive intervals stated as $[0,\ u), [u,\ 2*u), ..., [(M-1)*u,\ 1]$ and u is 0.02 is this paper. It is assumed that all line loading rates $R = |PL/PL_{\max}|$ are in the interval $[0, 1]$. n_m is the total number of lines with a loading rate that falls into the *m-th* interval $[(m-1)*u,\ m*u)$. NL is the total number of transmission lines.

The power flow entropy H provides a measure of power flow distribution uniformity. Accordingly, $H = 0$ when all transmission lines loading rates are within the same interval. In this case, the grid load distribution is homogeneous and all lines carry loads within their rated capacities. The maximum entropy $H = \log_2 M$ occurs when $n_m/NL = 1/NL$, i.e., number of lines in the arbitrary interval is identical. Therefore, higher power flow entropy means greater heterogeneity in power flow distribution. When entropy is high, a few transmission lines could carry heavy loads while others are lightly loaded. The heavily loaded lines could fail more easily and the massive transfer of power flow on such lines could trigger cascading failures. The power flow entropy can represent an index for the short-term operation defense against large-scale blackout.

In would be difficult to append (1) to the SCED formulation and optimize the power flow entropy directly. Therefore, we consider a penalty term that would reflect the heterogeneity of power flow distribution as the variance of all the transmission loading rates, states as,

$$pn_1 = \sum_{j \in \Omega_1} \left(R_j - \frac{\sum_{j \in \Omega_1} R_j}{NL} \right)^2, \text{ where } R_j = \frac{PL_j}{PL_{j,\max}} \tag{2}$$

where R_j is the load rate of the transmission line j, PL_j is the real power follow on transmission line j, Ω_1 is the set of all transmission lines. The first penalty term pn_1 is the load rate variance of all transmission lines which reflects the inhomogeneity of power follows a distribution. Under the same system load, a smaller pn_1 means a more uniform distribution of power flow. That is, the system is running in a more resilient status.

In addition to the effect of the global heterogeneity of power flow distribution, outages of heavily loaded lines which could result in large-scale power transfers are one of the critical causes of cascading failures. Since weather-related events could often trigger blackout, it is imperative to reduce the loading rate of transmission lines in areas affected by extreme weather. Therefore, the second penalty term is established as

$$pn_2 = \sum_{k \in \Omega_2} \left(\frac{PL_k}{PL_{k,\max}} \right)^2 \tag{3}$$

where Ω_2 is the set of transmission lines impacted by extreme weather according to the weather forecast. The second penalty is designed to decrease the local power flow of selected area which is forecasted to be affected by extreme weather where the impacted lines suffer from much higher failure probability.

2.2 Proposed Resilience-constrained Economic Dispatch

Traditional SCED is to determine the least production cost and efficient operation of a power system by dispatching the available generation resources to meet the system load demand while satisfying the operational constraints of the generation units and the real power flow constraints of the electricity grid. The classical formulation of SCED is written as

$$\min\ F=\sum_{i}^{NG} C_i\left(P_i\right) \tag{4}$$

$s.t.$

$$\sum_{i}^{NG} P_i = D \tag{5}$$

$$P_{i,min} \leqslant P_i \leqslant P_{i,max},\ \forall i \tag{6}$$

$$\left|PL_j\right| \leqslant PL_{j,max},\ \forall j \tag{7}$$

where, P_i is the real power generation of the unit i and D is the total system load, $P_{i,\min}$ and $P_{i,\max}$ is the lower bound and upper bound of generation output. The objective function (4) is to minimize the total production cost $C(P_i)$. For each unit, the production cost can be represented by a quadratic function $C_i(P_i)=a_iP_i^2+b_iP_i+c_i$. The equality constraint (5) and inequality constraint (6) represent real power balance constraint and unit generation capacity limits, respectively. The inequality (7) represents transmission network security constraints, in which there are AC power flow model and DC power flow model to be used to calculate the real power flow on a transmission line. In general, for the sake of computational efficiency, the DC power flow model is often used in the SCED problem. In DC model, the real power flow of transmission lines can be represented in matrix form (8), which is a function of individual generations, loads and phase shifter.

$$\mathbf{PL}=\mathbf{SF}\cdot\mathbf{P^{inj}} \tag{8}$$

where $\mathbf{SF}$ is the linear sensitivity factor matrix whose elements represent the sensitivity of real power flow on a transmission line to the nodal net real power injection, $\mathrm{P}^{inj}=K_p\cdot \mathrm{P}_i-K_D\cdot \mathrm{D}$ is the net injection, K_p is the bus-generator incidence matrix, K_D is the bus-load incidence matrix. Thus, the inequality (7) can be expressed by

$$-\mathbf{PL_{max}}\leqslant \mathbf{SF}\cdot\mathbf{P^{inj}}\leqslant \mathbf{PL_{max}} \tag{9}$$

Traditional SCED mainly aims at the minimizing the production cost of a system, thus the system load demands are mainly supplied by some cheaper generating units. In this way, there exists a situation that some transmission lines are in heavy load rate and some are in a low rate. As was proved by Ding et al. (2009), the more inhomogeneity the power flow distribution is, the more easily it evolves into self-organized criticality (SOC). The SOC is an important mark when a power system faces a high risk of cascading failures. Intuitively, some lines under heavy load or overload are more likely to fail, especially under extreme weather. The consequent large-scale power flow transferring may trigger the protection action. As a result, cascading failures and blackout could happen. Therefore, it is critical to improve the homogeneity of power flow distribution and avoid extreme weather affected transmission lines in heavy load rate for the resilience enhancement in terms of blackout prevention.

To improve the homogeneity of power flow distribution along with economic of a power system, two penalty terms pn_1 and pn_2 discussed in part A are added to the SCED objective function here. By adding the two penalty terms, the proposed resilience-oriented security-constrained economic dispatch model is

$$\min\ F=\sum_{i}^{NG} C_i\left(P_i\right)+\omega_1\cdot pn_1+\omega_2\cdot pn_2 \tag{10}$$

$$s.t.\ \ (2)\ (3)\ (5)\ (6)\ (8)\ (9)$$

where ω_1 and ω_2 are the coefficients of the two penalty terms, which are added to balance the huge difference between the production cost and two penalty terms in numerical values.

3. RESILIENCE ASSESSMENT

To compare the operational resilience of the system with the proposed RCED model and the system with traditional SCED model. In this section, a Monte Carlo-based resilience assessment framework considering the impact of extreme weather is proposed.

3.1 Line Fragility Modelling

As introduced by Ouyang et al. (2014), a fragility function describes the probability of failure of a structure or component related to the potential intensity of a hazard. To model the failure probability of a transmission line and a tower under windstorm, a general fragility curve shown in Fig. 1 is introduced to describe the function of failure probability and weather intensity (e.g. wind speed, m/s) (Panteli et al., 2017).

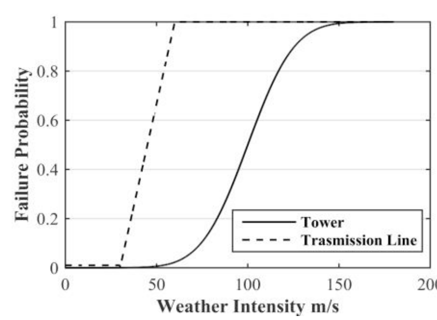


Fig. 1. Wind-related fragility curves of transmission lines and towers

The formulation of the transmission fragility curve is expressed as

$$p_w=\begin{cases} 0, & if\ w<w_{critical} \\ p_{hw}, & if\ w_{critical}\leqslant w\leqslant w_{collapse} \\ 1, & if\ w\geqslant w_{collapse}\end{cases} \tag{11}$$

where w is the wind speed, $w_{critical}$ is the wind speed at which the transmission line's failure probability start and $w_{collapse}$ is the wind speed at which the transmission line will almost be broken (considered to be 30m/s and 60m/s here, respectively). $P_{hw} = \dfrac{w - w_{critical}}{w_{collapse} - w_{critical}}$ is a linear function of wind speed. By mapping the weather profile to the fragility curve, the weather-dependent failure probability can be obtained.

3.2 Forced Outage Rate of Transmission Lines

Except for the weather condition, the failure probability of a branch will also be affected by its load rate. A line will unexpectedly be tripped if the load rate exceeds a certain level. If the load rate is greater than its thermal limit, the relays will trip this line promptly. According to Jia et al. (2016), the failure probability of a transmission line caused by the heavy load can be formulated as

$$p_r = \begin{cases} 1, & r \geqslant r_{\lim it} \\ \dfrac{r - r_{heavy}}{r_{\lim it} - r_{heavy}}, & r_{heavy} < r < r_{\lim it} \end{cases} \tag{12}$$

So far, the failure probability p_f of a transmission line can be calculated by considering the impact of weather condition and load rate together.

$$p_f = 1 - (1 - p_W) \cdot (1 - p_r) \tag{13}$$

To determine the status of a transmission line, the failure probability p_f is compared with a uniformly randomly generated number $r \sim U[0\ 1]$. If p_f is larger than r, the transmission line will be tripped. Otherwise, it remains in the system.

3.3 Resilience Assessment Framework

Based on the hidden cascading failures simulation process, the proposed Monte Carlo-based resilience assessment framework is shown in Fig.2. The detailed resilience assessment process is illustrated as follows:

1) The weather condition for different areas, system load, and network information are identified in the initialization step. The initial status of the transmission line is assumed under normal operation.
2) Based on the forecasted weather, obtain all transmission lines p_w according to the fragility curves as discussed and shown in Fig.1.
3) Execute the proposed RCED or traditional SCED and get the power flow distribution.
4) Select an initial outage line randomly and update all lines status.
5) Check whether islands occur. If there exist two or more isolated islands, simulation moves to step (9). Otherwise, go to step (6).
6) Run DC power flow and obtain the failure probability p_r caused by the heavy load.
7) Calculate the failure probability p_f, then make new outage lines and update all line status.
8) Check whether there are new outages occur. If so, repeat steps (5) - (7). If not, go to step (9).
9) A DC OPF with a particular objective function of minimizing load curtailments is executed for providing the number of load curtailments.
10) Repeat steps (4) - (9) until iterations reach the set limit.

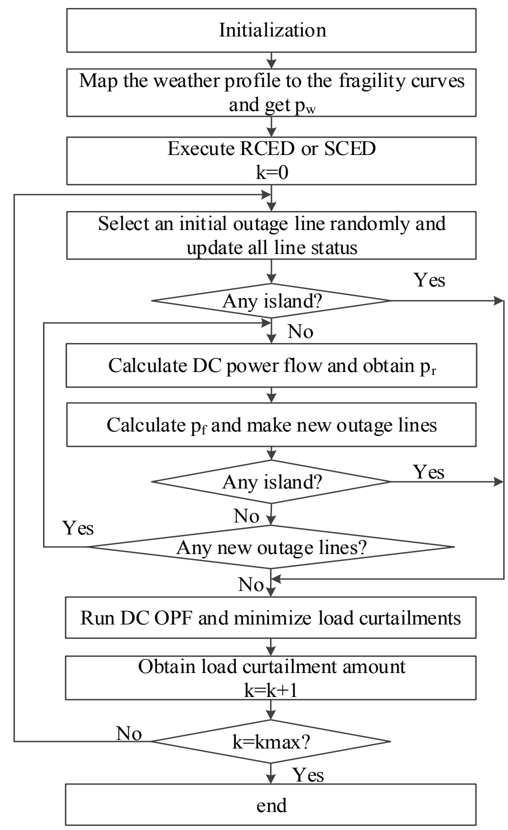


Fig. 2. Simulation procedure for resilience assessment

By recording load shedding amount of each iteration, together with $k_{\max}$, we can obtain the expected-energy-not-supply (EENS) of different operational strategies. Also, the cumulative probability distribution of the loss of load percentage under the extreme weather can be calculated and thus assess the resilience of the system.

4. CASE STUDIES

In this section, the proposed RCED and traditional SCED are applied to the standard IEEE 30-bus test system as shown in Fig. 3. Without loss of generality, we take the hurricane as the extreme weather for each case. One can discuss other extreme events based on the proposed model. The region forecasted to be impacted by extreme weather is marked in red circle. In order to illustrate the effectiveness of the proposed RCED model in comparison with traditional SCED, two case studies are performed. All case studies are tested in the MATLAB R2016b and Gurobi 7.1.0 solver.

4.1 Case 1: Base cases without resilience assessment possess

Case 1 is studied to verify the feasibility and effectiveness of the proposed RCED model in improving the power flow distribution homogeneity. The obtained results are shown in Table I.

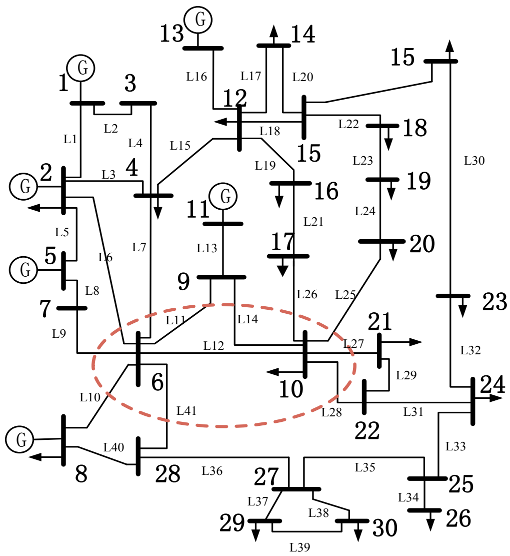


Fig. 3. IEEE 30-bus system and the region forecasted to be impacted by extreme weather

TABLE I
THE COMPARISON OF PROPOSED MODEL AND TRADITIONAL MODEL

System load	Model	Generation cost	Load rate variance of all lines	Load rate average of all line	Max. load rate	Average load rate of impacted lines
Base load	SCED	8495.17	0.056	0.339	1.000	0.473
	RCED	10374.05 (+22.1%)	0.016 (-71.4%)	0.261 (-23.0%)	0.583	0.292 (-38.2%)
150% Base load	SCED	14273.33	0.050	0.423	1.000	0.513
	RCED	16686.85 (+16.9%)	0.041 (-18.0%)	0.405 (-4.2%)	0.936	0.482 (-6.0%)

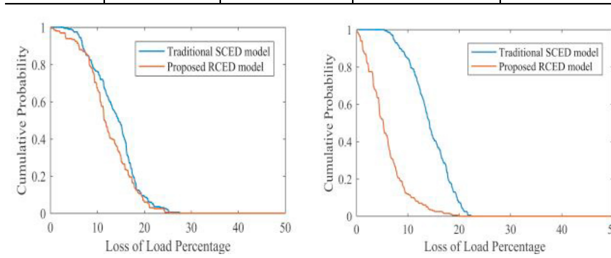
From Table I, for the base load, we can see an obvious decrease, up to 71.4%, in the load rate variance of all transmission lines in the proposed RCED model as compared with traditional SCED. The decline indicates the effectiveness of the first penalty term. Moreover, there is also 38.2% decrease in the average load rate of weather impacting lines because of the second penalty term in the objective function. In addition, the maximum load rate of RCED model is much smaller than that of the traditional model. With lower load rate, the probability of misoperation of a relay is greatly reduced. The benefits of power system resilience will be shown in Case 2. By increase system load to 150% base load, we can see that there is still a decrease in above three indexes. However, the declining percentage is smaller than that in base case. The load rate variance of all lines decreases 18% while in base load it is 71.4%. The same trend is followed by the average load rate. Two reasons may account for this result. The first one is that as the load demand increases, the number of units committed to generation increases, there is less dispatch ability and smaller improvement margin to adjust power flow distribution. The other reason is that the objective function of proposed RCED model is to minimize the sum of the variance of power flow, the load rate of impacted lines and the generation cost, in addition to improve the power flow distribution homogeneity. Therefore, there is a tradeoff between these three values. Moreover, the cheaper resources are consumed firstly with the increase of load, which means the available resource remained is much more expensive. Thus, the power flow distribution is not as good as base load case in the 150% base load level.

4.2 Case 2: Resilience Assessment of Two Models

Based on the power flow distribution obtained from Case 1, Case 2 will perform the resilience assessment of the proposed RCED model and traditional SCED model. Case 2 is to identify how much a loss of load will occur if the system is subject to extreme weather, the weather condition is included in Case 2. The detailed input data is as follows: $w_{critical} = 30\ m/s$, $w_{collapse} = 60\ m/s$ in the Equation (11), $r_{heavy} = 0.8$, $r_{limit} = 1.4$ in Equation (12). In resilience assessment simulation process, the maximum number of iterations $k_{\max} = 200$. The wind profile for transmission lines in region forecasted and to be impacted is assumed to have a speed between 50 m/s and 70 m/s while the wind speed of remaining transmission lines is set to be a random number between 0 m/s and 40 m/s. The obtained results of Case 2 are shown in Table II and Fig. 4.

TABLE II
THE OBTAINED RESULTS FOR DIFFERENT LOAD IN CASE 2

System load	Model	EENS (MW)	Average outage lines number	Average islands number
Base load	SCED	39.25	17.8	7.5
	RCED	34.90 (-11.08%)	13.9	5.2
150% Base load	SCED	60.65	25.4	6.4
	RCED	24.47 (-59.65%)	28.4	4.0



(a) (b)

Fig. 4. Cumulative probability curve of loss of load

As shown in Table II, the expected-energy-not-supply (EENS) of the proposed RCED model is smaller than that of traditional SCED model in both base load case and 150% base load case. In base load case, the gap between the two models is not very obvious because of the abundant generation resource. However, in the 150% base load case, the EENS is reduced by 59.65%. The number of average outage lines and that of the islands caused by system splitting are also counted.

The same trend is followed by the expected number of outage lines and that for islands. Therefore, a better performance in power system resilience will be achieved due to a higher homogeneity of power flow distribution in the proposed RCED model. Fig.4 (a) and (b) demonstrate the cumulative probability distribution of the loss of load percentage during the simulation process according to the resilience assessment framework in base load level and 150% base load level, respectively. In base load case the difference is not obvious between the proposed model and traditional model due to abundant schedulable resources. However, as load increases up to 150% base load, there is an obvious gap between these two curves. In the RCED model, the probability of loss of load over 10% is smaller than 0.1, there is barely loss of load over 20%. But for the traditional model, the probability of loss of load over 10% is nearly equal to 1. In addition, the loss of load percentage in the two models is both less than 30%. This indicates that the generation resources and line capacity are relatively abundant in the IEEE 30-bus test system. Even if the system is sampled to split into two or more islands, each island can be adjusted to balance the demand and supply with a certain amount of load shedding.

5. CONCLUSIONS

In this paper, a resilience-constrained economic dispatch is proposed. To compare the proposed RCED model with the traditional SCED model, a Monte Carlo-based resilience assessment framework is established. Case studies results prove that the proposed model can avoid some lines undertaking excessively heavy load, especially those transmission lines affected by extreme weather. The improvement in power flow distribution homogeneity can reduce the possibility of cascading failures, thus to reduce the load shedding under extreme weather and enhance the power system resilience. The generator capacities, system load demand and network topology and parameters have a great influence on the enhancement of power system resilience. In general, the higher system load demand, the smaller generation capacity, the smaller margin for resilience enhancement.

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