Multi-objective Optimization of Distribution Network Based on Model Predictive Control

Ming Wu¹, Lingfeng Kou¹, Hui Xie², Chanhui Ling³, Tao Rui³, Weixiang Shen⁴
1China Electric Power Research Institute, Beijing, China
2State Grid Electric Power Co. Ltd
3School of electrical engineering and automation, Anhui University, Hefei, Anhui, China
4Faculty of Science, Engineering and Technology, Swinburne University of Technology, Melbourne 3122, Australia

Abstract
With the increasing penetration of distributed generation (DG) in distribution network and the rising demand of electricity users, the uncertainty of distributed generation output and randomness of load will lead to over-voltage and power backward in distribution network. This paper proposes a multi-objective active and reactive power coordination optimal control strategy, which based on multi-time scale model predictive control (MPC). The objectives of proposed strategy consists of increasing distributed energy consumption, decreasing grid voltage deviation and decreasing system network loss, which are implemented in long time scale. And in short time scale, the energy storage active power is adjusted according to the prediction errors of load and new energy power generation. The effectiveness of the proposed optimization scheme is verified in simulation analysis.

Keywords: distributed Generation, model predictive control, active distribution network, multi-objective optimization, multiple time scales

Nomenclature

Abbreviation
DG Distributed Generation
ADN Active Distribution Network
MPC Model Predictive Control
OLTC On Load Tap Changer

Symbols
r Resistance
I Current
V Voltage
P Active Power
Q Reactive Power
S Apparent Power

t t-th time step
i i-th node
j j-th node

1. Introduction
The DGs are widely used due to their advantages of green environmental protection, flexible operation, and diversity of energy utilization. However, with the high-permeability distributed generation access to the distribution network, the safe operation of the system will be challenged [1-4], such as: voltage fluctuation, power backward. In order to solve these problems, many literatures have been deeply studied.
Reference [5] proposes a coordinated control optimization in multiple time scales based on optimal power flow, which can realize the global optimization strategy of active distribution network in a long-term scale, and implement an autonomous control strategy in a short time scale, respectively. In [6], with the increasing of the integrate DGs in the network, the management of network must be more active. Aiming at the above situation, the active voltage is controlled by coordinating the operation of DG's reactive power and on load tap changer (OLTC) to improve the hosting of DG. However, the above mentioned methods do not take into account the influence of the randomness of DG. MPC can solve the influence of uncertain factors because of it has the function of displaying the future dynamic behavior of the process, and it converts the open-loop control into a closed-loop control that can automatically modify the deviation. Therefore, MPC is increasingly applied in power systems to solve the problems caused by uncertain factors [7-9]. Reference [7] considers the traditional proportional integral control can not satisfy the requirement on the active distribution network (AND) due to the intermittent influence of distributed energy, a method based on MPC is proposed, and the control objective is to make the overall performance of the area optimal. In [8], the
author proposed a predictive control based on simplified discrete model for a buck converter. The predictive control value and state value are deduced by substituting the state of the model into the objective function which minimizing deviation of current , then according to the error between the model output and the actual system output to adjust the control value in the objective function. Reference [9] in order to solve the problem of overvoltage or undervoltage caused by high-permeability distributed generation access to active distribution network , the author proposed a voltage coordinated control method based on model predictive control, which the objective of control is to minimize adjustment of voltage. However, the control objectives of the above references are too single so that the multifaceted needs cannot be met.

Based on the above considerations, this paper proposes a MPC-based multi-objective optimization model for the distribution network. Both the active and reactive power control are considered in this model. The model is optimized in the stages of rolling and feedback. In the rolling optimization stage, taking the photovoltaic consumption, voltage quality and system loss as the integrated objectives to optimization. In the feedback correction stage, the minimum output deviation of the control unit is used as the target, then according to deviation to adjust the control value in the rolling optimization. The proposed model can not only reduce the loss of the network and guarantees the node voltage in the normal operating range, but also maximize the utilization of photovoltaics.

2. Model predictive control

Predictive control uses the predictive value to achieve rolling optimization control, and the accuracy of the prediction is constantly corrected according to the actual output of the system. The requirement of accuracy for model is not high in MPC, but it can achieve high quality control, which is in line with the characteristics of industrial process control. The MPC adopts the rolling optimization control. Compared with the unchanging global optimization, it not only realizes the optimal control, but also effectively solves the influence of the uncertain factors in the control process. The basic framework of MPC is shown in Figure 1. The basic framework includes three aspects: predictive model, rolling optimization, and feedback correction.

2.1 Predictive model

A collection of information with predictive functions, no matter what form of expression, can be used as a predictive model. Therefore, traditional models such as state equations and transfer functions can be used as predictive models.

2.2 Rolling optimization

The optimization process of predictive control is repeatedly optimized online with the advance of sampling time window, rather than optimizing it off-line, so it is called rolling optimization. As shown in Fig. 1. Taking $\Delta T$ as the time interval, the optimization goal only involves a limited time period from the time $t_0$ to the $M\Delta T$, and only the first $\Delta T$ time control action is realized, when the next sampling time $t_0+\Delta T$, the optimization process will move backwards by a time interval, then repeating the above process.

2.3 Feedback correction

The output value actually measured by the control object is compared with the model prediction output before the next sampling time to constitute an output error, then correcting the error. This process effectively prevents the deviation between the actual effect and the expected effect caused by environmental interference or model mismatch, and the anti-interference ability of the system is significantly improved.

![Figure 1 Frame diagram based on model predictive control](image)

3. Multi-objective optimization model based on model prediction

3.1 Rolling optimization phase

The rolling optimization is a long-term scale optimization model with 1h interval, the objectives of optimization are to minimum network loss, minimum node voltage deviation and maximum distributed photovoltaic(PV) utilization, the control states of the tunable units in the next 4h period are given. And only the first 1h control action is performed, the optimized time window continuously moves backwards at 1h
intervals, and the above optimization process is repeated until the condition is met.

### 3.1.1 Objective function

Considering the economy and applicability of the active distribution network, the objective function of rolling optimization should include the minimum network loss, and the expression is as follows:

\[
\min f_1 = \sum_{t=t_0}^{T} \sum_{i=0}^{n} \sum_{j=0}^{n} \gamma_{ij} l_{ij}^2
\]

where \( T \) is the scheduling interval of the rolling optimization phase; \( t_0 \) is the starting time of the scheduling period of the rolling optimization phase; \( n \) is the total number of nodes in the distribution network; \( i_0 \) is the starting node of the distribution network; \( w(i) \) is the last node of all branches with node \( i \) as the starting node; \( r_{ij} \) is the branch resistance with \( i \) as the first node and \( j \) as the last node; \( l_{ij} \) is the current of the \( ij \) branch at time \( t \).

In order to maximize the utilization of photovoltaics, load and energy storage devices are usually required to absorb PV as much as possible. The expression is as follows:

\[
\max f_2 = \frac{P_{\text{Load}}^{\text{total}} + P_{\text{ESS,oh}}^{\text{total}}}{P_{\text{PV}}}
\]

where \( P_{\text{Load}}^{\text{total}} \) is the total load of the active distribution network; \( P_{\text{ESS,oh}}^{\text{total}} \) is the total charging power in the active distribution network; \( P_{\text{PV}}^{\text{total}} \) is the total photovoltaic active power in the active distribution network.

Due to the randomness of the PV output and the volatility of the load, the voltage overrun problem will be caused. In this paper, under the premise of ensuring stable operation of the system, the target voltage minimum is the minimum target. The expression is as follows:

\[
\min f_3 = \sum_{t=t_0}^{T} \sum_{i=0}^{n} \frac{(V_{i}^t - V_{i}^{\text{spec}})^2}{\Delta V}
\]

where \( V_{i}^t \) is the voltage of the i-node at time \( t \) in the active distribution network; \( V_{i}^{\text{spec}} \) is the desired voltage value; \( \Delta V \) is the difference between the upper and lower limits of the voltage.

### 3.1.2 Target function normalization

The analytic hierarchy process is used to transform the three objective optimization model into a single objective optimization model in this paper.

The basic idea is divided into three steps:

a) Overall judgment - Comparing two of the \( n \) elements;
b) Qualitative judgment - Quantitative representation (through scalar);
c) The weight of each element is determined by a mathematical formula (feature value).

The objective functions of this paper are system network loss \( f_1 \), PV utilization rate \( f_2 \) and node voltage deviation \( f_3 \). Since the three objective functions need to be minimized after normalization, and the function \( f_2 \) is maximized, so the function \( f_2 \) should be reversed. The normalized function is:

\[
F = w_1 f_1 + w_2 f_2 + w_3 f_3
\]

The weight coefficients should be satisfied:

\[
\begin{align*}
\left| \alpha_1 \right| + \left| \alpha_2 \right| + \left| \alpha_3 \right| &= 1 \\
\alpha_1, \alpha_2, \alpha_3 &> 0, \alpha_3 < 0
\end{align*}
\]

### 3.2 Feedback correction optimization phase

As the accuracy of the system decreases with the increase of the time scale, the accuracy requirements cannot be met. Therefore, the feedback correction stage takes the short time scale of every 15 minutes interval as the optimization model, which greatly improves the accuracy of the model.

#### 3.2.1 Objective function

In the stage of feedback correction, the objective function is to minimize the deviation of active power output of energy storage.

\[
\min f = \sum_{i=1}^{N_{\text{oh}}} \left| P_i^e - P_i^{\text{roll}} \right|
\]

where \( P_i^e \) is the active output value of the energy storage device \( i \) in the feedback correction optimization; \( P_i^{\text{roll}} \) is the active output value of the energy storage device \( i \) in the rolling optimization.

### 3.3 Constraints

The contracts of power flow, photovoltaic operation and energy storage constraint are considered in the model. In addition, the amplitude of voltage and current will also be limited. Accordingly, The constraints of this paper can be represented as follows:

\[
\begin{align*}
\left( P_j - P_j^r - r_j l_j \right)^2 - \sum_{k=\text{out}(j)} P_k^r &= 0 \\
\left( Q_j - Q_j^r - x_j l_j \right)^2 - \sum_{k=\text{out}(j)} Q_k^r &= 0 \\
\left( V_j^t \right)^2 &= \left( V_j^{\text{spec}} \right)^2 - 2 \left( r_j P_j^r + x_j Q_j^r \right) + \left( r_j^2 + x_j^2 \right) \left( l_j \right)^2 \\
\left( P_j^r \right)^2 &= \left( V_j^{\text{spec}} \right)^2 + (Q_j^r)^2 \\
P_{\text{PV,j}} &= P_{\text{PV,j}}^r \\
\left( P_{\text{PV,j}}^r \right)^2 + (Q_{\text{PV,j}})^2 &\leq \left( S_{\text{PV,j}} \right)^2
\end{align*}
\]
In this paper, the CPLEX is used as the optimization tool, which completed in the MATLAB2016a [10].

![Figure 2 Topology of System](image)

<table>
<thead>
<tr>
<th>Table 1 Photovoltaic and energy storage capacity</th>
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<tbody>
<tr>
<td>Installation node</td>
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<td>3</td>
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<td>16</td>
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4. Case study

4.1 Simulation System

Topology of System is shown in Figure 2. The range of SOC (state of charge) of the energy storage device is from 20% to 90%, and the charge and discharge efficiency is 95%. The capacity of PV and energy storage installed equipment is shown in Table 1. In this example, the scheduling time interval is 1 hour and 15 minutes respectively, and the scheduling time window is 1 day.

\[
E_{SOC,i} + P_{ESS,dis,i} \eta_{dis} \Delta T - \frac{P_{ESS,dis,i}}{\eta_{dis}} = E_{SOC,i}^{t+1}
\]

\[
20\% \times E_{SOC,i}^{\text{max}} \leq E_{SOC,i}^{t+1} \leq 80\% \times E_{SOC,i}^{\text{max}}
\]

\[
\left(P_{ESS,dis,i}^{t}\right)^2 + \left(Q_{ESS,dis,i}^{t}\right)^2 \leq \left(S_{ESS,i}^{\text{max}}\right)^2
\]

\[
0 \leq P_{ESS,dis,i}^{t} \leq P_{ESS,dis,i}^{\text{max}}, D_{ch,i}^{t}
\]

\[
0 \leq P_{ESS,dis,i}^{t} \leq P_{ESS,dis,i}^{\text{max}}, D_{ch,i}^{t}
\]

\[
D_{ch,i}^{t} + D_{dis,i}^{t} \leq 1
\]

(11)

(12)

(13)

where \(P_{ij}^{t}\) and \(Q_{ij}^{t}\) are the active power and reactive power injection values of node j at time t, respectively; \(P_{ij}^{\text{max}}, Q_{ij}^{\text{max}}\) are the active power and reactive power of branch j at time t, respectively; \(\alpha(j)\) is the set of all end nodes with node j as the head node; \(P_{ij}^{\text{pred}}\) and \(Q_{ij}^{\text{pred}}\) are the active and reactive power of photovoltaic node i at time t, respectively; \(P_{ij}^{\text{pred}}\) is the predicted value of photovoltaic active output of node i at time t; \(S_{ij}^{\text{max}}\) is the maximum apparent power of the PV inverter at node i; \(E_{SOC,i}^{t}\) is the stored energy of node i at time t; \(\eta_{ch}, \eta_{dis}\) are charging and discharging efficiency of energy storage, respectively; \(E_{SOC,i}^{\text{max}}\) is the capacity limit of the energy storage device; \(P_{ESS,dis,i}^{\text{max}}\) and \(P_{ESS,dis,i}^{\text{max}}\) are the upper limits of charge and discharge of the energy storage device, respectively; \(P_{ESS,dis,i}^{\text{max}}\) is the maximum apparent power of the energy storage inverter at node i; \(D_{ch,i}^{t}\) and \(D_{dis,i}^{t}\) are the state of charge and discharge of the energy storage device, respectively. \(I_{ij}^{\text{max}}\) and \(I_{ij}^{\text{max}}\) are the upper limit amplitude of the current and voltage, respectively.

4.2 Simulation results

In this paper, the simulation results of the predictive control are compared with original results, and the effectiveness and superiority of the proposed method are verified by comparison.

The photovoltaic output and load prediction data of the system are shown in Figure 3. From the figure, we can see that the PV output curve on sunny day shows parabolic characteristics, and does not correspond to the peak hours of the county grid load, resulting in excessive photovoltaic energy is difficult to absorb. If this situation is not optimized, when the photovoltaic output is much higher than the load demand, PV energy will be sent out in large quantities, affecting the grid voltage eligibility rate and photovoltaic utilization.

Taking the prediction data of Fig.3 as an example. The optimization model of active distribution network is established, and the active and reactive power coordination optimization is carried out in multiple time
The corresponding optimization results are obtained, which proves the correctness of the proposed optimization scheme.

Figure 4 shows the scheduling plan values of each controllable device obtained after optimization. It can be seen from Fig.4(a) that during the period of high photovoltaic output level, the energy storage begins to absorb the active power and store the surplus photovoltaic power, which avoids the problem of power reversal. When the photovoltaic output is very small, the photovoltaic output cannot meet the user’s load demand. At this time, the energy storage system starts to discharge according to the actual situation, reducing the user's dependence on the large power grid on the transmission line. After 21:00, the energy storage discharge power is gradually reduced due to the reduction in load power demand.

Figure 4 (b), (c) are the reactive power output curves of energy storage and photovoltaic, respectively. Energy storage and photovoltaic reactive power can maintain the power balance of the system, performing reactive power compensation on the system, improving the power factor of the system, and reducing the loss on the transmission line.

The simulation results show that the energy storage system can effectively improve the self-absorption capacity of distribution networks with high permeability photovoltaics. As shown in the figure 5, the utilization rate of PV is lower before the optimization, and the lowest is about 47%. After optimization, the excessive energy is stored in the device, so that the utilization rate of photovoltaic energy is significantly improved.

The comparison diagram of network loss is shown in Figure 6. In the period of high photovoltaic output level, the load demand is lower than the photovoltaic output, resulting in a large number of photovoltaic outbound, thus the line loss is increased. But in the area after the optimal control, the total network loss is effectively reduced. By comparison, we can find that the optimized network loss is significantly lower than the original network loss, which indicates that the coordinated control technology proposed in this section can reduce the line loss of the regional distribution network.

Figure 7 shows the voltage amplitude of node 11. It can be seen that the node has a higher voltage amplitude around 14:00, at this time, due to the large output of the photovoltaic, the amplitude of the original node voltage exceeds the upper limit of the desired voltage amplitude of 1.05, which affects the safety of the system operation. But after optimization, the node voltage is well controlled near the desired voltage value of 1, and the optimization effect is remarkable.
5. Conclusion

This paper aims at high-permeability DG access to the distribution network, a multi-time scales active and reactive power coordination optimization control strategy is introduced. The strategy is based on MPC, the multiple objectives are taken as the optimization objective so that the purpose of meeting multiple requirements can be achieved at the same time. And the intermittent of the distributed generation and the volatility of load are both considered in this model, which can avoid the influence of uncertainties. The proposed coordinated control technique has proved its superiority and effectiveness through experimental simulation results. In this paper, the distributed generation is only photovoltaic, and the further studied can add other distributed generation sources such as wind energy.

Acknowledgement

This work was supported by the "National Key R&D Program of China (2016YFB0900400) " and "Sciences and technology project of State Grid Corporation of China (PD71-17-014) ".

References