Mixed-time rolling energy optimization of islanded microgrid considering source-load uncertainty

Y L Liu¹,², S H Miao¹ and Z W Liu¹

¹State Key Laboratory of Advanced Electromagnetic Engineering and Technology, Hubei Electric Power Security and High Efficiency Key Laboratory, School of Electrical and Electronic Engineering, Huazhong University of Science and Technology, Wuhan 430074 China

E-mail: hustler_lyl@163.com

Abstract. Effective energy optimization means make full use of distributed generation, energy storage and load resources in islanded microgrid, reduce system operation and maintenance costs, and increase the service life of equipment. Based on this, a hybrid rolling energy optimization method for islanded microgrid considering source-load uncertainty is proposed in this paper. Firstly, the source-load uncertainty model based on triangular fuzzy number is established, and the uncertainty programming theory is used to transform the model into a deterministic form. Then, considering the demand-side response, an islanded microgrid energy optimization model based on fuzzy chance-constrained programming is established. On this basis, in order to reduce the dependence of the model on prediction accuracy, a hybrid time division method based on sliding time window is proposed, and an adaptive adjustment method of model confidence is proposed to coordinate the robustness and economy of the model. Finally, an example is given to verify the correctness and effectiveness of the proposed energy optimization strategy.

1. Introduction

Overexploitation and utilization of fossil energy has brought serious problems of resource exhaustion and environmental pollution, and the global energy situation is becoming more and more serious. Renewable energy power generation is being vigorously developed all over the world, and the micro-grid composed of distributed generation, energy storage units and loads has attracted more and more attention [1-4].

Microgrid has flexible operation mode, which can usually operate in the grid-connected state, power exchange with external power grid, and as a completely independent islanded system running in the off-grid state [5, 6]. However, for some specific scenarios, such as small offshore islands, remote pastures and border guard posts, microgrids can only operate independently and autonomously. For the above islanded microgrid, due to the lack of large grid support and the errors of distributed generation and load forecasting [7,8], how to make full use of renewable energy while ensuring the safe and stable operation of the system and improving economic efficiency has become an urgent problem to be solved.

Some scholars have carried out relevant research on these issues. Literature [9,10] establishes a microgrid optimization model with the objective of minimizing daily operating cost, but uses deterministic model to describe renewable energy and load, without considering its prediction error. In
literature [11], the errors of wind power output and load forecasting are expressed by random variables. A dynamic economic dispatching model of microgrid based on chance-constrained islanded mode is proposed, and an improved particle swarm optimization (PSO) algorithm is presented to solve the model. Literature [12] proposes a robust regret optimal scheduling method for optical storage microgrid systems to suppress uncertain disturbances of photovoltaic output and load demand. Literature [13] Aiming at random factors such as fan output and photovoltaic output in microgrid operation, an economic operation model of islanded microgrid based on chance-constrained programming is established. However, the load-side resources in islanded microgrids are not considered in literature [11-13]. Literature [14] For islanded micro-networks with transferable loads, a transferable load model is established for dilution equipment, and an optimization strategy for daily operation energy control of micro-networks with the lowest cost is proposed. However, it is only applicable to islanded micro-networks and the application scenario is limited. Literature [15] considering the operation cost, system flexibility and demand response of day-ahead dispatching plan, an islanded optimal dispatching model for microgrid can improve the system's ability to cope with uncertainty to a certain extent.

Firstly, the source-load uncertainty of islanded microgrid is analyzed, and the triangular uncertainty model is used to express the source-load uncertainty of islanded microgrid. Considering the load-side resources and their respective operation constraints, an energy optimization model of islanded microgrid with the lowest operation cost as the objective function is proposed. In order to further reduce the impact of distributed generation fluctuations caused by abrupt weather changes and changes in energy supply and demand caused by abrupt load changes on the microgrid, a rolling optimization method based on sliding data window for hybrid long-time islanded microgrid is adopted. In order to improve the operation economy of the system and take into account the robustness of the system, the confidence of the fuzzy chance constraints in the model is adjusted adaptively. Finally, the uncertain programming theory is used to transform the optimization model into a deterministic model, and CPLEX software is used to solve the problem. An example is given to verify the correctness and effectiveness of the proposed energy optimization strategy.

2. Operation model of islanded microgrid system
The typical islanded microgrid studied in this paper consists of distributed power supply, diesel generator, energy storage device, load and so on. Among them, distributed power generation mainly includes wind power generation and photovoltaic power generation. The energy storage device is a storage power station containing batteries. The load is composed of flexible load and rigid load. The overall structure is shown in figure 1.

![Figure 1. Typical islanded microgrid structure diagram.](image)

2.1. Source-load uncertainty model based on triangular fuzzy variables
The distributed power supply of fans and photovoltaics (PV) in the microgrid has the characteristics of strong randomness and strong volatility, and there is still some error in prediction. At the same time, there are similar uncertainties in the prediction of the system's conventional load. For small autonomous microgrids, there may be insufficient historical operational data, and it is difficult to
establish accurate wind and light output and load size probability distribution models. Therefore, the fuzzy parameters are directly used to express the prediction error of the wind output and the normal load of the system.

The triangular fuzzy variable is a fuzzy for widely used in the study of uncertainty problems, and has been widely used in the field of power systems [16]. The triangular fuzzy variable is represented by a triplet \((k_1, k_2, k_3)\) consisting of clear numbers \((k_1 < k_2 < k_3)\), and its membership function can be expressed as equation (1).

\[
\mu(x) = \begin{cases} 
k_3 - x & k_2 < x < k_3 \\
k_3 - k_2 & x = k_2 \\
-x - k_1 & k_1 < x < k_2 \\
k_2 - k_1 & k_1 < x < k_2 \\
0 & \text{others}
\end{cases}
\]

(1)

\[\delta_{w}(t) = P_{w}^{pre}(t) \ast (-k_w, 0, k_w) \]
\[\delta_{pv}(t) = P_{pv}^{pre}(t) \ast (-k_{pv}, 0, k_{pv}) \]
\[\delta_{l}(t) = P_{l}^{pre}(t) \ast (-k_l, 0, k_l) \]

Where, \(\delta_{w}(t)\), \(\delta_{pv}(t)\) and \(\delta_{l}(t)\) respectively represent the fuzzy representation of wind power, photovoltaic and load forecasting errors. \(P_{w}^{pre}(t)\), \(P_{pv}^{pre}(t)\) and \(P_{l}^{pre}(t)\) respectively represent the forecasting values of wind power, photovoltaic and load power in t period. \(k_w\), \(k_{pv}\) and \(k_l\) are the membership parameters of wind power forecasting errors, photovoltaic output forecasting errors and conventional load forecasting errors [11]. From equation (2), the fuzzy expressions of wind power, photovoltaic and load forecasting can be obtained as shown in equation (3).

\[
\tilde{P}_{w}(t)\ = \delta_{w}(t) + P_{w}^{pre}(t) \ast (1-k_w, 1, 1+k_w) \\
\tilde{P}_{pv}(t)\ = \delta_{pv}(t) + P_{pv}^{pre}(t) \ast (1-k_{pv}, 1, 1+k_{pv}) \\
\tilde{P}_{l}(t)\ = \delta_{l}(t) + P_{l}^{pre}(t) \ast (1-k_l, 1, 1+k_l) 
\]

(3)

2.2. Flexible load scheduling model

The flexible loads which are involved in dispatching in the islanded microgrid can be divided into interruptible loads and shiftable loads. Due to the characteristics of the islanded microgrid itself, the flexible loads in the system is more certain than the flexible loads in the conventional power grid. Therefore, the following deterministic model is used to describe the flexible load.

- Shiftable loads

Common shiftable loads include washing machines, dishwashers and vacuum cleaners. The power consumption time of the shiftable load can be dispatched by the superior and shifted within a certain period of time, and generally has the characteristics of uninterrupted after starting. Its scheduling model can be described as equation (4).

\[
\sum_{i=1}^{K} u_{TL}^{m}(t) = T_{TL}^{m} \\
P_{TL}^{m}(t) = P_{TL}^{m} \cdot u_{TL}^{m}(t)
\]

Where, \(m \in N_{TL}\), represents the \(m\) th transferable load. \(u_{TL}^{m}(t)\) is the operating state of the shiftable loads during the period, 1 indicates operation, 0 indicates outage. \(P_{TL}^{m}\) indicates the rated power of
the shiftable load \( m \), \( P_{\text{TL}}^m(t) \) denotes the actual operating power at time period \( t \). \( T_{\text{TL}}^m \) denotes the total run time of shiftable load in a dispatching cycle.

- Interruptible loads

The interruptible loads are characterized by being interruptible and delayable after startup, and its power consumption can be adjusted within the allowable range. Its scheduling model can be expressed as (5).

\[
\begin{align*}
\sum_{i=1}^{T} u_{i,n}^m(t) &\geq \min T_{i,n}^m \\
P_{i,n}^m(t) &= P_{i,N,n}^m \cdot u_{i,n}^m(t) \\
\end{align*}
\]

Where, \( n \in N_{\text{IL}} \), represents the \( n \)th interruptible load. \( u_{i,n}^m(t) \) is the working state of the interruptible load during the period \( t \), 1 means running, 0 means outage. \( P_{i,N,n}^m \) is the rated power of the interruptible loads \( n \). \( P_{i,n}^m(t) \) denotes the actual operating power at time period \( t \).

In the actual optimized scheduling, the actual total flexible loads value for each scheduling period can be expressed as (6).

3. Rolling energy optimization model considering source-load uncertainty

3.1. Objective function

The objective function of islanded microgrid system is the minimum operating cost. Mainly considering the fuel cost of diesel generators and the operating cost of energy storage power stations. Its expression can be expressed as (7).

\[
\min C = C_{\text{DG}} + C_{\text{ESS}} 
\]

Where, \( C \) represents the total operating cost of the system during the optimization cycle. \( C_{\text{DG}} \) represents the operating cost of the diesel generator. \( C_{\text{ESS}} \) represents the operating cost of the energy storage plant.

- Diesel generator operating costs

The power generation cost of a diesel engine is mainly fuel consumption, and the energy cost can be expressed as equation (8).

\[
\begin{align*}
C_{\text{DG}} &= \sum_{i=1}^{T} [u_{i,G}(t) f(t) + C_{G}^{\text{on}} [1-u_{i,G}(t-1)]u_{i,G}(t)] \\
f(t) &= aP_{i,G}^2(t) + bP_{i,G}(t) + c \\
\end{align*}
\]

Where, \( C_{\text{DG}} \) is the operating cost of the diesel engine. \( P_{i,G}(t) \) is the output power of the diesel engine during the time period. \( C_{G}^{\text{on}} \) is the starting cost of the diesel engine. \( u_{i,G}(t) \) is the state variable, indicating the start-stop state of the diesel engine during the time period \( t \), if it is the power-on state, \( u_{i,G}(t) = 1 \), otherwise, \( u_{i,G}(t) = 0 \). \( f(t) \) is the fuel cost of the diesel engine during the period \( t \). \( a \), \( b \) and \( c \) is the fuel cost coefficient of the diesel engine.

- Energy storage power station operating costs

The energy storage operation cost includes operation and maintenance costs and depreciation expenses, excluding the charging cost, and can be equivalent to the quadratic function form of the discharge power, the expression can be expressed as equation (9) [17].
\[ C_{ESS} = \sum_{t=t}^{t} \frac{k_{ess} P_{eg}^2(t)}{2} \]  

Where, \( C_{ESS} \) is the operating cost of the energy storage power station, \( k_{ess} \) is the comprehensive cost coefficient of the operation of the energy storage power station, \( P_{eg}(t) \) represents the power generation of the energy storage power station during the period of \( t \).

### 3.2. Restrictions

The power balance constraints can be expressed as equation (10).

\[ P_G(t) + P_{eg}(t) + E[\tilde{P}_w(t)] + E[\tilde{P}_{pv}(t)] - P_{w}'(t) - P_{pv}'(t) = E[\tilde{P}_l(t)] + P_{RL}(t) + P_{ec}(t) \]  

Where, \( E[\tilde{P}_w(t)] \), \( E[\tilde{P}_{pv}(t)] \), and \( E[\tilde{P}_l(t)] \) respectively represent the fuzzy expectation of wind power, photovoltaic and common load power in \( t \) period. \( P_{w}'(t) \) and \( P_{pv}'(t) \) respectively represent the amount of wind power curtailment and PV power curtailmen in \( t \) period, the value of which is less than the predicted output of wind power. \( P_{ec}(t) \) represents The charging power of the energy storage station during the \( t \) period.

The positive and negative backup constraints can be expressed as equations (11) and (12).

\[
\begin{cases}
    C_{i1 \{ R_{up}(t) + \delta_{w}(t) + \delta_{pv}(t) \geq \delta_{l}(t) \}} \geq \alpha_{up} \\
    C_{i1 \{ R_{down}(t) + \delta_{w}(t) + \delta_{pv}(t) \geq \delta_{l}(l) \}} \geq \alpha_{down}
\end{cases}
\]  

\[
\begin{align*}
R_{up}(t) &= \min[P_{G}^{up}, P_{G}^{max} - P_{G}(t)] \\
&+ u_{eg}(t) \cdot \min[P_{G}^{up}, P_{G}^{max} - P_{G}(t)] \\
&+ u_{ec}(t) \cdot \min[P_{ec}^{up}, P_{ec}^{max} - P_{ec}(t)] \\
R_{down}(t) &= \min[P_{G}^{down}, P_{G}(t) - P_{G}^{min} ] \\
&+ u_{eg}(t) \cdot \min[P_{G}^{down}, P_{G}(t) - P_{G}^{min} ] \\
&+ u_{ec}(t) \cdot \min[P_{ec}^{up}, P_{ec}^{max} - P_{ec}(t)]
\end{align*}
\]  

Where, \( P_{G}^{max} \) and \( P_{G}^{min} \) are the upper and lower limits of the output of the diesel generator, respectively. \( P_{G}^{up} \) and \( P_{G}^{down} \) are the upslope and downhill power of the diesel generator per unit time respectively. \( \alpha_{up} \) and \( \alpha_{down} \) are the confidence levels to meet the positive and standby constraints and the negative standby constraints respectively.

The diesel generator operating constraints can be expressed as equation (13).

\[
\begin{align*}
P_{G}^{min} &\leq P_{G}(t) \leq P_{G}^{max} \\
P_{G}(t) - P_{G}(t-1) &\leq P_{G}^{up} \\
P_{G}(t-1) - P_{G}(t) &\leq P_{G}^{down} \\
T_{on}^t &\geq T_{on}^{min} \\
T_{off}^t &\geq T_{off}^{min}
\end{align*}
\]  

Where, \( T_{on} \) and \( T_{off} \) denote the duration and downtime of diesel generators before time \( t \).
respectively, while \( T_{\text{min}}^{\text{on}} \) and \( T_{\text{min}}^{\text{off}} \) denote the minimum duration and downtime of diesel generators respectively.

The storage energy station SOC constraint can be expressed as equation (14).

\[
\begin{align*}
SOC(t + 1) &= (1 - \delta_E)SOC(t) + \frac{\eta_c P_{\text{ele}}(t)}{Q_E} - \frac{P_{\text{ele}}(t)}{\eta_g Q_E} \\
SOC_{\text{min}} &\leq SOC(t) \leq SOC_{\text{max}} \\
SOC(0) &= SOC(T)
\end{align*}
\]

Where, \( SOC(t) \) denotes the charging state of the energy storage power station during the period of \( t \). \( \delta_E \) denotes the self-discharge rate of the energy storage power station, \( Q_E \) denotes the total capacity of the energy storage power station. \( \eta_c \) and \( \eta_g \) denote the charging and discharging efficiency of the energy storage power station, respectively. \( SOC(0) \) and \( SOC(T) \) are the initial and final state of charge respectively.

3.3. Mixed-time rolling optimization strategy based on sliding data window

The prediction accuracy of wind power and load increases with the decrease of time scale. Short-term prediction can provide prediction data with a 24-hour interval of 1 hour, which has a large time scale but relatively large error. Ultra-short-term prediction can provide data with a 4-hour interval of 5 minutes or 15 minutes, which has a small time scale but relatively high accuracy.

In order to make full use of the prediction data and reduce the impact of prediction errors on the optimization results, a hybrid rolling time optimization strategy based on sliding data window is proposed for the energy optimization of islanded microgrid. The total optimization time is 24 hours, and the division of time period is mainly based on the prediction scale and accuracy of short-term and ultra-short-term prediction. The first hour was divided into 12 5-minute intervals, and the interval after one hour was 1 hour, totaling 23. The schematic diagram is shown in figure 2.

![Figure 2. Mixed duration scrolling optimization period division.](image)

The short-term and ultra-short-term prediction data are updated every 1 hour, and the mixed-time and multi-period optimization is carried out at the same time. At the same time, the optimized data window is slid back for 1 hour, so that the optimization time is kept at 24 hours.

Because shiftable load has the characteristics of no interruption after start-up, it does not participate in rolling optimization, and only updates and optimizes the flexible load data at the initial period of optimization every day. The interruptible load can be interrupted and delayed after start-up, so it can participate in rolling optimization of mixed-time, but in order to avoid the interruptible load of the current day will not enter the next optimization day, the optimization time window of interruptible load will not slide back to the next day.

The rolling optimization based on sliding data window is an optimization in finite time domain, which can greatly reduce the dependence on accurate prediction of distributed power supply power and improve the ability to cope with unexpected situations such as weather changes.

3.4. Adaptive adjustment of fuzzy chance constraint confidence

This paper uses the form of fuzzy chance constraints to express the system standby constraints in the optimization model. However, at present, the confidence of fuzzy chance constraints in different
optimization periods is mostly expressed by the same fixed constant. If the value is too high, the model is too conservative, which leads to strong robustness but insufficient economy. If the value is too low, the robustness will be affected. In fact, in different optimization periods, the requirement of confidence is different. Therefore, this paper determines the confidence of the fuzzy chance constraints in the current optimization model according to the system state in different periods, which can effectively guarantee the coordination between robustness and economy in the whole optimization cycle.

When the percentage of forecasting error is the same, the greater the forecasting output, the greater the absolute error value and the greater the impact on load, so the higher the confidence required. When the proportion of Class I load in the load is relatively large, it also requires a high degree of confidence. Accordingly, the equation for calculating the self-adaptive confidence presented in this paper is shown in equation (15).

$$\alpha_c = k_{a1}\left[ P_{\text{w}}^{\text{pre}}(t) + P_{\text{pv}}^{\text{pre}}(t) \right] + k_{a2}\left( \frac{P_{\text{l}}^{\text{pre}}(t)}{P_{\text{l}}^{\text{pre}}(t)} \right) + \alpha_0 \tag{15}$$

Where, $k_{a1}$ and $k_{a2}$ are proportional coefficients. $\alpha_0$ is a constant term, which guarantees that the confidence level of the whole optimization cycle will not be lower than $\alpha_0$.

4. Model transformation and solution

4.1. Deterministic representation of fuzzy expectations

In this paper, the form of sampled fuzzy expectations is used to represent the power balance constraints of the system, so it is necessary to obtain the deterministic expression of the fuzzy expectations. For triangular fuzzy variables, the deterministic expression of their fuzzy expectations is expressed as equation (16).

$$E(\xi) = \frac{1}{3} (k_1 + k_2 + k_3) \tag{16}$$

$$\begin{align*}
E[\tilde{P}_w(t)] &= \frac{P_{\text{w}}^{\text{pre}}(t)}{3} (1-k_w+1+1+k_w) = P_{\text{w}}^{\text{pre}}(t) \\
E[\tilde{P}_{\text{pv}}(t)] &= \frac{P_{\text{pv}}^{\text{pre}}(t)}{3} (1-k_{\text{pv}}+1+1+k_{\text{pv}}) = P_{\text{pv}}^{\text{pre}}(t) \\
E[\tilde{P}_l(t)] &= \frac{P_{\text{l}}^{\text{pre}}(t)}{3} (1-k_l+1+1+k_l) = P_{\text{l}}^{\text{pre}}(t)
\end{align*} \tag{17}$$

The above equation can be used to obtain the expectations of wind power, photovoltaics and conventional loads as shown in equation (17). Therefore, the system power balance constraint shown in equation (10) can be converted into equation (18).

$$P_G(t) + P_{\text{lg}}(t) + P_{\text{w}}^{\text{pre}}(t) + P_{\text{pv}}^{\text{pre}}(t) - P_{\text{w}}'(t) - P_{\text{pv}}'(t) = P_{\text{l}}^{\text{pre}}(t) + P_{\text{ll}}(t) + P_{\text{le}}(t) \tag{18}$$

4.2. Clear equivalence class conversion of fuzzy chance constraints

In the optimal scheduling model proposed in this paper, the system rotation reserve constraints are fuzzy chance constraints. According to the theory of uncertain programming, a solution idea is to transform the specific form of fuzzy chance constraints into corresponding clear equivalence classes and make them deterministic constraints [18]. The general expression of fuzzy chance constraints is shown in equation (19).
\[ C_\alpha \{ g(x, \xi) \leq 0 \} \geq \alpha \]  

\[ g(x, \xi) = h_1(x)\xi_1 + h_2(x)\xi_2 + \cdots + h_n(x)\xi_n + h_0(x) \]  

Where \( x \) is the decision vector, \( \xi \) is the fuzzy vector. If all the fuzzy vectors \( \xi \) are triangular fuzzy parameters, \( \xi_i = (k_{i1}, k_{i2}, k_{i3}) \), and the constraints \( g(x, \xi) \) can be transformed into the equation (20). Then the above-mentioned fuzzy chance constraints can be transformed into corresponding clear equivalence classes [18]. When the confidence level is high, its clear equivalence class is shown in equation (21).

\[ (2 - 2\alpha) \sum_{i=1}^{n} [k_{i1}h_i^+(x) - k_{i2}h_i^-(x)] + (2\alpha - 1) \sum_{i=1}^{n} [k_{i3}h_i^+(x) - k_{i4}h_i^-(x)] + h_0(x) \leq 0 \]  

In the above equation:

\[ h_i^+(x) = \begin{cases}  h_i(x), & h_i(x) \geq 0 \\ 0, & h_i(x) < 0 \end{cases} \]  

\[ h_i^-(x) = \begin{cases} -h_i(x), & h_i(x) \leq 0 \\ 0, & h_i(x) > 0 \end{cases} \]  

The system rotation reserve fuzzy chance constraint shown in equation (11) satisfies the convertible form. The transformed spinning reserve constraint is shown in equation (24).

\[
\begin{align*}
R_{up}(t) & \geq (2\alpha_{up} - 1)[k_{L}P_{L}^{pre}(t) + k_{W}P_{W}^{pre}(t) + k_{PV}P_{PV}^{pre}(t)] \\
R_{down}(t) & \geq (2\alpha_{down} - 1)[k_{L}P_{L}^{pre}(t) + k_{W}P_{W}^{pre}(t) + k_{PV}P_{PV}^{pre}(t)]
\end{align*}
\]  

After dealing with the fuzzy constraints, the proposed fuzzy optimization model can be transformed into a deterministic optimization model. The transformed optimal scheduling problem is a mixed integer programming problem, which can be solved by commercial optimization software. In this paper, the commercial optimization software ILOG CPLEX 12.8.0 is used to solve the model.

5. Example analysis

5.1. Example data

In order to verify the effectiveness of the optimization model proposed in this paper, the islanded microgrid system data of a border guard post in Xinjiang is used as an example for simulation analysis. The system consists of wind and photovoltaic power generation devices, a diesel generator and energy storage power station. The maximum interruptible load power allowed to be removed is 10 kW. The parameters of diesel generator and energy storage power station are shown in table 1.

Figure 3 shows 24-hour forecast data of wind power output at the beginning of the optimization cycle.

| Table 1. Main operating parameters of diesel and energy storage power stations. |
|---------------------------------|-----------|
| parameters                      | value     |
| Diesel engine                   |           |
| min output (kW)                 | 50        |
| max output (kW)                 | 150       |
| climbing/landslide rate (kW/min)| 10        |
| Energy storage power station    |           |
| max charging and discharging power (kW) | 50  |
| capacity (kW/h)                 | 300       |
5.2. Load translation optimization
Because the shiftable load has the characteristics of no interruption after start-up, it does not participate in rolling optimization, and only updates and optimizes the shiftable load at the initial period of optimization every day. Firstly, the similarity between load curve and target curve (wind and solar power generation forecasting curve) is optimized. The system consists of 10 types of shiftable loads. The curve before the shiftable load shifting is shown in figure 4. The shiftable load curve after the translation optimization is shown in figure 5. By comparing the curves before and after load translation shown in figure 6, it can be seen that reasonable load translation optimization can change the shape of load curve to a certain extent, play the role of peak shaving and valley filling, and is conducive to the economic operation of the system.

5.3. Mixed-time rolling optimal scheduling
Assuming that the current time is 8 o’clock, the system performs a rolling optimization of mixing time. The updated mixing time prediction data of wind and photovoltaic power loads are shown in figure 7.
Fixed and adaptive confidence rolling optimizations are performed at 8:00, respectively. The confidence values are shown in figure 8. The results of optimization are shown in table 2. After adopting the optimization strategy of adaptive confidence, the daily operating cost is reduced by 186 yuan.

| Confidence level | Operation cost |
|------------------|----------------|
| Fixed confidence | ¥2575          |
| Adaptive confidence | ¥2389       |

Figures 9 and 10 are the output optimization results of diesel engine and energy storage station with fixed confidence and adaptive confidence respectively. It can be seen that in order to meet the confidence requirement, the system needs to increase standby, so the start-up time of diesel engine group also increases.

Figure 11 shows the SOC variation of energy storage plants with fixed confidence and adaptive confidence. The adaptive confidence reduces the number of conversion times of charging and discharging conditions of energy storage plants, and is beneficial to prolong the service life of energy.
storage plants. Figure 12 shows the curve of wind power curtailment and photovoltaic power curtailment with fixed confidence and adaptive confidence. The wind power curtailment and photovoltaic power with fixed confidence are 105.06 kW, while with adaptive confidence, the wind power and photovoltaic power curtailment are reduced to 31.85 kW, which increases the utilization rate of renewable energy.

Figure 11. Energy storage power station SOC curve.

Figure 12. Renewable energy curtailment power curve.

6. Conclusion
In this paper, a hybrid rolling energy optimization method based on adaptive confidence is proposed for islanded microgrid. Firstly, the fuzzy parameters are used to represent the source-load forecasting errors, and the load-side resources are fully taken into account. A day-ahead energy optimization model of islanded microgrid based on fuzzy chance-constrained programming is established to minimize the operation cost. In order to make full use of the short-term and ultra-short-term forecasting data of source and load and reduce the impact of forecasting errors, a hybrid rolling time optimization strategy based on sliding time window is proposed. In order to coordinate the robustness and economy of the system, an adaptive adjustment strategy of the confidence of the fuzzy chance-constrained model is proposed. Finally, the uncertain programming theory is used to transform the optimization model into a deterministic model, and the CPLEX is used to solve an example to verify the effectiveness of the proposed energy optimization strategy. The work of this paper provides a reference for the energy optimization of microgrid in islanded operation model.

Acknowledgments
The authors would like to thank the research The National Natural Science Foundation of China (51777088).

References
[1] Xie H, Zheng S, Ni M et al 2017 Microgrid development in China: A method for renewable energy and energy storage capacity configuration in a megawatt-level isolated microgrid IEEE Electrification Magazine 5 28-35
[2] Wang C, Wu Z and Li P 2014 Research on key technologies of microgrid T. China Electrotechnical Society 29 1-12
[3] Hajimiragha A, Zadeh M R and Moazeni S 2015 Microgrids frequency control considerations within the framework of the optimal generation Scheduling problem IEEE T Smart Grid 6 534-47
[4] Zhang Y, Rong Z, Zhang Y et al 2015 Study of grid demand response based on micro grid Power Syst. Prot. Contr. 43 20-6
[5] Guo L 2016 Research on energy scheduling optimization of microgrid in independent operation model (Beijing, China: North China Electric Power University)
[6] Zhu M, Su J, Guo L et al 2018 Real-time energy management strategy for islanded operation microgrid Power Syst. Prot. Contr. 46 92-100
[7] Wang F, Xu J and Li W 2017 Rolling optimal dispatch method of wind power based on distributed energy storage system J. Shandong Univ. (Engineering Edition) 47 89-94
[8] Zhang X, Zhang B and Wu X 2016 Optimal microgrid operation based on wind/PV power prediction Power Autom. Eq. 36 21-25+40
[9] He S, Zheng Y and Cai X 2014 Receding-horizon optimization for microgrid energy management Power Grid Technol. 38 2349-55
[10] Zhang Z, Wang J and Cao X 2015 An energy management method of islanded microgrid based on load classification and scheduling Autom. Electr. Power Syst. 39 17-23+109
[11] Ren J and Qu W 2016 Dynamic economic dispatch based on chance-constrained programming for islanded microgrid Power Autom. Eq. 36 73-8
[12] Wang G, Sun W, Li Q et al Robust regret optimal scheduling of microgrid with PV and battery Power Grid Technol. 41 106-11
[13] Wei F, Sui Q, Lin X et al Optimized energy control strategy about daily operation of islanded microgrid with wind / photovoltaic / diesel / battery under consideration of transferable load efficiency P. CSEE 38 1045-53+1281
[14] Li G and Zhai X 2018 Multi-objective optimal operation of isoland micro-grid based on analytic hierarchy process Power Syst. Pro. Contr. 46 17-23
[15] Yang L, Li H, Yu X et al 2018 Multi-objective day-ahead optimal scheduling of isolated microgrid considering flexibility Power Grid Technol. 42 1432-40
[16] Luo C, Li Y W, Xu H P et al 2017 Influence of demand response uncertainty on day-ahead optimization dispatching Autom. Electr. Power Syst. 41 22-9
[17] Liu J 2018 Research on optimization strategy of microgrid energy management (Nanjing, China: Nanjing Normal University)
[18] Liu B Z 2003 Uncertain Planning and Application (Beijing, China: Tsinghua University Press)