Automatic Shift with 4-parameter of Construction Vehicle based on Neural Network Model

Zhao Dingxuan Cui Gongjie
College of Mechanical Science and Engineering, Jilin University
Changchun, Jilin, China
cgj@email.jlu.edu.cn;

LI Yingjie
Aviation University of Airforce; College of Mechanical Science and Engineering, Jilin University
Changchun, Jilin, China
Gongjie Liu Shubo Zhang Yuankun
College of Mechanical Science and Engineering, Jilin University
Changchun, Jilin, China

***Abstract*—A new shift schedule with 4-parameter of construction vehicle was discussed and analyzed. The power train model of construction vehicle is vital to automatic shift and difficult to be expressed with mathematic model, while intelligent control is effective for solving the problem. A multi-layer back-propagation neural network (BPNN) model was proposed to describe the model of construction vehicle. The BPNN was trained based on input/output dada taken from experiment before that. Based on the BPNN, improved algorithms were proposed to accelerate calculation of optical shift point and control approach. Experimental results showed that the shift strategy with 4-parameter was better than that with 3-parameter and could improve the efficiency of torque converter and save energy, and BPNN was effective to improve shift decisions intelligence of construction vehicle.**

***Keywords*—Construction vehicle, Automatic shift, 4-parameter, back-propagation, neural network.**

I. INTRODUCTION

Construction vehicle usually works in the complicated and execrable environment and its load is changeful, so it is hard to operate. To relieve the driver's labor intensity and improve the power performance and fuel economy, automatic transmission is now widely used in construction vehicle, and the shift schedule plays a key role in automatic transmission of construction vehicle[1][2]

Nowadays, there are many shift schedules of construction vehicle, such as 2-parameter shift schedule, which use the throttle opening and vehicle speed as shift parameters, or 3-parameter shift schedule, where the 3 parameters are throttle opening and the speeds of the impeller and the turbine of hydrodynamic torque converter. However, all of those schedules mentioned above neglect the change of power that working pump consumed. In fact, when construction vehicle works, much engine power is consumed by working pump, and it can even reach to 40% ~ 60% of engine power at most. Furthermore, the working pump pressure is unstable. Considering the change of power consumption by working pump, a new shift schedule with 4-parameter is discussed, where parameters are the pressure of working pump, throttle opening, pump speed and turbine speed of torque converter. Due to the inner complex physical and chemical change in the course of engine operation, based on mechanism modeling or curve approximating, the precision of model obtained is usually limited[3].In the paper, a multi-layer back-propagation neural network (BPNN) model will be proposed to describe the model of construction vehicle and analyze the intelligent gearshift control.

II. MECHANICAL MODEL

A power train of construction vehicle with automatic transmission usually consists of six main components, such as diesel engine, oil pumps, torque converter, gearbox, output train, and vehicle. All components can be considered as rigid bodies, which are connected to each other by ideal rigid joints, clutches and force elements, as shown in Fig.1.

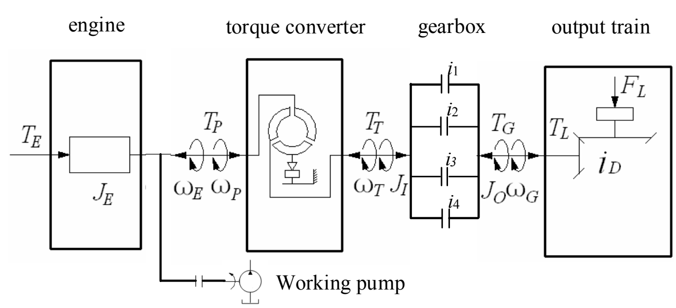

Fig.1. Power train model.

As is seen in Fig.1, the engine power is divided into two parts: one part is consumed to drive by torque converter, and the other one is consumed to operate by working pump.

III. SHIFT SCHEDUL

Torque converter is indispensable to construction vehicle, however, its efficiency is low. From the primary characteristic of YJ355 torque converter shown in Fig.2[4,5], we can see that there are two points which meet the operating condition of $\eta_c = \eta_{c\min}$ $\eta_{c\min}$,the lowest efficiency for construction vehicle, is usually selected as 0.75. So the whole operating condition of torque converter is divided into three regions by the two points, low efficiency range with low speed ratio, high efficiency range and low efficiency range with high speed ratio. The operating point of torque converter of construction vehicle moves to the low efficiency range with low or high

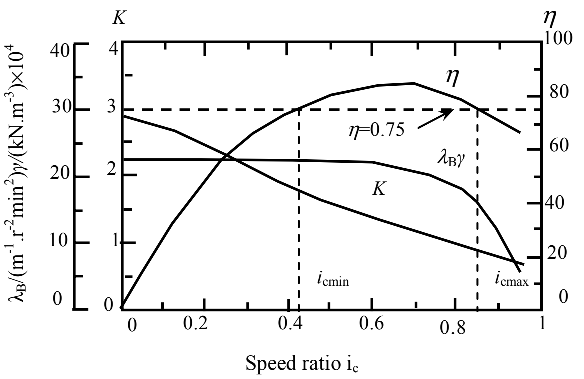

Fig.2 Primary characteristics of torque converter

speed ratio, as the vehicle resistance increases or decreases.

In order to make torque converter work in the high efficiency range, automatic transmission should downshift or upshift when the torque converter works in the low efficiency range with low or high speed ratio.

ZL50E, which has a gearbox with 4 shifts, is taken from an example to show how shift schedule is used. As is seen in Fig.2, the automatic transmission needs to downshift in the low efficiency range with low speed ratio, upshift in the low efficiency range with high speed ratio, and remain the same in the high efficiency range. If the efficiency still can not reach $\eta_{c\min}$ by shifting gear, the speed ratio should be adjusted.

The power consumed by working pump can be transformed to the corresponding equivalent throttle opening $\Delta\alpha$ [6], which is

$$\Delta\alpha = f(N_p) = f(p) \tag{1}$$

And the equivalent throttle opening is

$$\alpha_h = \alpha - \Delta\alpha = f(n_e, p) \tag{2}$$

Where α_h represents the equivalent throttle opening of diesel engine. The relation curve between p and $\Delta\alpha$ is shown as Fig.3, which is based on the experiment at the full throttle opening. Similarly, the relation curves can be obtained at diverse throttle opening, and they are saved in the memory of CPU in computer.

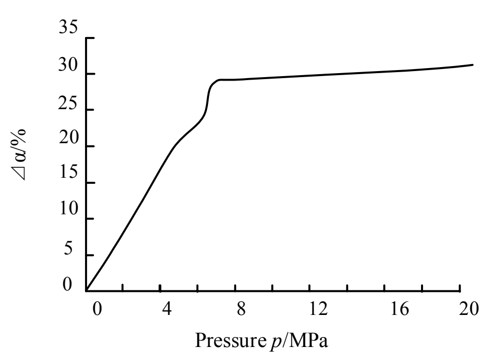

Fig.3 Relation of the pump pressure and equivalent throttle opening

IV. SHIFT SCHEDUAL BASED ON BPNN

Artificial neural networks, due to their excellent ability of non-linear mapping, generalization, self-organization and self-learning, have been proved to be of widespread utility in engineering, and are also steadily advanced into new areas[7,8]. BPNN, trained by back-propagation of errors, is perhaps the most popular network architecture today[9].

A. Topology of BPNN

The number of nodes on each layer is determined according to practical situation. In the paper, the input vector is $X(i, \alpha, p)$ and the output vector is $Y(y_1, y_2, y_3, y_4)$. According to the following empirical formula

$$s = \sqrt{0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35} + 0.51$$

from [10], the network has 5 nodes in hidden layer. So, the topology of BPNN used in this paper is 3—5—4, as is shown in Fig.4.

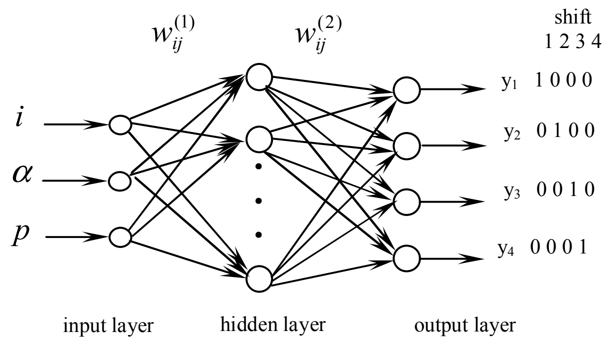

Fig.4. Topology of BPNN

Where *m, s* and *n* represent the numbers of input mode, the numbers of hidden mode and the numbers of output mode. $w_{ij}^{(1)}$ and $w_{ij}^{(2)}$ are weights of input layer and hidden layer respectively.

Y=(1 0 0 0),(0 1 0 0),(0 0 1 0),(0 0 0 1) represent from the first gear to the fourth one of gearbox.

B. Learning arithmetic of BP neural network model

Define $w_{ij}^{(1)}$ ($1 \le i \le 3$, $1 \le j \le 5$) as the weight connecting the *i*th input node with the *j*th hidden node. Define $w_{ij}^{(2)}$ ($1 \le i \le 5, 1 \le j \le 4$) as the weight connecting the *i*th hidden node with the *j*th output node. Similarly, $\theta^{(1)}$ and $\theta^{(2)}$ are the threshold nodes of the hidden layer and the output layer respectively. Then the above interrelationship forms a non-linear mapping from the input space vector $X \in R^m$ to the output space vector $Y \in R^n$.

Here, according to the input vector x, the *i*th output node of the hidden layer is

$$o_i(n) = f\left(\sum_{j=1}^{3} w_{ij}^{(1)}(n) x_j(n) - \theta_j^{(1)}(n)\right) \tag{3}$$

The *i*th output node of the output layer is

$$y_i(n) = f(\sum_{j=1}^{5} w_{ij}^{(2)}(n) o_j(n) - \theta_j^{(2)}(n)) \quad (4)$$

Where $f(x)$ refers to the activation function, and the most widely used activation function is the sigmoid function, which can be described as:

$$f(x) = \frac{1}{1+e^{-x}} \quad (5)$$

Then the square deviation for this step of training is

$$e_i^2(n) = \frac{(d_i - y_i(n))^2}{2} \quad (6)$$

The mean square deviation is

$$\boldsymbol{E}_{av}(\boldsymbol{n}) = \frac{1}{2n}\sum_{i=1}^{N} e_i^2(n) \quad (7)$$

Where N represents the number of the training samples, and d_i is the desired output.

Suppose the learning rate is η, the error signal of the jth node in the hidden layer is $\delta_j^I(n)$, and the error signal of the jth node in the output layer is $\delta_j^o(n)$, the BP algorithm can be described with the following formula (8)—(13):

$$\delta_j^O(n) = y_j(n)(1-y_j(n))(d_j(n) - y_j(n)) \quad (8)$$

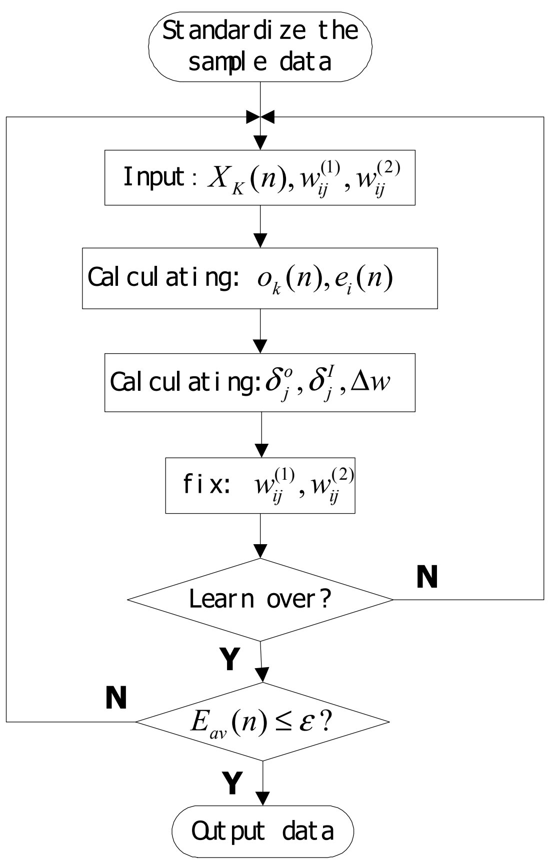

Fig.5 The flow chart of BPNN

$$\delta_j^I(n) = o_j(n)(1-o_j(n))\sum_{j=1}^{J} \delta_j^O(n) w_{ij}(n) \quad (9)$$

$$\Delta w_{ij}^{(1)}(n) = \eta \delta_i^I(n) \cdot x_{kj}(n) \quad (10)$$

$$\Delta w_{ij}^{(2)}(n) = \eta \delta_j^O(n) \cdot o_{kj}(n) \quad (11)$$

$$w_{ij}^{(l)}(n+1) = w_{ij}^{(l)}(n) + \Delta w_{ij}^{(l)}(n) \quad (12)$$

$$l = 1,2 \quad (13)$$

The calculating flow chart for BP neural network is shown as Fig.5.

C. *Improved BPNN*

BP Neural network has increasingly gained wide attention from researchers in recent years because of its high nonlinearity and strong ability of error tolerance. However, the traditional BP algorithm needs long convergent time, and sometimes the convergent results can not be obtained because of local minimum areas[11][12]. In this paper, an improved BP neural network is proposed to solve the problems.

1) Adding Momentum Term method

The momentum terms are added in weights and thresholds to avoid the local minimization, which can be expressed as

$$\Delta w_{ij}^{(l)}(n) = \eta D_{ij}^{(l)}(n) + \alpha \Delta w_{ij}^{(l)}(n-1) \quad (14)$$

$$D_{ij}^l(n) = -\frac{\partial E(n)}{\partial w_{ij}^l(n)} \quad (15)$$

$$l = 1,2 \quad (16)$$

Where α represents momentum coefficient. And $D_{ij}^{(1)}(n)$ and $D_{ij}^{(2)}(n)$ are the inverse gradient at the time of n in the hidden layer and output layer. Similarly, $D_{ij}^{(1)}(n-1)$ is the inverse gradient at the time of n-1. η is learning rate, which is a positive number between 0 and 1. Then the fluctuation in process of learning is alleviated and the constringency is improved.

2) adaptive learning rate method

Learning rate η plays a significant role in neural network, that is, if η is too big or too small, the neural network will oscillate or converge too slowly. The lower the learning rate is, the slower constringency speed is. A too big learning rate may cause excess modification which results in oscillation or divergence. So it is better to modify η according to the iterative error change quantity $\Delta E(n)$. If $\Delta E(n)$ is smaller than 0, it means that the iterative result is close to the global minimum, and that η should be doubled. If $\Delta E(n)$ is bigger than 0, it means that the iterative result deviates from the global minimum, and η should be halved. The algorithm of adaptive learning rate is provided as follows:

$$\Delta w_{ij}^{(l)}(n) = \eta(n) D_{ij}^{(l)}(n) \quad (17)$$

$$\eta(n) = 2^{\lambda}\eta(n-1) \quad (18)$$

$$\lambda = \mathrm{sgn}(\Delta E(n)) \tag{19}$$

$$\Delta E(n) = E(n) - E(n-1) \tag{20}$$

$$l = 1,2 \tag{21}$$

If Adding Momentum Term method is applied, formula(14) can be modified by the following formula(22):

$$\Delta w_{ij}^{(l)}(n) = \eta(n) D_{ij}^{(l)}(n) + \alpha \Delta w_{ij}^{(l)}(n-1) \tag{22}$$

Learning rate can be adjusted to suit the connecting weight during iterating, so the local minimum is avoided and the time of training is decreased. Improved BP algorithm has good nonlinear approximation ability, short convergent time and high discrimination rate.

D. Simulation results for improved BPNN

In order to show the effect of BPNN for four-parameter shifting schedule, a test simulation is carried out based on the input/output data which are obtained from a shift experiment on the automatic transmission system. The training calculations are made by MATLAB[13].

In the experiment, we choose the mean square error as 0.001 and the learning rate as 0.01. The simulation results based on traditional BPNN are shown in Fig.6, and the simulation results based on improved BPNN are shown in Fig.7. As is seen from the figure, the traditional BP algorithm criterion converges with the required accuracy after 1584 iterations. However, the improved BP algorithm only needs 242 iterations. The convergence rate of improved BPNN is quicker than that of traditional BPNN, and the training curve of error is smoother.

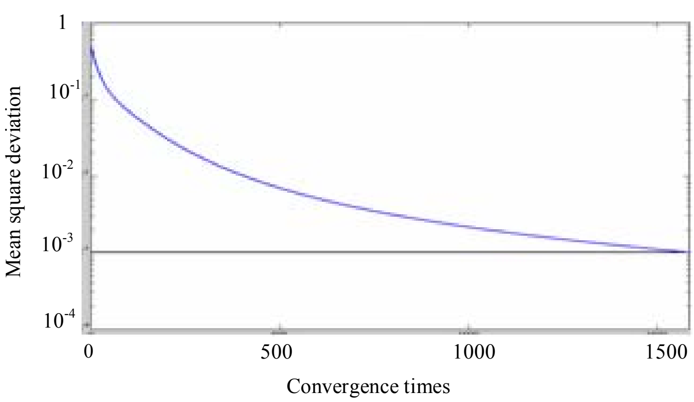

Fig.6 Convergence times of traditional BP algorithms

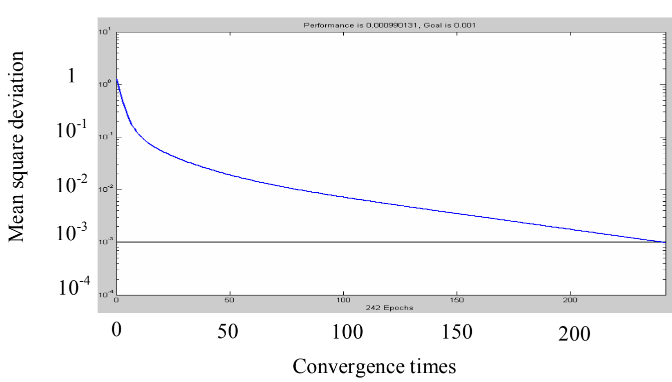

Fig.7 Convergence times of IBP algorithms

V. EXPERIMENTAL RESULT ANALYSIS

In order to validate the shift schedule, an experiment is carried out on the electronic-controlling test bench of construction vehicle, which consists of an engine, a torque converter, a working pump, an overflow valve, a gearbox, a speed increaser, and an electric eddy current dynamometer. The diesel engine is a power supply. The electric eddy current dynamometer is a power dissipation device used to simulate the load of construction vehicle, in which the brake load is controlled by adjusted winding current. The speed increaser is used to match the rotational speed of torque converter and that of the electric eddy current dynamometer. And the overflow valve is used to simulate the operating equipment.

In the experiment, the time interval is set to 2 seconds to restrain the shift cycle, that is, the next shift is permitted not less than 2 seconds after finishing previous shift. Furthermore, the time interval of separation and combination of the clutch is set to 0.02 seconds to avoid the phenomenon of friction component "overlap more" or "overlap less".

The efficiency of torque converter is controlled to be over 75%, and the experimental time is 100 seconds. The points, whose efficiency η_c is 75%, are considered as the judging shift points of automatic transmission. The experimental results are shown in Fig.8 and Fig.9. In Fig.8, the four curves are throttle opening curve, shift curve, the impeller and torque rotational speed curve of torque converter and efficiency curve of torque

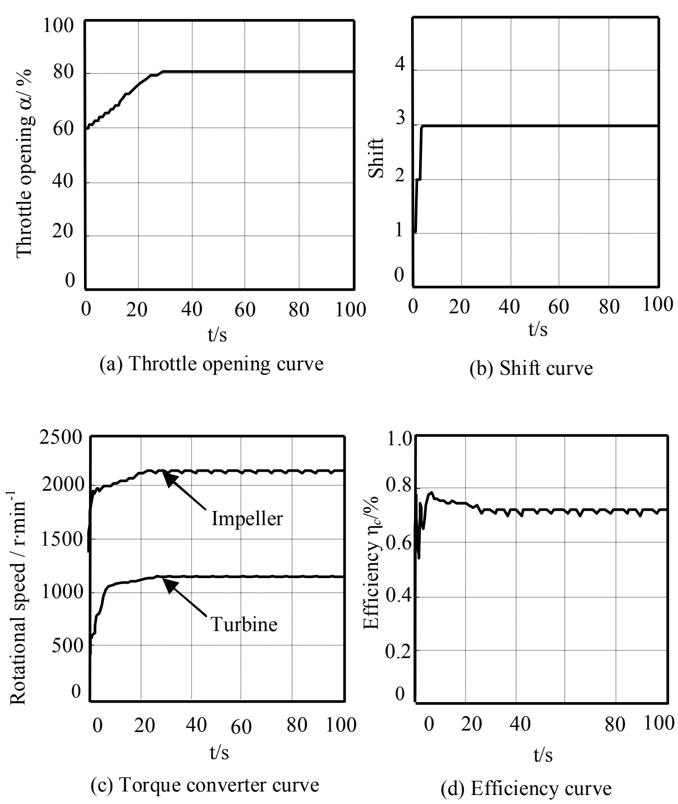

Fig.8 Experimental results based on throttle opening variation

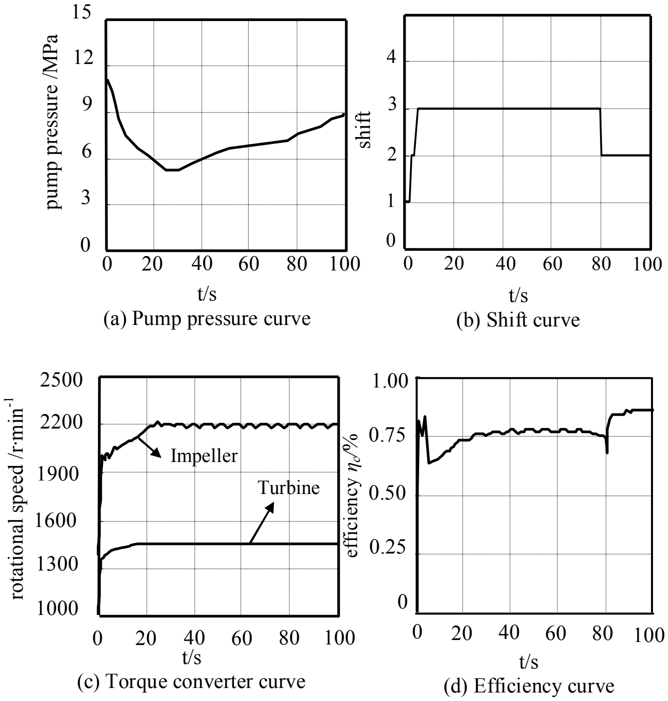

Fig.9 Experimental results based on pump pressure variation

converter in 100 seconds. Similarly, in Fig.9, the four curves are working pump pressure curve, shift curve, the impeller and torque rotational speed curve of torque converter and efficiency curve of torque converter in 100 seconds.

As is seen from Fig.8 and Fig.9, the automatic transmission will upshift if throttle opening increases. If the pressure of working pump decreases, the automatic transmission will upshift, too. So the shift schedule can make torque converter work in the high efficiency range. Similarly, when the pump pressure increases, that is, the load increases, the output power of the turbine converter will be decreased, and it will directly influence the efficiency of torque converter. So the gearbox will downshift to improve the drive power and its efficiency. The four-parameter shift schedule can be better adapted to the actual working condition according to the throttle opening and the pressure of working pump, and it can ensure the performance demand of construction vehicle better.

CONCLUSION

- A mechanical dynamical model of construction vehicle is developed for the whole power train and verified by experiment.
- Based on three-parameter shift schedule, a new four-parameter shift schedule is discussed and analyzed, which takes the influence of working pump into sufficient consideration. The experimental results show that four-parameter shift schedule can be better adapted to the actual working condition, and it improves the efficiency of torque converter according to different pressure of working pump.
- The automatic shift schedule based on IBPNN can identify the optional gear position and obtain control precision in shorter time, and provide the theoretical basis for the development of the intelligent control system of construction vehicle.

ACKNOWLEDGMENT

This paper was supported partly by the National Natural Science Foundation of China (59705005) and the Doctoral Degree Foundation of China (20020183003). The program designed for the simulation of BPNN in this paper was written with the tool-box of MATLAB R2006.b produced by the Math-Works, Inc.

REFERENCES

[1] Zhao Dingxuan, Ma Zhu, Yang Lifu, Huang Haidong and Gong Wenbin, “Analysis on the Power for Hydrodynamic-Mechanical Transmission System of Vehicle,” China Mechanical Engineering, 2001.08, vol12(8),pp.948-950.
赵丁选，马铸, 杨力夫, 黄海东, 宫文斌. 工程车辆液力机械传动系统的动力性分析. 中国机械工程.2001,12(8):948-950.

[2] Zhang Yong, Song Jian, Wu Di and Xu Chunxin, “Automatic Transmission Shift Point Control Under Different Driving Vehicle Mass,” SAE TECHNICAL PAPER SERIES, 2002-01-1258

[3] Shen S W, “Study on Intelligent Shift Strategy with the Humachine Technology,” SAE paper 973279

[4] Gong Jie, Zhao Ding-xuan, Chen Ying and Chen Ning, “Study on shift schedule saving energy of automatic transmission of ground vehicles,” Journal of Zhejiang University Science, China,voll5(7),pp.878-883.

[5] Wang Zhuo and Zhao Dingxuan, “An adaptive neuro-fuzzy inference system for engineering-vehicle shift decisions,” International Journal of Heavy Vehicle Systems 2002,vol9(4),pp.354-365.

[6] Yan Lei, Huang Haidong, Zhao Dingxuan, Ye Dan, Tang Xinxing and Jiang Guoqing, “Study on Automatic Shift Strategy of Construction Vehicle with four-parameter,” Transactions of the Chinese Society for Agricultural Machinery. 2005.04,vol36(4),pp.1-4.
闫磊, 黄海东, 赵丁选, 叶丹, 唐新星, 姜国庆. 工程车辆四参数自动换挡策略研究. 农业机械学报.2005,36(4):1-4.

[7] Q.M. Zhu, “A back propagation algorithm to estimate the parameters of non-linear dynamic rational models,” Applied Mathematical Modeling 27 (2003),pp. 169–187.

[8] A.G. Olabia and G. Casalino, “An ANN and Taguchi algorithms integrated approach to the optimization of CO2 laser welding,” Advances in Engineering Software 37 (2006),pp. 643–648.

[9] Y.L. Loukas, “Artificial neural networks in liquid chromatography: Efficient and improved quantitative structure–retention relationship models,” Journal of Chromatography A 904 (2000) 119–129.

[10] Gao Da-qi, “On Structures of Supervised Linear Basis Function Feedforward Three-Layered Neural Networks,” Chinese Journal of Computers, 1998,vol21(1), pp.80-86.
高大启. 有教师的线性基本函数前向三层神经网络结构研究，计算机学报. 1998, vol21(1):80-86.

[11] Shiwei Yu, Kejun Zhu and Fengqin Diao, “A dynamic all parameters adaptive BP neural networks model and its application on oil reservoir prediction,” Applied Mathematics and Computation 195 (2008) 66–75.

[12] Weiping Yan, Chengfeng Diao, Zhenan Tang and Xiao Li, “The study of gas sensor array signal processing with improved BP algorithm,” Sensors and Actuators B: Chemical.2000.07,Vol66(1-3),pp:283-285.

[13] Ding Chunfeng, Zhao Dingxuan, Tang Xinxing and Ye Dan.,” Experimetal study on Automatic shift system with four-parameter of construction vehicle,” Transactions of the Chinese Society for Agricultural Machinery.2006.01,vol37(1),pp.16-18.
丁春风，赵丁选，唐新星，叶丹. 工程车辆四参数自动变速系统的试验. 农业机械学报. 2006, 37(1):16-18.