

Research Article

An Evaluation Method of Mode Switching Quality for Double-Belt Continuously Variable Transmission

Lanchun Zhang , Zhongwei Zhu , Bin Huang , and Tianbo Wang 

School of Automotive and Traffic Engineering, Jiangsu University of Technology, Changzhou 213001, China

Correspondence should be addressed to Tianbo Wang; [wtbnjust@126.com](mailto:wtnjust@126.com)

Received 19 November 2020; Revised 7 January 2021; Accepted 18 January 2021; Published 28 January 2021

Academic Editor: Yang Li

Copyright © 2021 Lanchun Zhang et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

In order to improve the transmission efficiency and carrying capacity of conventional single-belt continuously variable transmission (CVT), one new type of dual-belt CVT is proposed in this paper. Under the situation that this new dual-belt CVT should be switched between single- and dual-belt modes frequently according to driver's intention and road conditions, so five objective evaluation indexes of mode switching quality for the dual-belt CVT are proposed, considering the aspects of vehicle power, comfort, and transmission durability comprehensively. Then, the objective evaluation model of mode switching quality is established by the BP neural network optimized by the genetic algorithm. It is found that the prediction results are consistent with the subjective evaluation. After analyzing the influence of the selected five evaluation indexes on the prediction results, it is obvious that these five evaluation indexes of mode switching quality for dual-belt CVT are reasonable.

1. Introduction

CVT (continuously variable transmission) provides a continuously variable speed ratio between the engine and the wheels. There is no need of changing gears. It gives full play to the dynamic characteristics of the engine and makes engine work in the area of high efficiency. Thus, it is regarded as the most ideal transmission device of the automobile.

At present, the successful CVT product on the market is the traditional metal single-belt CVT which has been mounted in millions of cars worldwide. However, there exist some weak points such as low transmission efficiency and weak carrying capacity [1] for single-belt CVT. So, its application is mostly limited to small or medium displacement cars.

In order to improve the carrying capacity of belt-type CVT, Chan et al [2] proposed a dual-rubber belt CVT. Efficient Drivetrains Inc. [3] proposed a similar dual-belt CVT which is called inline chain CVT. Two single chains were connected in series. Compared to a regular CVT, this inline CVT can operate closer around $i = 1$, which can increase the efficiency. However, this inline CVT also has some

disadvantages, such as being slightly larger in the vertical direction, needing two separated speed-ratio control systems, and the limitation of torque capacity of traditional single-belt/chain CVT. Based on Van Doorne's single-belt CVT, Wong et al [4] also proposed a dual-belt CVT. However, this novel dual-belt CVT must always work in two-belt mode, resulting in lower transmission efficiency when transmission torque is small. Besides, it has two servo actuation systems, leading to a more complex structure.

In order to improve the transmission efficiency and carrying capacity, one new type of dual-belt CVT is proposed by our project team [5]. It can work on single-belt drive mode or dual-belt drive mode according to driver's intention and road conditions. The transmission efficiency can be kept in higher value by changing between single- and dual-belt modes. Only one single-motor actuation system is used for our dual-belt CVTs to adjust the speed ratio. The mechanism and working principle of this new dual-belt CVT will be clarified in the first part of this paper.

Although this new dual-belt CVT can improve transmission efficiency and carrying capacity effectively, a certain impact will occur when switched between single- and dual-belt modes

frequently, exerting a great influence on the vehicle's power, comfort, and driveline durability [6]. Therefore, an effective control strategy of mode switching for dual-belt CVT is crucial. It is obvious that the control strategy relies on the evaluation method of the mode switching quality; thus, a comprehensive and effective evaluation method of mode switching quality is essential.

Due to the structural particularity of this dual-belt CVT, research about the mode switching evaluation method for this dual-belt CVT has not been found at present. In fact, the mode switching evaluation method of dual-belt CVT is somewhat similar to the gear shifting evaluation methods of other automatic transmissions with several gear locations, such as automatic transmission (AT) and dual-clutch transmission (DCT). Gear shifting time, variation of vehicle body acceleration, and impact degree are often taken as indexes of the objective evaluation method for AT or DCT. On the other hand, the subjective evaluation method, which is based on the subjective feelings of testers, is another common-used evaluation method. There are usually some uncertainties for the subjective method [7]. However, there is generally a correlation between the results of subjective and objective evaluation ways.

The professional evaluation software DART (Driveability Analysis and Rating Tool) was designed by British Ricardo Ltd. to calculate the vehicle body acceleration, impact degree, and other data by collecting the vehicle's real-time data [8]. The evaluation system of gearing shift comfort performance was proposed by AVL based on the neural network method to evaluate the vehicle shift smoothness, fuel economy, exhaust emissions, etc. [9]. Volvo also built an evaluation system on the basis of the neural network method, to judge the comfort performance of vehicle when shifting [10]. 5 static evaluation indexes and 3 dynamic evaluation indexes were selected by Liu et al [11, 12] to build a DCT shift quality evaluation system.

Due to the current research gaps, this article concentrates on a mode switching quality evaluation method for the new dual-belt CVT. An optimized BP neural network is introduced to establish an objective evaluation model for mode switching quality after the vehicle power, comfort, and driveline durability are considered, and the feasibility and accuracy are proved based on the subjective prediction results.

2. Working Principle of New Dual-Belt CVT

As shown in Figure 1, the new dual-belt CVT mainly includes 4 major components: two single-belt CVTs, speed-ratio/clamping force adjustment device, magnetic powder clutch, and planetary gear device which integrates power when the two belts are working simultaneously. Compared with the single-belt CVT, the dual-belt CVT has an additional set of belt and pulley.

When the transmission torque is small, it works in single-belt working mode. The first output shaft clutch is engaged, and the second output shaft clutch is disconnected. The right movable disc of driving pulley and the movable disc of the first driven pulley are forced to move left (or right)

by the right and left gears of the first speed-ratio controlling shaft, respectively, which are driven by the speed-ratio controlling motor. So, the distance between fixed and right movable disc of the first driving pulley and the distance between fixed and movable disc of the first driven pulley are changed. Then, the working radius of the first belt is changed, and the transmission ratio is changed finally. Under this situation, the driving force of engine is transferred to planet carrier through the first output shaft clutch and the first sun gear; meanwhile, the ring gear brake is working now. Finally, the driving force is output by the final drive.

When the transmission torque is large, it works in dual-belt working mode. The first and second output shaft clutches are simultaneously engaged. And the engine power is transferred by the first and second driven pulleys simultaneously. The working principle of the first pulley is the same as that under single-belt mode. As for the second pulley, the left movable disc of driving pulley and the movable disc of the second driven pulley are forced to move left (or right) by the right and left gears of the second speed-ratio controlling shaft, respectively, which are also driven by the speed-ratio controlling motor. So, the working radius of the second belt is changed. On the other hand, the working radius of the first belt is also changed under dual-belt mode. Under this situation, the driving force of engine is transferred to planet carrier through the first and second output shaft clutches and the first and second sun gears. The ring gear brake is not working now.

As the structure mentioned above, this new type of dual-belt CVT offers many advantages including larger transmission torque and higher transmission efficiency. The variable speed-ratio range of the transmission system can be enlarged greatly. So, the efficiency of the whole power system will be improved. However, this new dual-belt CVT should be switched between single- and dual-belt modes frequently according to driver's intention and road conditions, which exerts a great influence on the vehicle's power, comfort, and driveline durability. Therefore, to design a reasonable mode switching quality evaluation method for this new type, CVT is of great significance.

3. Modeling of Objective Evaluation Mechanism for Mode Switching Quality

3.1. Selection of Evaluation Index. The vehicle power performance, comfort, and driveline durability should be considered simultaneously when choosing certain mode switching quality evaluation indexes [6, 11, 12], based on the working principle above.

Firstly, the mode switching time of dual-belt CVT should be considered. It refers to the time it takes to change from single-belt mode to dual-belt mode, or vice versa. It mainly reflects the power performance of vehicle with dual-belt CVT. It also exerts a certain impact on vehicle driving comfort. The power transmission process is smoother, the feedback of driver's operation is faster, and so the passenger's comfort is better as the mode switching time is shorter.

The definition of mode switching time is

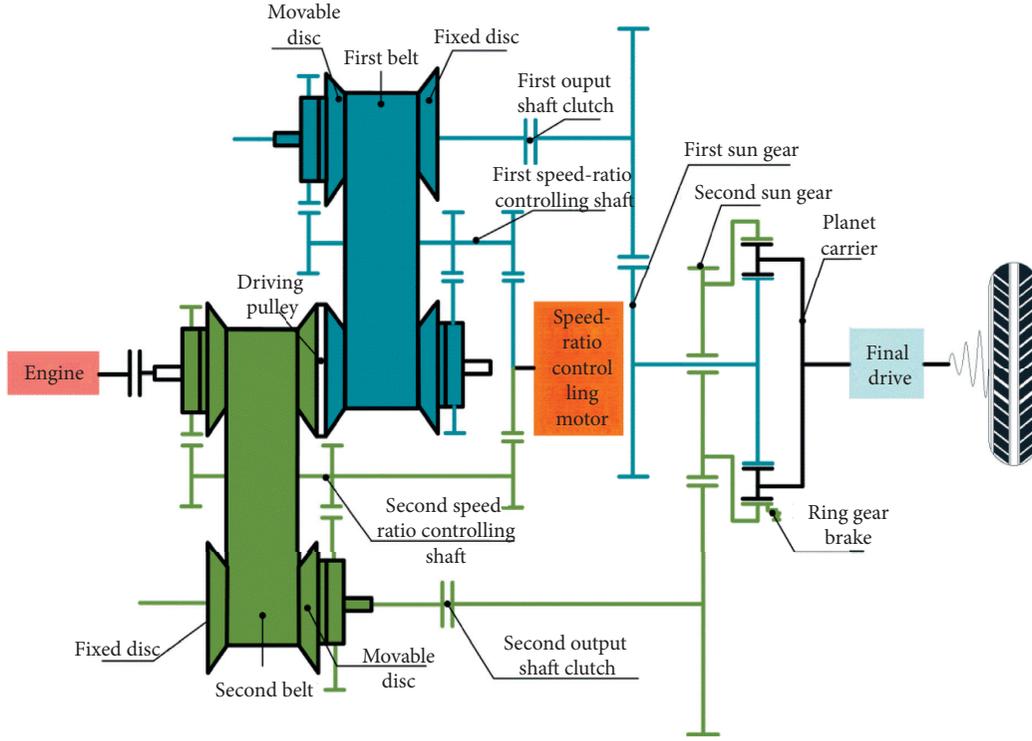


FIGURE 1: Schematic diagram of the structure of dual-belt CVT.

$$\Delta_t = t_e - t_s, \quad (1)$$

where t_e represents the starting time of mode switching and t_s stands for the ending time of mode switching.

Secondly, the longitudinal acceleration fluctuation of vehicle body is used in this paper to evaluate the driving comfort. This is because that the change of first or second output shaft clutch engagement state (as shown in Figure 1) will cause instantaneous power fluctuation with large longitudinal acceleration and will affect the comfort of passengers. It is defined as

$$\Delta a = |\max(a(t)) - \min(a(t))|. \quad (2)$$

Impact degree of vehicle body can also be used to evaluate driving comfort. The larger absolute value of the positive impact degree (j_{\max}) will cause more obvious the backward feeling of passengers, while the larger absolute value of the negative impact degree (j_{\min}) will lead to more obvious forward feeling [11, 12]. Both situations indicate that comfort is bad. The definition of impact degree is

$$j = \frac{da}{dt} = \frac{d^2v(t)}{dt^2}. \quad (3)$$

The impact peak is

$$j_{\max} = \max(|j_{\max}|, |j_{\min}|), \quad (4)$$

where a is the longitudinal acceleration of vehicle body, v indicates the speed of vehicle, j_{\max} means the positive impact degree peak, and j_{\min} denotes the negative impact degree peak.

Besides, the engine speed fluctuation is introduced as another index related to the comfort performance of the dual-belt CVT. The engine speed fluctuation caused by the switching action of dual-belt CVT would produce noise, and then the comfortability would be worse. The engine speed fluctuation is defined as

$$\Delta\omega_e = |\max(\omega_e(t)) - \min(\omega_e(t))|, \quad (5)$$

where $\omega_e(t)$ indicates the engine speed, $\max(\omega_e(t))$ represents the maximum engine speed during the entire data collection process, and $\min(\omega_e(t))$ represents the minimum engine speed.

Finally, in the aspect of driveline durability, the root mean square (RMS) value of the impact degree is used to represent the cumulative damage on the vehicle driveline components during the mode switching process. It is defined as

$$j_{\text{rms}} = \sqrt{\frac{\int_0^{\Delta t} j^2(t) dt}{\Delta t}}. \quad (6)$$

In summary, five indexes including mode switching time, longitudinal acceleration fluctuation, impact peak value, engine speed fluctuation, and root mean square value of impact are selected for dual-belt CVT to evaluate mode switching quality objectively.

3.2. Evaluation Mechanism Modeling. In order to evaluate the mode switching quality comprehensively, the aspects of vehicle power, comfort, and driveline durability should be considered together. So, the evaluation indexes mentioned

above should be taken into overall consideration. However, these indexes are coupled with each other, revealing strong nonlinear relationship, which makes it difficult to establish an accurate mathematical model. At present, the BP neural network has testified its success in the modeling of traditional AT and DCT shift quality objective evaluation methods, but it has weak points such as slow convergence speed and local minimization [13]. It is possible to improve the efficiency of the BP neural network and keeps it from the minimum point if the initial weight threshold of the BP neural network is assigned with the help of the genetic algorithm [14–16]. The BP neural network optimized by the genetic algorithm is updated in efficiency and accuracy, so an objective evaluation model of the mode switching quality for the dual-belt CVT is established based on the BP neural network algorithm optimized by the genetic algorithm (GA-BP).

The process of modeling is divided into the part of genetic algorithm optimization and the part of BP neural network, which is shown in Figure 2.

3.2.1. Data Preprocess. 500 sets of sample data are selected. Among them, 50 sets of data are taken as testing samples, and the others as training samples. Each set of data includes 5 objective evaluation values and corresponding subjective evaluation value. The objective evaluation value is collected from the experimental vehicle equipped with this type of dual-belt CVT, and the corresponding subjective evaluation value is derived from the average value of data from several experienced drivers.

As there will be significant differences in levels between different values, for example, the engine speed fluctuation is nearly three orders of magnitude more than other evaluation values, which will cause a large error in final prediction result, the sample data need to be normalized as follows:

$$x_k = \frac{x_k - x_{\min}}{x_{\max} - x_{\min}}, \quad (7)$$

where x_{\min} and x_{\max} represent the minimum and maximum value in the data group, respectively.

3.2.2. BP Neural Network Structure. There are 5 objective evaluation indexes, so the number of nodes in the input layer of the BP neural network is 5. The output is one comprehensive result, so the number in the output layer is 1. Considering that single hidden layer network could approach nonlinear functions, so the single hidden layer structure is selected in this paper to shorten the training time. To guarantee the accuracy, the number of hidden layer nodes is set as 12. So, the structure of the BP neural network is determined to be 5*12*1, which is shown in Figure 3.

3.2.3. Genetic Algorithm (GA). The genetic algorithm is used in this paper to get the initial weight and threshold of the BP neural network. It includes population initialization, fitness function, selection operation, cross operation, mutation operation, etc.

The population initialization method adopted in this paper is real number coding, and each individual contains four parts, including input layer/hidden layer weights, hidden layer threshold, hidden layer/output layer weights, and output layer threshold. Through the calculation $5 \times 12 + 12 \times 1 + 12 + 1 = 85$, the code length is determined as 85. The fitness of each individual is calculated by fitness function. And subsequent selection, crossover, and mutation operations are performed according to the fitness. In this paper, the real number coding is selected for population initialization; thus, the real number cross method is selected. The mutation operation is mainly divided into two steps: firstly, judging whether each individual is mutated; secondly, selecting random positions to mutate the mutated individuals.

3.2.4. BP Neural Network Training. Finally, the main program of the BP neural network and program of selection, crossover, mutation, and fitness calculation in genetic algorithm are realized. The relevant parameters of the genetic algorithm are set as follows: the initial population is 50, the number of evolutions is 200, the crossover probability is 0.6, and the mutation probability is 0.08.

4. Analysis of Prediction Results

The GA-BP neural network was trained 10 times according to data given in the previous section. The training time is 1.809 s, 1.592 s, 1.534 s, 1.576 s, 1.518 s, 1.486 s, 1.557 s, 1.595 s, 1.612 s, and 1.594 s, respectively. The average value is 1.587 s. It can be found that the execution time of the program is definitely within 2 s, which shows that the BP neural network training optimized by the genetic algorithm has good operating efficiency.

The fitness during the entire iteration process is shown in Figure 4. It can be seen that as the number of evolution increases, the fitness reaches a stable value quickly. It proves that the initial weights and thresholds obtained by the genetic algorithm can provide ideal results.

Moreover, the relative errors of 450 training samples between driver's subjective evaluation value and prediction results from objective evaluation model are shown in Figure 5. It reveals that the relative errors are all below 5%, which demonstrates the effectiveness of the GA-BP neural network and objective evaluation model.

In order to prove the correctness of proposed objective evaluation model based on 5 evaluation indexes further, each index is removed in turn. The relative errors of models based on only 4 evaluation indexes are obtained, as shown in Figure 6. 50 testing samples are considered here. It can be easily found that the relative error of the model with all 5 indexes is smaller; that is, the prediction accuracy is higher. It proves that 5 evaluation indexes selected in this paper are reasonable and accurate in the reflection of the mode switching quality for the dual-belt CVT.

In addition, the mean absolute value of relative error for each case is shown in Figure 7. It can be seen that removal of impact peak in the evaluation model will lead to the greatest

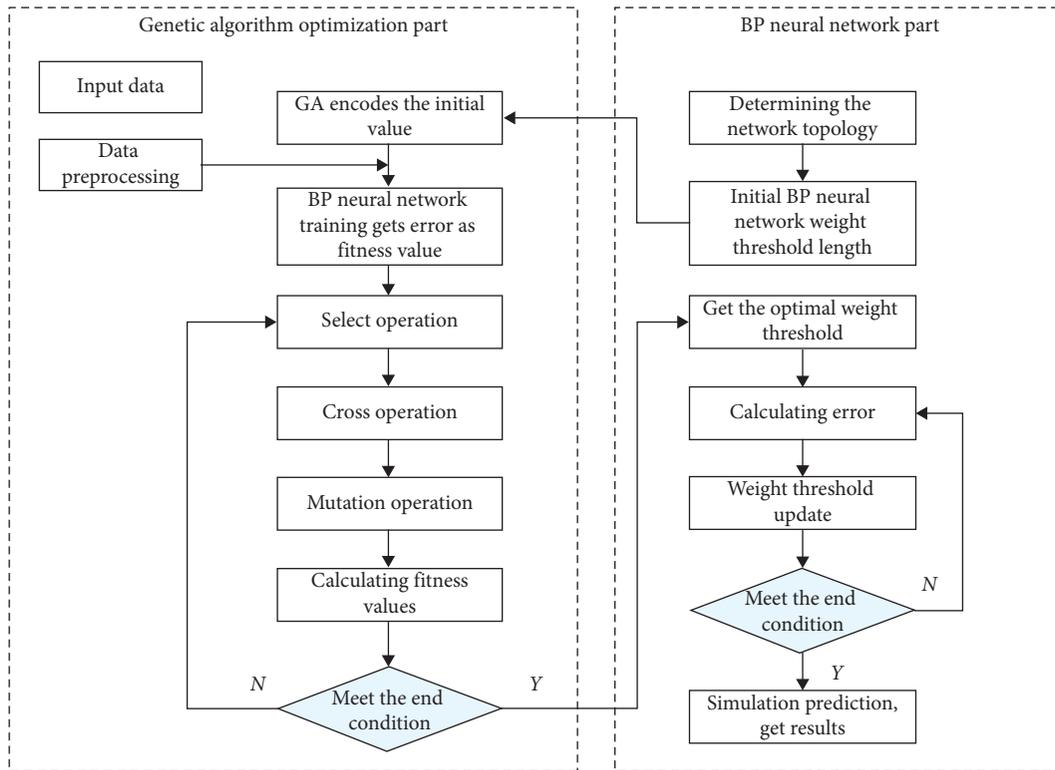


FIGURE 2: Modeling process of objective evaluation of mode switching quality of dual-belt CVT based on GA-BP.

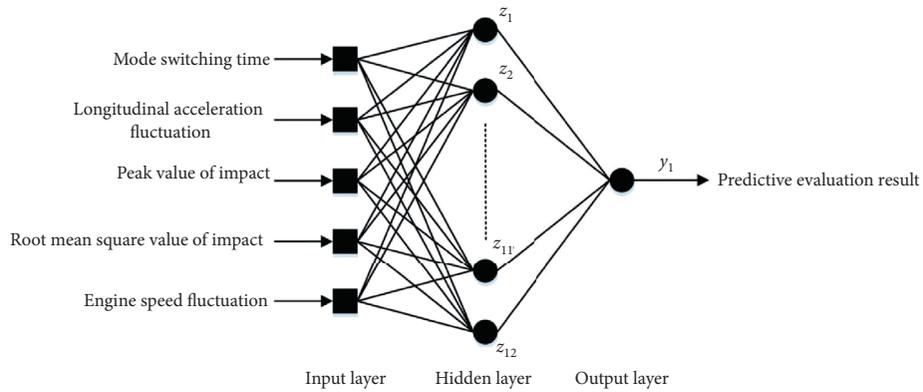


FIGURE 3: Schematic diagram of BP neural network structure.

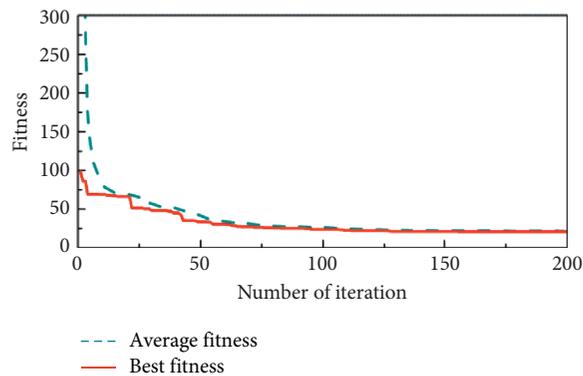


FIGURE 4: Fitness value of GA-BP.

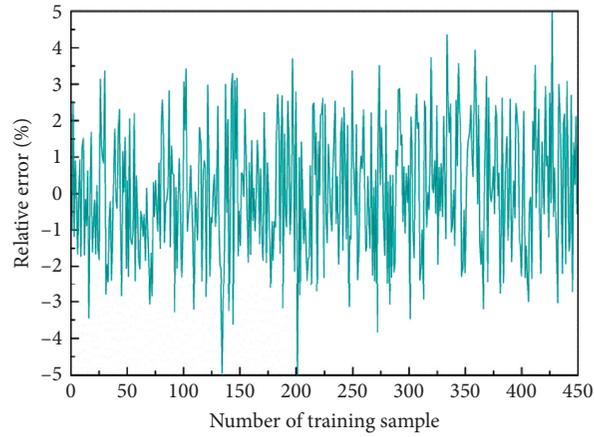


FIGURE 5: Relative error of 450 training samples.

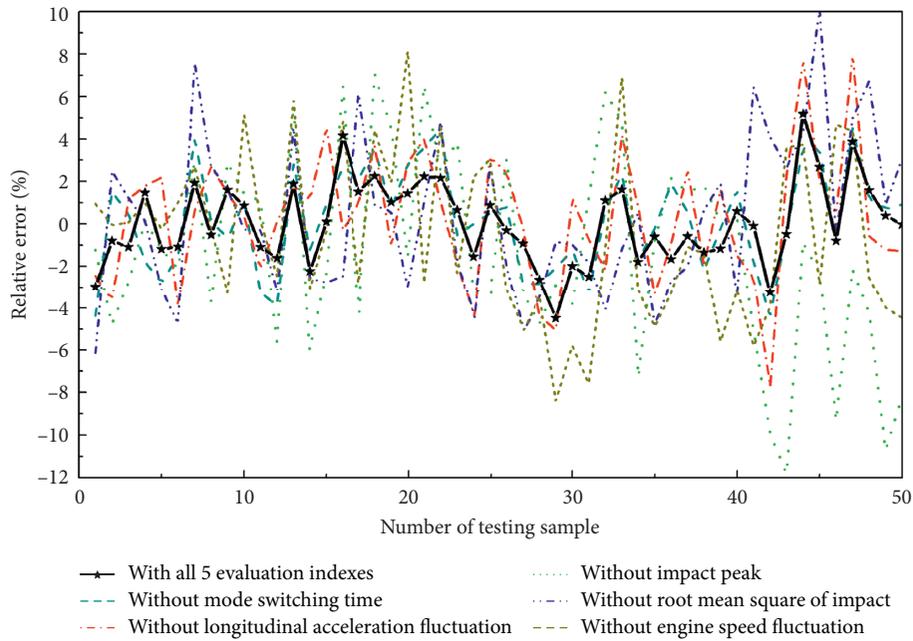


FIGURE 6: Relative error of 50 testing samples.

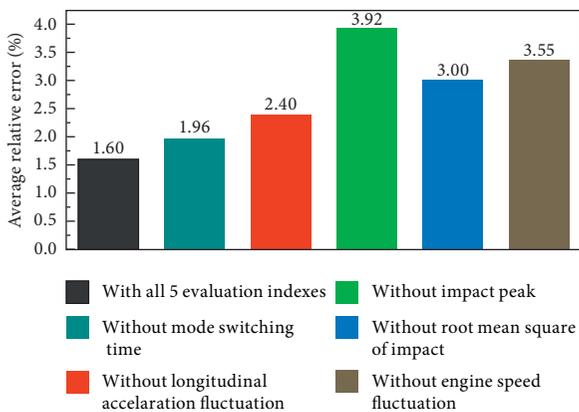


FIGURE 7: Comparison of average relative error between objective evaluation models.

prediction error, from an average value 1.6% to 3.92%. So, the impact peak has the greatest effect on the accuracy of evaluation model. According to the order of influence on prediction accuracy, the order is impact peak, engine speed fluctuation, impact RMS, longitudinal acceleration fluctuation, and mode switching time.

5. Conclusions

The mode switching quality evaluation method for a new dual-belt CVT was proposed in this paper. And the objective evaluation model for mode switching quality was established, considering the aspects of vehicle power, comfort, and transmission durability comprehensively. The main conclusions are as follows:

- (1) The mode switching quality evaluation method with 5 evaluation indexes, including mode switching time, longitudinal acceleration fluctuation, impact peak value, engine speed fluctuation, and root mean square value of impact, can evaluate the mode switching quality of new dual-belt CVT comprehensively.
- (2) The BP neural network optimized by the genetic algorithm is effective to establish the objective evaluation model of mode switching quality. The objective prediction results of the model are consistent with the subjective evaluation results.
- (3) The lack of any index in the evaluation model will lead to the increase of prediction error. According to the influence on prediction accuracy, the order is impact peak, engine speed fluctuation, impact RMS, longitudinal acceleration fluctuation, and mode switching time.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request and at <https://pan.baidu.com/s/1adXRPlfkUjeyUaWR4cYqHg>, visit code: 20f1.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research was funded by the National Natural Science Foundation of China (grant no. 51305175), Jiangsu Provincial Directional Plan Project of University Natural Science Research (grant no. 18KJD470002), and Changzhou Sci and Tech Program (grant no. CJ20180032).

References

- [1] D. Rotella and M. Cammalleri, "Direct analysis of power-split CVTs: a unified method," *Mechanism and Machine Theory*, vol. 121, pp. 116–127, 2018.
- [2] K. U. Chan, P. K. Wong, and H. W. Wu, *Preliminary Study on Design and Control of a Novel CVT*, JSAE Paper, Article ID 20097011, Yokohama, Japan, 2009.
- [3] A. W. Brown, J. Van Rooij, and A. A. Frank, "The design of an inline GCI chain CVT for large vehicles (No. 2004-40-0054)," *SAE Technical Paper*, 2004.
- [4] P. K. Wong, Z. Xie, Y. Chen, and L. M. Tam, "Development of a novel dual-belt van doorne's continuously variable transmission for automobiles - a preliminary study," *International Journal of Structural Stability and Dynamics*, vol. 18, no. 2, Article ID 1850016, 2018.
- [5] S. Liu and L. C. Zhang, "Bual-belt type continuously variable transmission for vehicle," China patent no. CN201510983052.X, 2017.
- [6] J. J. Wang and L. X. Xie, "Study on shifting quality evaluation technology of double clutch transmission (DCT) based on convolutional neural network," *Modern Manufacturing Technology and Equipment*, vol. 5, pp. 34–35, 2019.
- [7] J. Zhao, J. Liu, L. Yang, and P. He, "Exploring the relationships between subjective evaluations and objective metrics of vehicle dynamic performance," *Journal of Advanced Transportation*, vol. 2018, Article ID 2638474, 10 pages, 2018.
- [8] R. E. Dorey and E. J. Martin, "Vehicle driveability-the development of an objective methodology (No. 2000-01-1326)," *SAE Technical Paper*, 2000.
- [9] R. E. Dorey, J. D. McLaggan, J. M. S. Harris, D. P. Clarke, and B. A. C. Gondre, "Transient calibration on the testbed for emissions and driveability (No. 2001-01-0215)," *SAE Technical Paper*, 2001.
- [10] S. Schnetzler, J. Pettersson, and P. Murtonen, "Quality assurance of driver comfort for automatic transmissions (No. 2000-01-0175)," *SAE Technical Paper*, 2000.
- [11] H. Liu, Y. Lei, J. Zhang, J. Qiu, and Y. Li, "Shift quality optimization based on assessment system for dual clutch transmission (no. 2012-01-0060)," *SAE Technical Paper*, 2012.
- [12] J. Zhang, Y. Lei, C. Zong, H. Liu, and T. Hu, "Shift quality evaluation system based on neural network for DCT vehicles," vol. 8, pp. 4267–4271, in *Proceedings of the 2010 Sixth International Conference on Natural Computation*, vol. 8, pp. 4267–4271, IEEE, Yantai, China, August 2010.
- [13] H. Min, J. Chen, and L. Yugen, "Research on rockburst prediction based on BP neural network and GA," *Research & Development*, vol. 10, pp. 90–94, 2011.
- [14] Z. B. Shi, Y. Li, and T. Yu, "Short-term load forecasting based on LS-SVM optimized by bacterial colony chemotaxis algorithm," in *Proceedings of the 2009 International Conference on Information and Multimedia Technology*, pp. 306–309, IEEE, Jeju Island, South Korea, December, 2009.
- [15] Y. Zhang, T. Li, G. Na, G. Li, and Y. Li, "Optimized extreme learning machine for power system transient stability prediction using synchrophasors," *Mathematical Problems in Engineering*, vol. 2015, Article ID 529724, 8 pages, 2015.
- [16] Y. Li and Z. Yang, "Application of EOS-ELM with binary Jaya-based feature selection to real-time transient stability assessment using PMU data," *IEEE Access*, vol. 5, pp. 23092–23101, 2017.