Coordinated control of tie switch and soft normally open point for harnessing flexibility in active distribution systems

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Abstract. Integration of renewable energy source (RES) increases the volatility and uncertainty of active distribution systems while the limited line capacity hampers the accommodation of RES. Soft normally open point (SNOP) has the capability to control the power flow between distribution feeders accurately which can mitigate line congestion. SNOP is an effective flexibility resource in active distribution systems. However, currently it is impossible to replace all traditional tie switch by the SNOP considering the high cost of SNOP. In this paper, a coordinated control strategy considering the coexistence of tie switch and SNOP is proposed, in which a bi-level model is built. An index weighing the static insecurity probability is defined as the bridge between the two layers of the bi-level model. By solving the mixed integer nonlinear programming problem, the coordination between tie switch and SNOP is realized accounting for different characteristics of the two types of devices. Simulation results on a 33-bus test system demonstrate the effectiveness of the coordinated control strategy.

1. Introduction
For sustainable development, people's high attention to energy and environment brings great challenges to the development of distribution systems. But it's also an opportunity to accelerate the transition from traditional distribution systems to smart ones. The high penetration of RES may lead to great changes in power flow. The limited transmission capacity also hampers the accommodation of RES, thus increasing the congestion risk. In [1], the principle of mitigating congestion by flexible alternating current transmission device (FACTS) is analyzed, and the optimal location of thyristor-controlled series capacitor (TCSC) is solved by intelligent algorithm. Reference [2] changes the network topology by reorganizing the state of tie switch, thus changing the distribution of power flow.

Considering the influence of switching loss and impulse current, the tie switch cannot be switched frequently. It is difficult for the traditional network reconfiguration to adjust the power flow in real time. SNOP is a novel type power electronic device in place of tie switch. Compared with the switching operation, SNOP is more reliable and can even achieve real-time optimization. The application of SNOP will greatly harness the flexibility of the distribution network [3]. But because of the higher investment and operation cost of SNOP, it is impossible to replace the tie switch by SNOP completely in the short term. Therefore, both tie switch and SNOP should be taken into account as a whole in the operation optimization of distribution systems. Its optimization model will be a mixed integer nonlinear programming problem which needs to solve both discrete and continuous variables.
In this paper, a bi-level optimization model of distribution network operation with tie switch and SNOP is established, in which the inner model determines the optimal capacity configuration of SNOP by taking the congestion management into account. Then the state variables of system are obtained by power flow calculation and the judging condition of network reconfiguration is established. The outer model uses the gravitational search algorithm (GSA) to deal with the network reconfiguration of distribution systems with stochastic power flow. When the condition is satisfied, the status of tie switch is to be reorganized. Then the reconfigured network structure is feed back to the inner model. By this way, we realize the accurate solution of the optimization model with tie switch and SNOP. Finally, the optimization model is verified on IEEE 33-bus test feeder.

2. Bi-level model for coordinated control of tie switch and SNOP

2.1. A multi-scenario generation method considering uncertainty of wind power.
At present, it is generally considered that Weibull distribution is the best probabilistic description of wind speed. The probability density function of the Weibull distribution is defined as follow,

\[
f(x | \lambda, k) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k}
\]

In the equation (1), \(x\) denotes the wind speed, \(k\) denotes the shape parameter, \(\lambda\) denotes the scale parameter. A linear approximation equation is used as shown in

\[
Y = \begin{cases} 
0 & \text{if } X \leq V_{ci} \text{ or } X > V_{co} \\
\alpha + \beta X & \text{if } V_{ci} \leq X \leq V_{co} \\
M & \text{if } V_{no} \leq X \leq V_{co}
\end{cases}
\]

where \(Y\) denotes injected power, \(X\) denotes actual wind speed, \(M\) denotes the maximum power. \(V_{ci}, V_{co}, V_{no}\) denote cut-in wind speed, cut-out wind speed and normal wind speed. A five-point estimation method is used to discretize wind power distribution. The probability of zero power and rated power can be computed as follows:

\[
\begin{align*}
P_1 &= P\{Y = 0\} = P\{X \leq V_{ci}\} + P\{X > V_{co}\} \\

P_2 &= P\{Y = M\} = P\{V_{no} \leq X \leq V_{co}\}
\end{align*}
\]

For \(V_{ci} \leq X \leq V_{no}\),

\[
\begin{align*}
Y_2 &= \mu_Y + \sigma_Y z_2 & \text{and } P_2 = p_2 \left(1 - p_1 - p_3\right) \\
Y_3 &= \mu_Y & \text{and } P_3 = p_3 \left(1 - p_1 - p_2\right) \\
Y_4 &= \mu_Y + \sigma_Y z_4 & \text{and } P_4 = p_4 \left(1 - p_1 - p_2\right)
\end{align*}
\]

where \(\mu_Y\) denotes the expected value of \(Y\), and \(\sigma_Y\) denotes the standard deviation of \(Y\). \(z_i\) and \(p_i\) \((i = 2, 3, 4)\) can be obtained from probability theory.

2.2. Programming model of SNOP for mitigating congestion
A bi-level model for the coordinated control of tie switch and SNOP considering congestion is established. The inner model first establishes a programming model of SNOP which takes the congestion management into account. The discrete distribution of wind power is obtained by five-point estimation method. A multi-objective optimization model is established with congestion, line loss and installation cost of SNOP as targets. The positive semi-definite convex relaxation method is used to deal with the non-convex power flow constraints, and the branch and bound method is used to deal with the integer variables in the model. Finally, the global optimal solution is obtained.
2.2.1. Congestion index of distribution system. The closer the transmission power is to the upper limit, the greater the congestion risk. The accommodation of RES and the uncertainty of unit output may lead to power flow exceeding its threshold. Congestion index of power lines can be defined as

$$m := \sum_{(r,s) \in L} \left( \frac{S_{rs}}{S_{rs,\text{max}}} \right)^2 ; S_{rs} \geq S_{rs,\text{th}}$$

(5)

where $S_{rs}$ is the transmission power of power line and $S_{rs,\text{th}}$ is the preset threshold. If the transmission power is no less than the threshold, then it will increase the congestion risk of system. Similar to reference [7], equation (5) is equivalent to

$$m := \sum_{(r,s) \in L} \max \left( 0, \left( \frac{S_{rs}}{S_{rs,\text{th}}} \right)^2 \right)$$

(6)

2.2.2. Capacity allocation of SNOP. SNOP can reduce the congestion risk of system, but also has certain installation cost. Similar to (6), the objective function $f_1$ seeks to reduce the congestion risk.

$$f_1 = \sum_{s \in S} p(s) \sum_{(r,s) \in L} \max \left( 0, \left( \frac{S_{rs}}{S_{rs,\text{th}}} \right)^2 \right)$$

(7)

where $p(s)$ is the probability of each scenario in the five-point estimation method; $S$ is the set of various scenarios; $L$ denotes the set of lines; $S_{rs}(s)$ denotes the transmission power in line $(i, j)$.

The objective function $f_2$ seeks to reduce the active power loss of the system:

$$f_2 = \sum_{s \in S} p(s) \left\{ P_{\text{unc}}(s) + \sum_{(i,j) \in N_L} P_{\text{loss},i,SNOP}(s) + P_{\text{loss},j,SNOP}(s) \right\}$$

(8)

where $P_{\text{unc}}(s)$ denotes the active power borne by the upstream grid, the smaller the value, the smaller the active power loss. $N_L$ denotes the installation position of SNOP.

The objective function $f_3$ seeks to reduce the installation cost of SNOP:

$$f_3 = \sum_{(i,j) \in N_L} C_{ij}^{\text{SNOP}} S_{ij,SOP}$$

(9)

where $C_{ij}^{\text{SNOP}}$ is the unit installation cost of soft-switching.

1) Constraints of capacity

$$0 \leq S_{ij,SOP} \leq S_{ij,SOP}^{\text{max}}$$

(10)

$$S_{ij,SOP} = m_{ij} S_{ij,SOP}$$

(11)

where $S_{ij,SOP}^{\text{max}}$ is the maximum installation capacity of SNOP and $S_{ij,SOP}$ is the installation reference capacity of SNOP, such as 10 kVA, 100 kVA, etc. $m_{ij}$ is an integer variable.

2) Constraints of reactive power

$$\begin{cases} Q_{i,\text{sof}}^{\text{min}} \leq Q_{i,SOP}(s) \leq Q_{i,\text{sof}}^{\text{max}} \\ Q_{j,\text{sof}}^{\text{min}} \leq Q_{j,SOP}(s) \leq Q_{j,\text{sof}}^{\text{max}} \end{cases}$$

(12)

where $Q_{i,\text{sof}}^{\text{min}}$, $Q_{i,\text{sof}}^{\text{max}}$, $Q_{j,\text{sof}}^{\text{min}}$, $Q_{j,\text{sof}}^{\text{max}}$ are the minimum and maximum of the reactive power at one end of SNOP.
3) Constraints of active power

\[
\begin{align*}
& P_{i,\text{SOP}}(s) + P_{j,\text{SOP}}(s) + P_{i,\text{SOP}}^{\text{loss}}(s) + P_{j,\text{SOP}}^{\text{loss}}(s) = 0 \\
& P_{i,\text{SOP}}^{\text{loss}}(s) = A_i^{\text{SOP}} \left( \left( P_{i,\text{SOP}}(s) \right)^2 + (Q_{i,\text{SOP}}(s))^2 \right) \\
& P_{j,\text{SOP}}^{\text{loss}}(s) = A_j^{\text{SOP}} \left( \left( P_{j,\text{SOP}}(s) \right)^2 + (Q_{j,\text{SOP}}(s))^2 \right)
\end{align*}
\]  

(13)

In (13), \( A_i^{\text{SOP}} \) and \( A_j^{\text{SOP}} \) denote the loss coefficients at the two ends of SNOP, \( P_{i,\text{SOP}}(s) \), \( P_{j,\text{SOP}}(s) \), \( Q_{i,\text{SOP}}(s) \), \( Q_{j,\text{SOP}}(s) \) denote the active and reactive power injected at both ends of SNOP.

4) The power constraints of soft-switching are as follows

\[
\begin{align*}
\sqrt{P_{i,\text{SOP}}(s)^2 + Q_{i,\text{SOP}}(s)^2} & \leq S_{y,\text{SOP}} \\
\sqrt{P_{j,\text{SOP}}(s)^2 + Q_{j,\text{SOP}}(s)^2} & \leq S_{y,\text{SOP}}
\end{align*}
\]  

(14)

where \( S_{y,\text{SOP}} \) is the installation capacity of SNOP between node \( i \) and node \( j \).

5) Constraints of power flow

\[
\begin{align*}
P_{i,\text{DG}}(s) + P_{i,\text{SOP}}(s) + P_{i,\text{LD}}(s) &= Tr \{ \mathbf{\Gamma}_k W(s) \} \\
Q_{i,\text{DG}}(s) + Q_{i,\text{SOP}}(s) + Q_{i,\text{LD}}(s) &= Tr \{ \overline{\mathbf{\Gamma}}_k W(s) \}
\end{align*}
\]  

(15)  

(16)

where \( P_{i,\text{DG}}(s) \), \( P_{i,\text{SOP}}(s) \), \( P_{i,\text{LD}}(s) \) denote the active power of wind power, the active power of soft-switching, and the active power consumed by load. \( Q_{i,\text{DG}}(s) \), \( Q_{i,\text{SOP}}(s) \), \( Q_{i,\text{LD}}(s) \) denote the reactive power of wind power, soft-switching, and load. The definition of \( Tr \) can be obtained from [8] in which constraints of power flow are preconditioned.

\[
\begin{align*}
\left( V_{k}^{\min} \right)^2 & \leq Tr \{ \mathbf{M}_k W(s) \} \leq \left( V_{k}^{\max} \right)^2, k \in \mathcal{K} \\
Tr \{ \mathbf{\Gamma}_{\text{rs}} W(s) \}^2 + Tr \{ \overline{\mathbf{\Gamma}}_{\text{rs}} W(s) \}^2 & \leq \left( S_{\text{rs}}^{\max} \right)^2
\end{align*}
\]  

(17)  

(18)

The equation (17) denotes the constraint for voltage amplitude of node; the equation (18) denotes the constraint on transmission capacity of power lines. The proposed model is a complex nonlinear and non-convex optimization problem. In [8], a preprocessing method of power flow is chosen as the basis of solving the problem.

2.3. Multi-objective optimization model for reconfiguration of distribution network

The reconfiguration of distribution network is mostly considered to enhance efficiency where the objective is to minimize the active power loss. However, with the high penetration of distributed generation (DG), it brings some security problems. Therefore, this paper introduces the load balancing index to measure the security of the distribution network under the premise of considering the economic index. A mathematical multi-objective model of reconfiguration based on stochastic power flow is given below. We use it as an outer layer of the bi-level model.

2.3.1. Optimization model. The objective function of loss is

\[
f_i = \min \sum_{h(i, j \in h)} R_{y} \left( P_{y}^2 + Q_{y}^2 \right)/U_{j}^2
\]  

(19)
where \( b_i \) is the branch number; \( R_{ij} \) is the resistance; \( P_{ij} \) and \( Q_{ij} \) are the expected values of active and reactive power, and \( U_j \) is the voltage expectation.

The objective function for load balancing is

\[
f_2 = \min \sum_{i=1}^{N_s} \left( \frac{S_i}{S_{i_{\text{max}}}} - S_{i_{\text{ave}}} \right)^2, \quad S_{i_{\text{ave}}} = \left( \sum_{j=1}^{N_b} S_j / N_b \right)
\]

(20)

where \( S_{i_{\text{ave}}} \) is the average load rate of branch; \( S_i \) is the expectation of apparent power; \( S_{i_{\text{max}}} \) is the maximum capacity. The smaller the value of \( f_2 \) is, the more uniform the distribution of power flow is, and the higher the security of power network is.

1) Constraints of power flow

\[
\begin{align*}
&V_i \cos \theta_{ij} - V_j \cos \theta_{ji} + P_i - V_i \sum_{j=1}^{N_b} V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) = 0 \\
&V_i \sin \theta_{ij} - V_j \sin \theta_{ji} - Q_i - V_i \sum_{j=1}^{N_b} V_j (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij}) = 0
\end{align*}
\]

(21)

where \( P_i \) and \( Q_i \) are the active and reactive power injected by node \( i \), including input power, DG injection power and load demand power, \( V_i \) and \( V_j \) are voltage amplitudes of node \( i, j \). \( G_{ij} \) and \( B_{ij} \) are the conductance and susceptance of branch \( ij \), \( \theta_{ij} \) is the voltage phase angle difference of branch \( ij \).

2) Constraints of branch power

\[
S_j \leq S_{j_{\text{max}}}
\]

(22)

where \( S_j \) and \( S_{j_{\text{max}}} \) are the apparent power and its maximum value allowed through branch \( j \).

3) Constraints of voltage

\[
U_{i_{\text{min}}} \leq U_i \leq U_{i_{\text{max}}}
\]

(23)

where \( U_{i_{\text{min}}} \) and \( U_{i_{\text{max}}} \) are the minimum and maximum allowable voltage of node \( i \).

2.3.2. Solving model. Since this paper is based on stochastic power flow, the traditional reconfiguration algorithms, such as branch exchange method, are no longer perfect, although the computational efficiency is high. GSA is a random search algorithm based on the natural phenomena of universal gravity. By adjusting the mass and force of the individual moving towards the individual with large mass, the optimal solution is obtained. The mass of particle is determined by its fitness value, which is the objective function of distribution network reconfiguration. Because there are many branches in the distribution network, the individual is too long to deal with if coded directly. A piecewise strategy [9] is introduced to divide a whole solution space into several non-overlapping sub-solution spaces. This method shortens the coding length. This method not only preserves the randomness of search, but also inherits the thought of GSA.

3. Coordination between two layers of bi-level model

3.1. Index connecting two layers of model

A bi-level model with tie switch and SNOP is built for distribution network optimal operation. The operation of tie switch and SNOP has obvious timing characteristic since the tie switch cannot be switched frequently whereas the SNOP can change the transmission power in real time. It is no longer limited to a single time section, but extends to a longer time horizon, resulting in an increase in the dimension of decision variables. Then we define an index to determine periodically whether to start the network reconfiguration in the outer model, while the SNOP in inner model can change the power transmission in real time to deal with a series of problems such as voltage limit violation issues. The
main purpose of our network reconfiguration is to ensure the security of distribution system. We need to take the stochastic analysis of power system static safety into account[10]. The uncertainty of DG output increases the range of voltage fluctuation, and when the DG is connected centrally, the fluctuation is stronger, which easily leads to the voltage limit violation issues. Because of the radial operation of the distribution network, the minimum voltage amplitude of node is low.

The voltage fluctuation range is set to 0.94~1.01, and the voltage limit violation probability of each node $W_i$ and the static insecurity probability of distribution system $f_W$ are obtained.

$$W_i = 1 - \text{prob}\left\{0.94 \leq U_i \leq 1.01\right\}$$

$$f_W = 1 - \prod_{i=1}^{N}(1-W_i)$$

By setting the threshold of static insecurity probability, this paper takes it as the criterion to initiate network reconfiguration when the scenario is changed.

### 3.2. Coordinating process of the bi-level model

A bi-level model which coordinates tie switch and SNOP considering congestion has been built. The inner model first configure the capacity of SNOP. Then the state variables and static insecurity probability of the system are obtained by power flow calculation. The reconfiguration of network is decided by judging the static insecurity probability. If the condition is satisfied, the outer model will reorganize the state of tie switch, and feedback the updated network structure to the inner model. The flow chart of the algorithm is shown in Fig. 1.

![Flow chart of the bi-level model](image-url)
4. Simulation results

Simulations are conducted on the IEEE 33-bus test feeder as shown in Fig. 2. The voltage grade of the system is 12.66 kV, the active power of load is 3.16 MW, the reactive power is 2 Mvar. Node 1 is connected with the upstream grid and node 10, 30 is connected to the fan with a total installed capacity of 1.26MW. The dashed lines denote the position where tie switches and SNOPs are installed respectively. Tie switches are installed at 8-21, 18-33 and SNOPs are installed at 9-11, 12-22, 25-29.

![Figure 2. Structure of the IEEE 33-bus test feeder.](image)

The maximum capacity of SNOP is set at 400kVA. That is, the optimal solution of soft switching capacity may be 0 kVA, 100 kVA, 200 kVA, 300 kVA, 400 kVA. If the capacity of SNOP is set at 0 kVA, the SNOP is not installed there.

4.1. Optimal Capacity Configuration of SNOP

Table 1 shows the configuration results of SNOPs. The capacities of SNOPs in line 9-15, 12-22 and 25-29 are 300kVA, 100 kVA and 200 kVA, respectively.

| Line   | Capacity |
|--------|----------|
| 9-15   | 300kVA   |
| 12-22  | 100 kVA  |
| 25-29  | 200 kVA  |

The configuration results are all smaller than the maximum capacity, and they are all integer times of the 100kVA, which verifies the correctness of the model for determining the capacity of SNOP.

4.2. Optimization Results of the System

1) Influence of SNOP on Power flow.

The voltage amplitudes of nodes in each scenario are shown in Fig. 3. With the increase of wind power which is from scenario 1 to scenario 5, the application of SNOP makes the voltage range obviously narrow, and the quality of power supply of the whole system is improved effectively.

![Figure 3. The voltage amplitudes of nodes.](image)

In scenario 3~5, the voltage magnitude of node 10 is the largest among node 7~13. That is because the node 10 is directly connected to the fan, and the active power of fan changes the voltage amplitude
of node. In scenario 1~2, the voltage amplitudes of nodes decrease from node 1 to node 18. Therefore the active power regulation and reactive voltage supporting ability of SNOP can effectively alleviate the problem of the increase of voltage after the distributed generations are connected. It can further promote the accommodation of RES in distribution network.

| Scenario | 1 | 2 | 3 | 4 | 5 |
|----------|---|---|---|---|---|
| P (kW)   | -300 | -250 | -200 | -150 | -100 |
| Q (kVar) | 50 | 75 | 100 | 125 | 150 |

(a) Active power

(b) Reactive power

Figure 4. The active and reactive power of SNOPs.

The active and reactive power of SNOPs in various scenarios are shown in Fig. 4. The amount of active power transmitted by SNOP between node 12 and node 22 is very small, regardless of the direction of transmission. And the reactive power transmitted by SNOP 9-15 is huge which can maintain voltage in case the voltage of radiating line extending from node 1 falls too fast. Fig. 4 (b) shows that the reactive power of each SNOP is positive because there is no reactive power source in the system except for the upstream grid.

2) Comparison of congestion risk.

The congestion index is established in this paper to quantitatively evaluate the congestion risk of power flow, which is used to measure the congestion degree of transmission power in the line. In order to verify the effect of model on congestion management, two other schemes and the original network are compared with the model.

![Diagram of Congestion Risk Comparison](image)

Figure 5. Comparison of congestion risk.

The optimal plan 1 is the bi-level model which considers the coexistence of tie switch and SNOP in this paper. In the optimal plan 2, there is no SNOP in the IEEE 33-bus test feeder, meaning all five positions are equipped with tie switches. The operation optimization is carried out through network reconfiguration. The optimal plan 3 is to configure SNOP for maximum capacity rather than multi-objective configuration proposed in this paper.
As seen in Fig. 5, the congestion risk of system in optimal plan 2 is similar to the original network. The application of SNOP can reduce congestion risk effectively. Although the congestion risk of multi-objective configuration method is a little higher than the configuration method based on maximum capacity, it can save the installation cost of SNOP and achieve the desired effect of congestion management.

5. Conclusion
A bi-level model considering the coexistence of tie switch and SNOP to harness flexibility in active distribution systems is proposed. It synthetically considers the timing characteristic of tie switch and SNOP in operation. In the model, SNOP can adjust the transmission power in real time, and the tie switch can avoid being switched frequently. SNOP can reduce the active power loss of system and achieve an effective congestion management. The tie switch ensures the security of system by balancing the load and avoids the voltage limit violation issues. The two layers of the model can be connected effectively by static insecurity probability. In the model, the inner layer can pass the state variables of system to the outer layer, and the outer layer can feedback the updated network structure to the inner layer, in which a good coordinating process can be obtained. The effectiveness of the coordinated control for tie switch and SNOP is demonstrated. The proposed strategy has the capability to harness flexibility in active distribution systems.

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References
[1] P. Ramasubramanian, G. Uma Prasana, K. Sumathi, Optimal location of FACTS devices by evolutionary programming based OPF in deregulated power systems, British Journal of Mathematics & Computer Science. 2 (2010) 1 21-30.
[2] M.H. Shariatkhah, M.R. Haghifam, “Using feeder reconfiguration for congestion management of smart distribution network with high DG penetration,” in Integration of Renewables Into the Distribution Grid, CIRED 2012 Workshop. IET, Lisbon, Portugal, 2012, pp. 1–4.
[3] A.C. Rueda-Medina, A. Padilha-Feltrin, Distributed generators as providers of reactive power support—a market approach, IEEE Transactions on Power Systems, 28 (2013) 1 490-502.
[4] E. Rashedi, H. Nezamabadi-Pour, S. Saryazdi, GSA: A gravitational search algorithm, Information Sciences, 179 (2009) 13 2232-2248.
[5] X. Liu, W. Xu, Economic load dispatch constrained by wind power availability: A here-and-now approach, IEEE Transactions on Sustainable Energy, 1 (2010) 1 2-9.
[6] Q. Fu, D. Yu, J. Ghorai, “Probabilistic load flow analysis for power systems with multi-correlated wind sources,” in Power and Energy Society General Meeting, 2011 IEEE. IEEE, Detroit, MI, USA, 2011, pp. 1–6.
[7] M. Nick, R. Cherkouai, M. Paolone, Optimal siting and sizing of distributed energy storage systems via alternating direction method of multipliers, International Journal of Electrical Power & Energy Systems, 72 (2015) 33-39.
[8] J. Lavaei, S. H. Low, Zero duality gap in optimal power flow problem, IEEE Transactions on Power Systems, 27 (2012) 1 92-107.
[9] Q. Zhou, G.J. Zhang, J. Li, Z.S. Yang, Distribution network reconfiguration based on strategy of breaking up the whole into parts and improved binary differential evolution algorithm, Power System Technology, 36 (2012) 3 197-203.
[10] Y.F. Liu, B.H. Zhang, J.F. Li, K. Wang, Y. Duan, X.Z. Duan, S.J. Cheng, Probabilistic load flow algorithm considering static security risk of the power system, Proceedings of the CSEE. 31 (2011) 01 59-64.