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Construction and Application of Mathematical Model of Energy Economy

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This paper aims to explore the construction and application of the mathematical model of energy economy and to make the most accurate prediction of energy demand. By analyzing various factors affecting energy demand, it constructs a predictive index system and improves it with neural network model and particle swarm algorithm to predict future energy demand. It finds that accurate predictions can be made with this approach, and that the construction and application of the mathematical model of energy economy can provide an important theoretical basis for reasonable energy development strategies.

1. Introduction

Energy is an indispensable driver to social and economic development. It is an important strategic resource and plays a very important role in promoting and ensuring the sustainable, steady and healthy development of the social economy. With the rapid growth of social economy, the demand for energy continues to increase, and the contradiction between energy demand and supply also expands. Besides, the lack of necessary control measures will not only affect the upgrading and optimization of the industrial structure, but will even affect the economic growth. The construction and application of the mathematical model of energy economy can be remarkable in accurate forecasting of energy demand and formulating reasonable development strategies. The energy economic system itself is also a complex and non-linear system, affected by many factors in terms of demand. Research methods currently used are mainly regression analysis and consumption elasticity, which are not so effective in terms of accuracy. In view of this, this paper examines the systematic features of the mathematical model of energy economy, forecast the energy demand through nonlinear methods, and simulate biological neural networks to improve and optimize artificial intelligence. It establishes a neural network prediction mathematical model based on energy economic demands, and by combining its basic principles and implementation steps, validates the validity of the method by modeling historical data, thus providing a decision-making basis for subsequent management work.

2. Literature review

The approach to the construction of a mathematical model of wear elements of contact pairs of current collection devices (contact element and the contact wires) and electrical transport in view of the electric component was described. This mathematical model allows you to quickly assess the wear of the contact element and the contact wires and choose the optimal combination of materials reduces wear (Sidorov et al., 2015). The work was devoted to the investigation of mathematical models of drilling systems described by ordinary differential equations. The author continued the study done by the researchers from Eindhoven where the two-mass mathematical model of a drilling system was investigated. The modified version of the model, which took into account a full description of an induction motor, was studied. And it is shown that such complex effects as hidden oscillations may appear in these kinds of systems. These effects may lead to drill string failures and breakdowns (Leonov et al., 2014). A global, closed□loop, multiscale mathematical model for the human circulation including the arterial system, the venous system, the heart, the pulmonary circulation and the microcirculation was presented. A distinctive feature of the model is the detailed description of the venous system, particularly for intracranial and extra-cranial veins. Medium to large vessels are described by

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one□dimensional hyperbolic systems while the rest of the components are described by zero□dimensional models represented by differential□algebraic equations. Robust, high□order accurate numerical methodology is implemented for solving the hyperbolic equations, which are adopted from a recent reformulation that includes variable material properties (Müller and Toro, 2014). A quantitative and comprehensive evaluation of environ-economic benefits of anaerobic digestion (AD) of food waste was conducted on an operational project in China and the results of comprehensive evaluation conducted using fuzzy mathematical model were consistent with above results. Environmental benefits, energy consumption, and economic benefits of AD technology were 4.75, 3.58, and 1.36, corresponding to grades I, □, and IV, respectively. Single benefits decreased in the order of environmental impact>energy consumption>economic benefit, indicating that economic benefit is the restrictive factor in integrated environ-economic benefits of AD technology in practice. The established fuzzy mathematical evaluation model can realize comprehensive and quantitative evaluation of environ-economic benefits of AD technology; serve as valuable reference for perfecting evaluation systems, and assist in rational choice of renewable energy recovery technology from food waste (Chen et al., 2017).

A new method was introduced for incorporating short-term temporal variability of both power demand and VRE (variable renewables) into long-term energy-economy models: the RLDC approach. The RLDC approach was applied to REMIND-D, a long-term energy-economy model of Germany, which was based on the global model REMIND-R 1.2. Representing variability results in significantly more non-VRE capacity and reduces the generation of VRE in 2050 by about one-third in baseline and ambitious mitigation scenarios. Explicit modeling of variability increases mitigation costs by about one fifth, but power-to-gas storage can alleviate this increase by one third. Implementing the RLDC approach in a long-term energy-economy model would allow improving the robustness and credibility of scenarios results, such as mitigation costs estimates and the role of VRE (Ueckerdt et al., 2015). Energy efficiency policies play a key role in the transformation to a 'green energy economy'. In the paper, Ringel, et al. took stock of the impacts of the existing energy efficiency policy instruments in Germany and reviewed the energy, environmental and socioeconomic impacts of the country's latest energy efficiency and climate strategies for the year 2020. They find evidence supporting the findings of other studies that enhanced green energy policies will trigger tangible economic benefits in terms of GDP growth and new jobs even in the short term. Whereas policy makers have already acknowledged and implemented this conclusion in the case of renewable energies, the paper shows that striving for more ambitious energy efficiency policies represents a similar win–win strategy, which should be exploited to a much larger extent (Ringel et al., 2016). In a clean energy economy, green businesses play a central role by utilizing renewable energy technologies and employing green labour forces to provide clean energy services and goods. Their paper aims at analyzing factors driving the growth and survival of green businesses in the U.S. states, with hypotheses proposed on the impacts from clean energy policies and tax incentives, labour market conditions, and economic and political environments. A fixed effect regression analysis is applied with a panel data set of 48 continental states from 1998 to 2007 in the United States. The statistical analysis with a longitudinal data set reveals that the adoption of renewable energy policies, the permission of renewable energy credits imports, the stringency of minimum wage legislations, and presence of clean energy business associations are the major driving forces of the green business development in the U.S. states (Yi, 2014). Giraudet et al. discussed the results of a sensitivity analysis of Res-IRF, an energy–economy model of the demand for space heating in French dwellings. Res-IRF has been developed for the purpose of increasing behavioural detail in the modeling of energy demand. The different drivers of energy demand, namely the extensive margin of energy efficiency investment, the intensive one and building occupants, behaviour are disaggregated and determined endogenously. The model also represents the established barriers to the diffusion of energy efficiency: heterogeneity of consumer preferences, landlord–tenant split incentives and slow diffusion of information (Branger et al., 2015).

To sum up, the status of the construction of a mathematical model as well as energy economy is shown in this part, on which the study of the construction and application of mathematical model of energy economy will focus.

3. Method

3.1 Analysis of factors affecting energy demand

Energy demand is affected by many factors. Based on the research results of other scholars and following the principles of availability, comparability, practicality, and comprehensiveness, this paper looks at the following aspects that affect energy demand.

First, economic growth. It is the main factor, and with the rapid development of the social economy and continuous optimization of the industrial structure, its demand for energy will maintain a high level over a long period of time. Gross production value is used in this paper as indicators for measuring economic growth.

Second, energy consumption structure. It reflects the proportion of various energy consumption in the total consumption. China's energy consumption features coal and oil that are non-renewable, of low utilization rate, and can easily pollute the environment. The government is now vigorously promoting the development of renewable energy and clean energy, improving the energy consumption structure, and reducing energy consumption index. The energy consumption structure is shown in Figure 1.

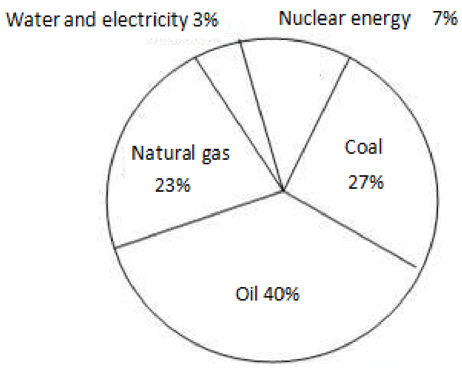

Figure 1: Distribution of energy structure

Third, people's living and consumption level. Improvements in people's living standards and changes in consumer attitudes and behavior can directly give rise to changes in the industrial structure, which in turn will affect the amount of energy consumption, especially the demand for high-quality energy such as electricity, liquids, and gaseous fuels.

3.2 PSO-BP model construction

BP neural network is a multilayer feedforward neural network characterized by forward transmission of signals and backward transmission of errors. In forward transmission, the input signal is processed layer by layer from the input layer, through the hidden layer, and to the output layer. The neuronal state of each layer only affects the state of neurons of the next layer. If the output layer does not get the desired output, it starts backward transmission and adjust network weights and thresholds according to the prediction error, so that the predicted output of the BP neural network will constantly approach the output expected. Substitute PSO-optimized weights and thresholds, as BP neural network initial weights and thresholds, into the BP network, train until they meet the network's performance indicators, that is, when the mean square error is lower than the preset error requirement or the maximum number of iterations is reached, stop the iteration and output the result. Otherwise, continue iterating until the algorithm converges. The neural network structure is shown in Figure 2, and the function curve, in Figure 3.

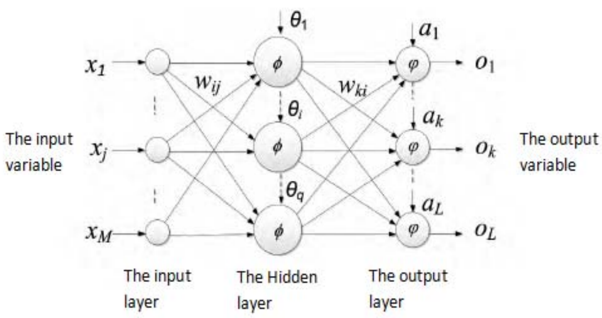

Figure 2: Neural network structure diagram

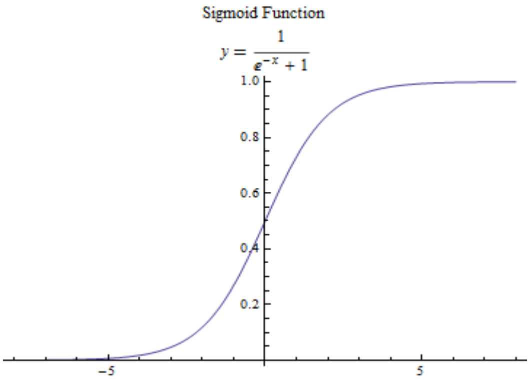

Figure 3: Sigmoid function curve

The running flow of the network is: After inputting a sample, obtain the feature vector of the sample, and then obtain the input value of the perceptron according to the weight vector. Use the Sigmoid function to calculate the output of each perceptron, and then take this output as the input of the next layer of perceptron, and so on, so forth, until to the output layer. To obtain the weight vector, constantly adjust the weight vector by minimizing the loss function. This method can also be used to solve the weight vector here. We need to first define the loss function. As the output layer of the network has multiple output nodes, we need to sum the squared differences of each output node of the output layer. In a multi-layer neural network, the error surface may have multiple local minima, which means that with the gradient descent algorithm, we may figure out local minima instead of global minima. The schematic diagram of a single neuron is shown in Figure 3 and Figure 4.

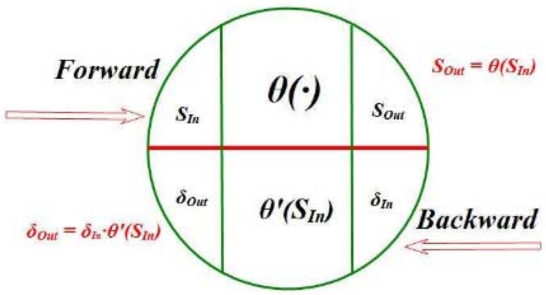

Figure 4: Internal schematic of individual neurons

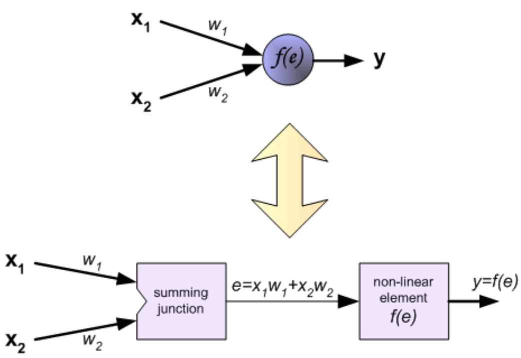

Figure 5: Individual neurons

The error signal of the input layer is related to the difference between the expected output and the actual output of the network, and directly reflects the output error. The error signals of the hidden layers are related to the error signals of the previous layers, and are transmitted back from the output layer layer by layer. It can be seen that the BP algorithm belongs to δ learning rules, and this type of algorithm is often referred to as

error gradient descent algorithm. The δ learning rule can be seen as a generalization of Widrow-Hoff (LMS) learning rules. The LMS learning rules have nothing to do with the transformation functions used by the neurons, and therefore do not require the derivative of the transformation function. The δ learning rules, on the contrary, requires the transformation function to be derivative.
This is why the Sigmoid function was used earlier. Backward feedback starts from the last layer, or the output layer. The purpose of training neural networks for classification is that the output of the last layer can describe the category of data records. For example, for a binary problem, we often use two neural units as the output layer, and if the output value of the first neural unit of the output layer is larger than the second neural unit, we deem that this data record belongs to the first category. Otherwise, it belongs to the second category. In the design of the network, the expected error value should also be determined by comparison training to a suitable value, which is determined relative to the required number of hidden layer nodes. In general, two networks of different expected error values can be trained simultaneously, and one of the networks is ultimately determined by a combination of factors. The selection of neural network hidden layer neurons follows such a principle: Where the problems can be solved, add one or two neurons to speed up the decline of error rate.
Although the standard particle swarm optimization algorithm is fast in convergence and strong in versatility, such a process only uses the individual optimal and global optimal information, hence overly fast disappearance of population diversity, as well as such drawbacks as premature convergence, inefficient later-stage iteration, or the dilemma of local optima, which increases the difficulty of finding a global optimal solution. Therefore, the idea of mutation in the genetic algorithm is used to reinitialize some qualified particles with a certain probability, so as to maintain the diversity of the population through mutation operations, expand the search space of the population, and enable the particles to jump out of the current local optimal position to search for global optimal values in a larger space.
As for the structure of the neural network, the larger the prediction index system is and the more indicators there are, the more complex the model and the greater the uncertainty the prediction result will be. The generalization ability of the model will decrease as a result, and the time for calculation will increase. Therefore, it is necessary to quantify the previously determined indicators that affect energy demand, and to reduce the number of indicators where information loss is minimized, hence the dimensionality reduction of sample indicators.
This paper chooses a three-layer BP neural network model. Without any universal method, the number of hidden layers is determined out of experience or multiple tests. Since the number of hidden layers will affect the learning time, the effect of fitting, and the generalization ability of the model, we need to determine an optimal number of hidden layer units. According to the research findings of relevant scholars, the number of hidden layers is related with the requirements of the question and the number of input and output indicators. Use the Sigmoid function for the hidden layer, and Pureline function for the output layer, as is shown in Figure 5.

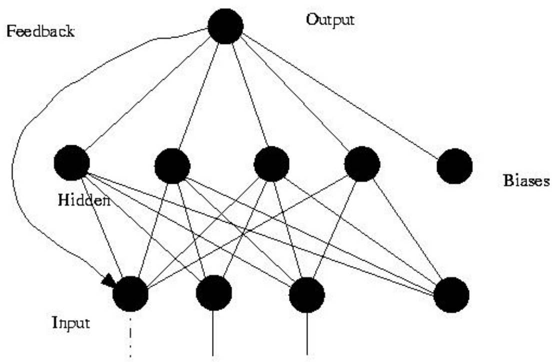

Figure 6: Feedback Neural Networks

4. Results and discussion

Table 1: Energy demand from 2014 to 2018

Time	2014	2015	2016	2017	2018
Demand	26998.5	*28455.2*	29965.3	31475.6	33854
Proportional increase (%)	4.5	5.3	5.7	5.9	6.6

The future energy demand is shown in Table 1 below.
We can see that energy demand will continue to grow in the future, at an average growth rate of around 5.5%. The pace of growth will accelerate, and the demand in 2018 will reach a higher level. Therefore, policymakers need to consider how to take effective measures to address the contradiction between supply and demand imbalances in response to the rapidly growing energy demand. While maintaining the supply capacity, we need to speed up the adjustment of energy consumption structure and build a safe, stable, economic, and clean modern energy supply security system as required for scientific development. Specifically, to provide a strong energy guarantee for social development, we should further improve the energy structure and layout, increase the efficiency of energy use, gradually reduce the energy consumption per unit of GDP, and make breakthroughs in the development of new energy sources.

5. Conclusion

The rational use of energy resources can directly determine the direction of economic development, and the planning of energy structure is also the focus of current research work. The construction and application of mathematical models can effectively improve the prediction of energy demand. The BP artificial neural network model mentioned in this paper can simulate the structure and function, and effectively raise the accuracy of the prediction results. Neural networks have unparalleled advantages in dealing with non-linear problems, and prediction control can well adapt to constrained variable operations. Neural networks can be tapped to fully approximate any complex nonlinear functions. As parallel distributed processing algorithms can be adopted for quick and real-time calculation, a neural network identification model can be constructed as a prediction model. Moreover, mathematical models are widely used for prediction, and different mathematical models can be used to different types of prediction and actual conditions. Data mining algorithms may also be used for the analysis of these data, and different parts of the model may be re-adapted in different forms.

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