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CLASSIFICATION AND DECISION-MAKING OF FULLY MECHANISED MINING TECHNOLOGY PATTERN FOR THIN SEAM

As one of the most important decision-making problems in fully mechanised mining, the corresponding mining technology pattern is the technical foundation of the working face. Characterised by complexity in a thin seam fully mechanised mining system, there are different kinds of patterns. In this paper, the classification strategy of the patterns in China is put forward. Moreover, the corresponding theoretical model using neural networks applied for patterns decision-making is designed. Based on the above, optimal selection of these patterns under given conditions is achieved. Lastly, the phased implementation plan for automatic mining pattern is designed. As a result of the industrial test, automatic mining for panel 22204 in Guoerzhuang Coal Mine is realised.

Keywords: Thin seam, Fully mechanised mining technology pattern, Classification, Decision-making

1. Introduction

The reserves of a thin seam (less than 1.3 m in thickness) are enormous in China. Among 95 national key coal enterprises, more than 750 thin seams exist in 445 coal mines. There are approximately 6.5 billion tons of thin seams found in recoverable reserves. The thin seams make up 20% of total recoverable coal reserves [1,2]. The intensity of coal excavation in China has remained significantly high, and it is of the utmost importance to balance the productivity of the mines and excavate the thin seams. Current examples are in minefields in Huaibei, Huainan, Zibo, Yanzhou, Xuzhou, Handan and Yulin.

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Currently, the intensity of excavating thin seam is increasing. However, these coal mines have been in long-term difficulties because of high labour intensity, low mechanisation, safety and economic efficiency. Limited by the detrimental factors, the production of thin seam takes merely 10.4% of the total coal production nationwide [3], which is extremely inharmonious concerning the recoverable reserves. Therefore, efficient excavating technology for thin seam has become the focus of social concern.

In China, developed fully-mechanised mining technologies include longwall mining involving coal shearer [4], or coal plough, auger mining, and room and pillar mining by a continuous miner. The latter two have been rarely used due to their low recovery rates. Coal shearer has the advantages of high cutting efficiency, coal-rock breaking ability and adaptability. It is the primary approach for thin seam excavation [5]. Among the mechanised working faces of a thin seam, those involving coal shearers takes 85% according to incomplete statistics. Without explanation, fully-mechanised mining technology in this paper involves shearer [6].

A fully mechanised mining technology pattern (FMMTP) is the technical foundation of the working face. It plays a leading role in the man-machine working environment. With the development of fully mechanised mining technology for a thin seam, diversified FMMTPs are derived for a thin seam based on the different geological conditions, mining environment, equipment matching and management level.

An innovative classification strategy of the FMMTPs in China is put forward from existing research findings. For the patterns decision-making, the corresponding theoretical model using a neural network is established. Under given conditions, optimal selection of these patterns is achieved. Moreover, the phased implementation plan for automatic mining patterns is designed and implemented.

2. Classification of FMMTPs for thin seam

There are several classification methods of FMMTPs for a thin seam. According to the control mode of the shearer, it can be divided into four patterns: Machinery-tracked FMMTP, Subdivision controlled FMMTP, Automatic FMMTP and Intelligent FMMTP [7-10].

Machinery-tracked FMMTP is how the operator controls the shearer to complete the coal cutting process while remaining behind the shearer. The operator usually bends over to control the shearer.

In the subdivision controlled FMMTP, the length of the working face is divided into several equal-length segments according to the distance of the remote control shearer. A shearer operator is prearranged in a segment. The shearer will be operated remotely by the operator in a designated segment in turns to complete coal cutting of the full-length in the working face.

As for automatic FMMTP, the shearer is automatically operated to complete coal cutting according to the operating parameters preset. Currently, presetting can be achieved by sampling cut or advanced geological exploration. Using memory cutting, visual video surveillance and shearer positioning technology, automatic FMMTP can be realised.

Intelligent FMMTP is developed by injecting human consciousness and thinking. Compared with the automatic FMMTP, the artificial intelligence of the pattern is improved, such as coal-rock identification. Therefore, it belongs to a higher level FMMTP. Concerning future development, it is a promising and necessary approach to realised unmanned mining for the thin seam [11]. Table 1 is the detailed technical comparison of several FMMTPs.

TABLE 1

Technical comparisons of several FMMTPs

FMMTP	Characteristics	Advantages	Disadvantages
Machinery-tracked	The shearer operator is involved in the simultaneous controlling shearer	Strong adaptability, low equipment investment and mature technology	High labor intensity, low safety
Subdivision controlled	Operator was assigned to control the shearer in turns at each section,	Reduced labor intensity, low equipment investment and mature technology	Many workers
Automatic	Assistant memory cutting, visual video surveillance and positioning technology	Fewer people freed the shearer driver.	Poor adaptability, must have manual intervention
Intelligent	Increase of artificial intelligence factors, such as the identification of coal	Unmanned, Artificial Intelligent decision making	Immature technology

The above patterns belong to different development stages of fully mechanised mining technology. With the continuous development and improvement in China, the FMMTP is entering into the automatic pattern and stepping forward the intelligent pattern.

3. Decision-making method of FMMTP for thin seam

Generally, a fully mechanised mining system of the thin seam is very complex and changeable. It is impossible to predict or determine the correlation accurately between related factors and results in the system. The decision-making of FMMTP is a typical nonlinear programming problem. Using an artificial neural network, a non-linear model for decision-making is constructed. In the paper, BP neural network is selected for the decision-making. In the model, the complex decision-making system of FMMTPs is considered as a black box. The sample data is imported into the neural network. The correlation between factors is hidden in the hidden layer of the network, and the weights in the network are adjusted by an error feedback mechanism. Using this method, the impact of human factors on modelling will be reduced, and the objectivity of the decision-making will also be improved [12].

3.1. Principle of BP neural network

BP neural network is the error backpropagation algorithm based on supervised learning. It can achieve nonlinear mapping of "input-output" arbitrarily and has a stronger ability in adaptive learning [12,13]. BP is the multilayer feed-forward network composed of nonlinear elements, as shown in Fig. 1.

The signals propagation in the BP network can be divided into working signals forward propagation and error signals backpropagation. In working signals forward propagation, signals are transmitted from the input layer to the output layer via a hidden layer. When the signal value of the output layer can not meet the requirement of output expectation, the error signals backpropagation will be carried out. The backpropagation starts from the output layer. The error

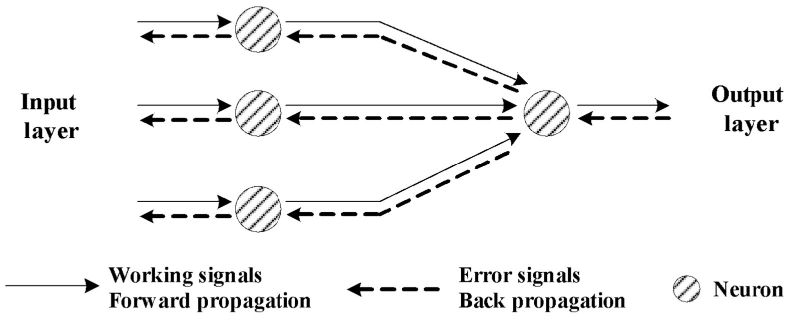
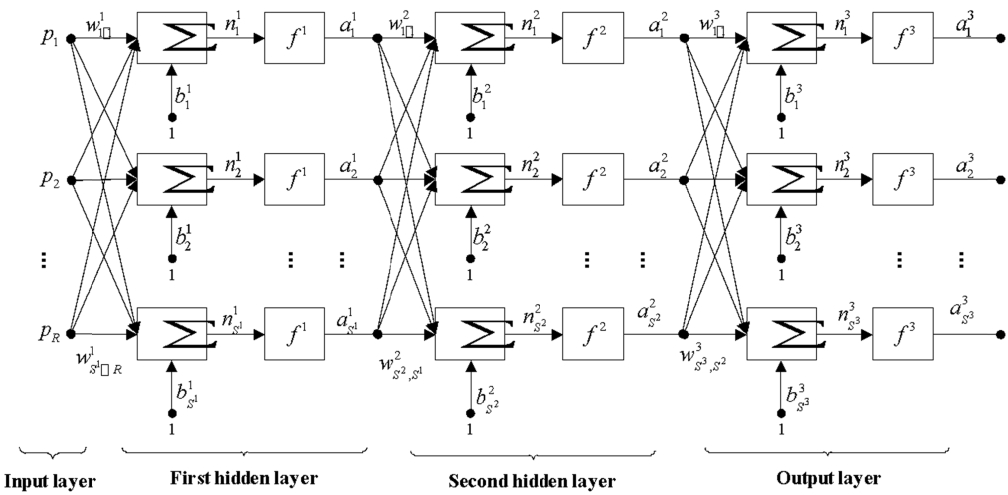


Fig. 1. Signal propagation in BP network

signal is the difference between the output value and the expected value. By adjusting network weights, the output signal value will meet the requirements in the error signals backpropagation. According to FMMTP decision making for a thin seam, BP neural network with double hidden layers [14,15] can meet the expected requirements, as shown in Fig. 2.



$$a^1 = f^1(W^1P + b^1) \qquad a^2 = f^2(W^2a^1 + b^2) \qquad a^3 = f^3(W^3a^2 + b^3)$$

$$a^3 = f^3(W^3(f^2(W^2(f^1(W^1P + b^1)) + b^2)) + b^3)$$

Note: p is the value of the input layer, w is the weight, Σ is the accumulator and b is the bias of the network.

Fig. 2. BP network with two hidden layers

Every layer in the network is composed of weight vector $\boldsymbol{W}$, bias value vector $\boldsymbol{b}$, input value vector $\boldsymbol{n}$ and output value vector $\boldsymbol{a}$.

In the weight matrix, the first subscript is the number of the target neuron and the second is the source neuron number. The superscript represents the target layer number. Taking $w^2_{1,3}$ as an example, it represents the weight value connecting the third neuron in the second layer to the first neuron in the first layer.

For bias values, the subscript is the number of neurons. The superscript represents the layer number of the bias vector. For example, b_2^1 represents the bias value implanted into the second neuron in the first layer.

Neural network input subscript is the neuron number and superscript is the source layer number of the input vector. For example, n_2^1 represents the net input value implanted into activation function from the second neuron in the first layer.

The output subscript represents the neuron number of the output layer, and superscript is the number of output layers. For example, a_2^1 represents the output value of the second neuron in the first layer.

Supposing a BP neural network with n input neurons, where the input layer is $x = (x_0, x_1, \cdots, x_{n-1})^T$, $x \in R^n$, the first hidden layer $x' = (x'_0, x'_1, \cdots, x'_{n_1-1})^T$, $x' \in R^{n_1}$, the second hidden layer $x'' = (x''_0, x''_1, \cdots, x''_{n_2-1})^T$, $x'' \in R^{n_2}$, and the output layer $y = (y_0, y_1, \cdots, y_{m-1})^T$, $y \in R^m$. The weight and threshold between the input layer and the first hidden layer are w_{ij} and θ_j, respectively. The weight and threshold between the first layer and the second layer are w'_{ij} and θ'_k, respectively. The weight and threshold between the second hidden layer and the output layer are w''_{kl}, and θ''_l, respectively.

BP neural network is a model with supervised learning. Supposing P learning samples $(x^1, t^1), (x^2, t^2), \cdots, (x^p, t^p)$. Using the error between actual output $y^1, y^2, \cdots, y^p$ and ideal output $t^1, t^2, \cdots, t^p$, network connection weights and thresholds are modified by the BP algorithm. In this way, the output of the network will approximate the ideal value. Training will stop in the BP network when the total error reaches 10^{-5}. The training flow in the BP network is illustrated in Fig. 3.

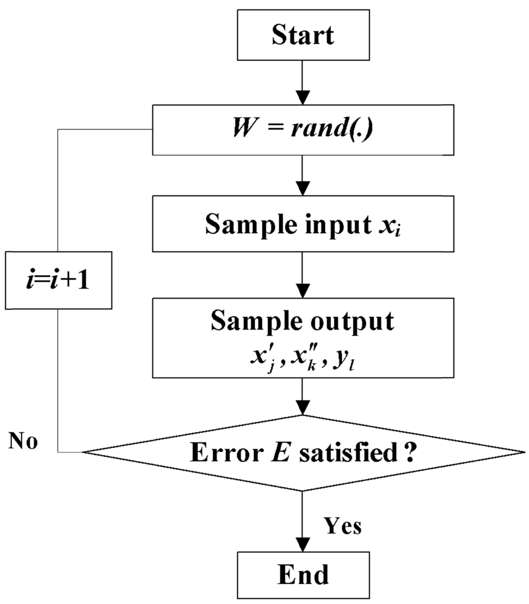


Fig. 3. Training flow in BP network

For the whole sample space, the total network error can be expressed as:

$$E_T = \frac{1}{2}\sum_{P_l=1}^{P}\sum_{l=0}^{m-1}(t_l^{P_l} - y_l^{P_l})^2 \tag{1}$$

Note: E_T is the total network error; P is the number of the learning samples; m is the dimension of output vector; $y_l^{P_l}$ is the l-th dimension actual value of output vector for the P_l-th sample; $t_l^{P_l}$ is the l-th dimension ideal value of the output vector for the P_l-th sample.

3.2. BP network construction

1) Input layer

The input layer should cover FMMTP evaluation indexes, can be expressed as $x = (x_0, x_1, \cdots, x_g)^T$. According to the actual conditions of FMMTP and technical experience, these indexes can be divided into 2 process parameters, 6 geological factors and 1 equipment level. Process parameters are composed of mining height and length of the working face. Geological factors consist of coal seam dip, coal thickness variation coefficient, fault, gas, hydrology and exploration precision.

The input layer contains quantitative and qualitative indexes. Quantitative indexes such as mining height, length and coal seam dip angle are basic parameters of working face, which can be obtained by investigation and statistical analysis. The other four quantitative indexes including fault, gas, hydrogeology and coal seam thickness variation coefficient can be determined by membership function [16].

(1) Quantitative indexes

- Fault

  Taking fault density q_1, length coefficient q_2 and drop coefficient q_3 into consideration, comprehensive analysis of the fault impact on mining is conducted. The membership function of fault can be expressed as:

$$\mu_{\underline{a}}(q_1, q_2, q_3) = \frac{2}{1 + \exp(4.2\times10^{-3}q_1 + 3.4\times10^{-4}q_2 + 3.1\times10^{-2}q_3)} \tag{2}$$

  Where q_1 is the number of faults per unit area in working face, which is calculated by $q_1 = n/s$. n is the number of faults in the statistical scope, and s is the area of the statistical scope, km^2. Length coefficient q_2 is the sum of length per unit area in working face, which is obtained from $q_2 = \sum_{i=1}^{n} l_i / s$. Where l_i is the extended length of the i-th fault, m. Drop coefficient q_3 is the ratio of drop to mining height, which is calculated by $q_3 = \frac{1}{n}\sum_{i=1}^{n}\frac{h_i}{m}\frac{1}{\ln(m+1)}$. Where h_i is the drop of ith fault in the working face and m is the mining height.

- Gas

  According to "Coal Mine Safety Regulations" [17], mines can be divided into three categories according to the risk level: I, II and III, which represent low gas mine, high gas mine, coal and gas outburst mine, respectively. Combined with the neural network model established in this paper, the gas condition is quantified from 0 to 1. According to the opinions and scores of industry experts, 1, 0.5 and 0.2 are assigned to these mines respectively in the network.

- Hydrogeology
  According to "Regulations on Water Prevention and Control in Coal Mines" [18], hydrogeology in the coal mine is divided into simple, medium, complex and extremely complex according to the risk level, which is expressed as I, II, III and IV respectively. Combined with the neural network model established in the paper, the hydrologic condition is quantified from 0 to 1. According to the opinions and scores of industry experts, 0.8, 0.6, 0.4 and 0.2 are assigned to the four kinds of hydrogeology respectively in the network.
- Coal seam thickness variation coefficient
  Coal seam thickness variation coefficient γ is a comprehensive index to measure the coal thickness variation degree, which can be calculated by $\gamma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(X_i - X)^2} / X$.
  Where n is the number of effective boreholes in the working face. X_i is coal thickness in the ith borehole. X is the average thickness.

(2) Qualitative indexes
Qualitative indexes such as exploration precision and equipment level are quantified by fuzzy mathematics [19]. Supposing $f(x)$ is the membership function about fuzzy number x, where x is expressed as a triangular fuzzy number $x = (m, a, b)_{LR}$. That is to say $m - a < x < m + b$ and $f(x) \in [0,1]$. Within the scope of $(m - a, m)$ and $(m, m + b)$, $f(x)$ is linear monotone increasing and monotone decreasing function respectively [20], as shown in Fig. 4.

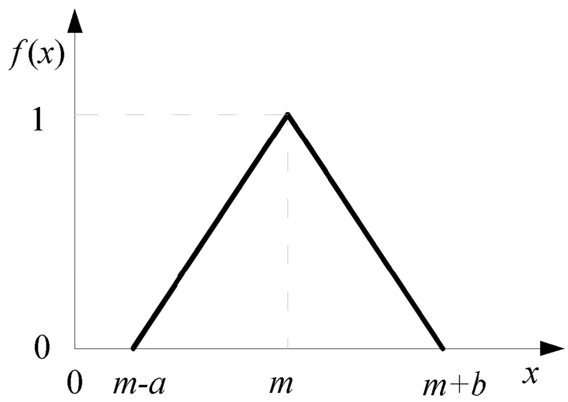


Fig. 4. Triangular fuzzy numbers

Qualitative indexes are expressed by profit indexes, of which priority increases with its value. The decision makers have 6 choices [21], namely $VB = (0,0,0.2)_{LR}$, $B = (0.2,0.2,0.2)_{LR}$, $W = (0.4,0.2,0.2)_{LR}$, $M = (0.6,0.2,0.2)_{LR}$, $G = (0.8,0.2,0.2)_{LR}$, $VG = (1,0.2,0)_{LR}$, as shown in Fig. 5.

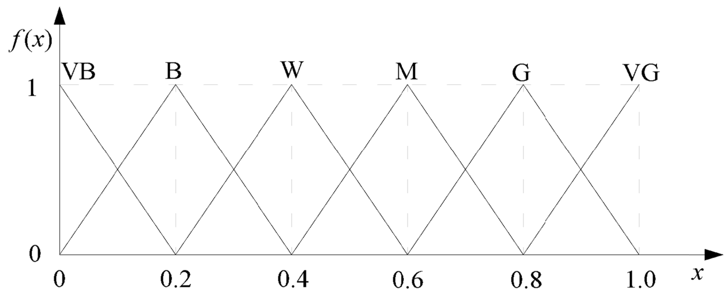


Fig. 5. Fuzzy expressions

Using Yager index [22], the fuzzy numbers are defuzzified in this paper, which can be calculated by $f(x) = F(m, a, b) = (3m - a + b)/3$. As a result, the corresponding Yager index and fuzzy value of these qualitative indexes are obtained, as shown in Table 2.

TABLE 2

Fuzzy value of qualitative indexes

No.	Attribute value	Exploration precision	Equipment level	Yager index
VB	$(0,0,0.2)_{LR}$	Very low	Very low	0.067
B	$(0.2,0.2,0.2)_{LR}$	Low	Low	0.2
W	$(0.4,0.2,0.2)_{LR}$	General	General	0.4
M	$(0.6,0.2,0.2)_{LR}$	Medium	Medium	0.6
G	$(0.8,0.2,0.2)_{LR}$	High	High	0.8
VG	$(1,0.2,0)_{LR}$	Very high	Very high	0.933

2) Output layer

FMMTP and production capacity of the working face are selected as the output layer. Production capacity is characteris ed by daily output. Thus, output layer can be expressed as $y = (y_0, y_1)^T$, where y_0 is FMMTP and y_1 is daily output. According to the input and output of daily output, the network for FMMTP decision-making can be further validated. Table 3 is the FMMTP output value defined in the network.

TABLE 3

User-defined FMMTP output value in the network

FMMTP	Output value	FMMTP	Output value
Machinery-tracked	1	Automatic	3
Subdivision controlled	2	Intelligent	4

3) Hidden layer

According to the relevant research, the prediction effect of a BP neural network with double hidden layers is better than that with only one when the number of neurons in the input layer is more than 3 [23]. The number of neurons in the hidden layer can not be determined by an ideal formula. Generally speaking, the more neurons there are, the more accurate the calculation will be. However, it will increase the time of learning. Meanwhile, fault tolerance will be reduced when the number of neurons is too small. Considering the convergence speed and the output error [24], the number of neurons in each hidden layer is set to 9 using repeated training. Based on the above, a „9-9-9-2“ BP neural network for FMMTP decision-making is established, which is composed of double hidden layers with 9 neurons, an input layer with 9 neurons and an output layer with 2 neurons.

4) Training samples

The precision and reliability of the network are closely related to training samples. 158 samples about FMMTP are collected from fully-mechanised mining working faces in China. Among them, samples 1 to 146 are training samples, and 147 to 156 are validating samples. The other two, 157 and 158, are predicting samples, as shown in Table 4.

TABLE 4

Samples of neural network

No.	Panel	Coal mine	Mining height [m]	Length [m]	Dip [°]	Thickness variation coefficient	Fault	Gas	Hydro-geology	Exploration precision	Equipment level	FMMTP	Output [t/d]
1	112±89	Huang-sha	0.90	50	23	0.101	0.78	0.5	0.6	0.6	0.8	3	720
2	8102	Gan-zhuang	1.30	240	4	0.041	1	1	0.8	0.933	0.933	3	3300
3	11604	Geting	1.22	34	9	0.051	0.15	1	0.8	0.8	0.4	2	626
4	14459	Xiaotun	1.10	120	4.5	0.268	0.55	1	0.6	0.4	0.2	1	1600
…	…	…	…	…	…	…	…	…	…	…	…	…	…
145	3602	Nantun	1.00	165	4	0.113	0.20	1	0.8	0.2	0.2	1	990
146	8812	Tangsh-angou	1.60	99	2	0.086	0.95	1	0.6	0.8	0.933	3	3030
147	94702	Xuecun	1.30	150	16	0.150	0.68	1	0.8	0.8	0.933	3	4400
148	8-22110	Liumao	2.10	180	4.5	0.165	0.54	0.5	0.8	0.8	0.8	3	3000
…	…	…	…	…	…	…	…	…	…	…	…	…	…
156	3303	Daiz-huang	1.30	113	4	0.430	0.80	1	0.6	0.6	0.4	1	2266
157	43101	Liang-shuijing	1.20	160	1	0.211	1	1	0.6	0.8	0.933		
158	22204	Guoer-zhuang	1.30	158	24	0.512	0.43	1	0.8	0.933	0.933		

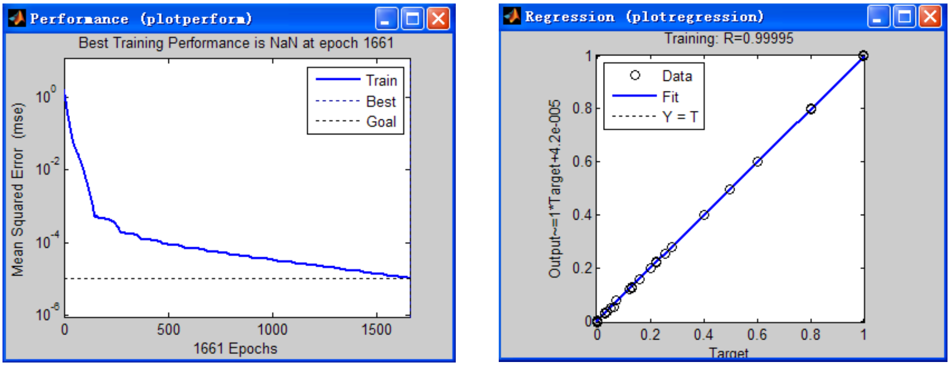
5) Algorithm selection

Several BP neural network algorithms are provided in the MATLAB toolbox, which can meet the demand of FMMTP decision making. BP neural network constructed using MATLAB has strong operability and high practicability. Taking iteration efficiency, convergence success rate and variance into consideration, the network trained by BP algorithm with momentum term and variable step size is optimally selected for FMMTP decision-making and daily output prediction [25].

4. FMMTP decision-making for thin seam

4.1. Network training

Network training ends until the mean square deviation reaches 10-5. The deviation and the linear regression curve between output and the target value are described in Fig. 6. As illustrated in Fig. 6(b), it concludes that the training effect can meet the demand while the linear regression index is 0.99995. Fig. 6 shows the change of mean squared error during network training.



(a) Deviation curve (b) Regression curve between output and target value

Fig. 6. Training results

4.2. Network validating

To validate the effect of the trained network above, the validating samples used in the network. The corresponding FMMTP and daily output can be obtained. By fitting it with the target value, a group of optimal neural networks are selected, which can be applied for FMMTP decision making in predicting samples.

(1) FMMTP

Based on the validated samples, the corresponding ideal output of FMMTP can be described and shown in Fig. 7. The FMMTP output value range in the network is [0.5, 4.5].

The validating accuracy e is used for evaluating and selecting the network. It is determined by the probability of the output value falling into the ideal interval. When output values of all validating samples are in the ideal interval, the validating accuracy e is 100%. To ensure the network prediction accuracy, about 200 network training are carried out. Among them, 100 are validated with an accuracy e of 70% or more are preliminarily screened.

Among 100 groups of networks, the number of networks with an accuracy of 100% is 49, which are selected for FMMTP evaluation and prediction. The networks with an accuracy of less than 100% are deleted. The result of rejecting a given sample is based on the ideal process mode output of the validating sample. Taking sample 147 as an example, the actual process mode value is 3, as shown in Table 4. The ideal value interval of the network output is [2.5,3.5]. As a result, the output not in this range will be deleted.

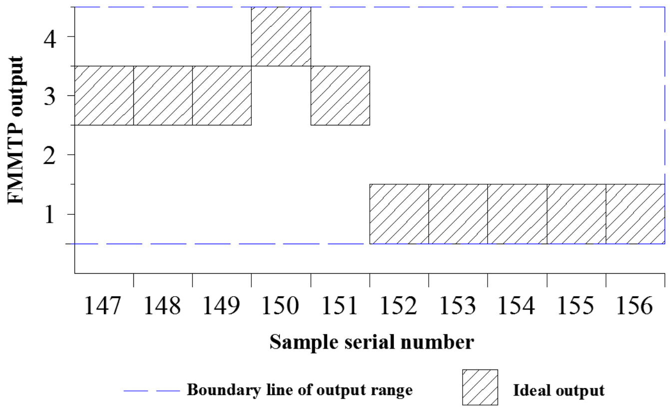


Fig. 7. Ideal FMMTP output of validating samples

TABLE 5

FMMTP output and accuracy using validating samples

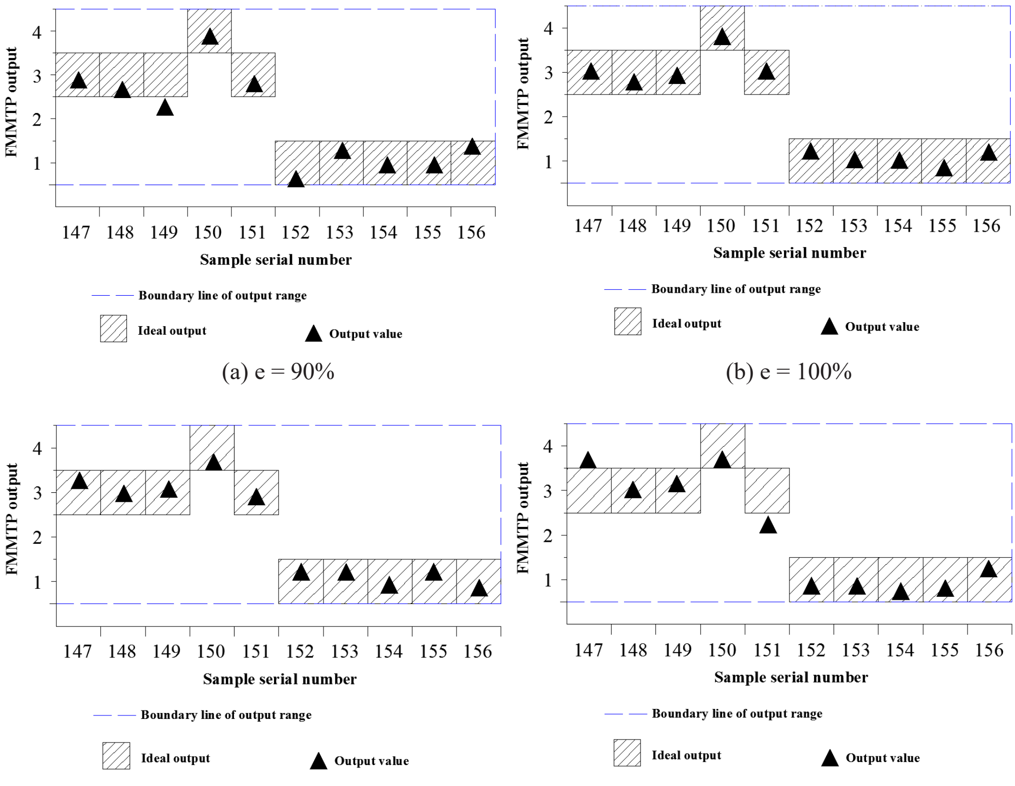
Network Sample	1	2	3	4	5	6	7	…	99	100	Ideal Output
147	2.9	3.2	3.4	3.6	3.2	2.8	3.0	…	2.6	2.9	[2.5,3.5]
148	2.6	2.7	3.1	3.1	2.6	2.5	2.6	…	3.2	2.6	[2.5,3.5]
149	2.4	3.1	3.2	3.3	2.8	2.4	2.6	…	3.3	2.6	[2.5,3.5]
150	3.9	3.7	3.5	3.6	3.6	2.9	3.0	…	3.6	3.8	[3.5,4.5]
151	2.6	3.3	2.9	2.3	2.8	3.3	2.9	…	3.3	2.1	[2.5,3.5]
152	0.5	1.2	1.3	0.9	1.2	0.8	1.2	…	0.3	1.1	[0.5,1.5]
153	1.0	1.1	1.3	0.9	1.0	0.9	0.8	…	0.8	0.8	[0.5,1.5]
154	0.7	1.0	0.9	0.6	0.7	1.8	0.9	…	1.7	0.7	[0.5,1.5]
155	0.7	0.8	1.3	0.8	0.9	0.6	0.6	…	2.2	1.1	[0.5,1.5]
156	1.3	1.2	0.8	1.3	1.1	1.0	1.3	…	0.8	0.8	[0.5,1.5]
Accuracy *e* [%]	90	100	100	80	100	90	100	…	70	90	

Taking the first four networks as examples, the validating results of FMMTP output are obtained, as shown in Fig. 8.

(2) Daily output of working face

Corresponding to above 49 networks, daily output and the average of working faces were also obtained, as shown in Table 6.

Using the mean square error (MSE), the relationship between output and the target value is fitted. To analyse the validating results of daily output, three networks are randomly selected, as shown in Fig. 9(a), (b), (c). MSEs are 3.25×106 [t/d], 1.92×106 [t/d], 3.15×106 [t/d] respectively. Nevertheless, the MSE is only 0.49×106 [t/d] using the average output value, as shown in Fig. 9(d). Compared with a single network, the prediction accuracy is improved, and the result has more credibility. Therefore, the average daily output from a multi-group neural network is used for daily output prediction.



(a) e = 90% (b) e = 100%

(c) e = 100% (d) e = 80%

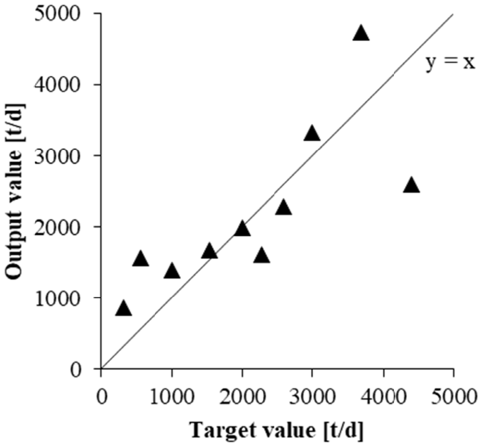
Fig. 8. Testing results of FMMTP in the first four networks

TABLE 6

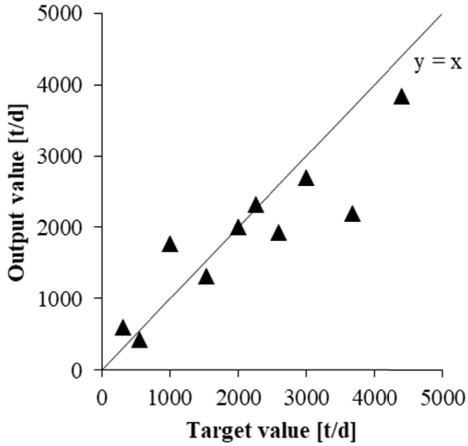
Daily output of validation samples in 49 networks with accuracy 100%

Network **Sample**	**1**	**2**	**3**	**4**	**5**	**6**	**…**	**48**	**49**	**Minimum value [t/d]**	**Maximum value [t/d]**	**Average [t/d]**	**Ideal output [t/d]**
147	2594	3842	2544	3448	3538	3415	…	3017	2185	2180	5605	3500	4400
148	3331	2693	4087	3445	5264	4740	…	4123	3475	1869	5264	3589	3000
149	1669	1324	1476	2003	1845	2435	…	1596	1286	782	2751	1765	1538
150	1386	1778	1647	1665	1581	1900	…	1689	859	548	4100	1489	1000
151	863	605	338	301	541	839	…	480	621	251	999	584	312
152	1564	419	495	1061	1011	168	…	304	376	126	1564	645	556
153	1989	2002	2005	1990	1997	1996	…	2009	1995	1989	2009	1995	2000
154	2288	1929	1736	2376	1466	3345	…	3356	3511	920	3994	2478	2600
155	4741	2192	4305	4022	3000	2386	…	4486	3589	1413	6666	3781	3684
156	1618	2314	1916	2167	2966	2273	…	3288	3114	1564	4555	2600	2266
MSE/10^6 [t/d]	3.25	1.92	3.15	1.10	2.78	4.14	…	1.93	3.45	1.02	8.6	0.49	

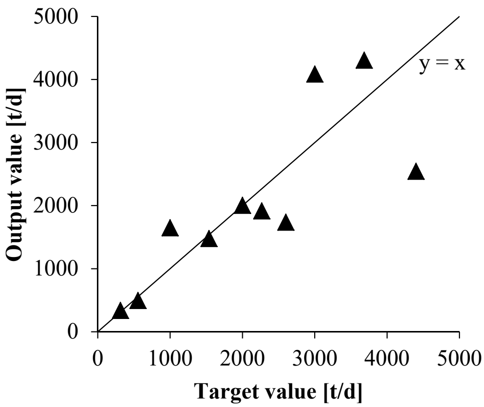
From the comparison between the predicted result and the actual output, it can be concluded that the error range of the output is about ±300 [t/d], which can meet the engineering requirements of production prediction. The feasibility and accuracy of the FMMTP evaluation model are verified from another side.



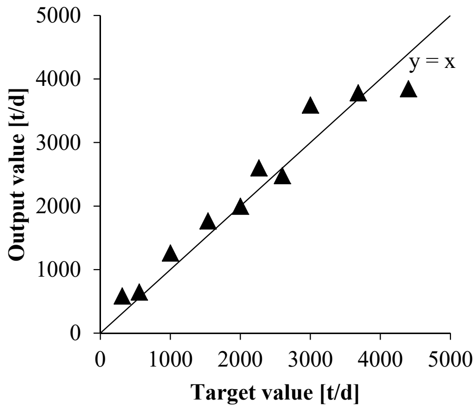
MSE=3.25×10^6 [t/d]



(b) MSE =1.92×10^6 [t/d]



(c) MSE =3.15×10^6 [t/d]



(d) MSE =0.49×10^6 [t/d]

Fig. 9. Validating results of daily output

4.3. Network prediction

Using the 49 networks for prediction, the FMMTP decision-making and daily output prediction are carried out for panel 43101 in the Liangshuijing and 22204 in Guoerzhuang coal mine. The results of the FMMTP decision-making are shown in Table 7, and the average daily output prediction corresponding to the FMMTP is shown in Table 8.

TABLE 7

Results of FMMTP decision-making

Predicted value Panel	[0.5,1.5]	[1.5,2.5]	[2.5,3.5]	[3.5,4.5]
	Probability [%]	Probability [%]	Probability [%]	Probability [%]
43101	1	25	66	8
22204	7	16	71	6

TABLE 8

Average daily output prediction

Predicted value Panel	[0.5,1.5]	[1.5,2.5]	[2.5,3.5]	[3.5,4.5]
	Output [t/d]	Output [t/d]	Output [t/d]	Output [t/d]
43101	1492	2061	2486	1367
22204	987	2487	3156	1148

Based on the above , the results of FMMTP evaluation and average daily output prediction are drawn, as shown in Fig. 10 and Fig. 11.

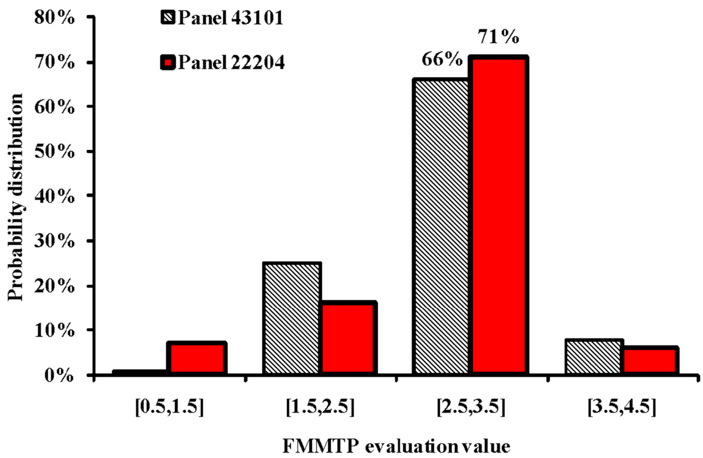


Fig. 10. Results of the FMMTP evaluation

In conclusion, the FMMTP prediction for thin seam using a multi-group neural network obeys the normal distribution. According to the normal distribution, the priorities of FMMTPs are determined. The FMMTP with maximum probability is optimally selected. Based on the above, automatic FMMTP is selected for panel 43101 and panel 22204, with a probability of 66% and 71%, respectively.

The average daily output of the working face is related to the corresponding FMMTP. The average daily output predictions are quite different under different FMMTPs. Under automatic FMMTP, the average daily output of panel 43101 and panel 22204 are 2486 t/d and 3156 t/d, respectively.

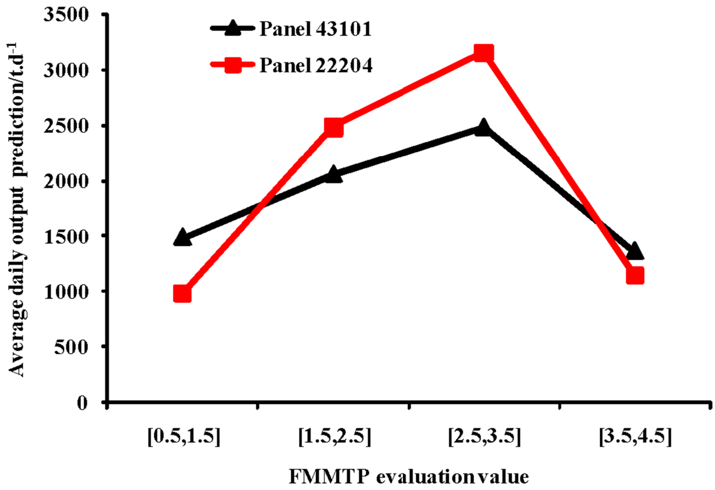


Fig. 11. Results of average daily output prediction

5. Industrial test

Automatic FMMTP is adopted in panel 22204 during normal mining in the Guoerzhuang coal mine. To ensure the stability of automatic mining, a step-by-step implementation scheme is proposed and applied. In the first step, machinery-tracked FMMTP works for about 15 days. Then, subdivision controlled FMMTP is adopted and takes 15 to 20 days. In the last step, automatic FMMTP is applied during normal mining operations. In the above three stages, the number of workers in the panel per day is 39, 43 and 23 respectively. The number of workers and work efficiency of the three models are obtained, as shown in Fig. 12.

Compared with the machinery-tracked FMMTP, the number of workers is reduced by 41% in automatic FMMTP. Shearer drivers, hydraulic support workers and scraper conveyor drivers

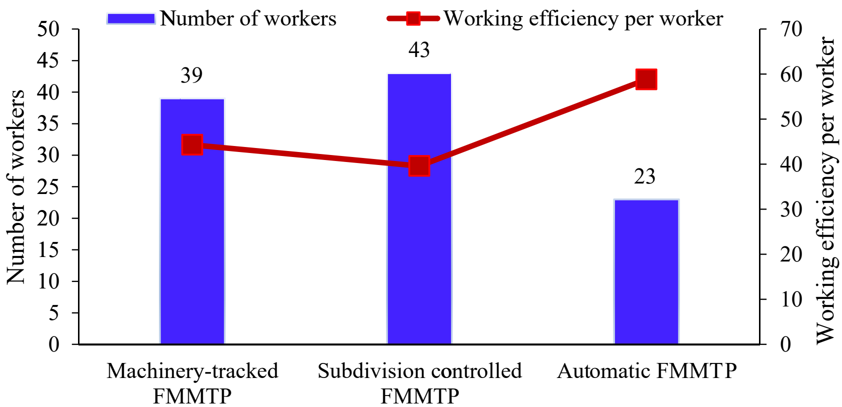


Fig. 12. The number of workers and work efficiency of the three FMMTPs

are liberated from the narrow working face. The working efficiency per worker has increased from 44.3 t to 58.8 t. There is an increase of 32.8 percent. The goal of reducing labour intensity and increasing efficiency for thin seam is achieved by automatic FMMTP.

Automatic FMMTP is realised in panel 22204. The average daily output during automatic mining reached 2883t per day, which is consistent with the results of network prediction. It verifies the accuracy of FMMTP evaluation and production prediction.

6. Conclusion

(1) The classification of FMMTPs for thin seam is put forward. According to the control mode of the shearer, FMMTPs can be divided into four patterns: Machinery-tracked FMMTP, Subdivision controlled FMMTP, Automatic FMMTP and Intelligent FMMTP. The above patterns belong to different development stages of fully mechanised mining technology. With the continuous development and improvement in China, the FMMTP is entering into the automatic pattern and stepping forward the intelligent pattern.
(2) Corresponding BP neural network for thin seam FMMTP evaluation with double hidden layers is established. FMMTP decision-making for thin seam is realised. As a result, FMMTP prediction for thin seam obeys the normal distribution. FMMTP with maximum probability is optimally selected. Automatic FMMTP is selected for panel 43101 in Liangshuijing and panel 22204 in the Guoerzhuang coal mine, with a probability of 66% and 71% respectively.
(3) The implementation plan of automatic FMMTP for panel 22204 is designed and carried out in the Guoerzhuang coal mine. The ideal application effects have been achieved by industrial tests. The FMMTP evaluation for thin seam provides a good technical reference for FMMTP decision-making and implementation.

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