Adaptive height adjusting strategy research of shearer cutting drum

W. Li*[1], *Q. G. Fan, Y. Q. Wang* and *X. F. Yang

Shearer height adjusting is a key technology for shearer automation. Considering constraints of present shearer height adjusting, this paper built grey-markovian memory cutting algorithm after analyzing traditional shearer memory cutting algorithm. We firstly constructed prediction mechanism using grey model, then determined state transition probability matrix using markovian, so as to revise feedback of grey model and achieve automatic height adjusting. Finally we simulated this model to get reliability. By comparing grey-markovian memory cutting algorithm with traditional memory cutting algorithm, it is concluded that the grey-markovian model has higher efficiency and accuracy.

Key words：*shearer, height adjusting, memory cutting, grey model, markovian*

Introduction

In modern fully-mechanized workface, shearer is the key mechanical equipment for the whole workface automation, while height adjusting of cutting drum is vital for shearer automation. At present, cutting drum height adjusting of shearer mainly uses artificial operation, that is, the shearer driver operates the shearer to adjust vertical position of the cutting drum. However, bad working conditions such as great coal dust, poor visibility and strong noise make the driver hard to accurately determine the cutting state whether the cutting drum is cutting the roof rock or the floor rock visually and aurally (Mowrey, 1991).

Avoiding shearer cutting the roof or floor rock, previous work focus on coal-rock interface identification (Qin, 1993), such as natural γ ray probe method, stress pick analysis method, infrared detection method, multi-sensor data fusion method, and so on. Some have been applied in industrial site and work effectively. However, natural γ ray probe method has errors due to complex geological condition, because the natural γ ray probe detector demands some γ ray radiation for the roof or floor rock. The stress picks analysis method and infrared detection method can only determines cutting into rock identification with indetermination of top coal thickness. While multi-sensor data fusion method has been in experiment and has no industrial application (Ren, 2003).

Form above discussion, it appears that the coal-rock interface identification way is immature, So a memory cutting way is proposed by some coal mining group, which identify coal rock by automatic controlling. For example, the U.S. JOY Company, Germany Eickhoff Corporation and German DBT Company have developed typical coal products. But this memory cutting way is indirect coal-rock interface identification, and needs artificial operation. Furthermore, intensive studies of shearer memory cutting methods have been probed into. (Liu et al., 2004) proposed a memory program-control mode for automatic reappearing, after sensor sampling the drum data in real time and computer storage, the shearer automatic control was obtained using feedback from the adjusting high cylinder displacement. But drum data can hardly determine cutting state adequately. (Yao, 2006) designed a memory cutting controller based on embedded system. Taking cutting motor current as shearer cutting state identification, the memory cutting controller changes when cutting motor current increased indicating cutting the rock, nevertheless, single group sensor may result in mixed interference. (Zhang, 2007) researched a prediction memory cutting strategy, which predicts height adjusting data in next cutting loop using data from the finished cutting loop, but prediction precision is not guaranteed. (Wang et al., 2009) proposed a self-adaptively memory cutting strategy based on immune algorithm, by establishing immune data set judging whether the shearer is cutting rocks, but it needs a large number of prior data, which demands high requirements for hardware.

From the above methods introduced, it appears that no methods are fully automatic or accurate enough, it is necessary to carry out new ways to realize shearer automation. This paper proposed a new shearer memory cutting strategy combining multi-sensor data fusion strategy with grey-markovian chain. In the strategy, data fusion from the cutting motor current sensor and vibration sensor is predictive for warning of cutting the rock, and then self-adaptive adjusting is done immediately using grey-markovian prediction controller to reconfirm warning. Furthermore, alarm for artificial adjusting is implemented if warning still exists after self adaptive adjusting. Otherwise the shearer was shutdown if warning lasted for a long time.

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Shearer working face mathematical model

Shearer height adjusting closely relates to drum height, as the shearer has certain tilt degree along the working face forward and propel, which will influence height adjusting, firstly we built mathematical models, figure1 shows shearer uplink cutting schematic. Angle between shearer and horizon line is β, angles between two rock arms and horizon line are respectively α and θ, and the arm is L. Shearer drum height is given by (1):

$$H_2 = H_1 + L \times \sin(\alpha - \beta) \tag{1}$$

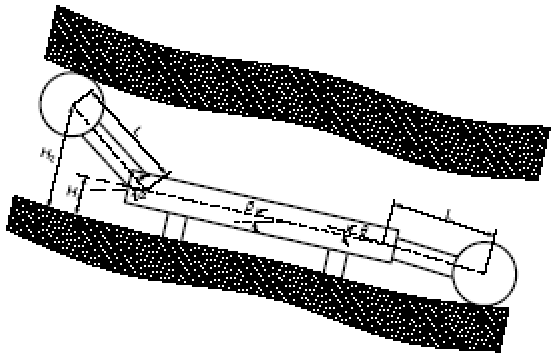

Fig. 1. Shearer uplink cutting schematic.

Also, the shearer has tilt angle along working face propel, as shown in center distance between shearer drum and shearer base is L_1, then we get:

$$\Delta H = L_1 \times \tan(\varphi) \tag{2}$$

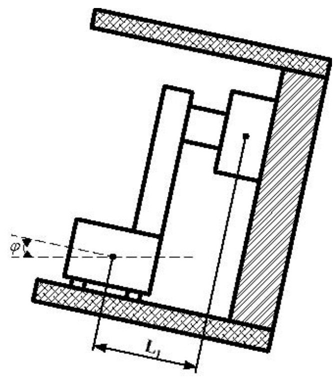

Fig. 2. Shearer side view along working face propel.

Combining equation (1), we get shearer drum height by (4):

$$H' = H_1 + L \times \sin(\alpha - \beta) - L_1 \times \tan(\varphi) \tag{4}$$

where α, β and φ can be obtained by tilt sensors.

Analysis of traditional shearer memory cutting principle

Fig. 3 shows traditional shearer memory cutting principal, the number of cutting sample points is N. The working face forward direction is X, and the working face propel direction is Y. The shearer drum height is H. The traditional shearer memory cutting process is:

1. Recording different sampling points $H1_i$ (i=1, 2,..,N) at the first working face D_1, and the sampling points are obtained from normal cutting at D_1 ;

2. While the shearer working at D_2, let be $H2_i = H1_i$ (i=1, 2,.., N) . When the value of $H2_i$ cannot satisfy shearer conditions, adjusting the shearer drum height by artificially control, and recording the new value $\overline{H2}_i$ of the sampling points, then let be $H2_i = \overline{H2}_i$;
3. While the shearer working at D_3, let be $H3_i = H2_i$ (i=1, 2,.., N) . When the value of $H3_i$cannot satisfy shearer conditions, adjusting the shearer drum height by artificially control, and recording the new value $\overline{H3}_i$ of the sampling points, then let be $H3_i = \overline{H3}_i$.

Keeping the cutting cycle according to above process at the fully mechanized coal face, practice proves that this method has certain effect. But it needs to adjust by artificially control and re-sampling after 5～6 cutting cycle as complex coal mine geological conditions accuracy and efficiency should be improved.

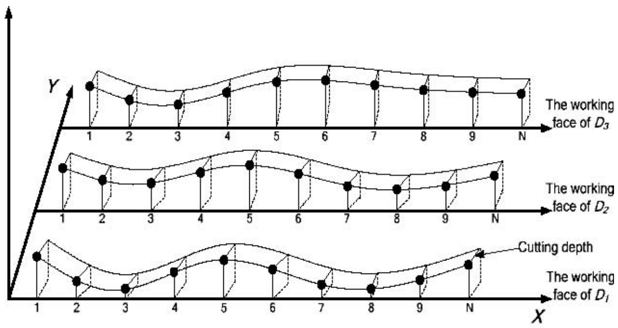

Fig. 3. Schematic diagram of shearer memory cutting principle.

Improved shearer memory cutting strategy

A coupling model of grey-markovian is proposed in this paper, which will realize adjusting the next sampling point data adaptively when the shearer cutting the rock. Grey prediction model is suitable for small sample data; however, it is based on index prediction, and without considering the randomness of the actual situation, so accuracy is not satisfied (Deng, 2002). Yet, Markovian can determine the unknown parameters quantitatively by judging transition probability (Givan et al., 2003), and Markovian is applicable in randomness process and is well complementary with Grey prediction model.

Using grey prediction model GM (1, 1) as memory cutting prediction algorithm, which is a model included single variable of first order differential equation. Let drum height data sequence of the shearer sampling point be:

$$H^{(0)} = (H^{(0)}(1), H^{(0)}(2), \cdots, H^{(0)}(n))$$

Generating new sequence $H^{(1)}$ after one-accumulate of $H^{(0)}$:

$$H^{(1)} = (H^{(1)}(1), H^{(1)}(2), \cdots, H^{(1)}(n))$$

Where

$$H^{(1)}(k) = \sum_{i=1}^{k} H^{(0)}(i)(k = 1, 2, \cdots, n)$$

Generating mean sequence $H^{(1)}$ is given by (5):

$$z^{(1)}(k) = 0.5\, H^{(1)}(k) + 0.5\, H^{(1)}(k-1) \quad (k = 2, \cdots, n) 。 \tag{5}$$

Establishing grey differential equation is given by (6):

$$H^{(0)}(k) + az^{(1)}(k) = b \qquad (k = 2, \cdots, n) \tag{6}$$

Define

$$Y_1 = (H^{(0)}(2), H^{(0)}(3), \cdots, H^{(0)}(n))^T \quad , \quad u = (a, b)^T \quad , \quad B = \begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{pmatrix}.$$

According to the least-square method, when $u=(a, a)^T=(B^T B)^{-1}B^T Y_1$, solving $Min:(J(u)=(Y_1-Bu)^T(Y_1-Bu)$. And after Laplace transform and inverter, we get:

$$H^{(1)}(k+1) = (H^{(0)}(1) - \frac{b}{a})e^{-ak} + \frac{b}{a} \qquad (k = 2, \cdots, n) \tag{7}$$

Residual error is obtained by the prediction result of the grey model. And transition probability can be determined by analyzing and classifying of residual error status. The residual error sequence is divided into several states with the variation of the shearer drum height, and marked as: $A_1, A_2, \cdots, A_n$.

$P_{ij}^{(m)}$ is given by (8),which is transformed by residual error sequence from A_i to A_j in m -step.

$$p_{ij}^{(m)} = m_{ij}^{(m)} / M_i \tag{8}$$

Where $m_{ij}^{(m)}$ is matrix of state probability element and $P_{ij}^{(m)}$ is m -step state transferring probability, state transferring probability matrix of shearer drum height residual error $R^{(m)}$ is given by (9):

$$R^{(m)} = \begin{pmatrix} p_{11}^{(m)} & p_{12}^{(m)} \cdots & p_{1j}^{(m)} \\ p_{21}^{(m)} & p_{22}^{(m)} \cdots & p_{23}^{(m)} \\ \vdots & \vdots & \vdots \\ p_{31}^{(m)} & p_{32}^{(m)} \cdots & p_{33}^{(m)} \end{pmatrix} \tag{9}$$

Given $R^{(m)}$ and original state E_i, Markovian can be figured out for grey prediction model revision. Model evaluation scheme is built by analyzing residual error $\delta(k)$, and $\delta(k)$ is given by (10):

$$\delta k = H^{(0)}(k) - H(k) \tag{10}$$

Where $H^{(0)}(k)$ is sampling data, $H^{(1)}(k)$ is cutting height which corresponding to the sampling data. Relative residual error is given by (11):

$$\varepsilon(k) = ((H^{(0)}(k) - H^{(1)}(k)) / H^{(0)}(k)) \times 100\,\% \tag{11}$$

Average residual error rate $\bar{\varepsilon}$ is given by (12):

$$\bar{\varepsilon} = \frac{1}{n-1}\sum_{k=2}^{n}\left|\varepsilon(k)\right| \times 100\% \tag{12}$$

Model credibility ρ is given by (13):

$$\rho = (1 - \bar{\varepsilon}) \times 100\% \tag{13}$$

Unbiased estimation S of System variance is given by (14):

$$S^2 = \frac{\sum_{k=1}^{n} \delta_k^{\,2}}{n-2} \times 100\% \tag{14}$$

Where n is the number of sampling data.

System Simulation and Analysis

We get a part of shearer drum height data from a coal face, which has a thick coal seam with a stabile roof, having a coal face length of 50 m. The shearer depth is 1 m, while the number of sampling points is N=50, and sampling data $H^{(0)}$ is obtained along the working face, the shearer drum height data is shown in figure 4.

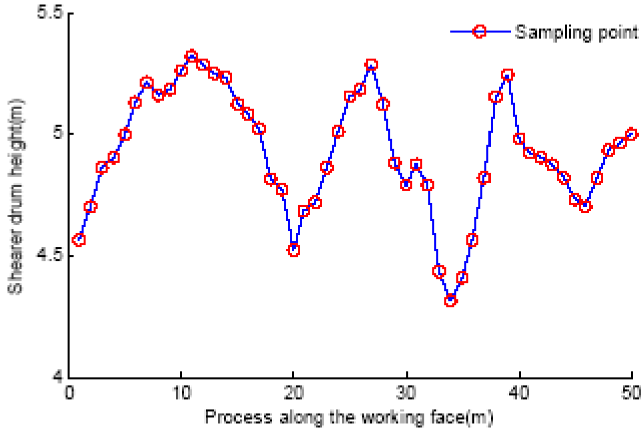

Fig. 4. Drum height simulated data of shearer working face.

Simulation of traditional shearer memory cutting algorithm

We simulated the traditional shearer memory cutting algorithm to get shearer drum height, as well as residual error. Figure 5 shows shearer drum height based on traditional algorithm. T_1, T_2, T_3, T_4 and T_5 are cutting change cycle edge and include sampling points number is [4, 11, 5, 6, 5].

$$\overline{T} = \sum_{i=1}^{5} T_i / 5 = 6.2.$$

The result shows that it needs to adjust drum height by artificially control and re-sampling after 6.2 cutting cycle averagely, efficiency is low.

The results of residual error are shown in figure 6. Depending on formula (10); we calculated residual error $\delta(k)$ of shearer drum height. The average residual error rate ε =3.22 %, the model

credibility ρ= (1-3.22 %) ×100 %=96.78 %, and regression estimation standard deviation S=0.0031.

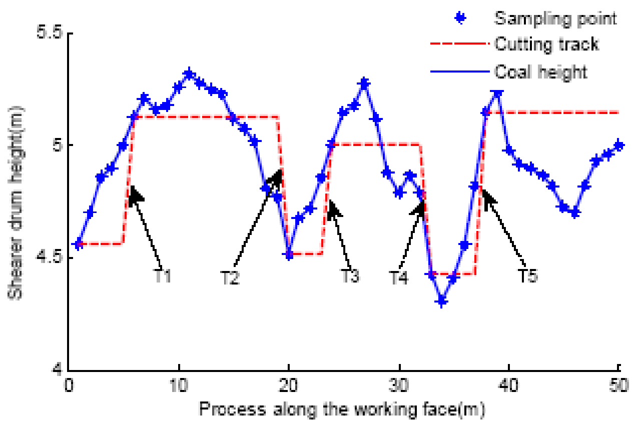

Fig. 5. Simulation analysis of traditional shearer memory cutting algorithm.

Results show that traditional shearer memory cutting algorithm is basic credibility. However, according to figure 6, residual error rates of some points has wide fluctuations, for example, at the point of (5), appeared the maximum, and MAX =8.8 %. The abrupt residual error rate indicates model instability.

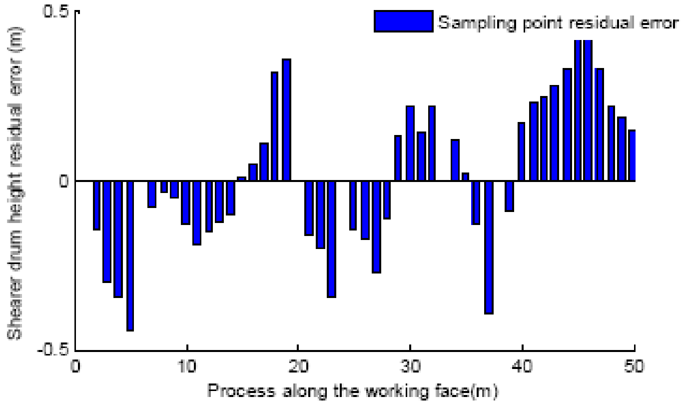

Fig. 6. Residual error plot of traditional shearer memory cutting algorithm.

Simulation of grey-markovian shearer memory cutting algorithm

We simulated the improved shearer memory cutting algorithm to get shearer drum height, as well as residual error. Sampling data are substituted in formula (5), (6) .Get a=-0.012, b=3.23, then albino equation can be calculated as (14):

$$H^{(1)}(k+1)=(H^{(0)}(1)+323)e^{0.012k}-323 \qquad (k=1,2,\cdots,n-1) \tag{14}$$

where $H^{(0)}(1)$ =4.56, which is the first data in figure 4, prediction sequence is shown in figure 7.

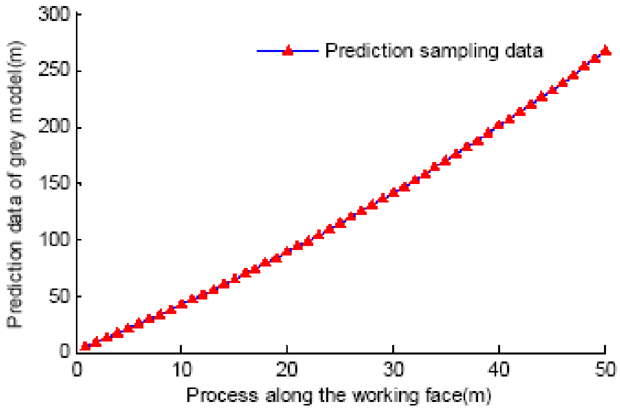

Fig. 7. Grey index prediction result. k

Then we need to reduction prediction $\overline{H^{(0)}(k)}$.

$\overline{H^{(0)}(k+1)}=H^{(1)}(k+1)-H^{(1)}(k)$, $\overline{H^{(0)}(1)}=H^{(0)}(1)$ We get sequence of $\overline{H^{(0)}(k)}$, which is shown in figure 8.

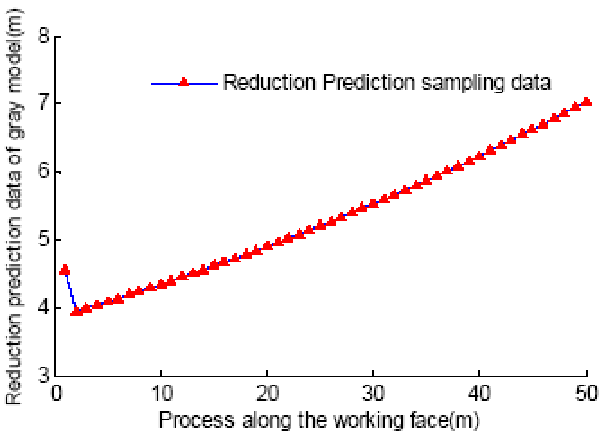

Fig. 8. Grey prediction reduction result.

We obtained $\delta(k) = H^{(0)}(k) - \overline{H^{(0)}(k)}$ by initial predictions of grey model, as shown in figure 9.

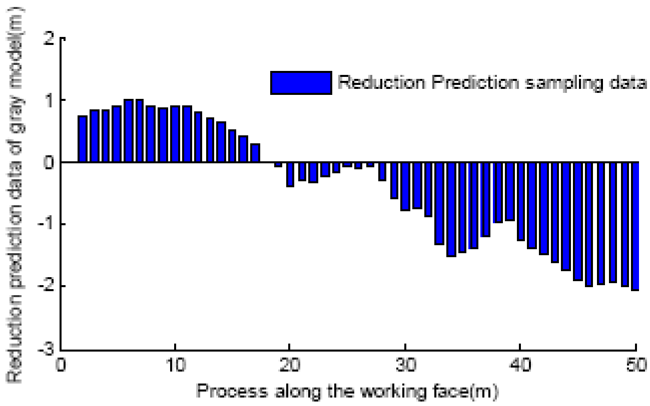

Fig. 9. Residual error data.

Division of residual error state is shown in table 1.

Tab. 1. State division of residual error.

State	Boundary
***E*1**	**(-2.5,-1.5]**
***E*2**	**(-1.5,-0.5]**
***E*3**	**(-0.5,0]**
***E*4**	**(0,0.5]**
***E*5**	**(0.5,1.5]**

We transfer state of 50 sampling points, and get the whole state transferring probability matrix $R^{(m)}$.

$$R^{(m)} = \begin{pmatrix} 1/3 & 1/3 & 1/6 & 0 & 1/6 \\ 1/5 & 3/5 & 1/5 & 0 & 0 \\ 0 & 2/7 & 3/7 & 0 & 2/7 \\ 0 & 2/3 & 0 & 0 & 1/3 \\ 0 & 2/5 & 0 & 3/5 & 0 \end{pmatrix}$$

After coupling with markovian to revise grey model according to the state transferring probability matrix $R^{(m)}$, we get simulation analysis of new shearer memory cutting algorithm, as shown in figure 9, and residual error is shown in figure 10.

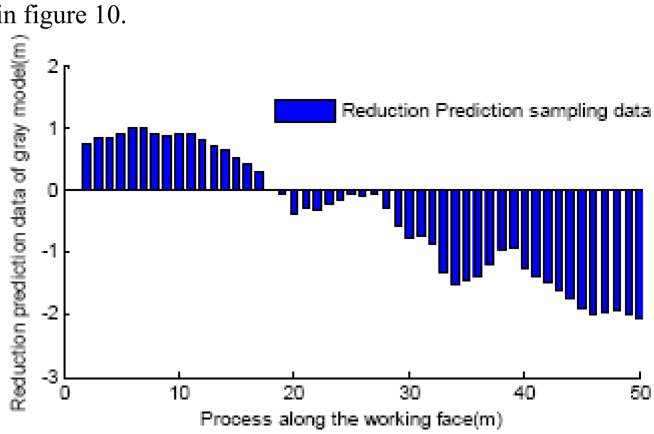

Fig. 9. Residual error data.

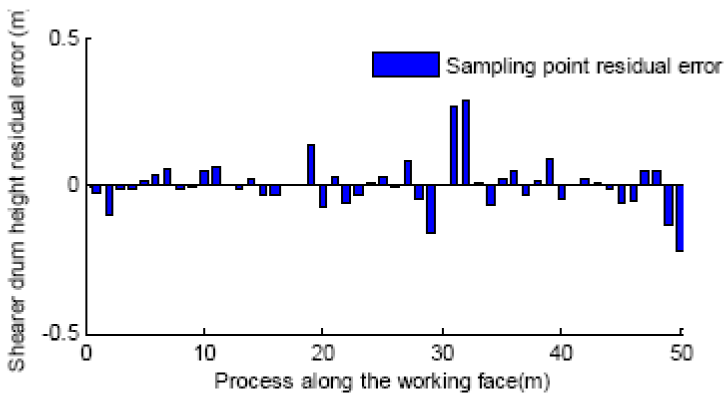

Fig. 10. Residual error plot of new shearer memory cutting algorithm.

In figure 10, average residual error rate $\bar{\varepsilon}$ =0.7 %, model credibility

$$\rho = (1 - 0.7\,\%) \times 100\,\% = 99.3\,\%,$$

and regression estimation standard deviation S=0.0018. At the point of $H^{(0)}$ (32), appeared $\varepsilon(k)$, and MAX $\varepsilon(k)$the maximum $\varepsilon(k)$=4,8 %. Results show that the grey-markovian model has high credibility and good stability, especially, it doesn't need to adjust drum height by artificially control and re-sampling, makes the shearer become more automatic.

Summary and Conclusion

Firstly we have established shearer drum height adjusting model for shearer height adjusting automation. Subsequently we have proposed a self-adaptive shearer memory cutting strategy through analysis of traditional shearer memory cutting algorithm, and have built grey-markovian coupling model theoretically. Finally we have established simulation model for the newly-built shearer memory cutting algorithm, and have proved high efficiency by comparison of the two algorithms.

Self-adaptive shearer drum height adjusting is a key technology for shearer automation. And fully mechanized mining automation includes collaborative automation of shearer, hydraulic support and scraper conveyor. As shearer automation is only one factor for fully mechanized mining automation, next our main research focus on collaborative auto control of the three machines.

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