Energy Consumption Control and Optimization of Large Power Grid Operation Based on Artificial Neural Network Algorithm

Xuan Gong

ABSTRACT

Green, energy-saving, efficient and reliable smart grids have become one of the most important development areas in the world. An artificial neural network algorithm based on cranial nerve principle proposed in this paper provides reference for power flow analysis, reasonable dispatching and control decision-making of smart grids. At the same time, new EMS (Energy Management System) structure and strategy are introduced to optimize resource allocation and energy management. Based on the single-layer network control theory of large power grid, BP neural network including genetic algorithm is constructed and combined with regression analysis to realize the optimization of power analysis. In addition, a neuron controller is set up in the distributed unit to collect, monitor and control the parameters and send them to the high-level central controller, forming a multi-level three-dimensional network to analyze and make decisions, accurately predict the energy consumption of power grids, and improve the control level of the energy consumption of smart grids.

Key Words: Smart Grids, GA-BP Neural Network, Genetic Algorithm, Regression Analysis, EMS

Introduction

Driven by the consciousness of energy saving and environmental protection, Smart Grid (also called "Grid 2.0") has been supported and developed by governments around the world in recent years (Harvey and McCormick, 2009; Hu et al., 2016). Integrating the latest technologies of computer, communication and automation and combining with the traditional power technologies, it greatly improves the intelligent level of the power grid, and provides the basic guarantee for the self-healing of power grids, and the connection of renewable resources and distributed power supply (Salomoni et al., 2011). During the construction of smart grids, the structural complexity, nonlinearity, and fluctuation of grid-connected power generation of renewable energy all have adverse effects on the reliability control and energy optimization management of power grids, and smart grids require very high real-time performance, network architecture and predictive control decision-making mechanisms are increasingly ineffective in controlling the entire grid and its endings (Mckee et al., 2013). Artificial neural network (ANN) is an abstract model of human neural network based on the research of modern neuroscience (Isah et al., 2017; Tichanek and Tropek, 2015). It is an attempt and application of new theory of brain science in other fields. The research of smart grids involves many disciplines such as electricity, communication, automation and computer, and the new cranial nerve principle has the abilities of data collection, analysis and decision-making, which bring new ideas for reliability control and energy control of smart grids (Irina and Juha, 2008).
Then, based on the artificial neural network of cranial nerve principle and the feasibility analysis by genetic algorithm and regression analysis, this paper constructs the decision structure of multi-level three-dimensional network, which provides a new idea for power predictive control and energy management optimization of smart grids.

**GA-BP Neural Network**

*Artificial neural network*

Artificial neural networks (ANN) have great advantages in dealing with nonlinear problems with many irregular variables. It is capable of efficiently operating and computing multiple sets of data, independently completing self-organization, self-training, and self-learning. It is particularly suitable for ambiguously addressing problems with many influencing factors and inaccurate conditions (Zhang et al., 2010). Figure 1 below shows the neuron information processing model of the artificial neural network. X is the input, W is the weight, Function is the transfer function, Bias is the offset, and Threshold is the threshold.

![Figure 1. Neural Network of Artificial Neural Network Processing Model](image)

**BP neural network**

BP neural network is a multi-layer feedforward neural network which is optimized and improved on the basis of traditional artificial neural network (MLP). The BP neural network uses the back-propagation algorithm for training, and makes full use of the good approximation performance of the neural network in dealing with nonlinear problems. It is the most widely used model in the engineering field (Harbold et al., 2013), and its basic structure is shown in Figure 2.

BP neural network is generally composed of input layer, hidden layer and output layer. Raw data, or multiple sets of data of the upper layer can be input to the input layer of the next neuron at the same time, data can be transmitted among input, hidden, and output layers in one-way manner, and the data processed by the upper layer can be transmitted to any neuron in the next layer. The hidden layer is typically multi-layered and finally output at the output layer (Gleitmann et al., 2007; Diaz et al., 2008; Wang and Xie, 2016).

![Figure 2. Back Propagation Neural Network](image)

Error back propagation algorithm is the main characteristic of BP neural network, and mainly embodied in the self-learning, organization and training of the implicit layer (Tarasov, 2006; Liu et al., 2013). When the error between the output value and the theoretical value exceeds the allowable range, the error back propagation is triggered for the data to learn again, and revise the weight W among the hidden layers, so that the output value is a little closer to the theoretical value. This operating mode of continuously learning, training back propagation, re-learning, re-training and re-back propagation is the main characteristic of BP neural network. It can reduce the output error and converge to the theoretical value by continuously adjusting the weighted average. However, the lack of reasonable algorithm control to the learning and training process may lose the engineering application value because the convergence period is too long.

BP neural network generally adopts negative gradient direction data transfer (Tarasov, 2006; Liu et al, 2013), that’s, BP neural network adjusts the threshold and weight between different layers to make the data transfer along the transfer function the fastest.

\[ X_{n+1} = X_n - a_n \times g_n \quad (1) \]

Where,
Xₙₚ - Matrix after weighted average and threshold processing in the upper layer;
Xₙ₊₁ - Output data after processing of this layer;
αₙ - Training rate of neural network;
gₙ - Gradient of the transfer function on the upper layer.

This paper adopts artificial neural networks based on the neural network of cranial nerve principle to predict the power of power grids, and constructs three layers of BP neural network, including input layer Xᵢ, hidden layer Sᵢ and output layer Yᵢ. The average weight between the X layer and the S layer is Wᵢᵢ, the average weight between the S layer and the Y layer is Vᵢⱼ and the offset is θ. Assuming that the input variable matrix is netᵢ, the modeling formula is as follows. The input layer-input variable matrix netᵢ operates according to the algorithm and outputs are as follows:

\[ Yᵢ = f(\text{net}_ᵢ), k=1, 2, 3, ..., k \] (2)

\[ \text{net}_k = \sum_j (Vᵢⱼ Yⱼ) - θ_k \] (3)

Hidden layer - input variable matrix netᵢ, according to the algorithm, the output is:

\[ Yⱼ = f(\text{net}_ⱼ), j=1, 2, 3, ..., j \] (4)

\[ \text{net}_j = \sum_k Wᵢⱼ - θ_j \] (5)

The transfer function is a unipolar Sigmoid function:

\[ f(x) = \frac{1}{1 + e^{-x}} \] (6)

The formula for calculating forward propagation error is as follows:

\[ E = \frac{1}{2} \sum_k (t_k - y_k)^2 \] (7)

Take Y, net to get the expansion of Formula:

\[ E = \frac{1}{2} \sum_k [t_k - f((Vᵢⱼ Yⱼ - θ_k)]^2 = \frac{1}{2} \sum_k [t_k - f((Vᵢⱼ f(∑_i Wᵢᵢ - θ_i) - θ_k)]^2 \] (8)

As can be seen from the above formula, the error of the BP network is a function of the multi-layer weighted average value W, V, and the trapezoidal descent parameter that adjusts and reduces E most effectively satisfies:

\[ ∆Wᵢⱼ = -η \frac{∂E}{∂Wᵢⱼ} \] (9)

\[ ∆Vᵢⱼ = -η \frac{∂E}{∂Vᵢⱼ} \] (10)

Where, η ∈ (0, 1) is learning rate constant.

The BP neural network analysis process has back propagation learning and training, so robustness is stronger (Grote et al., 2010; Barnett et al., 2013). In order to control the convergence period within a reasonable range for engineering applications, the analysis process is set to end when any of the following conditions are met:

When the error E is less than the set value, the artificial neural network analysis process ends.

The number of learning times reaches the set upper limit, and the artificial neural network analysis process ends.

Genetic algorithm

![Figure 3. GA-BP Neural Network Process Flow Diagram](image)

BP neural network has some disadvantages in practical application, such as larger space of location search and longer period of convergence of large data (Cloern et al., 2010; Mueller and Geist, 2011). In this paper, genetic algorithm is introduced on the basis of BP neural network. Genetic algorithm can optimize the weight, threshold and learning rate among layers, so as to accelerate global search, shorten convergence time and output more reasonable prediction value. The BP neural network based on genetic algorithm is referred to as GA-BP neural network (Genetic Algorithm–Back Propagation Neural Network). GA-BP neural
network transplants selection-hybridization-mutation in bionics into artificial neural network, and its algorithm flow is shown in Figure 3.

In MATLAB, the genetic algorithm is programed as follows:

\[
W = W = W_{\text{min}} + \frac{\text{Bin}_{2n-1}}{2n-1} [W_{\text{max}} - W_{\text{min}}] \quad (11)
\]

\[
F_i = k \sum_{i=1}^{n} \text{abs}(y_i - o_i) \quad (12)
\]

\[
f_i = k/F_i \quad (13)
\]

\[
P_i = \frac{f_i}{\sum_{i=1}^{n} f_i} \quad (14)
\]

\[
\{a_{kj} = a_{kj}(1 - b) + a_{ij}b \}
\]

\[
\{a_{ij} = a_{ij}(1 - b) + a_{kj}b \} \quad (15)
\]

\[
f(g) = R(1 - \frac{g}{G_{\text{max}}})^2 \quad (16)
\]

\[
a_{ij} = \begin{cases} 
  a_{ij} + (a_{ij} - a_{\text{max}}) * f(g) & (r > 0.5) \\
  a_{ij} - (a_{\text{min}} - a_{ij}) * f(g) & (r \leq 0.5)
\end{cases} \quad (17)
\]

The interpretation of variables and constants in MATLAB is shown in Table 1.

**Table 1. MATLAB Variable and Constant Definitions**

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Definitions</th>
</tr>
</thead>
<tbody>
<tr>
<td>(W_{\text{max}})</td>
<td>Weight, Threshold and Study Rate Encode Range High Limit</td>
</tr>
<tr>
<td>(W_{\text{min}})</td>
<td>Weight, Threshold and Study Rate Encode Range Low Limit</td>
</tr>
<tr>
<td>(a_{\text{max}})</td>
<td>Genetic Calculation High Limit</td>
</tr>
<tr>
<td>(a_{\text{min}})</td>
<td>Genetic Calculation Low Limit</td>
</tr>
<tr>
<td>(n)</td>
<td>Output Layer Final Output Unit Quantity</td>
</tr>
<tr>
<td>(o_i)</td>
<td>BP Neural Network No. i Cell Final Output Value</td>
</tr>
<tr>
<td>(y_i)</td>
<td>BP Neural Network No. i Cell Estimate Output Value</td>
</tr>
<tr>
<td>(k)</td>
<td>Genetic Algorithm Constant Parameter</td>
</tr>
<tr>
<td>(F_i)</td>
<td>BP Neural Network No. i Cell Init Fitness Value</td>
</tr>
<tr>
<td>(P_i)</td>
<td>Probability of No. i Cell to Be Selected</td>
</tr>
<tr>
<td>(b)</td>
<td>Random Value in Range [0,1]</td>
</tr>
<tr>
<td>(G_{\text{max}})</td>
<td>Maximum Routine Times</td>
</tr>
<tr>
<td>(g)</td>
<td>Current Routine Times</td>
</tr>
<tr>
<td>(R)</td>
<td>Random Value in Range [0,1]</td>
</tr>
</tbody>
</table>

\[
W_{x,50\times50} = \begin{bmatrix}
0.1230 & 0.0843 & 0.0956 & \ldots & 0.1152 & 0.1534 & 0.1872 \\
0.3370 & 0.2918 & 0.4542 & \ldots & 0.4910 & 0.3342 & 0.4151 \\
0.2710 & 0.2613 & 0.2611 & \ldots & 0.2970 & 0.3239 & 0.2741 \\
0.7770 & 0.7252 & 0.9213 & \ldots & 0.8823 & 0.9032 & 0.6978 \\
0.9011 & 0.8832 & 0.8193 & \ldots & 0.7988 & 0.9123 & 0.9002 \\
0.3101 & 0.4320 & 0.3819 & \ldots & 0.3665 & 0.2561 & 0.1892 \\
\end{bmatrix} \quad (18)
\]
Regression analysis and prediction

The prediction results of linear regression prediction analysis are as follows: Define $\beta_0$ as the fixed component coefficient, $\beta_1$ as the slope component coefficient, $Y_i$ as the output power of the power grid, $X$ as the variables such as flow, wind speed, light intensity and temperature. Get the following formula:

$$Y_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ij} + u_i, \ i=1, 2, 3, ..., n \quad (21)$$

Obtain component coefficient:

$$\bar{Y}_i = \frac{1}{n} \sum_{j=1}^{n} Y_{ij} \quad (26)$$

$$\bar{X}_i = \frac{1}{n} \sum_{j=1}^{n} X_{ij} \quad (27)$$

$$SE = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}{n-2}} \quad \text{(Standar Error)} \quad (28)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}{\sum_{j=1}^{n} (Y_i - \bar{Y})^2} \quad \text{(Coefficient of determination)} \quad (29)$$

$$S_\beta = \frac{SE}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X}_i)^2}} \quad (30)$$

$$t_\beta = \frac{\beta_j}{S_\beta} \quad \text{(Degree of freedom is n-2)} \quad (31)$$

$$Y = 0.0492 + 0.0282X_1 + 0.0133X_2 + 0.00551X_3 + 0.00138X_4 + 0.0158X_5 \quad (32)$$

The variation curves of the predicted value and the real value of the 17-day power generation power obtained through the program calculation is shown in Figure 5, and the variation of the predicted value and the real curve is basically consistent.

$$W_{x, 50x50} = \begin{bmatrix}
0.2671 & 0.3504 & 0.3688 & ... & 0.3526 & 0.3005 & 0.3041 \\
0.3311 & 0.2960 & 0.4421 & ... & 0.3913 & 0.3551 & 0.3246 \\
0.2710 & 0.2613 & 0.2611 & ... & 0.2970 & 0.3239 & 0.2741 \\
0.3311 & 0.2960 & 0.4421 & ... & 0.3913 & 0.3551 & 0.3246 \\
0.2710 & 0.2613 & 0.2611 & ... & 0.2970 & 0.3239 & 0.2741 \\
\end{bmatrix} \quad (19)$$

$$W_{x, 50x1} = \begin{bmatrix}
0.8973 & 16.1343 & 20.1592 & ... & 81.8374 & 23.4883 & 18.9278 \\
0.7980 & 0.9801 & 0.8831 & ... & 0.8970 & 0.8932 & 0.7799 \\
0.3571 & 0.2778 & 0.2239 & ... & 0.1883 & 0.1239 & 0.2019 \\
0.8931 & 0.8671 & 0.3567 & ... & 0.8344 & 0.8871 & 0.9850 \\
0.7980 & 0.9801 & 0.8831 & ... & 0.8970 & 0.8932 & 0.7799 \\
\end{bmatrix} \quad (20)$$

Figure 5. GA-BP Neural Network Predicted Value and Actual Value Curve

Figure 6. Regression Analysis Predicted Value and Actual Value Curve

The above formula is programmed in MATLAB and brought into the actual monitoring data of the previous 6 days. The curves of the predicted data obtained, and the actual data on July 17 are compared in Figure 6.

It can be seen from the analysis results that GA-BP neural network has higher prediction.
accuracy and stronger robustness, but its analysis process is more complex and convergence period is longer, so it is suitable for the occasions required for lower time-limit and higher accuracy. The prediction process of regression analysis is simpler and its convergence period is shorter, but its accuracy and robustness are worse than those of artificial neural networks, so it is mainly used when the accuracy requirement is not very high. The prediction performance of GA-BP neural network analysis and regression analysis is shown in Table 2. In order to take into account the accuracy, robustness and short periodicity of prediction, GA-BP neural network can be combined with regression analysis for the prediction.

\[ \hat{y}_k(t) = Y_k(t)u(t) + (1 - u(t))\hat{y}_k(t) + y_wk(t) \] (33)

**Smart Power Grid Control Optimization Based on Artificial Neural Network**

**Construction of structure model**

Each distribution unit of the new generation of smart grids has its own independent controller, which can independently monitor the power parameters of the unit, make low-level decisions, handle emergency line faults, and send data to the central controller using optical fiber network and Ethernet. The central controller has more advanced calculation and analysis capability and optimization control algorithm. After analyzing the prediction, the central controller sends corresponding instructions to the unit controller, so as to maximize power supply stability and power quality and save energy consumption.

This study builds an optimal management structure model of smart grid for energy control based on cranial nerve principle. As shown in Figure 7, there are three levels in decision-making strategies: direct control by unit controller, coordinated control and predictive control by central controller. The priority of the three decision-making levels increases gradually, the control accuracy increases in turn and energy management is more optimized.

After the analysis and calculation, the formula for the lower decision-making layer control strategy is as follows:

\[ J_{\text{LDM}_a} = \frac{1}{2} \sum_{k=0}^{T-1} \left[ \beta_0 (P_{a,T} - \bar{P}_a)^2 + \alpha_0 (X_{a,t+1} - \bar{X}_a)^2 + \gamma_0 (P_{a,t} - \bar{P}_a)^2 \right] \] (34)

The time domain discrete model of the energy storage section is:

\[ X_{s,a}(k+1) = \begin{cases} X_{s,a}(k) - \eta_c P_a(k) \Delta T - W_h, & P_a(k) < 0 \\ X_{s,a}(k) - \frac{P_a(k) \Delta T}{\eta_d} - W_h, & P_a(k) > 0 \\ X_{s,a}(k) - W_h, & P_a(k) = 0 \end{cases} \] (35)

where \( P_a(k) \geq 0 \) is necessary condition of \( \delta_a(k) = 1 \) (36)

\[ X_{s,a}(k+1) = X_{s,a}(k) - \frac{1}{\eta_d} \gamma_a(k) \Delta T - \frac{P_a(k) \Delta T}{\eta_d} - W_h \] (37)

Assume \( P_{a,t}^U - \bar{P}_a^U = 0 \), get the upper decision layer control strategy:

\[ J_{\text{UDM}_a} = \sum_{a=1}^{T-1} \left\{ \sum_{a=1}^{M} \left[ (C_{a,t} + \frac{f_a f_c C_H}{\sum_{a=1}^{M} P_{a,t}} A_{\text{max}}(U_{a,t}, 0) - B_{a,t} \Delta T) \text{max} (U_{a,t}, 0) + \gamma_a(P_{a,t}) + \frac{f_a f_{a,t}}{\sum_{a=1}^{M} P_{a,t}} C_{a,t} \Delta T \right] + \frac{\sum_{a=1}^{M} C_{a,t}}{\sum_{a=1}^{M} R_{a,t} I_{a,t} \Delta T} \right\} \] (38)

Where, \( P_{a,t} \) is a known quantity, and other relevant variables and electricity prices are set values. So \( J_{\text{UDM}_a} \) is only related to \( \sum_{a=1}^{M} R_{a,t} I_{a,t} \), indicating that the energy management of smart

**Table 2. Comparison of GA-BA Neural Network and Regression Analysis Prediction**

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy</th>
<th>Routine Cycle</th>
<th>Robustness</th>
</tr>
</thead>
<tbody>
<tr>
<td>GA-BP Neural Network Analysis Prediction</td>
<td>99.38%</td>
<td>Uncertain</td>
<td>Strong</td>
</tr>
<tr>
<td>Regression Analysis Prediction Method</td>
<td>92.10%</td>
<td>8 min</td>
<td>Weak</td>
</tr>
</tbody>
</table>
grids can be optimized by detecting the output power of load, and the optimum structure scheme of EMS can be obtained.

Verification of GA-BP neural network model
GA-BP neural network structure model based on cranial nerve principle is adopted to program and analyze the water power, wind power and photovoltaic power generation system of the city, and the load operation on a certain day is selected to carry out predictive control. It’s clear on that day, and the wind continues to be about 7 levels; there is no rain and snow in upstream, and water flow is stable. The load power, energy storage unit power and power output of the three types of power plants are shown in Figure 8 below.

As can be seen from the above figure, in terms of power generation, the output power of the hydropower generation is relatively stable, the fluctuation of the wind power generation at night is large, and the photovoltaic power generation has no output at night and reaches the maximum output power at noon in the daytime. The energy storage unit provides output as a backup power supply system during peak power consumption. At 11 noon, the load power suddenly rises rapidly, and the charging amount of the energy storage unit correspondingly drops rapidly. At 19 o’clock in the evening, the load power reaches the peak again. At this time, the fluctuation of the wind power generation is large, and the discharge power of the energy storage unit is well adjusted to ensure the smooth operation of power grids.

It’s clear that smart grids have good EMS real-time performance under control optimization of GA-BP neural network analysis and prediction based on cranial nerve principle. When the load power increases, the upper decision-making layer can command the energy storage unit to reduce the energy storage or switch to the discharge state immediately through the central controller, so as to maintain the stability of power grids, reduce the loss of fossil fuel for thermal power generation, and achieve the goal of energy saving and emission reduction.

Conclusions
Along with the vigorous implementation of smart grids in China, more renewable energy generation and flexible transmission are applied to large power grids, which will inevitably increase the complexity, fluctuation, nonlinearity and instability of smart grids. The rapid development of artificial intelligence technology provides a new idea to solve the power grid problem for the next generation of EMS. This study adopts the artificial neural network based on the cranial nerve principle, constructs the BP structural model of artificial neural network, and reach the main conclusions as follows:

With the artificial neural network based on the cranial nerve principle, this paper studies single-layer network control theory of large power grids, establishes BP neural network containing genetic algorithm, and constructs power forecasting model of power grids. With strong global searching ability and short convergence time, the model can reasonably obtain predicted value of power grids.

This study introduces the new EMS (Energy Management System) structure and strategy, constructs a three-level three-dimensional network analysis and prediction model, which provides a reference for power flow analysis, reasonable scheduling and control decision of smart grids.

This study adopts the GA-BP neural network structure model to program and analyze the hydraulic, wind and photovoltaic power generation system. The verification results show that the GA-BP neural network analysis and prediction model has good real-time performance of EMS, and can optimize the power analysis in combination with regression analysis method.
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References