Reactive power optimization of dynamic power system based on QPSO algorithm

Dong Ang¹ and Song Xin²

¹Yancheng Teachers University YanChen, Jiang Su, China
²Yancheng Teachers University YanChen, Jiang Su, China

Email: 3349788107@qq.com

Abstract. During the operation of the power system, there is a certain loss when electrical energy transmitting through the line. The losses in the line are usually dominated by active network losses. The current research mainly uses reactive power optimization to reduce the reactive power loss in the system. Traditional reactive power optimization is optimized for a certain static time, and the state of the equipment in the line does not change, which is meaningless for actual engineering. A full-text optimization model is established for the purpose of reducing active network loss. The QPSO algorithm is used to dynamically optimize the load of a certain place for different periods of time. Based on the optimization results, we control the the operating status to reduce the active network loss in the line.

1. Introduction

With the increasing use of electricity by demand-side users, the power network’s load on electricity is also increasingly heavy. We must solve the most important question is that How to ensure the power quality while increasing the load on the power grid. There are more and more standards for measuring power quality, and the most widely used standard is still voltage stability[1].

At present, the static reactive power optimization is to use the collected load data at a certain static moment for optimization. In static reactive power optimization, the operating status of each control equipment in the system does not change after optimization. However, in actual operation, the system load changes in real time. Therefore, traditional static reactive power optimization is no longer applicable. In order to improve the power quality in the actual network and reduce the active network loss in the line, the research on dynamic reactive power optimization is gradually accepted by people[2].
At present, the research difficulty of dynamic reactive power optimization lies in the establishment of a dynamic reactive power optimization model[3]. When we establish the model, we should take into account that the operating state of the control equipment changes with the load when the system running. Dynamic reactive power optimization is accompanied by changes in the load in each time period. According to the intelligent algorithm, the transformer transformation ratio and the number of capacitor switching groups are reduced to reduce the active network loss in the line[4-5]. The current research on dynamic and dynamic reactive power optimization mainly has two ways. One is to change the operating state of the control equipment in the line. The core of this way is to use the mathematical inequality and the number of times the equipment is operated within a certain period of time to constrain it[6]. The other way is to use the segmented optimization method to limit the number of times the control equipment operates. This core of this way is to reasonably divide the load curve according to the control characteristics of the load and the voltage in the system[7].

The focus of this article is how to divide the load of a certain period of time into several optimized intervals at equal intervals[8-9]. The division of time period is based on the fact. In the actual load process, the load data of adjacent time periods are not divided into the same optimization interval. When there is a large difference in load data between adjacent periods, it is divided into different optimization intervals. The same optimization interval is optimized using the static reactive power optimization algorithm to obtain the data change amount of each time period[10]. According to the obtained data change amount, the control equipment is controlled to operate so as to reduce the active network loss in the line and achieve the purpose of dynamic reactive power optimization.

2. Reactive power optimization model of static power system

The traditional reactive power optimization is aimed at the data of each node at a certain static time. After collecting the data, Use the optimization algorithms to reduce active network loss[11].

Active network loss:

$$\min f_1 = P_{\text{loss}} = \sum_{k=1}^{N} G_k (\delta_i - \delta_j) \left( v_i^2 + v_j^2 - 2v_i v_j \cos (\delta_i - \delta_j) \right)$$  \hspace{1cm} (1)

f1 is the minimum amount of network loss in the optimization process, N is the number of branches in the line; i, j represents the phase angle component of the voltage of each node of i, j; the conductance of the i-j branch is Gk; the voltages of nodes i and j are respectively Represented by Vi and Vj.

In the process of power network optimization, follow the basic power status:

$$\begin{align*}
V_{G_{\text{min}}} &\leq V_{G} & H \in N_G \\
T_{T_{\text{min}}} &\leq T_{T} & I \in N_T \\
Q_{G_{\text{min}}} &\leq Q_{G} & J \in N_G
\end{align*}$$  \hspace{1cm} (2)

$V_{G}$: generator terminal voltage of each period; $T_{T}$ is the position of the transformer tap position. $Q_{G}$:

3. Model and scheme of reactive power optimization for dynamic power system

3.1. Quantum-behaved particle swarm optimization

Quantum-behaved Particle Swarm Optimization (QPSO) is an improved intelligent algorithm based on PSO algorithm[12]. The traditional PSO algorithm has limitations in selecting the optimal solution for the population iteration and the particle orbit model. In this paper, the QPSO algorithm is used to prevent particles from falling into a locally optimal state when searching for neighboring particles. The particle position update formula is shown in formula (3):
\[
X(t+1) = P_{ij}(t) \pm \frac{L_{ij}(t)}{2} \ln \left( \frac{1}{\mu(t)} \right) \mu(t) eU(0,1)
\]

\[
P_{ij}(t) = \frac{c_1 r_1 P_{ij}(t)+c_2 r_2 jG_j(t)}{c_1 r_1 j(t)+c_2 r_2 j(t)}, \quad 1 \leq j \leq N
\]

\[
\lim_{t \to \infty} L_{ij}(t) = 0
\]

\(X(t+1)\) is the current position of the particle \(t+1\), \(P_{ij}(t)\) particles is the local attractors which control the direction of optimization of particles. \(G_j(t)\) is the global optimal position of \(j\). \(L_\star (i, j) (t)\) is the characteristic length of the potential well, which controls the search range of particles during the iteration process. Using the group's average optimal position of the particles to control \(L_\star (i, j) (t)\) during the iteration process Distance is regulated.

The formula of the population particle at the average optimal position distance is shown in formula (6):

\[
C(t) = (C_1(t), C_2(t), \ldots, C_D(t)) = \frac{1}{N} \sum_{i=1}^{N} P_i(t) = \left( \frac{1}{N} \sum_{i=1}^{N} P_{i,1}(t), \frac{1}{N} \sum_{i=1}^{N} P_{i,2}(t), \ldots, \frac{1}{N} \sum_{i=1}^{N} P_{i,D}(t) \right)
\]

\(D\) is the particle dimension and \(N\) is the particle population size.

The length of the particle potential well satisfies the expression (7):

\[
L_{ij}(t) = 2 * \alpha * |C_j(t) - X_{ij}(t)|
\]

\(\alpha\) is a contraction expansion factor. Import (7) into formula (3) to get the iterative formula (8) of the final particle position:

\[
X_{ij}(t+1) = p_{ij}(t) \pm \alpha |C_j(t) - X_{ij}(t)| \ln \left( \frac{1}{\mu(t)} \right)
\]

3.2. Dynamic reactive power optimization model

The dynamic model aims to establish a dynamic reactive power optimization model in a certain period of time. The model can reduce the active network loss while stabilizing the voltage in the line:

\[
F = \min \sum_{t=0}^{n} P_{\text{loss}}(V_{Gli}, T_i, Q_{Gli}) \quad n \in N
\]

\[
P_{ti} = V_{ti} \sum_{j=1}^{n} V_{tj} (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad neN
\]

\[
Q_{ti} = V_{ti} \sum_{j=1}^{n} V_{tj} (G_{ij} \cos \theta_{ij} - B_{ij} \sin \theta_{ij}) \quad neN
\]

\[
\begin{cases}
V_{Glimin} \leq V_{Gli} \leq V_{Glimax} & I \in N_{G} \\
T_{Glimin} \leq T_{Gli} \leq T_{Glimax} & I \in G \\
Q_{Glimin} \leq Q_{Gli} \leq Q_{Glimax} & I \in N_{G} \\
S_{TK} \leq S_T & k = 1, 2, 3
\end{cases}
\]

\(F\): minimum network loss in a specified period; \(P_{ ti}\): active power in a specified period; \(Q_{ ti}\): reactive power in a specified period; \(V(Gli)\): The extreme voltage of the generator; \(T_i\): the position of the transformer tap position in each period; \(Q (Gli)\): the reactive power compensation capacity in each period; \(STK\): the number of times the on-load transformer tap position is operated in each period.
3.3. Dynamic Reactive Power Optimization Scheme

Reactive power optimization in the traditional sense is optimized for a certain time, and its goal is to reduce the active power loss of the line at a certain time[13]. However, in actual operation, the load changes from moment to moment, and the number of operations and service life of the control equipment in the line strictly adheres to the “Code for Operation of National Grid Line Equipment”. The action of the control equipment is required in each time period, and cannot be changed at any time as the load changes. This article is based on the static reactive power optimization in a certain period of time. Based on the actual load change in each time period as a reference, taking actions to change the number of transformer switching groups, the working state of the reactive power compensation device, and stabilize the actual voltage in the line. After taking the above measures, ensure the stable operation of the system[14].

3.4. Control division at load moment

The difficulty of dynamic reactive power optimization lies in how to reasonably divide the load curve in a certain long period of time, so as to achieve a continuous load change curve, transforming the dynamic change into visible static Work optimization. The basis for dividing the time period is that the more dense the divided segments within a certain time period, the closer the optimization curve is to the true value, and the optimization result is the more accurate. Otherwise, the more the actual optimization result deviates from the true value. Take the electricity consumption of residents in Henan, China for 0-24 hours as an example. Figure 1: The peak hours of power consumption throughout the day are mainly concentrated in the four periods of 6:00 to 7:00, 10:00 to 11:00, 18:00 to 19:00, 21:00 to 22:00. Power consumption in these four periods is much higher than in other periods. Set the adjacent time with high power consumption as the moment to control the operation of the device, and the time period with little fluctuation in power consumption can be divided. Controlling a period of time for equipment movements to ensure stable system operation while reducing equipment movements.

![Figure 1](image)

**Figure 1.** 0-24 hours actual power consumption in Henan, China

3.5. Dynamic reactive power optimization to optimize practical steps

Traditional static reactive power optimization is optimized for the power system at a certain static time. Dynamic reactive power optimization is optimized for load changes over a period of time. During the optimization process, the number of transformer switching groups and the amount of compensation of the reactive power compensation device are changed for system control[11]. During the actual system operation, the output of the generator set and the compensation amount of the reactive power compensation device have not changed much in a certain quarter. Because the change amount of the generator set and the reactive power compensation device does not change much within a fixed period of time. So in this particle, it is set to an approximate invariant in this article. Taking actions to Change
the number of switching groups of the transformer in the actual line, and then controlling the amount of reactive power in the line, and finally achieve the purpose of reducing the active network loss of the system. The core of this optimization is to control the operation status of the equipment to facilitate the control of the equipment's movement at the next moment. Specific steps:

1. Import the load curve in each period into the database.
2. Randomly generate a population, and assign each particle of the generated population to the initial two-point position and parameters.
3. Use the QPSO to perform Iterative operation of particle swarm. During the iteration, each particle parameter meets the constraint condition of formula(2). Store the operation results obtained in this iteration to a new storage space.
4. Import the new data obtained in step(3), and repeat step(2) on the basis of this new data. The speed of the pattern data generated at this time does not change, and the position is no longer initialized. The essence of this optimization is to perform another optimization based on the previous running data. The control equipment in the system changes the state according to the optimized result of the QPSO algorithm, and adjusts the position of the transformer tap position.
5. Repeat step(4) until the simulation of the load variables in the period is completed.
6. According to QPSO, derive optimized data, and control equipment actions based on the data.

Finally, the position data of the action device is exported.

4. Examples and results analysis

4.1. Example

Example source: A certain area of Jiangsu, China, obtained the data volume of a certain day through load forecasting as the load of the IEEE-14 node. The amount of data obtained from the load forecast is normalized and then substituted into the system for simulation. The IEEE-14 node system includes 5 generators, 3 transformers, and a reactive power compensation device connected to the system. The number of system nodes is 14, and the functions of each node are as follows: the reference node is set to 1 node (connected to the earth, balanced node), the PV node is set to 2, 3, 6, 8; the capacitor merged node is set to 9; The nodes are 1, 2, 3, 6, 8; the remaining nodes are set as PQ nodes. Transformer installation branch: 5-6, 4-7, 4-9, PQ, PV node voltage standard value range [0.90, 1.10] (reference capacity of IEEE-14 node is 100MVA); on-load transformer The ratio is [0.90, 1.10], and the adjustment step size of each gear is set to 0.0125; the value range of the parallel capacitor is [0, 0.5], and the adjustment step size of each capacitor is 0.05. Dynamic optimization needs to optimize the imported data for each period.

According to the optimized data, control the equipment status in the power system and calculate the optimized network loss value.
Figure 2: 0-12 hours load data forecast map of Henan, China

4.2 Simulation analysis

The QPSO algorithm is an improvement over the traditional Particle Swarm Optimization algorithm. The QPSO algorithm, PSO algorithm, and Differential Evolution Algorithm (DE) are optimized for static reactive power, and the effects of the optimization are compared. Get the network loss chart shown in Figure 3:

Figure 3. Static loss optimization of three algorithms

QPSO, PSO, and DE algorithms are compared in static optimization. We can find that the QPSO algorithm has the smallest active network loss during the static optimization process. Compared with the PSO algorithm, the QPSO algorithm has slightly more iterative convergence times than the PSO and the final network loss value is less than the PSO. It is proved that the QPSO algorithm is feasible in static and reactive power optimization.

During the static optimization of the algorithm, the QPSO algorithm has obvious advantages in the final result. According to the previous description, the dynamic reactive power optimization adopted in this paper is based on the static reactive power optimization, which turns the movement into static. Figure 1 is a load forecast data chart of a certain place in Henan, China for 12 hours. Based on the static time QPSO algorithm, the two-point method is optimized. 0-12 hours are divided into 6 periods, and a 14-node model is used for dynamic reactive power optimization. According to the
optimized value, adjust the number of transformer switching groups in the system to optimize the entire system.

![Graph showing dynamic optimization of the number of transformer switching groups in each period.](image)

**Figure 4.** Dynamic optimization of the number of transformer switching groups in each period

Transformer 1 is located between busbars 5-6. Its value substitution represents the number of switching groups of the transformer. Transformer 2 and 3 are located between busbars 4-9. The value represents the number of switching groups in the system. Table 1 shows the number of switching groups of the transformer and the network loss data of the reactive power optimization in each period.

| period (h) | transformer1 | transformer2 | transformer3 | Ploss     |
|------------|--------------|--------------|--------------|-----------|
| 0-2        | 10           | 10           | 9            | 0.09756   |
| 2-4        | 9            | 8            | 9            | 0.09784   |
| 4-6        | 8            | 8            | 8            | 0.10078   |
| 6-8        | 12           | 14           | 12           | 0.10514   |
| 8-10       | 14           | 16           | 14           | 0.10599   |
| 10-12      | 16           | 18           | 16           | 0.10624   |

It can be seen from the data in Table 1 that as the time period increases, the network loss value in the system gradually increases. Compared with static reactive power optimization, the effect of network loss optimization gradually becomes worse. However, considering the actual transformer operation times and service life limitations, the transformer cannot frequently change the number of switching groups, so the optimization effect is not as good as the static reactive power optimization effect. But dynamic reactive power optimization is more practical and can be applied to engineering well.

### 5. Conclusion

Compared with static reactive power optimization, dynamic reactive power optimization has no static effect when optimizing the system network loss value, but dynamic reactive power optimization is more suitable for practical engineering. Each optimization of the dynamic reactive power optimization is based on the previous optimization. According to the optimization results of the intelligent algorithm, the operating status of the control equipment in the system is changed to achieve the purpose of optimizing by time. This paper uses the QPSO algorithm. This algorithm has a clear
advantage over traditional PSO algorithms in static optimization. Applying QPSO algorithm to dynamic reactive power optimization has also achieved significant results.

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