Comparison on the Application of BP Neural Network and Logistic Regression in the Study of Technology Life Cycle

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Abstract. The research on technology life cycle can be used in technology transaction, technology prediction, technology evaluation and so on. It is an important reference basis for enterprise strategy making, government policy making and so on. This study constructed a BP neural network model based on the patent accumulative quantity to judge the TLC, and compares the results with the logistics regression method which is the more mature in academic circles. It is found that it is feasible to use BP neural network to study TLC with a better result on technology prediction and no difference in identifying TLC phase compared to logistics regression.

1. Introduction
The TLC is an important index to reflect the history, present situation and future trend of the development of technology. It is the basis of the formulation of enterprise technology strategy, the reference of industry development potential, and the basis of government policy making. How to effectively judge the TLC is of great significance from both micro and macro aspects. The study of life cycle originates from the study of the development trend of things in natural ecosystem from emergence to extinction. And then it turns out that the life cycle of things in social system is similar to that of natural ecosystem of which the achievements and theories have been gradually popularized and applied. The concept of TLC originated from the product life cycle theory proposed by Harvard Professor Raymond V in 1966[1]. Then Abernathy and Utterback clearly put forward the concept of TLC in 1978. It is that the development process of technology can be divided into four phases according to its characteristics: seed phase, ascent phase, maturity phase and decline phase[2]. Arthur Little gave a further explanation of the meaning of the "four-phase" TLC according to the degree of integration of technology and products[3]. Harvey(1984) and Khalil(2000) divided the TLC into six phase: development phase, verification phase, technology application phase, expansion phase, maturity phase, recession phase[4][5]. No matter how many phases the TLC is divided into, scholars have a basic consensus on the characteristics of the whole process of technological development connected by these phases. It is that technology progression “advances slowly at first, then accelerates, and then inevitably declines” (Foster, 1986: 20)[6].

There are many methods to identify the life cycle phase of technology with no authoritative method, because different methods have their own unique advantages and limitations in a specific situation. Common qualitative methods include Delphi method, TRL technology maturity method and so on,
which are more subjective relaying on experience. Common quantitative analysis methods include S-curve method, scientific measurement method, patent analysis method and so on, which are often limited by the amount of data, parameters, and models selected. Whether qualitative and quantitative methods, the models based on patent databases are widely used to analyze the TLC. This is because the patent itself contains a lot of previous secret technology knowledge, revealing information about the development of the technology. At the same time, patents can reveal the commercial potential of technology because patent applications are designed to protect possible commercial applications[7].

The development trend characteristics of TLC Foster mentioned accords with the general form of S-curve. Andersen(1999) pointed out that the evolution of the number of patent applications could reflect the attractiveness of technology to investment. And the S-curve model formed from the numbers of patent application is widely used in the prediction of TLC. (e.g. Chang et al.,2009. Tseng et al.,2011). Among them, Logistics Regression is more mature in the fitting of S curve, but its hypothesis is that the curve is centrosymmetric at the inflection point, which may be different from the actual situation of the evolution of patent quantity. With the development of data mining technology in recent years, some methods based on machine learning are emerging, such as: using self-organization mapping method to predict patent trend[8]; using deep neural network to construct patent life prediction model[9]; Using wide and deep neural network and a recurrent neural network to realize technical prediction[10], using neural network algorithm for short time series to calculate technical life cycle and so on[11]. These methods have been optimized to some extent, and patent data can be analyzed in depth in order to explore the TLC more accurately.

ANN is a nonlinear and adaptive information processing system composed of a large number of processing units interconnected. It is an intelligent method that can be used to predict and estimate. Its ability in optimizing prediction provides a greater opportunity for the analysis of patent database[12]. ANN shows significant ability to fit nonlinear data, even data sets with incomplete and error information[13]. For patent database with incomplete information, the life cycle of technology can be predicted by using the learning ability of ANN. In this study, the patent database is analyzed by ANN model to construct the technical life cycle curve. Meanwhile, it is compared with the technical life cycle S-curve based on logistic regression.

2. Method

There are four stages to construct the TLC model using ANN and patent database in this study. The specific methods and operations involved in each stage are as follows:

Stage 1: patent search

The patent database is used to search the related patents of the technology to be identified. Select a appropriate time stage and step size, then the cumulative number of patents at each time point could be obtained.

Stage 2: data fitting by BP neural network model

With the time point as input and the cumulative numbers of patents as output, a BP neural network (as shown in Figure 1) could be established to explore the relationship between input and output. In order to improve the generalization ability of neural network and avoid the over-fitting, an appropriate processing method should be selected according to the data characteristics. For the shallow BP network constructed in this study, the Bayesian regularization method is selected to train the network, which will reduce the weight and bias of the network to force the network response to be smoother and reduce the possibility of over-fitting. This method can be achieved by the trainbr functions in the Matlab. The Bayesian regularization method usually works well on the input and output in the range of [-1,1], so the input data should be normalized before the network is trained.
Stage 3: data fitting by logistic model

Set the time point as the independent variable and the cumulative number of patents as the dependent variable, the patent data could be regressed base on logistic model. Appropriate parameter estimation method was selected to ensure the rationality of the prediction results. The trend of patent quantity change was predicted by the fitting curve.

Logistic equation is defined as:

\[ x_i = \frac{1}{c + ae^{bt}} \]  

(1)

where the \( x_i \) usually represents the time variable; \( a, b, c \) is the parameters of the model. And iterative method was selected for parameter estimation as below:

\[ \frac{x_{i+1} - x_i}{x_{i+1}} = 1 - \frac{x_i}{x_{i+1}} = 1 - \frac{1}{1 + ae^{bt+1}} = \left(1 - e^{b}\right) - c \left(1 - e^{b}\right) x_i \]  

(2)

then new variable \( z_i \), new parameters \( \gamma, \beta \) can be defined as:

\[ z_i = \frac{x_{i+1} - x_i}{x_{i+1}} ; \quad \gamma = 1 - e^{b} ; \quad \beta = -c \left(1 - e^{b}\right) \]  

(3)

Thus function (2) could be transferred to function (4):

\[ z_i = \gamma + \beta x_i \]  

(4)

The \( a, b, c \) estimates can be obtained by estimating \( \gamma \) and \( \beta \) according to the data samples, thus the fitted logistic curve could be obtained.

Stage 4: comparing fitting results from stage 2 and stage 3

Compare the morphology, inflection point and saturation point of the TLC curve obtained in stage 2 and 3.

3. Empirical analysis

In this paper, fluidized-bed combustion boiler technology was selected as an example to construct its technology life cycle curve. Fluidized-bed combustion boiler is a kind of boiler with fluidized bed combustion mode. It has the characteristics of strengthening combustion and heat transfer at low temperature. At the same time, its high utilization rate of fuel and low emission rate of pollutants make its application in boiler industry develop rapidly.

Stage 1: Patents search of fluidized-bed combustion boiler

Based on Dwiend patent database, relevant patent data was collected to predict the life cycle of fluidized combustion bed boiler technology. A total of 661 patents were retrieved from 1972 to 2020. Set the step size as 1 year, and the annual cumulative number of patents is shown in figure 2.
Stage 2: data fitting by BP neural network model

Set the year as the input feature and the cumulative number of patents as the output, a BP neural networks with ten hidden layers (the number of hidden layers is estimated according to the size of input and output data and empirical formula) was constructed and the activation function is Sigmoid function. Bayesian regularization method was used to improve the generalization of the network, and gradient descent method was used to reduce the loss function.

Stage 3: data fitting by logistic model

Set the year of patent application as independent variable, the cumulative number of patents as dependent variable. The yule iterative algorithm is used to estimate the parameters of logistics regression. The growth curve of the patent accumulative quantity is shown in “logistic prediction” in figure 3. The saturation value of the cumulative number of patents reached 906 in the year 2071. The point of 90% maturity level is in the year 2031 and the inflection point is in the year 2015.

Stage 4: comparing fitting results from stage 2 and stage 3

The fitting results from both the BP neural network model and logistics regression model turn out to be S-curve as figure 3 shows. And the fitting effect of the neural network is better, of which the actual value deviates from the predicted value to a smaller extent. From the point of view of the changing degree, the maturity level of technology will reach 90% at the same year of two curves, that
is, there is no difference between the boundary point of technology from mature phase to recession phase identified by the two different model. And the difference between the boundary point of technology from growth phase to maturity phase is within 5 years of the two model.

4. Discussion
The empirical part takes fluidized bed boiler technology as an example to study the different performance of BP neural network and logistics regression in predicting TLC. The results and causes can be discussed in the following ways:

Firstly, according to Fisher’s theory, the time point in which the 10%, 50% and 90% of the saturation quantity of patents reach could be regarded as the 3 boundary points of the four phases of TLC. The empirical results show that the two model each performs well in identifying the phases of TLC with few differences. But the neural network works better than the logistic regression under the condition of small data scale.

Secondly, the saturation quantity of patents and the whole duration of TLC differs, because the property of the logistic function causes the curve to change slowly in the process of approaching the maximum value but the neural network was not affected by this. The differences in the prediction of patent quantity development may be caused by the logistic S-curve’s centrosymmetric about the inflection point, so it is possible to underestimate the patent growth rate when forecasting under the data size limit. And BP neural network can correct the deviation from the actual situation caused by strict symmetry of logistics curve.

There is not an certain conclusion that which method is superior to the other. Whether BP neural network model or logistics regression should be selected depends on the purpose of studying TLC. If the purpose is technology prediction, using BP neural network could get a better reflection of real situation. If the purpose is identifying the life phase of technology, both methods could do well but the logistics regression is easier to operate.

5. Conclusion and prospect
A quantitative method for identifying the TLC is offered in this study which can be applied for diverse technologies and parties. However, there is still room for improvement in the method. Using patent as the univariate input may have the problem of insufficient reliability. In the subsequent research, more measuring indicators of technology can be introduced as multivariable input to construct neural network to study TLC.

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