Regional Demand Forecasting of Refined Oil under Alternative Energy Market's Competition

Wan Zhang and Yongtu Liang

***Abstract*—Refined oil, including gasoline, diesel, et al., is an important fuel for transportation and other industries. With the promotion of new energy, the demand for refined oil market has formed a competitive relationship with the alternative energies' market. It is necessary to design and transform the refined oil supply chain to meet market requirements and ensure the balance of supply and demand. Forecasting the demand of refined oil market is the important basis for designing and transforming the refined oil supply chain. Because BP neural network shows strong adaptability when solving multi-parameter nonlinear problems, this paper proposed a BP neural network model from the analysis of conventional influence factors and special impact factors such as the share of alternative energies' market. The actual data was tested to prove that the model could reflect the relationship between the market share of alternative energy and the market demand of refined oil. Analysis was given about the future development of the refined oil market and alternative energy based on the experimental results.**

***Index Terms*—Demand forecasting, refined oil, alternative energies competition, BP neural network.**

I. Introduction

Refined oil, i.e., gasoline, jet fuel, kerosene, diesel, lubricating oil, et al., has a great impact on transportation industry [1], [2]. Although new energy vehicles [3]-[6] and electric trains are gradually replacing traditional ones, the number of internal combustion engines, those still in their service life, is much more than we thought. Moreover, the fuels of passenger aircraft, transport aircraft, and military equipment cannot be replaced by non-fossil fuels currently. One of the prerequisites for designing a reasonable refined oil supply chain network is to clarify the market demand for refined oil products in a region, and to predict the demand changes of the commodities at this stage or in the future. Accurate prediction is benefit to adjust the scale of the refinery and arrange transportation plans to ensure the stability of the refined oil supply chain.

Refining capacity in China will continue to expand. In 2018, the processing capacity of China's refineries will reach 882 million tons per year. After the local refineries with backward production capacity have been eliminated in the past two years, the capacity will accelerate to expansion, and the main refineries will be expanded and rebuilt in the future. It is estimated that by 2022, the processing capacity of China's refineries will exceed about one billion tons. From the perspective of the demand side, domestic demand for refined oil products is not optimistic in recent years. Apparent consumption of refined oil products in 2017 was 320 million tons, up only 2% year-on-year. In terms of varieties, gasoline demand growth has almost stagnated, and diesel demand has experienced negative growth. The demand growth of kerosene is relatively good, with an annual growth rate of around 10%. The proportion of refined oil used in transportation industry has been rising, and it has become the absolute main force of refined oil consumption. But energy market is not satisfied with fossil fuels. Technological advancement helps greatly in achieving some means of harvesting energy from the renewable sources and to use them as the source of new, clean and sustainable energy to meet the world's energy demand [7]-[9]. The alternative energy sources of refined oil mainly include natural gas, electricity, fuel methanol, fuel ethanol, biodiesel and coal-to-liquid. The diversification of travel mode also has a certain substitution for refined oil consumption, such as the emergence of public bicycles. In recent years, the scale of domestic alternative fuel consumption has continued to rise. According to PetroChina Company, the total size of alternative fuels in 2017 was approximately 37.06 million tons, accounting for 11.5% of the final consumption of refined oil products, of which natural gas substitution was the largest, accounting for 64%. about. Therefore, it is necessary to forecast and analyze the demand of the refined oil market, which can provide an effective basis for the design and transformation of the refined oil supply chain.

Demand forecasting refers to estimating the demand for the entire product or a specific product within a certain period in the future [10]-[12]. Demand forecasting methods are broadly divided into qualitative forecasting methods and quantitative forecasting methods. In the last few years, several works have been performed on consumer segmentation, profile characterization, demand analysis and prediction from the data recorded by real-world sensors. The forecasting of energy supply and demand is the core of an energy planning models [12]. The selection of a forecasting method is mostly based on data availability and the objectives of the tool and planning exercise. According to reviewed literature, Neural Networks (NN) structure with two hidden layers produced best results for the monthly load forecasting, the peak load forecasting and the daily total load forecasting modules. NN is the preferred machine learning tool and are known as both feedforward and backpropagating networks,

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Wan Zhang is with Instituto Superior Técnico, University of Lisbon, Portugal and the National Engineering Laboratory for Pipeline Safety/Beijing Key Laboratory of Urban oil and Gas Distribution Technology, China University of Petroleum-Beijing, P. R. China (e-mail: zhang.wan@tecnico.ulisboa.pt).

Yongtu Liang is with National Engineering Laboratory for Pipeline Safety/Beijing Key Laboratory of Urban oil and Gas Distribution Technology, China University of Petroleum-Beijing, Beijing 102249, P.R. China (e-mail: liangyt21st@163.com).

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where a number of inputs are weighted in order to provide a predictive outcome. Neural networks are good for detecting non-linearities and therefore preferred as a predictive tool in electrical load forecasting, yet also often criticized for low transparency and lack of interpretability because of the black box approach, and using large amount of data [13]. Artificial Neural Network (ANN) is a research focus in the field of artificial intelligence since the 1980s, and has been used to forecast the energy's demand at the field of electricity, domestic water, daily necessities and car sales [12], [14]-[18]. The purpose of this paper is to use the machine learning method to predict the demand and development prospects of the refined oil market by considering the factors affecting the demand for refined oil market, especially the impact of alternative energy on fossil fuels.

II. Methodology

A. Impact Factors

In China, gasoline consumption is mainly concentrated in transportation and domestic consumption. Diesel is widely used in trucks, railway locomotives, water transport and generators. From the perspective of consumption structure, the factors that affect the regional demand for different types of oil products are not the same. In this paper, we study the demand for gasoline and diesel fuel, which are the most common fuels transported by pipeline. The market demand for gasoline almost fully concentrates on the road transport sector for vehicle in China. For diesel, the road transportation is the key but not the entire component of demand. Therefore, we provide each forecasting method separately.

B. Demand Forecasting Model

BP neural network is a multi-layer feedforward network, trained by error inverse propagation algorithm. The topology model includes input layer, hidden layer and output layer, as shown in Fig. 1. The BP neural network is used to propose the demand forecast model of refined oil market. The economic indicator of strong correlation is the input variable, and the demand of refined oil market is the output variable.

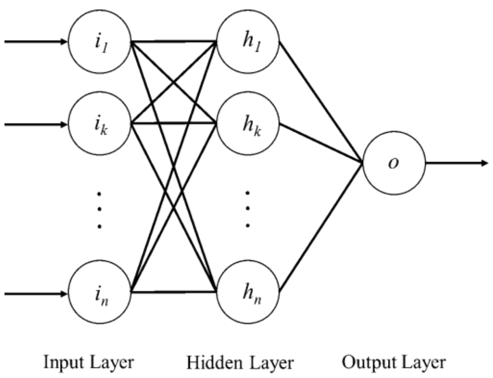


Fig. 1. Topology structure of BP neutral network.

The set $X_i = (X_{i1}, X_{i2}, \cdots, X_{in})$ is the economic indicator vector for the year i, and $Y_i = (y_i)$ indicates the demand vector for the year i. The economic indicators from the first year to the year $n-1$ are taken as input samples P, and the demand from the second year to the year n is taken as the output sample r. The BP neural network is trained with the input samples P and the output sample r. After the training is completed, the input indicators X_n of the year n can predict the demand of the year $n+1$ in this network. According to Kolmogorov's theorem, the three-layer BP neural network can determine the number of hidden layer nodes according $n_1 = 2n+1$, and the algorithm flow is following in Fig. 2.

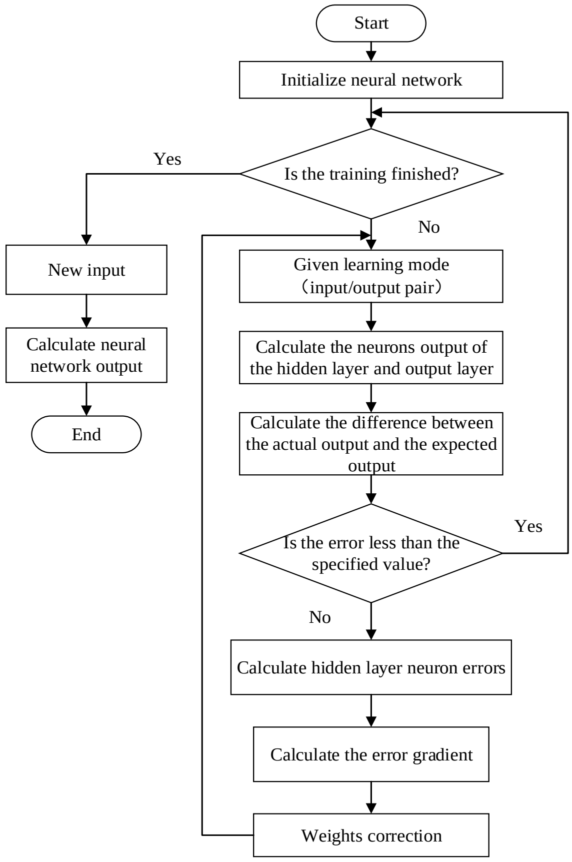


Fig. 2. BP neural network algorithm flow chart.

III. Results and Discusses

A. Data Sources

Due to the much more factors affecting the demand for refined oil market, this paper starts from the actual analysis and selects the population density, car ownership and life span, the transformation and sales volume of new energy vehicles, the number of public bicycles, etc. of a region in 2005-2015 to research. Data came from the refined oil sales company and the National Bureau of Statistics of China. The demand of refined product oil in the cities of mid-China is shown in Fig. 3.

B. Results

According to the modeling method of BP neural network, the impact factors from statistics are as the input of neural network and trained. As can be seen from the neural network training process of Fig. 4, the relative error of the actual output and the expected output can be less than a given accuracy after training.

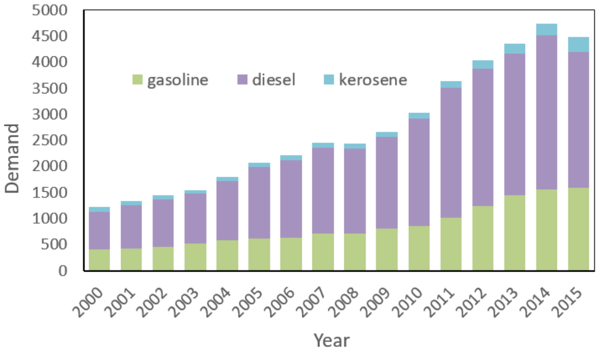


Fig. 3. Demand of refined oil in the cities of mid-China.

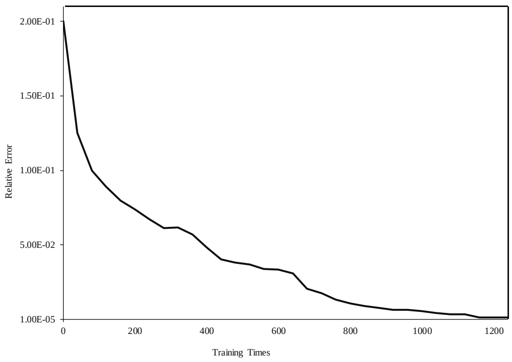
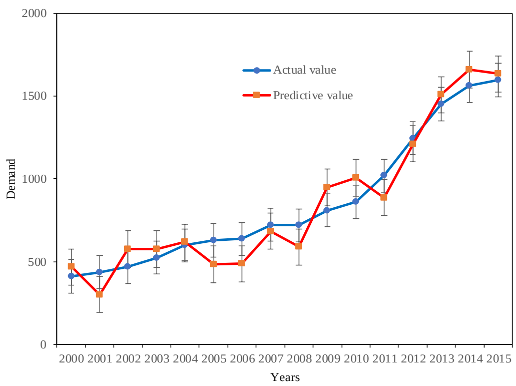
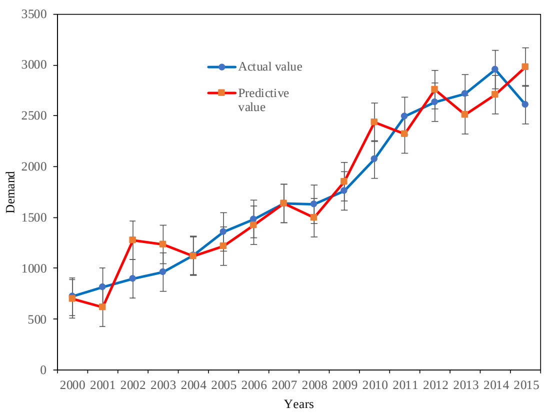


Fig. 4. Training process of neural network.

First, the model forecasted the demand of refined oil in 2005-2015, and compare with the actual sales of refined oil in the same periods. It can be found from Fig. 5 that the demand of gasoline and diesel is basically consistent with the trend of actual demand, and the relative error is less than 15%.



(a)



(b)

Fig. 5. Comparison of forecast results with actual data from 2005-2015: (a) Gasoline (b) Diesel.

Based on the data of 2005-2015, the model predicted the market demand of gasoline and diesel in 2016-2031, as shown in Fig. 6. Within 10 years, the market demand of refined oil is still increasing, but the growth rate is slow. After eight years, the demand of gasoline is the first to start to decrease, and diesel also shows the same trend after 10 years.

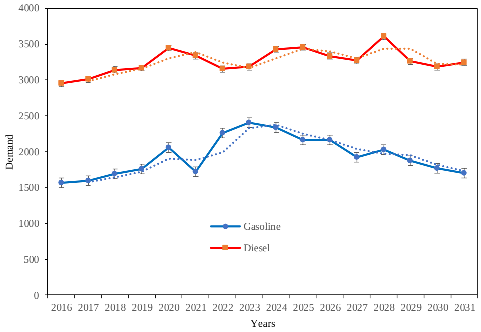


Fig. 6. Demand forecasting of gasoline and diesel in 2016-2031.

China's diesel consumption may enter a period of slow growth or platform. The growth rate of diesel consumption has begun to slow down due to various factors such as industrial production capacity and alternative energy sources. Diesel is currently mainly used in transportation, and its application is being affected by many alternative energy sources. Firstly, compressed natural gas vehicles (CNG) and electric vehicles have been widely used in public transportation in recent years. Secondly, LNG has replaced diesel as a large passenger. The main fuel for cars and heavy goods vehicles; the construction of rail transit and high-speed rail has also reduced the demand for diesel locomotives; in addition, with China's emphasis on air quality, the emission standards for vehicles and ships have been upgraded, and diesel has gradually been replaced by light fuel oil. Although the growth of output value of the transportation industry has a great impact on the growth of diesel consumption from the long-term cointegration relationship, diesel consumption is likely to be unable to sustain the growth of the previous stage due to the impact of alternative energy, infrastructure construction and national policies. Trends, while entering a period of slow growth or consumption platform, may even decline. There is a long-term cointegration relationship between private car ownership and domestic gasoline consumption, and the growth of the former has a very large impact on the latter, which will be the most important factor determining the future consumption of gasoline in China. It is estimated that by 2023, gasoline consumption in the living sector will exceed the transportation sector and become the dominant gasoline consumption in China.

IV. Conclusion

As one of the most important fuels, refined oil still plays an irreplaceable role in the transportation and other fields today. However, the development of alternative energy markets is bound to affect the demand for traditional energy. This paper uses BP artificial neural network to predict the demand of refined oil market, considering various factors such as population density and car ownership, and regarding alternative energy as an important factor. The results show that refined oil is still the important fuel for social and economic development, and its demand will continue to increase slowly in 10years. Alternative energy sources such as natural gas, electric power, biofuels, et al., are gradually being promoted, but they are still not mature in terms of the development, equipment modification, and key technology to be broke through. With the development of sustainable energy and the government's policy toward new energy, fossil fuels will gradually be replaced, and the market share and demand will gradually decrease.

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Wan Zhang received the bachelor degree in oil and gas storage and transportation engineering from China University of Petroleum-East China, Qingdao, China. He is currently working toward the Ph.D. degree in oil and gas storage and transportation engineering at China University of Petroleum-Beijing (CUPB), Beijing, China. His current research interests include pipeline scheduling optimization, topological structure optimization, logistics, and supply chain management of refined oil.

Yongtu Liang received the B.Eng. degree from China University of Petroleum-East China, Dongying, China, in 1995 and the M.S. and Ph.D. in oil-gas storage and transportation engineering in 2001 and 2009 from China University of Petroleum-Beijing (CUPB), Beijing, China. He is currently a professor at China University of Petroleum-Beijing, Beijing, China. His current research interests include long-distance pipeline transportation, multiphase pipeline transportation, and field gathering and transportation. He has presided over three National Natural Foundations and five provincial foundations, and has published 64 papers in many top international journals and conferences.