Multiobjective optimization of microgrid based on SOM clustering and Markov chain

Junshuo Huang¹, Jian Chen², Juhao Fang³* and Shiliang Hou

¹ School of Electrical & Automation Engineering, Nanjing Normal University, Nanjing, Jiangsu, 220000, China
² School of Electrical & Automation Engineering, Nanjing Normal University, Nanjing, Jiangsu, 220000, China
*Corresponding author’s e-mail: 13222755733@163.com

Abstract. In the current distribution system, the participation of solar power generation system in operation has been the main topic in the field of distribution system research. However, because of climate and other factors, it will increase the difficulty of calculation to study the 8760 hours of sunshine of solar power distribution system at least one year, so it is necessary to simplify the data. Firstly, this paper designs matlab program based on SOM clustering analysis method, which integrates solar power generation and load, and simplifies at least several cases. Then, a matlab program is designed based on the Markov key to integrate the generating capacity and load change in multi scenario, and the weight value of each scenario is calculated by Markov, so as to achieve the goal of multi scenario integration.

1. Introduction
With the rapid development of global photovoltaic industry, solar energy can be easily and quickly converted into electricity with the development and progress of technology. Solar power generation plays an increasingly important role in modern power system. At present, the time-varying load can not be predicted, coupled with power equipment accidents and earthquakes and other disasters, making the solar power generation system unstable[1]. Because of climate and other factors, the solar power generation system has a strong uncertainty, there is no sunshine at night, and the light is very weak in rainy days, the solar power station can’t work normally, which affects the safe and stable operation of the micro grid. Therefore, it is unrealistic to plan and construct the power generation system with fixed value[2]. In the process of power grid construction, it is necessary to consider as many situations as possible and make careful planning according to the probability of each event[3].

2. Algorithm for solving multi-objective optimization model

2.1 The basic theory of SOM neural network
SOM neural network is a competitive network. In the competitive layer, the neurons in the surrounding area of the winning neuron are stimulated to varying degrees, while the neurons outside the adjacent area of the neuron are inhibited, forming a mode of taking the winning neuron as the center, the neighboring neurons encourage each other, and the far neurons suppress each other[4]. As shown in Figure 1. The competitive characteristics of neurons: the middle intensity is the highest, the two sides are gradually weakened, and those far away from the winning neurons are inhibited[5].
The clustering steps of SOM neural network are as follows:

1. **Initialization of connection weight**
   - Randomly select the value between [0, 1] as the value of initial weight \( w_{ij} \), and \( w_{ij} \) is different from each other.

2. **Input sample mode**
   - With a certain probability, the n-dimensional phasor \( x \) is taken from the sample input space, indicating that the grid is applied to the activation mode[6].

3. **Find winning node**
   - Calculate the Euclidean distance \( d_j \) between the input data and the output neuron, select the node that produces the minimum as the most matched neuron, that is, the winning unit.

\[
    d_j = \left\| x - \hat{w}_j \right\| = \sqrt{\sum_{j=1}^{m} (x - \hat{w}_j)^2} \quad (1)
\]

4. **Weight adjustment**
   - Adjust the connection weight phasor of the output node. The weight phasor of neurons is adjusted by updating the formula.

\[
    w_{ij}(t+1) = w_{ij}(t) + \alpha(t, N)[x_i^p - w_{ij}(t)] \quad i=1, 2, \ldots, n \quad j \in N^*_j(t) \quad (2)
\]

   Where: \( w_{ij}(t) \) is the weight of neuron \( i \) to \( j \); \( \alpha(t, N) \) is the function of the training times and the topological distance \( j^* \) between the \( j \) neuron in the neighborhood and the winning neuron \( N \).

5. **Repetitive training**
   - Repeat step 3 and step 4, until all data are learned, SOM neural network learning is completed[7].

After multiple cycles, the adjacent neurons will approach each other, and the two-dimensional neighborhood diagram of SOM neurons is shown in Figure 2.

**Figure 1. neuron interaction mode**

**Figure 2. two-dimensional neighborhood diagram**

2.2 **The basic theory of Markov chain**
Markov prediction method is an application of Markov chain in the field of industrial engineering. Through the division of the state of things, the initial probability and transition probability matrix of
each state are obtained, and then the future state change trend of things is predicted[8]. The best scheme of engineering can also be solved by Markov steady-state probability matrix. When the Markov chain reaches a stable state, the state probability is the steady-state probability. The stable condition of Markov chain is that the one-step transition probability matrix is the standard probability matrix[9]. If the conditions are met, the stable state will be achieved after k-step transfer[10], and the solution of the steady-state probability is as follows:

When it is stable, there is 
\[ S^{(k+1)} = S^{(k)} \], that is 
\[ S^{(k)} = S^{(k)} P = S^{(k)} \]

Suppose \( S^{(k)} = (x_1, x_2, \ldots, x_n) \) and \( \sum_{i=1}^{n} x_i = 1 \) are state vectors after k-step transition, and the one-step transition probability matrix is 
\[ P = \begin{bmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \ddots & \vdots \\ P_{n1} & \cdots & P_{nn} \end{bmatrix} \]

According to \( S^{(k+1)} = S^{(k)} P = S^{(k)} \), the expansion is as follows:
\[ S^{(k)} = (x_1, x_2, \ldots, x_n) \]

The following equations are obtained:
\[ (P_{11} - 1) P_{21} \cdots P_{1n} x_1 = 0 \]
\[ P_{12} (P_{22} - 1) P_{22} \cdots P_{2n} x_2 = 0 \]
\[ \vdots \]
\[ P_{n1} \cdots P_{nn} x_n = 0 \]

Order
\[ P_i = \begin{bmatrix} (P_{11} - 1) & P_{21} & \cdots & P_{1n} \\ P_{12} & (P_{22} - 1) & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & 1 \end{bmatrix} \]

Then: 
\[ P_i S^{(a)} = B, \quad S^{(a)} = P_i^{-1} B \]

That is to say, the steady-state probability matrix P of Markov chain is obtained.

3. Research on Multiobjective Optimization of microgrid based on SOM and Markov chain

3.1 Research object and parameters
This paper takes a typical microgrid in the coastal area of China as an example, and the required irradiance data is taken from the large-scale application demonstration area of photovoltaic power generation. The annual average total radiation of the power station is 5020.8mj/m²[11]. According to the sample data, the daily photovoltaic output curve is obtained. From the curve, it can be seen that the power generation increases with the increase of light intensity[12]. Generally speaking, the power generation in the morning is gradually increasing, while the power generation in the afternoon is
gradually decreasing. As shown in Figure 3, the typical solar power generation in summer is zero at night, and the solar power generation in the daytime reaches its maximum at about 2:00 p.m., gradually increasing in the first half of the day and decreasing in the second half of the day[13]. The 24-hour load power demand is shown in Figure 4.

3.2 Verification experiment of multiobjective optimization method for microgrid

Firstly, the input layer of SOM is 8760 nodes and the output layer is 16 nodes, Use MATLAB software to train the samples[14]. After 180 times of training, the classification begins to stabilize. 8760 hours of data are distributed on the neurons corresponding to the plane where the output layer is located. The distribution of various situations in the competitive layer is shown in Figure 5.

It can be seen from the figure that SOM neural network can classify the data well. The classification results are more detailed and meet the experimental requirements[15]. The 9 clustering centers of 8760 hour data are as follows:

| state | Generation capacity | load | Difference value | Sample size |
|-------|---------------------|------|------------------|-------------|
| 1     | 11489.86            | 74272.59 | -71680.2        | 907         |

Figure 3. daily characteristics of photovoltaic output  
Figure 4. Load power demand curve  
Figure 5. distribution of each case in the competition layer
The importance of various situations changes with different working conditions. In order to facilitate the decision-maker to choose the corresponding optimal solution under different working conditions, table 2 gives the corresponding optimal scheme under different conditions[16]. The decision-maker can improve the table according to the needs, and then find the target weight vector under the actual working conditions.

Table 2. Optimal schemes corresponding to different situations

| state | Initial probability | failure rate | interruption frequency | Blackout cycle | Average continuous working time of equipment | Time of power failure | Power failure time |
|-------|---------------------|--------------|------------------------|----------------|---------------------------------------------|----------------------|------------------|
| 1     | 0.1035              | 0.33         | 0.034                  | 29.278         | 3.030                                       | 299.198              | 906.660          |
| 2     | 0.0968              | 0.55         | 0.053                  | 18.783         | 1.818                                       | 466.382              | 847.968          |
| 3     | 0.0220              | 0.75         | 0.017                  | 60.606         | 1.333                                       | 144.540              | 192.720          |
| 4     | 0.0672              | 0.68         | 0.046                  | 21.884         | 1.471                                       | 400.297              | 588.672          |
| 5     | 0.0126              | 0.10         | 0.001                  | 793.651        | 10.000                                      | 11.038               | 110.376          |
| 6     | 0.2858              | 0.43         | 0.123                  | 8.137          | 2.326                                       | 1076.55              | 2503.608         |
| 7     | 0.0957              | 0.48         | 0.046                  | 21.769         | 2.083                                       | 402.399              | 838.332          |
| 8     | 0.1134              | 0.78         | 0.088                  | 11.306         | 1.282                                       | 774.840              | 993.384          |
| 9     | 0.2034              | 0.14         | 0.028                  | 35.117         | 7.143                                       | 249.450              | 1781.784         |

4. Summarizes
In this paper, the SOM neural network clustering method is used to cluster the power generation and the load of industrial and residential areas, and nine different cases are obtained. The clustering results of SOM neural network are analyzed in detail, the clustering center value is obtained, and the relationship between power generation and load is determined according to the center value. Then the markov model of solar power generation is established and the steady-state transfer probability is obtained by analyzing the transfer matrix. Finally, five reliability indexes are selected and analyzed.

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