

# Study on Detection and Fault Diagnosis System of Transmission of Coal Cutter Based on Improved BP Neural Network

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To improve the fault diagnosis effect of transmission of coal cutter and ensure the smooth work of coal cutter, the detection and fault diagnosis system of transmission of coal cutter is designed and analyzed in this study. Based on the improved BP neural network and the internal Web remote fault diagnosis technology, this study designs and tests the detection and fault diagnosis system of transmission of coal cutter. It is found that the accuracy of fault diagnosis is 100% by using sample input neural network, indicating that the detection and fault diagnosis system of transmission of coal cutter designed by the improved BP neural network algorithm has high accuracy and practicability.

## 1. Introduction

The fully-mechanized coal mining work can't be conducted without the support of coal cutter. However, because of the special downhole operation environment and the difference of operation level, it is difficult for the coal cutter to avoid faults in the operation. It can be seen that the detection and fault diagnosis of transmission of coal cutter is a systematic and complicated work. How to correctly identify and judge the fault and how to maximize the efficiency of coal cutter plays an important role in improving the level of safety production. Based on this, this study explores the detection and fault diagnosis system of transmission of coal cutter, which is of great significance. Based on the improved BP neural network and the internal Web remote fault diagnosis technology, the detection and fault diagnosis system of transmission of coal cutter is designed and tested in this study.

## 2. Literature review

Coal cutter is one of the most important devices for mechanization and modernization of coal mine production. It is a large complex system which integrates machinery, hydraulic and electrical. The transmission device of coal cutter is an important part of coal cutter, and it is closely related to the efficiency of coal mining. The transmission device of coal cutter is the frequent fault area of coal cutters, especially the gears and bearings of the transmission. The detection and fault diagnosis of the transmission device of coal cutter is of great significance for coal mine safety production.

Due to harsh work environment, the gears in coal cutters are prone to crack and by analyzing the gear dynamic response, useful crack detection indicators could be obtained. The coal cutter gear systems are always subjected to multi-frequency excitations. Jiang et al. established a nonlinear gear dynamic model taking multi-frequency excitations into account in their work and defined a meshing stiffness coefficient to model the crack fault influence on the gear model. Moreover, they analyzed the amplitude–frequency of the model main resonance by means of multi-scale method, and calculated the model dynamic response by the incremental harmonic balance method. The numerical simulation results showed that the dynamic response of the presented gear model provided strong chaotic characteristics and the chaotic degree of the gear dynamics increased with the deterioration of the crack level. The simulation and experimental analysis also demonstrated that the multi-frequency excitation-based gear dynamic model was more correct than the single-frequency excitation-based model in representing the system dynamics (Jiang et al., 2016). In order to detect

rolling bearing cracks using a variational approach, Jiang et al. put forward an original method that appropriately incorporated bi-dimensional variational mode decomposition (BVMD) into discriminant diffusion maps (DDM) to analyze the nonstationary vibration signals recorded from the cracked rolling bearings in coal cutters. In addition, the VDDM was able to simultaneously process two-channel sensor signals to reduce information leakage. The experimental validation using rolling bearing crack vibration signals demonstrated that the VDDM separated the raw signals into four intrinsic modes, including one roller vibration mode, one roller cage vibration mode, one inner race vibration mode, and one outer race vibration mode (Jiang et al., 2016). Reliable condition monitoring and fault diagnosis is an important issue for the normal operation of coal cutter gear systems. Intrinsic deterioration indicators are always hidden in the vibration response of the gearboxes, and it is often very difficult to correctly extract them due to nonlinear/chaotic nature of the vibration signal. Li et al. proposed a new adaptive nonstationary vibration analysis method to extract useful quantitative indicators for hybrid gear faults decoupling detection. In addition, they estimated the center frequencies of the narrow bands of intrinsic modes contained in the vibration signal adaptively by the variational model decomposition (VMD) to determine the bandwidth of the modes. At last, the performance was compared with existing techniques. The analysis results showed that the proposed method had high performance on quantitative hybrid faults detection in the coal cutter gear system (Li et al., 2016). The influence factors, including low speed, heavy load, high environmental temperature, high humidity, heavy dust, accelerate the gears failure rate. For this reason, Li and Peng put forward a multi-degree of freedom (MDOF) gear nonlinear model, which considered gear tooth characters, in their work. In addition to the nonlinear factors of the gear meshing, they also took into account the nonlinear effect of the support bearings in this new model. In order to reliably estimate the gear backlash and bearing clearance, they employed the fractal theory to calculate the nonlinear backlash and clearance from the tribological aspect. Numerical simulations were used to calculate the gear dynamics of the presented model, and the results were validated using experimental data. The results proved that the proposed MDOF gear model with the fractal estimation method provided more reliable dynamic response than that of the other two methods and the simulation result obtained with suitable fractal dimension was consistent with the experimental data (Li and Peng, 2016). Coal mine dust may lead to coal miners' pneumoconiosis and dust explosions, thus being seriously harmful to human beings. Li et al. used a wetting agent to improve the efficiency of water infusion for mine dust control. Therefore, selecting an optimal wetting agent is crucial to this practice. Li et al. measured surface tensions, contact angles, and capillary imbibitions of the wetting agent lauryl sodium sulfate (SDS), sodium dodecyl benzene sulfonate (LAS), sodium dioctyl sulfosuccinate (AOT), and SDS compounded with five additives on a coal-seam sample in the laboratory. The results indicated that, in order to select an optimal compound wetting agent, it is necessary to calculate a capillary force rising factor or to conduct capillary imbibition tests besides the measurements for surface tension and contact angle; a compound wetting agent made of 0.10 wt% SDS + 0.05 wt% NaAc is optimal for the wettability enhancement of this coal (Li et al., 2016).

The determination of the correct design support capacity of shield supports is the key to the safe control of strata within the vicinity of long-wall coal panels. There are a number of design methods that have been developed, dependant on the prevalent geological and mining conditions. However, these methods have been found to be inappropriate to the design of the supports for long-wall panels practising either high seam height extractions or the top-coal caving methods practised within many Chinese underground thick seam mines. Wang et al. proposed a dynamic simulation method to determine the shield support capacity required for these conditions. Based on the geological conditions experienced on the first caving event of the main roof, they determined the shield support capacity for the four case study mine coal panels and the performance of the installed support capacities was compared. The results showed that the predicted support capacities compared well with the performance of the supports installed within the case study mines (Wang et al., 2015). Zhang et al. used cutting pick primarily in footing excavation such as coal mining and roadway excavation, so the performance of cutting tooth directly affected the mining capacity, the driving efficiency, and the service life of the tool. The quality of domestic mining pick was lower than that abroad, especially the tooth body wear of the whole shearer picks accounts for half of its overall failure. Thus tooth body 40Cr was treated by various heat treatment processes in the experiment, so as to improve the hardness and wear resistance of cutting tooth, analyze the surface wear scar of morphology, and research the wear mechanism, thus improving work efficiency, and easing the labor intensity of workers underground (Zhang et al., 2013). Griffith et al. applied 3D digital elevation models and the 3D boundary element method (BEM) approach to efficiently calculate the pre-mining topographically perturbed stress field in the vicinity of the Carroll Hollow coal mine in eastern Ohio. It was found that regions of elevated compressive stress in the mine corresponded to areas in which cutter roof failure was a common source of roof instability. Furthermore, both the magnitude and inclination of the principal stresses calculated from the 3D topographic BEM model were found to be consistent with observed failure distributions within the mine. They also proposed that the approach outlined could be efficiently applied to the mine planning process in order to mitigate or avoid potentially hazardous mining conditions (Griffith et

al., 2014). Ordin and Metel’Kov gave the analysis of basic mechanisms in variation of output of long-wall face versus its length in the cutter–loader and scrape conveyor system in underground mining of flat-lying coal beds. Then, based on the analysis of interaction between cutter–loader and scrape conveyor, they determined the dependence between the maximum output of long-wall face and the long-wall length (Ordin and Metel’Kov, 2015). In underground mining of horizontal and gently dipping coal beds with longwall method in the direction along the strike using power-driven machines (makes 90% of total coal mining in Russia), the strata control involves roof caving behind the support units as they advance. The application of this mining system results in displacement of large volumes of rocks in the Earth’s interior. It has been found that rock caving in a closed space has a small time gap: roof is stable for a short duration, then weak rocks of the weakest bottom layer of the roof fall and, later on, large blocks of the upper roof collapse. Along with the unit-by-unit generation of electric energy, Prokopenko et al. expected the grouped generation: when extended spans in long-walls were caved, a few support units would simultaneously generate electric energy. They also used electric energy generated and accumulated by all (150-250) units of powered support for internal mine supply instead of non-conventional energy. The results suggested that the proposed method offered a possibility to utilize a huge energy potential of the process of production-induced transformation of lithosphere (Prokopenko et al., 2015).

In summary, the above researches mainly focus on the coal cutter and fault diagnosis, but it is not combined with improved BP neural network. Therefore, based on the above studies, the detection and fault diagnosis system of transmission of coal cutter is explored, which is of great significance. Based on the improved BP neural network and the internal Web remote fault diagnosis technology, the detection and fault diagnosis system of transmission of coal cutter is designed and tested.

### 3. Principle and Method

The processing of information in the neural network often takes neurons as the basic unit. Neurons contain a large number of information processing characteristics, such as the innate state of excitatory inhibition of neurons, susceptibility of neurons, learnability, delay and fatigue of synapses of neurons, and transformation between neuron pulse and potential. All these characteristics fully demonstrate the superiority of neurons in information processing. Artificial neural network is a network interconnected by a large number of processing units, which has the basic characteristics of human brain, such as abstraction, simplified thinking and simulated thinking. The general neuron model should have H elements: (1) in the neuron model, for a group of connected neuron  $i$  and neuron  $j$ , the connection strength is usually referred to as weight, often expressed as  $W_{ij}$ , without of limitation of positive or negative values. Delivery points are different from those of human brain neurons. (2) An input signal accumulator is often used to reflect the temporal and spatial integration function of neurons.  $F$  (3) excitation function, which represents the relationship between input and output in neurons, is often used to limit the input and output of neurons. (4) Typical artificial neuron model diagram is shown in Figure 1.

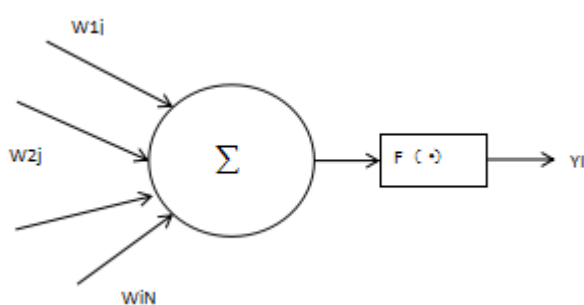


Figure 1: Artificial neuron model diagram

The structure of the artificial neural network is divided into a recursive network and a feedforward network. In the recursive network, several neurons are interconnected into an interconnected neural network, as shown in Figure 2. After some neurons pass through the input layer to the output layer, they are fed back to the neurons in the front or the same layer at the same time, so signals can flow from the forward and reverse flow ports. In Figure 2,  $V_i$  represents state of time,  $X_i$  is an input value,  $X_i$  is a converged output value, and  $i = 1, 2, 3, 4, \dots, n$ .

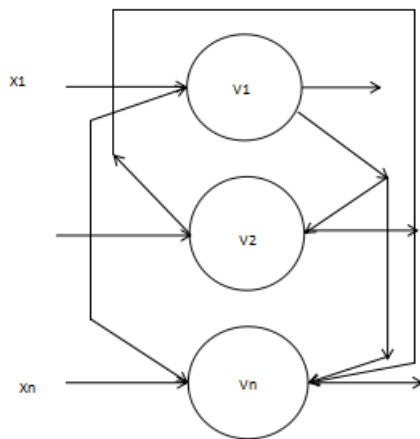


Figure 2: Recursive feedback network

In this study, the realization of BP neural network is the realization of feedforward network structure, where there is only one input FF layer and one output layer and there may be several or an intermediate hidden layer. The selection of specific number should be judged according to experience. There is no connection between each layer of neurons, but the input layer and the hidden layer, the hidden layer and the output layer are connected with each other. The learning process of BP neural network can be divided into two parts: one is forward propagation. In the forward propagation process, the input mode is transmitted to the output layer through the separate processing of the input layer and the hidden layer, and the reverse propagation processing is performed if the desired output is not obtained in the output layer. The other one is backward propagation. In the process of the backward propagation, the error value can be obtained from the desired output and the real output, and in the course of the backward propagation, the weight between the layers is continuously modified until the mean square error is smaller than the target value. The process of continuously modifying the weight is a training process, and the training mode is repeated until convergence is obtained and the error is minimized. The flow chart of BP neural network algorithm is shown in Figure 3.

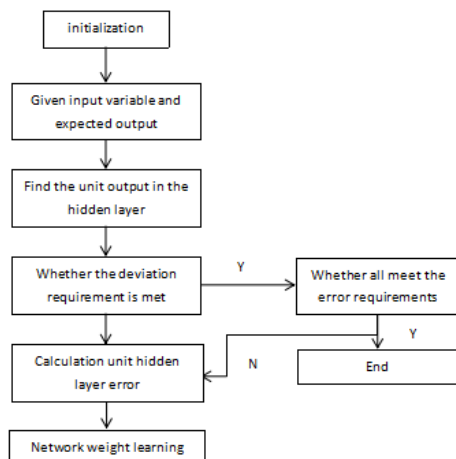


Figure 3: BP neural network algorithm flow chart

In fact, the so-called knowledge reasoning of neural network is to judge the new samples on a very mature network. Network training refers to the regular learning process of a network on its samples, and the purpose of network training is to make the network model have the correct mapping ability to the new data outside the training samples, namely, the generalization ability. Generalization is an attribute of the artificial neural network. Generalization ability is applied to knowledge reasoning. The quality of knowledge reasoning depends on whether neural network can find the true law from the training sample. The generalization ability and quality of the training sample, as well as the structure of neural network and the complexity of the problem

itself are closely related to each other. In the fault diagnosis expert system of tamping truck, with the increase of training times and learning time of BP neural network to fault sample, the generalization ability of neural network becomes stronger and stronger, and the error of neural network to training sample decreases gradually. When the minimum error is reached, the training is stopped.

The overall structure of remote fault diagnosis system: the whole system is logically divided into two parts. One part is vehicle-mounted signal detection system and the other one is the expert diagnosis system. The vehicle-mounted signal detection system has been developed by engineers of the project team, and has been formally put on-line. This system has little correlation with the research contents of this subject, so it is not mentioned here. The expert diagnosis system is divided into server system and client system. The logical structure of the whole system is shown in Figure 4.

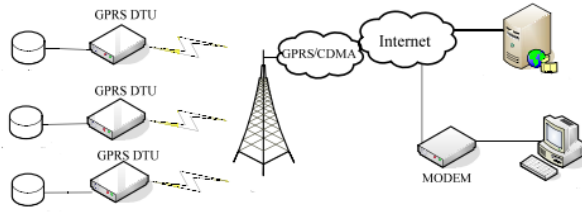


Figure 4: GPRS networking solution

The expert system consists of server and client. The client is stored, processed, inferred and finally converted into fault knowledge for fault diagnosis by the vehicle-mounted signal diagnosis system. The fault diagnosis expert system is mainly divided into H parts, including vehicle-mounted signal source, database knowledge base and processing system, and client system. Their respective duties are: sending the vehicle-mounted signal to web service database as a diagnosis data source; performing reasoning diagnosis on the signal source of the web service to form diagnosis knowledge into the knowledge base. The client system is operated by the remote maintenance personnel so that the fault knowledge expressed in the previous knowledge base is comprehensively analyzed and the final diagnosis result is given.

The core of the expert diagnosis system is also a fault knowledge base which stores diagnosis knowledge and previous experience. After the data in the signal database is analyzed by the inference engine, the complex electric signal is converted into knowledge that can be understood by human beings to be stored in the knowledge base to form the smart step diagnosis analysis. There is little initial knowledge in the knowledge base, so the knowledge base needs to be continuously updated to meet various fault diagnosis requirements. However, the updating is accomplished by knowledge expression and machine learning, and the preliminary diagnosis analysis and the final diagnosis analysis obtained by the inference engine are combined by machine learning. So as to form complete fault knowledge stored in the fault knowledge base. This facilitates the management of coal cutter. The system also provides a complete system of spare parts preparation that analyzes the fault source during machine learning and carries out probability statistics on the fault components. The failure rate is arranged so as to facilitate the component preparation, thereby achieving the asynchronous effect and improving the efficiency.

#### 4. Result and Analysis

On the gear transmission system experiment table, the faults of bearing inner race and broken tooth are simulated. The fault characteristic parameters extracted after wavelet packet decomposition are taken as the input of the improved neural network and the fault classification is taken as the output of the network. The structure of the network is as follows: 16 input nodes (neurons), 2 output nodes. The number of nodes in the hidden layer is determined according to empirical formula, which should be selected between 5-14. The training time, convergence speed and network performance of the network with different number of nodes in the hidden layer are compared. The corresponding relationship between the fault type and the output is shown in Table 1.

Table 1: Correspondence between fault type and output

Status	Output coding	
Bearing inner ring failure	1	0
Broken tooth failure	0	1

The actual simulated fault signal of gear transmission system is conducted feature extraction, and then the actual output of neural network obtained by fault identification is shown in Table 2. It can be seen that the diagnosis accuracy is 100%, and accurate fault diagnosis result is obtained.

*Table 2: The actual output of neural network obtained by fault identification*

Status	Output coding	
Bearing inner ring failure	0.92	0.04
Broken tooth failure	0.03	0.94

## 5. Conclusions

In this study, the fault signal of gear transmission system is extracted by wave packet fault feature, and then the fault identification of gear transmission system is carried out by using the improved neural network. The result shows that this method for the fault diagnosis of gear transmission system is feasible and effective.

This study provides some reference for the research of fault diagnosis system and BP neural network fault diagnosis algorithm. It is inevitable that there are many shortcomings and many details to be improved and optimized for limited time problem and limited level. In that next step, the fault diagnosis system and the fault diagnosis algorithm will be further studied. For example, the functional modules in the expert system will be divided more accurately and reasonably and the improved BP neural network algorithm will be optimized in more detail.

## Reference

- Griffith W.A., Becker J., Cione K., Miller T., Pan E., 2014, 3D topographic stress perturbations and implications for ground control in underground coal mines, *International Journal of Rock Mechanics and Mining Sciences*, 70, 59-68, DOI: 10.1016/j.ijrmms.2014.03.013
- Jiang Y., Li Z., Zhang C., Hu C., Peng Z., 2016, On the bi-dimensional variational decomposition applied to nonstationary vibration signals for rolling bearing crack detection in coal cutters, *Measurement Science and Technology*, 27(6), 065103, DOI: 10.1088/0957-0233/27/6/065103
- Jiang Y., Zhu H., Li Z., Peng Z., 2016, The nonlinear dynamics response of cracked gear system in a coal cutter taking environmental multi-frequency excitation forces into consideration, *Nonlinear Dynamics*, 84(1), 203-222, DOI: 10.1007/s11071-015-2409-2
- Li J., Zhou F., Liu H., 2016, The selection and application of a compound wetting agent to the coal seam water infusion for dust control, *International Journal of Coal Preparation and Utilization*, 36(4), 192-206, DOI: 10.1080/19392699.2015.1088529
- Li Z., Jiang Y., Wang X., Peng Z., 2016, Multi-mode separation and nonlinear feature extraction of hybrid gear failures in coal cutters using adaptive nonstationary vibration analysis, *Nonlinear Dynamics*, 84(1), 295-310, DOI: 10.1007/s11071-015-2505-3
- Li Z., Peng Z., 2016, Nonlinear dynamic response of a multi-degree of freedom gear system dynamic model coupled with tooth surface characters: a case study on coal cutters, *Nonlinear Dynamics*, 84(1), 271-286, DOI: 10.1007/s11071-015-2475-5
- Ordin A.A., Metel’Kov A.A., 2015, Analysis of longwall face output in screw-type cutter-loader-and-scraper conveyor system in underground mining of flat-lying coal beds, *Journal of Mining Science*, 51(6), 1173-1179, DOI: 10.1134/s1062739115060452
- Prokopenko S.A., Ludzish V.S., Kurzina I.A., Sushko A.V., 2015, Alternative source of energy in operation of power-driven machines in coal mines, *Gornyi zhurnal/Mining Journal*, 1, 75-77, DOI: 10.17580/gzh.2015.11.15
- Wang J., Yang S., Li Y., Wang Z., 2015, A dynamic method to determine the supports capacity in longwall coal mining, *International Journal of Mining, Reclamation and Environment*, 29(4), 277-288, DOI: 10.1080/17480930.2014.891694
- Wu Q., Shi Y.B., Lu X.M., 2018, Odor Identification and Data Transmission Method of Harmful Gas in Chemical Environment, *Chemical Engineering Transactions*, 68, 181-186, DOI: 10.3303/CET1868031
- Zhang N., Wang S.C., Shi N., Chen H., 2013, The Abrasive Resistance Study about the Cutting Picker 40Cr of Coal Cutter, In *Applied Mechanics and Materials*, Trans Tech Publications, 387, 227-230, DOI: 10.4028/www.scientific.net/amm.387.227