

Optimal Strategies for Distribution Network Reconfiguration Considering Uncertain Wind Power

Zhiwei Cui, Xiaoqing Bai, Peijie Li, Bin Li, Jie Cheng, Xiangyang Su, and Yi Zheng

Abstract—The uncertainty of wind power can cause side-effects in distribution network reconfiguration. For reducing the impact from uncertainty in distribution network reconfiguration, the hard strategy of compressed air assisted wind turbine system (CAAWTS) and the soft strategy based on robust optimization are proposed in this paper. Since the energy storage capacity of CAAWTS is generally small, the performance of the hard strategy is limited. The soft strategy based on robust optimization by creating an uncertain set is applied to enhance the performance of the hard strategy. The proposed robust optimization model of distribution network reconfiguration is then solved by the maximum explicit method. Numerical examples show that the proposed hard and soft strategies can effectively solve the influences of uncertain wind power on the problem of distribution network reconfiguration, while the economic performance of the system can be improved.

Index Terms—Distributed generation, distribution network, energy storage system, reconfiguration, robust optimization.

NOMENCLATURE

N	Set of buses, $i \in N, j \in N$.
T	Set of times, $t \in T$, the time interval is Δt .
L	Set of lines, $l \in L$.
N_{action}	Maximum switching action times.
M	A large positive constant.
C	The number of CAAWTS.
$(C_{\text{load}}, C_P, C_S)$	The electricity sale price (¥/MW·h), electricity generation price (¥/MW·h) and switching action price (¥/Action).
$(\kappa\beta)$	Correlation coefficient between power and energy.
$(\eta_e, \eta_{vc}, \eta_{vp})$	The working coefficients of the energy of gas tank, compressor, and expander, respectively.
$(E_{\text{min}}^t, E_{\text{max}}^t)$	Minimum and maximum energy allowed in a gas tank at t .
$(P_{\text{vp}, \text{min}}^t, P_{\text{vp}, \text{max}}^t)$	Minimum and maximum power allowed for an expander at t .

$(P_{\text{vc}, \text{min}}^t, P_{\text{vc}, \text{max}}^t)$	Minimum and maximum power allowed for a compressor at t .
$P_{0 \text{ max}}$	Maximum real power allowed for the root node.
$P_{\text{DG}i, \text{max}}$	Maximum real power allowed for distributed generation at bus i .
$\tan \delta$	Power factor of distributed generation.
$(V_{i, \text{min}}, V_{i, \text{max}})$	Minimum and maximum voltage allowed at bus i .
$I_{ij, \text{max}}$	Maximum current flow allowed on line i, j .
V_i^t	Voltage at bus i at t .
θ_{ij}	The angle between the bus voltage i and j .
P_0^t	Real power demand of root node at t .
S_l	Switching action times.
α_l	Branch l connection state, if it connected, is 1, whereas $\alpha_l = 0$.
α_{l0}	Initial state of branch l .
(G_{ij}, B_{ij})	Conductance and susceptance between node i and j .
(P_{Gi}^t, Q_{Gi}^t)	Real and reactive power output at bus i at t .
$(P_{\text{DG}i}^t, Q_{\text{DG}i}^t)$	Real and reactive power output of distributed generation at bus i at t .
$(P_{\text{Load}i}^t, Q_{\text{Load}i}^t)$	Real and reactive load demand at bus i at t .
$Q_{\text{Com}i}^t$	Reactive power compensation at bus i at t .
β_{ij}	Binary variable; equals 1, if bus j is the parent of bus i , and 0, otherwise.
$P_{\text{wind}i}^t$	Wind power at bus i at t .
$(P_{\text{vp}i}^t, P_{\text{vc}i}^t)$	Expander and compressor output at bus i at t .
E_i^t	Energy in a gas tank at bus i at t .
(dvp_i, dvc_i)	Binary variable to indicate the status of energy storage. If stores energy (1,0), or releases energy (0,1).

I. INTRODUCTION

ACTIVE distribution networks usually build a closed loop network frame but it is radially operated to assure the safety of the grid [1]. Distribution network reconfiguration has been proposed [2] to improve reliability, reduce line loss, balance load and improve power quality. Reconfiguration in the distribution network is based on the changes in load, and changing the switches to closed and open to achieve transfer loads among the lines, whose purpose is to improve their reliability and economy.

At present, the proportion of distributed generation (DG) is gradually increasing in the distribution system. It has certain advantages in reducing network losses and improving economy [3], [4]. However, DG has the characteristics of

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Z. W. Cui, X. Q. Bai (corresponding author, e-mail: baixq@gxu.edu.cn), P. J. Li, B. Li, X. Y. Su and Y. Zheng are with the Guangxi Key Laboratory of Power System Optimization and Energy Technology, Guangxi University, Nanning 530004, China.

J. Cheng is with the WindMagics Energy Co. Ltd., Wuhan 430206, China.

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uncertainty, such as wind power and photovoltaics, which are not appropriate for considering the output power of DG as parameters. Considering the uncertainty of renewable DG output power and load variability, reference [5] proposed a long-term method of reconfiguration to maximize the benefits of DG allocation. Furthermore, considering the influence of DG uncertainty in the distribution network reconfiguration, the profit of the system can be further improved [6], [7].

The methods of solving uncertain power in the distribution network as presented in literature fall into two general categories: soft strategy and hard strategy. The soft strategy focuses on the mathematical models and the algorithms, while the distribution network reconfiguration algorithms considering uncertainty currently are stochastic optimization (SO) [8], a heuristic method [9] and robust optimization (RO) [10]. The stochastic optimization can only consider a finite number of scenarios, and the computation efficiency of the heuristic method is low as well. In contrast, the optimal solution obtained by the RO model includes all the uncertainties on a specific set [11], while the computing consumption of RO is moderate. The RO method has been applied to solve the reconfiguration problem that takes into account the uncertainty of load demand or renewable energy [12].

The hard strategy considers using physical equipment, such as energy storage devices, to solve the uncertainty in the power system. For solving the prediction error of renewable energy, it computes the optimal base-point conventional generation and storage schedule by operating a storage portfolio via receding horizon control [13]. In the network containing an energy storage system, an adjustable robust optimization method is proposed for the uncertainty of renewable energy. This method can solve the problem of DG uncertainty through coordinated control of the energy storage system using quadratic programming [14], [15].

By eliminating the side effects of uncertainty on the distribution network reconfiguration, such as low economy and reliability, a robust optimal method considering uncertain power is proposed in this paper by combining physical equipment, for instance, CAAWTS, which is used to coordinate wind power [16]. However, the energy storage capacity of the CAAWTS system is at a kilowatt level, which is not enough to solve the uncertainty of wind power. Thus, a distribution network reconfiguration model based on robust optimization is proposed and solved by the explicit maximum value method. The proposed model is reformulated as a deterministic mixed-integer second-order cone programming problem based on Jordan frames, which can be solved efficiently by using an existing solver, such as CPLEX [17] or Gurobi [18]. Furthermore, this model considers the reconfiguration optimization of the 24 periods in a day, which has been validated by dynamic reconfiguration in a simulation. Simulation studies show that the proposed model of reconfiguration has a high effect on improving the utilization rate of wind energy in the distribution network, reducing power losses and increasing the operational stability level of the distribution network.

This paper is organized as follows. In Section II, based on Jordan frames, a mixed-integer second-order cone optimization reconfiguration model is proposed in detail. In Section III,

the RO model is presented, as well as the simulation process and the flow chart of the simulation. Numerical experiments are provided in Section IV. Finally, the conclusions are presented in Section V.

II. NETWORK RECONFIGURATION

With the connecting of DGs and energy storages to the existing system, the distribution network has to change its traditional operational mode. Assume that all lines are equipped with sectionalizing or tying switches. The proposed model is defined to determine the minimum cost subject to operating constraints. The network cost is equal to the summation of the network operational costs in the total system and the switching operational costs. The objective function of the problem can be expressed as:

$$\text{Minimize } C_p \sum_{t=1}^T P_0^t + C_s \sum_{l=1}^L S_l \quad (1)$$

Subject to the following constraints:

A. Power Flow Equation Constraints

For improving the efficiency of the calculation, this paper uses a second-order cone programming method based on Jordan frames to establish the power flow equation. Jordan values and Jordan frames are treated equivalently to eigenvalues and eigenvectors from the original problem. The power flow equation can be expressed by coned relaxation using Jordan frames [19].

The active/reactive power balance constraints are

$$P_{Gi}^t + P_{DGi}^t - P_{Loadi}^t = \sum_{j \in N(i)} \alpha_{ij} [-G_{ij}(V_i^t)^2 + V_i^t V_j^t (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij})] \quad (2)$$

$$Q_{Gi}^t + Q_{Comi}^t - Q_{Loadi}^t = \sum_{j \in N(i)} \alpha_{ij} [B_{ij}(V_i^t)^2 + V_i^t V_j^t (G_{ij} \sin \theta_{ij} - B_{ij} \cos \theta_{ij})] \quad (3)$$

where

$$\begin{cases} \lambda_i^t = (V_i^t)^2/2 \\ \lambda_j^t = (V_j^t)^2/2 \\ f_{pi}^+ = V_i^t V_j^t \cos \theta_{ij} \\ f_{pi}^- = V_i^t V_j^t \sin \theta_{ij} \\ 4\lambda_i^t \lambda_j^t = (f_{pi}^+)^2 + (f_{pi}^-)^2 \end{cases} \quad (4)$$

Equations (2) and (3) become

$$P_{Gi}^t + P_{DGi}^t - P_{Loadi}^t = \sum_{j \in N(i)} \alpha_{ij} (-G_{ij} \lambda_i^t + G_{ij} f_{pi}^+ + B_{ij} f_{pi}^-) \quad (5)$$

$$Q_{Gi}^t + Q_{Comi}^t - Q_{Loadi}^t = \sum_{j \in N(i)} \alpha_{ij} (B_{ij} \lambda_i^t + G_{ij} f_{pi}^- - B_{ij} f_{pi}^+) \quad (6)$$

In (4), $\lambda_i^t \geq 0$ and $\lambda_j^t \geq 0$, the following formula can be derived based on [19].

$$\|[(V_i^t)^2/2 - (V_j^t)^2/2, V_i^t V_j^t \cos \theta_{ij}, V_i^t V_j^t \sin \theta_{ij}]\|_2$$

$$\begin{aligned}
&= \sqrt{(\lambda_i^t - \lambda_j^t)^2 + (f_{pi}^+)^2 + (f_{pi}^-)^2} \leq (V_i^t)^2/2 + (V_j^t)^2/2 \\
&= \lambda_i^t + \lambda_j^t
\end{aligned} \quad (7)$$

Its structure is shown in Fig. 1.

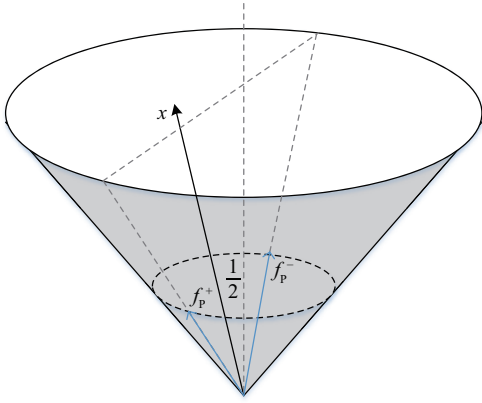


Fig. 1. Jordan frames in a cone.

B. System Operational Constraints

1) Power-output limit of the power substation:

$$P_0^t \leq P_{0\max} \quad (8)$$

2) Active power-output limit of DG:

$$0 \leq P_{DGi}^t \leq P_{DGi,\max} \quad (9)$$

3) Reactive power-output of DG:

$$Q_{DGi}^t = P_{DGi}^t \tan \delta \quad (10)$$

4) Voltage magnitude limits:

$$V_{i,\min} \leq V_i^t \leq V_{i,\max} \quad (11)$$

5) Maximum allowable current carrying capacity of transmission lines [20]:

$$(I_{ij}^t)^2 = \alpha_{ij}(G_{ij}^2 + B_{ij}^2)(\lambda_i^t + \lambda_j^t - 2f_{pi}^+) \leq I_{ij,\max}^2 \quad (12)$$

Noted that the line l is connected to the switch status of the corresponding node i and node j as in α_{ij} . It can be expressed as α_l too. However, α_l is a discrete variable, which can lead to the complexity of power flow constraint equations.

C. Network Radiality Constraints

Constraint (13) is used to guarantee the network radially, but it is not sufficient. Thus, spanning tree constraints are used in this paper, that is, α_l will be replaced by two binary variables β_{ij} and β_{ji} . Furthermore, it is necessary to limit the number of switching actions to ensure the service life of the switchgear. Therefore, it can be expressed by the following constraint [21]:

$$\sum_{l=1}^L \alpha_l = N - 1 \quad (13)$$

$$\beta_{ij} + \beta_{ji} = \alpha_l \quad (14)$$

$$\sum_{j \in N(i)} \beta_{ij} = 1 \quad (15)$$

$$\beta_{0j} = 0 \quad (16)$$

$$\beta_{ij} \in \{0, 1\}, \quad i = 1, \dots, n \quad j \in N(i) \quad (17)$$

$$0 \leq \alpha_l \leq 1, \quad l = 1, \dots, m \quad (18)$$

$$\sum_{l=1}^L |\alpha_l - \alpha_{l0}| \leq N_{\text{action}} \quad (19)$$

Equation (14) indicates that every node has exactly one parent beside the substation node, while (15) indicates that the substation node has no parent nodes. For the absolute value of the constraint (19), (19) can be denoted by the following constraints since $|\alpha_l - \alpha_{l0}| = \max\{\alpha_l - \alpha_{l0}, \alpha_{l0} - \alpha_l\}$:

$$\sum_{l=1}^L S_l \leq N_{\text{action}} \quad (20)$$

$$S_l \geq \alpha_l - \alpha_{l0}, S_l \geq \alpha_{l0} - \alpha_l, l = 1, \dots, L \quad (21)$$

D. A Compressed-air-assisted Wind Turbine System

DG in this paper is wind power. A compressed air assisted wind turbine system (CAAWTS) is adopted to improve the consumptive ability of the power grid with DG. It provides an adaptive structure to reduce the deviation between wind energy and load. From an energy point of view, the storage system serves as a buffer between the mechanical power of the wind power and the electric power to the load. A more detailed discussion about CAAWTS can be found in our previous study [16]. We have derived the relationship between the power of CAAWTS and the pressure, the volume, the moment, the angle and the angular velocity. As a result, the relationship between power and energy can be obtained, and a dynamic mathematical model of CAAWTS is established as follows:

$$0 \leq P_{DGi}^t \leq P_{\text{wind}i}^t + P_{\text{vpi}}^t - P_{\text{vci}}^t \quad (22)$$

$$P_{\text{vpi}}^t = \kappa E_i^t + \beta \quad (23)$$

$$E_i^{t+1} = \eta_e E_i^t + \eta_{vc} P_{\text{vci}}^t \Delta t - P_{\text{vpi}}^t \Delta t / \eta_{vp} \quad (24)$$

$$E_{\min}^t \leq E_i^t \leq E_{\max}^t \quad (25)$$

$$E_0^t \leq E_i^{\varphi, T} \quad (26)$$

$$P_{\text{vp}, \min}^t \leq P_{\text{vpi}}^t \leq P_{\text{vp}, \max}^t \quad (27)$$

$$P_{\text{vc}, \min}^t \leq P_{\text{vci}}^t \leq P_{\text{vc}, \max}^t \quad (28)$$

$$P_{\text{vpi}}^t \cdot P_{\text{vci}}^t = 0 \quad (29)$$

Equation (22) indicates the relationship between wind power, energy storage, and distributed generations. It is noted that (29) is a complementary constraint, which can be expressed as the following using Big-Mmethod [10]:

$$\begin{cases} P_{\text{vpi}}^t \leq M(1 - d_{vp_i}) \\ P_{\text{vci}}^t \leq M(1 - d_{vc_i}) \\ d_i = d_{vp_i} + d_{vc_i} \\ 0 \leq d_i \leq 1 \end{cases} \quad (30)$$

Thus, the deterministic optimization reconfiguration model (DOR) (1), (4)–(18), (20), (21), (23)–(28), (30) is proposed. Note that CAAWTS is not enough to eliminate the uncertainty of DG because its capacity is only at a kilowatt-level, but the capacity of a distribution network is mostly at a megawatt-level. The RO method is proposed to eliminate uncertainty further in the next section.

III. ROBUST OPTIMIZATION FOR UNCERTAINTY IN WIND POWER

A. Uncertainty Set

The uncertain parameters in the DOR include the wind power (P_{windi}^t), and load (P_{Loadi}^t) during each t . The predicted values of P_{windi}^t and P_{Loadi}^t can be obtained based on a time series forecasting method. However, the level of uncertainty of P_{windi}^t is much higher than that of P_{Loadi}^t since the wind power has greater volatility and intermittence than load in general. Therefore, in this paper, only wind power (P_{windi}^t) during t is considered as an uncertain parameter for the sake of simplicity, which is denoted as $\tilde{P}_{windi}^t$. Nevertheless, the uncertainties of P_{Loadi}^t can be considered in the same way.

The uncertainty set ψ_i of $\tilde{P}_{windi}^t$ for the aggregator i in a given T is defined as the following [10]:

$$\psi_i(\varepsilon, v_i, P_{wind}^t) := \left\{ P_{wind}^t : \exists \gamma_i^t \in \mathbb{R}^T \text{ s.t. } \tilde{P}_{windi}^t \in \left[P_{windi}^t - \varepsilon P_{windi}^t |\gamma_i^t|, P_{windi}^t + \varepsilon P_{windi}^t |\gamma_i^t| \right], |\gamma_i^t| \leq 1, \frac{1}{T} \sum_{t=1}^T |\gamma_i^t| \leq v_i \right\} \quad (31)$$

Note that the set ψ_i contains all possible values of wind power P_{windi}^t in the range $[P_{windi}^t - \varepsilon P_{windi}^t |\gamma_i^t|, P_{windi}^t + \varepsilon P_{windi}^t |\gamma_i^t|]$. The value of v_i represents the uncertainty level of ψ_i , where a larger v_i shows a higher level of uncertainty.

Since $|\gamma_i^t| \leq 1$ and $\frac{1}{T} \sum_{t=1}^T |\gamma_i^t| \leq v_i$, when $v_i = 0$, the set (31) can be considered a nominal deterministic case P_{windi}^t . As v_i increases, the range of the uncertainty set ψ_i enlarges. It means that a more significant deviation of the total wind power from the predicted value is considered. When v_i reaches its maximum, it is the worst case that the system needs to deal with. Then, the resulting RO model contains the worst-case scenarios that the system needs to deal with, and the system is protected against a higher degree of uncertainty.

B. RO Model

Define the vector of decision variables x . The DOR model can be expressed in the following form:

$$\begin{aligned} \min & f(x) \\ \text{s.t.} & g(x) \prec 0 \end{aligned} \quad (32)$$

where represents the objective function without uncertain variables, and represents the constraint conditions without uncertain variables.

Then, defining the set of uncertainty parameters, $\varphi = [\gamma_i^t]$ and $\psi = \prod_{i=1}^d \psi_i$, the following RO model can be established based on (31).

$$\begin{aligned} \min & \max_{\varphi} f(x, \varphi) \\ \text{s.t.} & g(x, \varphi) \prec 0, \forall \varphi \in \psi \end{aligned} \quad (33)$$

where represents the objective function with uncertain variables, and represents the constraints condition with uncertain variables.

P_{windi}^t in (22) is replaced with $\tilde{P}_{windi}^t$, and the constraints of the original uncertain parameters can be changed as:

$$0 \leq P_{DGi}^t \leq \tilde{P}_{windi}^t + P_{vpi}^t - P_{vci}^t \quad (34)$$

$$\begin{aligned} P_{G0}^t + \beta_0^t \sum_{i=1}^{N_R} \zeta_i (\tilde{P}_{windi}^t - P_{windi}^t) - P_{G0,max}^t &\leq 0, \\ P_{G0}^t - \beta_0^t \sum_{i=1}^{N_R} \zeta_i (\tilde{P}_{windi}^t - P_{windi}^t) - P_{G0,min}^t &\geq 0 \\ \forall \zeta_i : \|\zeta_i\|_\infty &\leq \Gamma_R, \forall \zeta_m : \|\zeta_m\|_\infty \leq \Gamma_L \\ P_{j,DG}^t + \beta_j^t \sum_{i=1}^{N_R} \zeta_i (\tilde{P}_{windi}^t - P_{windi}^t - P_{vpi}^t + P_{vci}^t) & \\ - P_{j,DG,max}^t &\leq 0, \\ P_{j,DG}^t - \beta_j^t \sum_{i=1}^{N_R} \zeta_i (\tilde{P}_{windi}^t - P_{windi}^t - P_{vpi}^t + P_{vci}^t) &\geq 0 \\ \forall \zeta_i : \|\zeta_i\|_\infty &\leq \Gamma_R, \forall \zeta_m : \|\zeta_m\|_\infty \leq \Gamma_L \end{aligned} \quad (35)$$

Compared with the solution of the DOR model which can only ensure the feasibility for a single scenario, and that of the stochastic optimization method which considers limited quantities of scenarios of $\tilde{P}_{windi}^t$, the RO model considers all possible scenarios of $\tilde{P}_{windi}^t$ using the uncertainty set ψ_i . However, the RO model becomes complicated in trying to solve directly. Therefore, the robust counterpart approach, such as relaxation, duality properties, or explicit maximization [22], by removing the uncertainties, is applied to solve the proposed RO model in this paper.

C. Computable Conversion of RO

The constraints of (34)–(36) involving uncertainties are the wind power output. They are not computable. The explicit maximum method can effectively eliminate uncertainty which is primarily based on finding the maximum value of uncertain parameters so that the maximum analysis of uncertainty is achieved. Considering an element oriented uncertainty constraint, its uncertain parameters $\varphi \in \psi$ belong to a standard ball.

$$(c^T \varphi + d) + (A\varphi + b)^T x \leq 0 \quad \forall \varphi : \|\varphi\|_p \leq 1 \quad (37)$$

where φ satisfies $\max_{\|\varphi\|_p \leq 1} q^T \varphi$ equal to $\|q\|_{p^*}$, and $\|\cdot\|_{p^*}$ represents the dual p -norm, and $1/p + 1/p^* = 1$ [23]. Therefore, robust constraints can be represented as:

$$(b^T x + d) + \|c + A^T x\|_{p^*} \leq 0 \quad (38)$$

The constraints (34)–(36) with uncertainty parameters are represented in the following form without uncertainty parameters.

$$P_{DGj}^t - P_{windj}^t - \beta_j \|P_{windi}^t\|_{p^*} - P_{vpj}^t + P_{vcj}^t \leq 0 \quad (39)$$

$$\begin{aligned} P_{G0}^t + \left\| \beta_0^t \sum_{i=1}^{N_R} (\tilde{P}_{windi}^t - P_{windi}^t - P_{vpi}^t + P_{vci}^t) \right\|_{p^*} & \\ - P_{G0,max}^t &\leq 0 \\ P_{G0}^t - \left\| \beta_0^t \sum_{i=1}^{N_R} (\tilde{P}_{windi}^t - P_{windi}^t - P_{vpi}^t + P_{vci}^t) \right\|_{p^*} & \\ - P_{G0,min}^t &\geq 0 \\ P_{j,DG}^t - \left\| \beta_j^t \sum_{i=1}^{N_R} (\tilde{P}_{windi}^t - P_{windi}^t - P_{vpi}^t + P_{vci}^t) \right\|_{p^*} & \end{aligned} \quad (40)$$

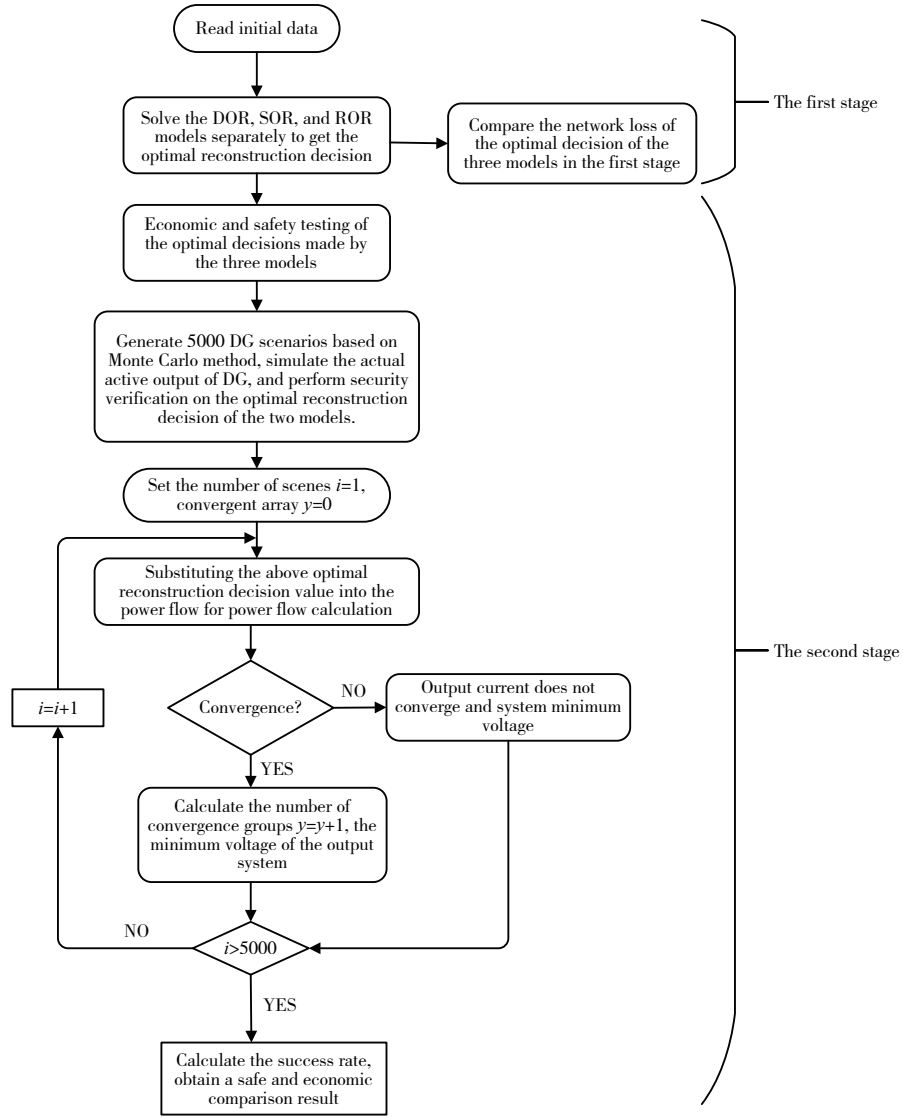


Fig. 2. Flow chart of the simulation.

$$\begin{aligned}
 & -P_{j,DG,\max}^t \leq 0 \\
 & P_{j,DG}^t - \left\| \beta_j^t \sum_{i=1}^{N_R} (\tilde{P}_{windi}^t - P_{windi}^t - P_{vp_i}^t + P_{vc_i}^t) \right\|_{p^*} \geq 0
 \end{aligned} \quad (41)$$

The robust optimization reconfiguration model (ROR) (1), (4)–(18), (20), (21), (23)–(28), (30), (39)–(41) does not contain any uncertainty. Furthermore, this model has been a mixed-integer second-order cone programming problem, which can be efficiently solved by GUROBI.

The simulation process is as follows.

Step1: Constructing a network reconfiguration model by the cone relaxation method

Step2: Describing the uncertainty set

Step3: The uncertain model is transformed into the deterministic model solved by the maximum explicit method.

Step4: The DOR, SOR, and ROR are solved respectively, and their optimal decisions are obtained respectively.

Step5: The Monte Carlo method is used to simulate the

output of wind power, and the results of calculating the security economy are compared by iteration.

Figure 2 illustrates in detail how the proposed hard and soft strategies effectively solve the influences of uncertain wind power on the problem of distribution network reconfiguration.

IV. NUMERICAL RESULTS

Three tests are used for simulation. They are IEEE-16 with 13 nodes and 16 lines [24], IEEE-33 with 33 nodes and 37 lines [5], and PG& E-69 with 69 nodes and 73 lines [24], respectively. The duration of each dispatch interval t is 1 h and the value of T is 24. The 24-hour base load curve is obtained by scaling the actual hourly loads in the northwestern United States [25]. The wind power curve is used as the predicted values are utilized by scaling the actual wind power of the Irish wind farm on January 1, 2013 [26]. Two CAAWTSs are installed on No. 7 node of IEEE-16, three CAAWTSs are installed on No. 10 node of IEEE-33, and No. 20 node of PG&E-69, respectively. Maximum capacity of CAAWTS is

200 kW. η_e , η_{vc} and η_{vp} are 0.9, 0.65 and 0.65 respectively. The test environment is Matlab 2014 with a 2.53 GHz Duo CPU and 8 GB of RAM, and the models are solved by Gurobi 7.1.

Three models are formulated to compare the effects of different methods on reconfiguration. They are DOR, stochastic optimization reconfiguration (SOR), and ROR, respectively, where SOR considers uncertainty by using the scenario-tree analysis method and ROR using the uncertain set of DG. To satisfy the economic benefits of the distribution network reconfiguration, it is assumed that the switching action for the distribution network reconfiguration is only allowed if the expected network loss can be reduced more than 1 kW. The simulation process consists of two stages as follows:

The first stage (scheduling decision-making stage): DOR, SOR, and ROR are solved respectively, and their optimal decisions are obtained respectively.

The second stage (actual operation/verification stage): The Monte Carlo method is used to simulate the output of wind power. Then, the security of the optimal decision made in the first stage is verified, and their economy is compared. Finally, we compare the expected value and the variance of the objective function obtained by convergence and non-convergence.

A. Comparison and Analysis of the First Stage Optimal Decision

1) The Utilization Rate of Wind Energy

The daily peak load is at 12:00 and 20:00 since a large number of users use electricity at the same time. Due to the natural characteristics of the wind, the original wind power has less output at 12:00 and 20:00, which cannot be used for the peak-load shifting. For solving this problem, CAAWTS is used to adjust the output of DG in each dispatch interval through its energy storage device. Figure 3 shows that the DG power curve of DOR and ROR reach a peak at 12:00 and 20:00 respectively, but SOR does not. That is, both DOR and ROR can obtain benefits from the operation of CAAWTS, which can improve the utilization ratio of wind, and shift the peak-load as well. The advantage of CAAWTS in partial controllability of wind energy is fully realized by using both DOR and ROR. It can be seen that the optimization effect of DOR in the first stage is the best by comparing the DG power curve of the three models since DOR did not consider any uncertainty. The optimization results of SOR are the worst.

The energy storage device is integrated into the CAAWTS, and the output of DG power in each dispatch interval can be adjusted through the stored energy. The curve of stored energy in the CAAWTS is shown in Fig. 4. At the initial and the end time, the energy in the air tank is set to be consistent for keeping the energy balance and enable CAAWTS to continue working. Based on the curve of the daily load in Fig. 3, it can be seen that the peak load consumption happens at 12:00 and 20:00, respectively. Figure 4 shows that DOR and ROR have an energy storage period before 12:00 and 20:00 respectively, then release the stored energy afterword. However, SOR only has an energy storage period before 12:00, but has two periods of releasing during the day. It is demonstrated that all three

models can shift the peak-load during a day, while DOR and ROR have relatively better performance on the utilization efficiency of the energy storage device than SOR.

As shown in Fig. 5, the output power of the root node by

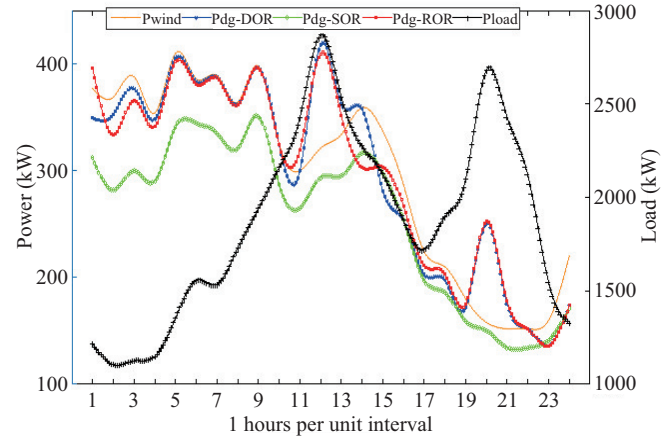


Fig. 3. DG power curve under different models.

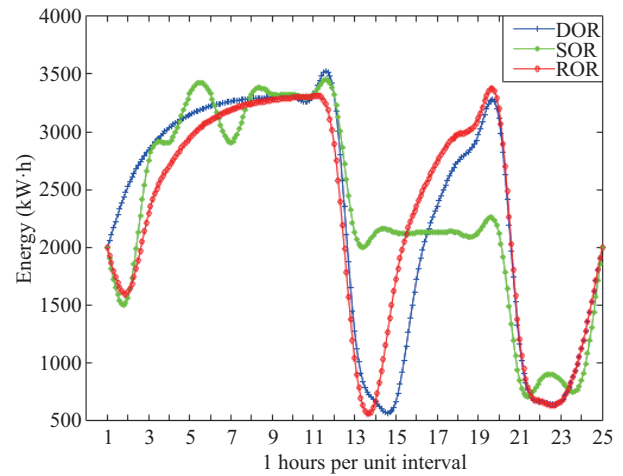


Fig. 4. Energy change of energy storage under different models in the IEEE-16.

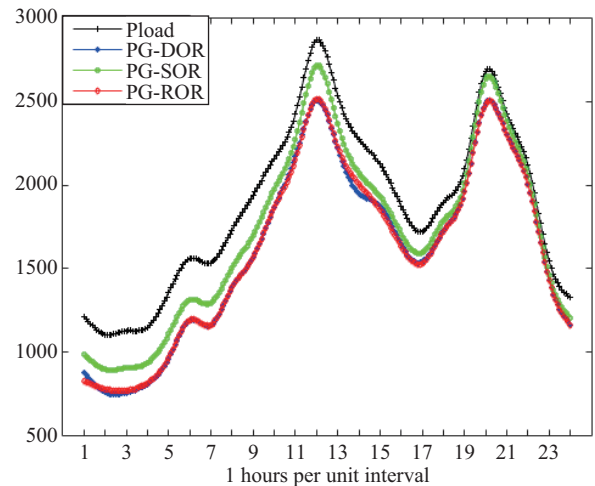


Fig. 5. Generator output curve under different models in the IEEE-16.

DOR, SOR or ROR can follow the change of the active load. However, the peak-valley difference using SOR is the largest since the CAAWTS in the SOR model did not effectively take advantage. In contrast, the peak-valley of DOR and ROR are relatively small, which indicates that the CAAWTS can be used to achieve peak shifting and valley filling.

2) The Influence of the Maximum Number of Switching Action for Power Network Loss

Figure 6 shows the active power network loss of DOR, SOR, and ROR under different maximum switching action times. The total system active power loss of all three models tends to decrease with the increase of the switching action numbers. When the maximum switching action number is equal to or more than 6, the power network loss of all models is relatively small. Furthermore, they are keeping almost the same values, and even the maximum switching action number is getting larger. Therein, the power network loss of DOR is mostly reduced, that of ROR is second, and that of SOR is the worst. When the models consider uncertainty, the optimization effect is always conservative, but ROR is better than SOR.

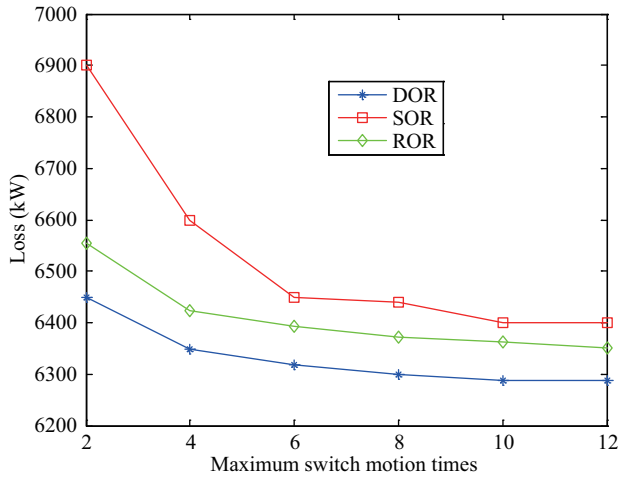


Fig. 6. Daily power Loss versus the number of switch motions in IEEE-16.

Table I lists the power network losses and the costs of different models when $N_{\text{action}} = 6$. The results show that all models combined with hard and soft strategies can reduce power network losses. DOR reduces the power network loss the most since it did not consider any uncertainty in the first stage. Both SOR and ROR take account of uncertainty in the models, but SOR cannot shift the peak-load during a day. Therefore, ROR can reduce the power network losses more than SOR.

TABLE I
POWER LOSSES OF THE THREE MODELS

Models	Initial losses (MW)	Optimization losses (MW)	Optimization rate (%)	Power generation cost (¥)
DOR	9.8561	6.3814	35.254	21046.65
SOR	9.8561	7.4921	23.985	21723.47
ROR	9.8561	6.6412	32.618	21162.91

In the hard strategy with CAAWTS, the mechanical power of DG, named wind power in this study, is compressed into

energy storage and is released as electric power when necessary. In a sense, the output powers of DG can be considered as being dispatchable partially by controlling P_{vpi}^t and P_{vci}^t in a CAAWTS using soft strategy. Figure 7 shows that the daily output power curves of DG after coordinating with CAAWTS of ROR under different numbers of switching actions from 2 to 12. It is obvious that different switching action numbers affect the DG output power. With the increase of switching action, the optimization effect of daily output powers of DG tends to move to astable value, when the switching action is 6.

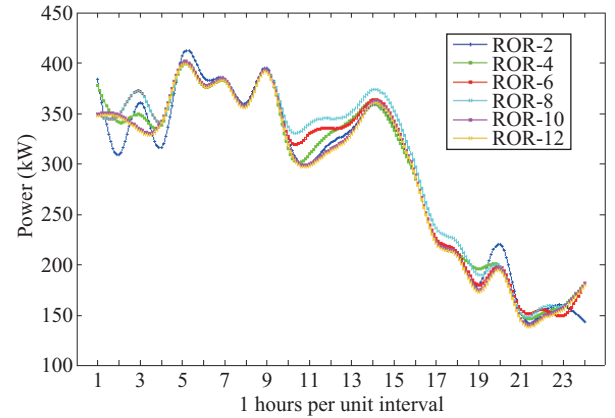


Fig. 7. DG output curve under different switching numbers.

Different numbers of switching action also affect the air energy storage of CAAWTS. The daily variation energy curve of air energy storage in the CAAWTS system is shown in Fig. 8 under different numbers of switching actions from 2 to 12. With the increase of switching action, the optimization effect of daily variation energy in CAAWTS tends to move to astable value, when the switching action is 6.

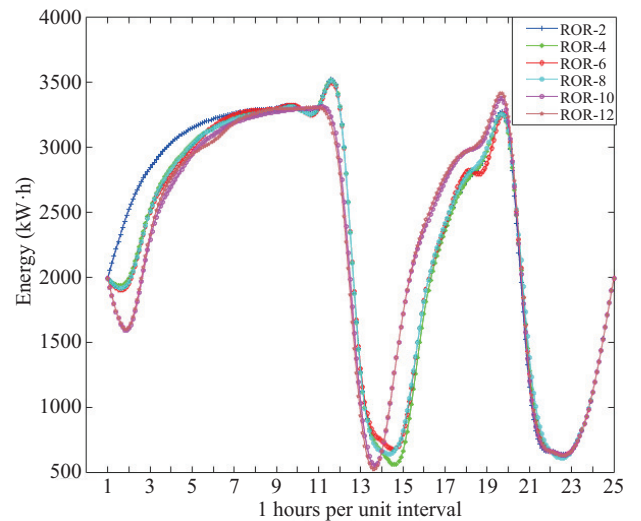


Fig. 8. Energy storage change curve under different maximum numbers of switching action.

Therefore, we can set the maximum switching action number to $N_{\text{action}} = 6$ for each model, since the optimal power network loss can be obtained.

Figure 9 shows that P_{vp}^t and P_{vc}^t of CAAWTS during a 24-period in IEEE-16 using ROR when the maximum switching action number is 6. It can be seen that CAAWTS compresses energy when wind power is high, and CAAWTS releases power when wind power is low as expected.

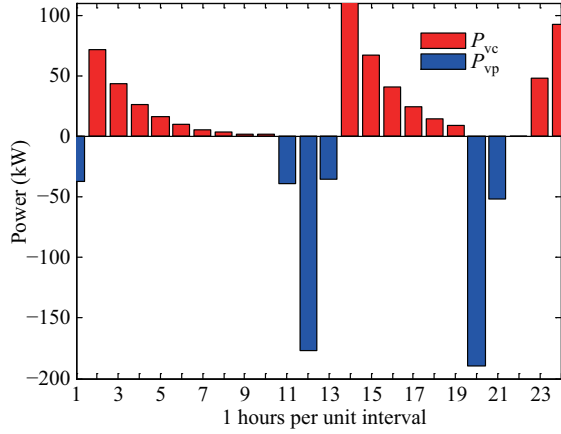


Fig. 9. Change of expander and compressor output under ROR model in IEEE-16.

3) The Influence of the Uncertainty Level of Wind Power

Figure 10 shows that the network loss curves under different uncertain level of ν_i . With the increase of the uncertainty level, the network loss is increasing. This is due to the conservatism of robust optimization in order to satisfy the possibility of all the uncertain parameters. In order to ensure that the optimal decision is adapted to all the scenarios, the economy is sacrificed.

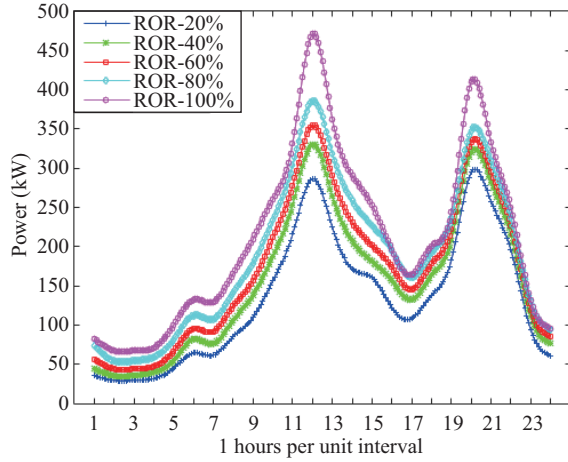


Fig. 10. Power loss curve under different uncertain levels.

B. Comparison and Analysis of the Second Stage Operation

The comparison and analysis of the economy, security, and stability for the first stage optimal decision among different models are presented in this sub-section. The Monte Carlo method is used to randomly generate 1,000 wind power scenarios, and each wind power scenario has 24 sequential values. The optimal daily decision by each model from the first stage is analyzed using the snapshot power flow calculation

for each interval t . We consider that it is successful if the instant power flow calculation of t converges. Otherwise, it failed. Therefore, the success rate is equal to the ratio of the numbers of convergent power flow to $24 \times 1,000$.

1) Comparison of Success Rates of Different Models

Table II shows the comparison results of the success rates of the power flow calculation in the second stage for IEEE-33 and PG&E-69.

TABLE II
COMPARISON OF THE SUCCESS RATES OF THREE RECONSTRUCTION MODELS IN IEEE-33 AND PG&E-69

Scenes	Uncertainty level (%)	The success rates of IEEE33 system (%)			The success rates of PG&E69 system (%)		
		DOR	SOR	ROR	DOR	SOR	ROR
1	20	79.26	84.67	100	85.63	94.31	100
2	40	67.67	78.21	100	69.25	78.92	100
3	60	52.98	70.13	100	50.31	71.14	100
4	80	41.84	50.41	100	42.66	53.48	100
5	100	31.53	35.62	100	33.10	38.69	100

With increasing the uncertainty level of the variables, the success rates of DOR and SOR is decreasing, and that of DOR is the worst since the optimal decision of DOR in the first stage did not consider uncertainty at all. Conversely, the success rate of ROR always maintains 100% since ROR has considered uncertainty in the first stage. The results show that the optimal reconfiguration decision of ROR ensures the safe and stable operation of the system. Compared with DOR and SOR, ROR has strong robustness, and it can effectively adapt to the uncertainty of DG output power.

2) Cost Comparison of Different Models

Equation (42) is applied to obtain the system economic profit of the three models. Note that the penalty cost is $S_{\text{loss}}^t = 0$ if the power flow calculation is convergent at t . Otherwise, S_{loss}^t is set to a large number such as 500 in this study, which is: $\sum_{t=1}^T C_{\text{load}} \sum_{j=1}^{\text{Nload}} P_{j,\text{load}}^t / 2t$.

$$Fe = \sum_{t=1}^T (C_{\text{load}} \sum_{j=1}^{\text{Nload}} P_{j,\text{load}}^t - C_p P_0^t - S_{\text{loss}}^t) - C_s \sum_{l=1}^m s_l \quad (42)$$

The economic efficiency in the IEEE-33 and PG&E-69 are shown in Figs. 11 and 12, respectively. It can be seen from the scatter plot that ROR has the best economic performance in the second stage, and the spots are more concentrated than the others. Because ROR can ensure the safety of the distribution network, it has the best economy in the scenario simulation. SOR is not as robust as ROR, and its dispersion degree is high. The economic benefits of DOR are the worst. The results verify the effectiveness of the proposed robust optimization model and method.

3) Comparison of Robustness Among Three Models

Figure 13 is the expected values and the mean square error of the second stage of the IEEE-33 and the PG&E-69. The results of the analysis show that ROR is the most consistent with the operation of the power system, and its economy is the best compared with DOR and SOR.

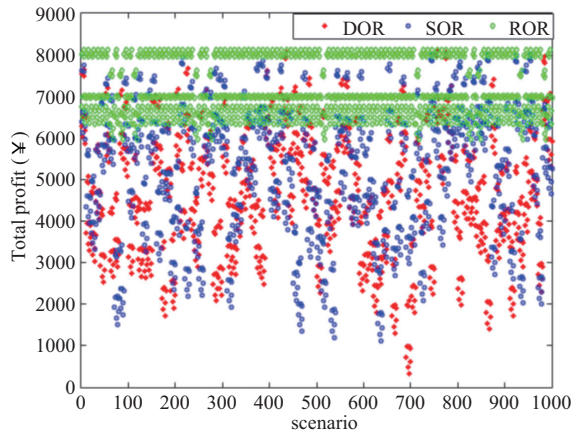


Fig. 11. IEEE-33 profit of three models in stage II.

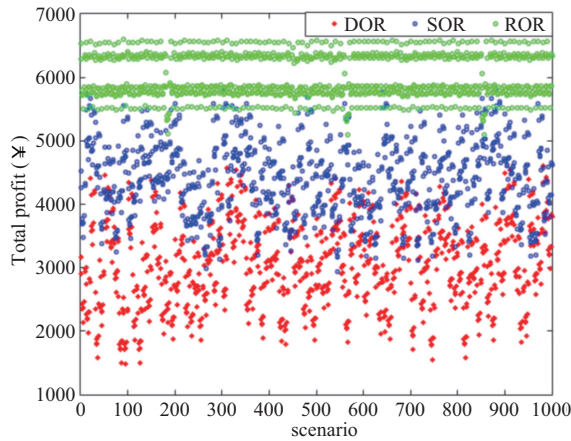


Fig. 12. PG&E-69 profit of three models in stage II.

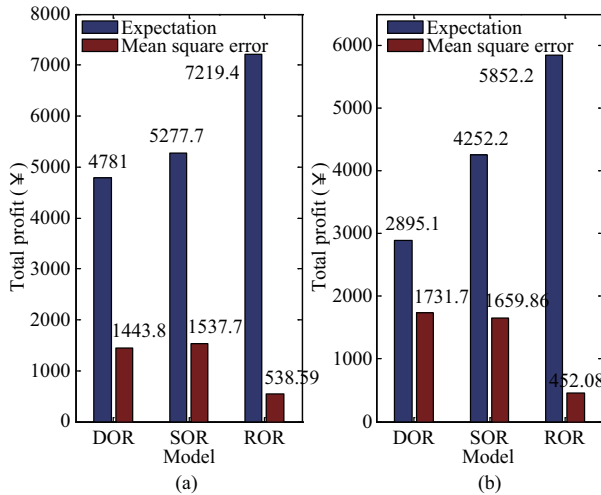


Fig. 13. Expected values and mean square error. (a) IEEE-33. (b) PG&E-69.

V. CONCLUSION

In this paper, the hard strategy with CAAWTS and the soft strategy based on robust optimization are used to solve the problem of distribution network reconfiguration considering uncertain output power of DG. The compressed air energy storage in CAAWTS is used to make a certain adjustment for

the output power of DG, such as wind power. The feasibility of the proposed ROR model and method is verified by numerical simulation. Especially, ROR can achieve 100% power flow convergence in all simulation scenarios, and ROR can achieve the best economy compared with DOR and SOR as well. The proposed ROR with hard and soft strategies has the best effect for solving the optimization problem of the distribution network reconfiguration with uncertain parameters, which can effectively improve the safety of the distribution system and improve the economic performance of the system.

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Bin Li received her B.E. degree in Electric Power Systems and Automation from Zhejiang University, Hangzhou, China, in 1997, and her M.E. and Ph.D. degrees in Electric Power Systems and Automation from Guangxi University, Nanning, China, in 2001 and 2011, respectively, where she is currently an Associate Professor with the Guangxi Key Laboratory of Power System Optimization and Energy Technology. Her current research interest includes optimization theories and their applications in power systems.



Jie Cheng received his B.S. degree from Wuhan University, Wuhan, China, in 2005 and his Ph.D. degree at the University of Nebraska-Lincoln, Lincoln, Nebraska, USA, in 2016, respectively.

He is currently a product director at WindMagics Energy Co. Ltd., Wuhan, China. And he is a registered Professional Engineer in California. His research interests include: microgrid, renewable energy integration, distributed generation, and energy storage.



Zhiwei Cui received his B.S. degree in Electrical Engineering from Guangxi University (GU), China, in 2015, and his M.S. degree in Electrical Engineering from Guangxi University (GU), China, in 2018. He currently works at Guangxi Power Grid Co., Ltd. His main research direction: distribution network planning and robust optimization.



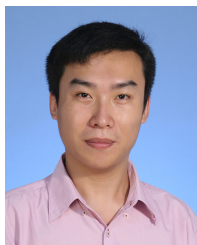
Xiangyang Su received his B.S. degree in Electrical Engineering from Guangxi University (GU), China, in 2017. Currently, he is a Masters student at Guangxi Key Laboratory of Power System Optimization and Energy Technology, GU. His current research interests include robust optimization for uncertainties of power systems, smart grid, and optimization power flow.



Xiaoqing Bai received her B.S. and Ph.D. degrees in Power Engineering from Guangxi University (GU), Nanning, China, in 1991, and 2010 respectively. She was a Post Doctoral Research Assistant at the University of Nebraska-Lincoln from 2012 to 2015. Currently she is a Professor at the Institute of Power System Optimization, Guangxi University. Her research interest is in power system optimization based on SDP and robust optimization.



Yi Zheng received her B.S. degree in Electrical Engineering from Hunan University (HU), China, in 2016, and her M.S. degree in Electrical Engineering from Guangxi University (GU), Nanning, China, in 2019. She is currently an engineer at the State Grid Henan Electric Power Corporation Maintenance Company. Her research interests include robust optimization for uncertainties of power systems, smart grid, and renewable energy.



Peijie Li received his B.E. and Ph.D. degrees in Electrical Engineering from Guangxi University, Nanning, China, in 2006 and 2012, respectively. From 2015 to 2016, he was a visiting scholar with the Argonne National Laboratory, Lemont, IL, USA. He is currently an Associate Professor at Guangxi University. His research interests include optimal power flow, small-signal stability, and security constrained economic dispatch and restoration.