УДК 681.518
DOI: 10.17277/vestnik.2024.04.pp.547-557

A MATHEMATICAL MODEL FOR PREDICTING FAILURES OF A SELF-CONTAINED SELF-RESCUER

V. G. Matveykin, P. K. Praveen, B. S. Dmitrievsky, A. A. Terekhova

Department of Information Processes and Control, terehova.aa@mail.tstu.ru; TSTU, Tambov, Russia

Keywords: grey Markov model; mathematical model; prediction; SCSR failure; self-contained self-rescuer; Smart and automated SCSR; system state.

Abstract: Mining is one the most hazardous industries in the world. There are various means of safety which safeguard the miners working underground, with self-contained self-rescuer being one of them. In this article, the grey Markov SCGM (1,1)c model has been used to predict the failure of SCSRs due to human error. It is taken into account that SCSR failures are dynamic in nature and the model is adjusted to improve accuracy. The criterion of state separation is obtained, and the matrix of the probability of state transition is given. The accuracy of the proposed model has been verified. It is suggested by this article that the time has come to develop and use smart and automated SCSRs that can diagnose the faults themselves and help the miners during the escape.

Introduction

Self-contained self-rescuers (**SCSR**) are devices used by miners to evacuate themselves in the event of an emergency in a mine. There are two types of SCSRs: 30-minute and 60-minute, each of which is used once.

Compliance with norms and standards is a key factor in ensuring the safety of miners [1, 2]. According to the adopted norms, strict selection and quality testing of SCSRs is required. The tests are divided into laboratory tests – 50 % of the samples (minimum 6 units) are tested in an accredited laboratory according to the IS15803-2008 standard and practical tests, when the remaining SCSR samples undergo a performance test under conditions close to real ones, for example, at a rescue station. SCSR testing parameters and their limit values are given in Table 1.

Even if the above provisions are met, there is still a possibility that the device may fail during actual use or emergency use due to various reasons including human error.

Mathematical modeling Mathematical model selection

A large number of papers are devoted to mathematical modeling [3 – 12]. We use the grey Markov SCGM (1,1)c prediction model to study or predict the failures of SCSRs in emergency situations arise due to human error in the care and maintenance of SCSRs
[13 – 15]. We have selected the grey Markov model to forecast or assess the errors due to following reasons:

1. Error is not regular and it cannot be generalized.
2. It is randomly scattered.
3. Information on raw data is limited.

Table 1

SCSR test parameters and limit values

Parameter	Acceptance Level
Rated Duration (as per label)	Not less than 90 % of the specified duration
Inhalation Oxygen Concentration (% by vol.)	Not less than 21*
Inhalation Carbon Dioxide Concentration (% by vol.)	Not more than 1.5**
Maximum inhalation temperature dry bulb	Not more than 55 °C
Inhalation breathing resistance	Not more than 10 mbar
Exhalation breathing resistance	

* A short term deviation to a level of not less than 17 % for a period of not more than two minutes at the beginning of the test is permissible.

** Throughout the rated duration of the apparatus, carbon dioxide concentration of the inhaled air shall not exceed 3.0% (by volume).

4. Information is not valid for all the stake holders (for all the mining companies or mining players); hence we can say that information is neither perfect and nor certain.

Every mining company is not weak on budgets, hence it is very difficult to model such scenarios based on a probabilistic statistical model or mathematical statistics methods. The grey Markov SCGM (1,1)c is quite suitable for complex mathematical models.

Mathematical model development

Since human errors cannot be generalized, we can say that the error data is random. Taking into consideration of randomness of data, failure of SCSRs in time series $x^{(0)}$ can be expressed as

$$x^{(0)} = \left\{x^{0}(1), x^{(0)}(2), ..., x^{(0)}(n)\right\}. \tag{1}$$

First, $x^{(0)}$ is integrated as follows, where

$$\bar{x}^{(1)} = \left\{\bar{x}^{(1)}(2), \bar{x}^{(1)}(3), ..., \bar{x}^{(1)}(n)\right\}; \tag{2}$$

$$\bar{x}^{(1)}(k) = \sum_{m=2}^{k} \bar{x}^{(1)}(m), \ k = 2, 3, ..., n \tag{3}$$

$\bar{x}^{(0)}$ is a close mean value generated sequence for $\bar{x}^{(0)}$

$$\bar{x}^{(1)} = \left\{\bar{x}^{(1)}(2), \bar{x}^{(1)}(3), ..., \bar{x}^{(1)}(n)\right\}; \tag{4}$$

where

$$\bar{x}^{(1)}(k+1) = \frac{x^{(0)}(k+1) + x^{(0)}(k)}{2}. \tag{5}$$

Random human errors in maintenance of SCSRs can lead to the failures of SCSRs; such failures of SCSRs are dynamic in nature and given that the integral sequence of failures of SCSRs time series is expressed as $\left\{x^{(0)}(k)\right\}$ that is associated with satisfaction trend of non-homogeneous index discrete-function expressed as

$$f_r(k) = b\,\mathrm{e}^{a(k-1)} - c\,.$$

Thus the data of $x^{(1)}(k)$ is fit to $f_r(k)$

According to the grey system cloud prediction method, the grey system SCGM (1,1)c prediction model can be expressed as

$$\frac{dx^{(1)}(k)}{dk} = ax^{(1)}(k) + u, \quad k \geq 2\,. \tag{6}$$

Its time response function can be expressed as follows

$$x^{(1)}(k) = \left[x^{(1)}(1) + \frac{U}{a}\right]\mathrm{e}^{ak} - \frac{U}{a}\,, \tag{7}$$

where

$$a = \frac{\ln \sum_{k=2}^{n} x^{(0)}(k-1) x^{(0)(k)}}{\sum_{k=2}^{n}\left(x^{(0)}(k-1)\right)^2}\,; \tag{8}$$

$$b = \frac{(n-1)\sum_{k=2}^{n}\mathrm{e}^{a(k-1)}\bar{x}^{(1)}(k) - \left(\sum_{k=2}^{n}\mathrm{e}^{a(k-1)}\right)\left(\sum_{k=2}^{n}\bar{x}^{(1)}(k)\right)}{(n-1)\sum_{k=2}^{n}\mathrm{e}^{2a(k-1)} - \left(\sum_{k=2}^{n}\mathrm{e}^{a(k-1)}\right)^2}\,; \tag{9}$$

$$c = \frac{1}{n-1}\left[\left(\sum_{k=2}^{n}\mathrm{e}^{a(k)}\right)b - \sum_{k=2}^{n}\bar{x}^{(1)}(k)\right]. \tag{10}$$

If, $\bar{x}^{(1)}(1) = b - c$, $U = ac$, $\bar{x}^{(1)}(k)$ is reverted, the grey system SCGM (1,1)c prediction model in originality can be expressed as

$$\hat{x}^{(0)}(k) = \frac{2b\left(1-\mathrm{e}^{-a}\right)}{1+\mathrm{e}^{-a}}\mathrm{e}^{a(k-1)}\,. \tag{11}$$

Then, the grey precision index *Y*(*k*), residual error ε(*k*) and the relative error Δ*k* can be calculated as follows:

$$Y(k) = \frac{x^{0}(k)}{x^{(0)}(k)}\,; \tag{12}$$

$$\varepsilon(k) = \hat{x}^{(0)}(k) - x^{0}(k)\,; \tag{13}$$

$$\Delta k = \frac{|\,\varepsilon(k)\,|}{x^{0}(k)}\,. \tag{14}$$

Equations (12) – (14) are the indicators of the grey fitting accuracy, which also reflect the degree of deviation in the predicted values to the original set of data.

Amended residual SCGM (1,1)c model to predict failures in SCSRs

The data for statistics of the failures of SCSRs due to non-maintenance could be larger and as a human's behaviour is highly uncertain, therefore, regularity cab be weak in nature or may not be very strong. Hence, it is incorrect to predict accuracy based only on SCGM(1,1)c in order to predict SCSR failures due to human errors in SCSR maintenance. In order to improve the accuracy of the prediction rate and meet closely to the actual situation, the model is corrected to improve the accuracy. The amended principle and steps are as follows:

1. The first time residuals data sequence has the following predicted value and the actual value, respectively:

$$\varepsilon^{(0)}(k) = \hat{x}^{(0)}(k) - x^{0}(k), \quad k = 1, 2, ..., n; \tag{15}$$

$$\varepsilon^{(0)}(k) = \left\{\varepsilon^{0}(1), \varepsilon^{0}(2), ..., \varepsilon^{0}(n)\right\}. \tag{16}$$

2. Processing residuals correction sequence is as follows,

if

$$M = \left(1 + e^{-a}\right)^{-1}\left(1 - e^{-a}\right)^{b},$$

then the SCGM (1,1) prediction can be expressed as

$$\hat{x}^{(0)}(k) = 2e^{a(k-1)}M .$$

If $\varepsilon^{(0)}(k) \geq 0,\ k = 1, 2, ..., n,$ the SCGM (1,1)c model can be expressed as

$$\hat{\varepsilon}^{(0)}(k) = 2e^{a_1(k-1)}M_1$$

and a_1, b_1 and M_1 can be obtained in the same manner as a, b and M as earlier used method.

Hence, the first time residual corrected SCGM (1,1)c model can be expressed as

$$\hat{x}_{\varepsilon_1}\varepsilon^{(0)}(k) = 2\left(e^{a(k-1)}M - e^{a_1(k-1)}M_1\right). \tag{17}$$

If $\varepsilon^{(0)}(k) < 0,\ k = 1, 2, ..., n$, the first time residuals corrected SCGM (1,1)c model can be expressed as

$$\hat{x}^{(0)}_{\varepsilon_1}(k) = 2\left(e^{a(k-1)}M + e^{a_1(k-1)}M_1\right). \tag{18}$$

If the first time the residuals amendment could not meet the accuracy of the required forecast, a second residual correction shall be carried out and so on until the required accuracy requirements are meet.

The residual correction generic model can be expressed as

$$\hat{x}_{\varepsilon_2}\varepsilon^{(0)}(k) = \hat{x}_{\varepsilon_1}\varepsilon^{(0)}(k) - 2e^{a_2(k-1)}M_2\, ,. \tag{19}$$

where

$$\varepsilon_1\varepsilon^{(0)}(k) \geq 0,\ k = 1, 2, ..., n,$$

and

$$\hat{x}_{\varepsilon_2}\varepsilon^{(0)}(k) = \hat{x}_{\varepsilon_1}\varepsilon^{(0)}(k) + 2e^{a_2(k-1)}M_2\, , \tag{20}$$

where

$$\varepsilon_1^{(0)}(k) \leq 0,\ k = 1, 2, ..., n.$$

Amended Markov SCGM (1,1)c model for prediction of failures in SCSRs

The curve that we obtained as a result of forecasting SCGM(1,1)c is, in fact, an exponential curve, and the result of forecasting is a smooth curve. Since, human errors are the main part of the failures of SCSRs, the SCGM (1,1)c model solely applied cannot meet the required accuracy for the forecast. Markov's theories have no aftereffect, that is to say, the future of the system is only related to the current state and there is no effect from the past state. Meanwhile, the Markov model is adopted to predict state trends through the transfers of probability which it can adapt to the randomness and variability of the state. Application of Markov theory to make corrections in the SCGM (1,1)c prediction model of failure of SCSRs due to non-maintenance as a human error can better solve the variability and randomness in maintenance of SCSRs caused by human errors to improve the prediction accuracy.

State divided criterion for the prediction of failures in SCSRs

Failures in SCSRs due to non-maintenance could change annually and are dynamic non-stationary random process. Therefore, the indicators of precision fitting the prediction shall also be variable and random as the boundary and connotation of the different annual states can change. Hence, an adaptive state divided criterion needs to be obtained, and the criterion should be consistent with the basic timing trend of the Failures of SCSRs due to non-maintenance.

Hence, k was divided into m states, and each state can be expressed as

$$E_i \in [\varepsilon_{1i}, \varepsilon_{2i}], \quad i = 1, 2, ..., m, \tag{21}$$

where

$$\varepsilon_{1i} = Y(k) + A_i; \quad \varepsilon_{2i} = Y(k) + B_i,$$

E_i is expressed as i state, ε_{1i} and ε_{2i} are, respectively, expressed as the upper and lower bounds of the i state, A_i and B_i are constants determined according to prediction data.

Since k is a time function, ε_{1i} and ε_{2i} will be changed with time, so the state possesses variability.

When we say that the state is divided, the numbers of different intervals can be reasonably divided according to the actual situation. If our raw data will be less, the interval division shall be less to increase the number of transfers between the various states, and thus the transfer law shall be more objectively reflected between states.

Conversely, if raw data will be more, the interval division shall be less to excavate more information from a large number of data to improve the prediction accuracy. It will be suitable to adapt the clustering classification method to determine class number and classification intervals due to fewer data and the uncertain status of failures of SCSRs due to non-maintenance as a human error.

Developing state transition rate matrix for the prediction of failures in SCSRs

Let the original number of samples is expressed as s $M_{ij}(k)$ from the state E_i transiting to the state E_j by k step, and the number of occurrences of the state E_i is expressed as M_i, so state transition probability can be expressed as

$$\overline{P_{ij}}(k) = \frac{M_{ij}(k)}{M_i}, \quad i, j = 1, 2, ..., \overline{M}, \tag{22}$$

$M \times M$ state transition probability matrix can be obtained as

$$P(k)=\begin{bmatrix} P_{11}(k) & P_{12}(k) & \cdots & P_{13}(k) \\ P_{21}(k) & P_{22}(k) & \cdots & P_{23}(k) \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1}(k) & P_{m2}(k) & \cdots & P_{m3}(k) \end{bmatrix}. \quad (23)$$

Determining the predictive value for the prediction of failures in SCSRs

The state transition probability matrix k reflects all statistical regularities of state transition, and the future system state steering can be predicted by investigating the matrix. In the actual analysis of the process, one step transition probability matrix is generally only examined. Given that predicted moment object is in the state E_k, investigating the k row of (1) can get the following below results;

1. If max $P_{ij} = P_{kl}$, the next time system should most likely shift from the state E_k to the state E_l.

2. If there are two or more probability values identical or similar to k row in the matrix $P(1)$, the future state steering will be difficult to determine; it needs to consider probability transition matrix $P(2)$ or $P(n)$ $(n \geq 3)$.

The system's future state is determined by investigating the state transition probability matrix, and the grey change interval of relative prediction value in the future moments will also be determined; it can be expressed as $[\varepsilon_{1i}, \varepsilon_{2i}]$. The predicted value of the future moment can be expressed as the interval median as $Y'(k)$

$$Y'(k)=\frac{x^{0}(k)}{x^{(0)}(k)}=\frac{1}{2}(\varepsilon_{1i}+\varepsilon_{2i})=Y(k)\frac{1}{2}(A_i+B_i). \quad (24)$$

Error analysis

In order to examine the precision and accuracy of the proposed model, ground tests are required to determine the error between the forecast value and actual value. In this study, we use the relative percentage error (**RPE**) analysis to assess the model precision and accuracy.

Relative percentage error analysis

Relative percentage error compares the real and predicted values at specific time k. The RPE is defined as equation (14). The total model precision can be defined by average relative percentage error (**ARPE**) as below

$$\text{ARPE}=\frac{1}{n}\sum_{k=1}^{n}\text{RPE}, \text{ where } k = 2, 3, 4. \quad (25)$$

Analysis

A field study shall be able to determine the accuracy of the model. Since the field data is very difficult to get and study cannot be carried out, this mathematical model is accurate and it will determine the desired results.

We simulate a data point of one of the cluster of mines with 2500 employees going underground every day to check the accuracy of the SCGM (1,1)c mathematical model. This cluster of mines has a total of 2500 units of SCSRs, but they are not maintained to proper safety standards or there is a human negligence in maintaining those SCSRs. On forceful annual check or during the escape exercise annually, the rate of failure of SCSRs is illustrated below. The number of failed SCSRS in one of the mines from 2018 to 2022 are shown in Table 2.

Table 2

Values of failed SCSRs in one of the mines from 2018 to 2022

No.	Year	Annual failure of SCSRs
1	2018	54
2	2019	50
3	2020	52
4	2021	55
5	2022	47

Analysis based on SCGM (1,1)c prediction model

Based on the above data and calculations done on MATLAB, the values for *a* and *b* were 0.0072 and 7.359e + 03, respectively, then the grey prediction model was established. The obtained data from SCGM (1,1)c analysis of data with grey precision index are shown in Table 3.

Table 3

SCGM (1,1)c analysis of data with grey precision index

No.	Year	Real value	Prediction value	Relative error	Grey precision index, %
1	2018	54	52.93	0.01	102
2	2019	50	52.55	0.05	95
3	2020	52	52.18	0.003	99
4	2021	55	51.81	0.05	106
5	2022	47	51.44	0.09	91

Analysis of results based on SCGM (1,1)c prediction model

The analysis of results based on SCGM (1,1)c prediction model suggests that if the negligence on the maintenance of SCSRs due to human error happens, it results into the SCSRs failures. The grey precision index suggests that it can predict close to accurate results for the SCSRs failure or the said conditions.

This analysis implies that on an average 50 people are at risk of carrying failed SCSRs, which might not work or might not work in full capacity during the actual escape. Accidents in the mines cannot be assessed in advance and people working underground if they are carrying failed SCSRs; they are risking their lives and it can result into big fatal accident.

Conclusion

Mines are vulnerable to accidents and people's safety becomes one of the priority assignments in case of mine accidents. With the help of an appropriate SCSR, a person can easily escape in various accident conditions such as influx of toxic gases or increase in explosive gases or when the mine environment has become suffocating. Given the life of the apparatus which is 10 years and maintaining such apparatus manually for such long period and following all the norms of the regulatory authority is a daunting task although it is in the benefit of the people.

Therefore, the time has come to think beyond to use a SCSR which is smart and which need not to be monitored all the time which can diagnose the faults by itself and can raise alarm in case of any fault. By using such SCSRs, miners can always be updated of the health of the SCSRs and it will give ultimate confidence to their preparedness of self-escape.

References

1. Matveykin V.G., Nemtinov V.A., Dmitrievsky B.S., Praveen P.K.: Development and implementation of network based underground mines safety, rescue and aided rescue system, *J. Phys: Conf. Ser.*, 2019, vol. 1278, no. 1, pp. 012017, doi: 10.1088/1742-6596/1278/1/012017
2. Matveykin V., Samarin V., Nemtinov V., Dmitrievsky B., Praveen P.K. Design Theory of Network Based Smart Self-Contained Self-Rescuer with Sensor Technology. *International Scientific Conference Energy Management of Municipal Facilities and Sustainable Energy Technologies* (EMMFT 2019), 2020, vol. 2, pp. 178-186, doi: 10.1007/978-3-030-57453-6_15
3. Bityukov V.K., Emel'yanov A.E. [Generalized Mathematical Model of a Network Control System with a Competing Access Method], *Transactions of the Tambov State Technical University*, 2012, vol. 18, no. 2, pp. 319-326. (In Russ., abstract in Eng.)
4. Kudryashov V.S., Tikhomirov S.G., Ryazantsev S.V., Ivanov A.V., Kozenko I.A. [Simulation method of a multiply-connected digital system for controlling ammonia synthesis], *Transactions of the Tambov State Technical University*, 2017, vol. 23, no. 4, pp. 572-580, doi: 10.17277/vestnik.2017.04.pp.572-580 (In Russ., abstract in Eng.)
5. Popov N.S., Luzgacheva N.V., Chan M.T. [To the method of constructing an expert system for assessing industrial safety], *Transactions of the Tambov State Technical University*, 2013, vol. 19, no. 1, pp. 43-51. (In Russ., abstract in Eng.).
6. Serov A.Yu., Smorgonskij A.V. [Acting computer model of the manufacturing enterprise], *Ekonomika i matematicheskie metody* [Economics and mathematical methods], 2009, vol. 45, no. 3, pp. 40-47. (In Russ., abstract in Eng.)
7. Dmitrievsky B.S. [Business management model for planning knowledge-intensive enterprise], *Pribory i Sistemy. Upravleniye, Kontrol', Diagnostika* [Instruments and Systems. Management, Control, Diagnostics], 2007, no. 5, pp. 66-68. (In Russ., abstract in Eng.)
8. Saif M.N.M., Matveykin V.G., Dmitrievsky B.S., Bashkatova A.V., Mamontov A.A. [Mathematical Models of Multiply-Connected Control Objects], *Transactions of the Tambov State Technical University*, 2019, vol. 25, no. 1, pp. 53-62, doi: 10.17277/vestnik.2019.01.pp.053-062 (In Russ., abstract in Eng.)
9. Panchenko I.S. *Extended abstract of Candidate's of Engineering thesis*, Tambov, 2012, 16 p. (In Russ.).
10. Dzhambekov A.M., Shcherbatov I.A. [Optimal control of the catalytic reforming process of gasoline fractions], *Transactions of the Tambov State Technical University*, 2017, vol. 23, no. 4, pp. 557-571, doi: 10.17277/vestnik.2017.04.pp.557-571 (In Russ., abstract in Eng.)
11. Saif M.H.M., Matveykin V.G., Dmitrievsky B.S., Bashkatova A.V., Mamontov A.A. [Control of Objects with Interrelated Values], *Transactions of the Tambov State Technical University*, 2019, vol. 25, no. 2, pp. 206-218, doi: 10.17277/vestnik.2019.02.pp.206-218 (In Russ., abstract in Eng.)
12. Matveykin V.G., Dmitrievsky B.S., Panchenko I.S. Designing a management system for an innovation-production system, *Transactions of the Tambov State Technical University*, 2011, vol. 17, no. 2, pp. 289-296. (In Russ., abstract in Eng.)

13. Jiang X.-C., Chen S.-F. Application of Weighted Markov SCGM(1,1)c Model to Predict Drought Crop Area, *Systems Engineering – Theory & Practice*, 2009, vol. 29, no. 9, pp. 179-185, doi: 10.1016/S1874-8651(10)60072-5

14. Wang J., Liang D., Xu Y., Luo Y., Zhang W., Guo Q., Xia W., Zeng G. The research of the application of grey Markov SCGM (1,1) model in the prediction of source water quality, *Proc. 2nd International Conference on Applied Mathematics, Modelling, and Intelligent Computing* (CAMMIC 2022), 2022, vol. 12259. doi: 10.1117/12.2641081.

15. Azadeh A., Ghaderi S.F., Sohrabkhani S. A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran, *Energy Policy*, 2008, vol. 36, no. 7, pp. 2637-2644, doi: 10.1016/j.enpol.2008.02.035

Математическая модель прогнозирования отказов автономного самоспасателя

В. Г. Матвейкин, П. К. Правин, Б. С. Дмитриевский, А. А. Терехова

Кафедра «Информационные процессы и управление», terehova.aa@mail.tstu.ru; ФГБОУ ВО «ТГТУ», Тамбов, Россия

Ключевые слова: скрытая марковская модель; математическая модель; прогнозирование; отказ SCSR; автономный самоспасатель; интеллектуальный и автоматизированный SCSR; состояние системы.

Аннотация: Одной из самых опасных отраслей промышленности на планете является горнодобывающая. Существуют различные средства безопасности, защищающие шахтеров, работающих под землей, среди которых следует выделить автономный самоспасатель. Использована скрытая марковская модель и модель формирования кластеров для прогнозирования отказа автономных самоспасателей из-за человеческой ошибки. Принимается во внимание, что отказы автономного самоспасателя носят динамический характер, и модель корректируется для повышения точности. Получен критерий разделения состояний и дана матрица вероятности перехода состояний. Проверена точность предложенной модели. Предполагается, что необходимо разработать и использовать интеллектуальные и автоматизированные самоспасатели, которые могут сами диагностировать неисправности и помогать шахтерам во время эвакуации.

Список литературы

1. Matveykin, V. G. Development and implementation of network based underground mines safety, rescue and aided rescue system / V. G. Matveykin, V. A. Nemtinov, B. S. Dmitrievsky, P. K. Praveen // J. Phys: Conf. Ser. – 2019. – Vol. 1278, No. 1. – P. 012017. doi: 10.1088/1742-6596/1278/1/012017

2. Design Theory of Network Based Smart Self-Contained Self-Rescuer with Sensor Technology / V. Matveykin, V. Samarin, V. Nemtinov [et al.] // International Scientific Conference Energy Management of Municipal Facilities and Sustainable Energy Technologies (EMMFT 2019). – 2020. – Vol. 2. – P. 178 – 186. doi: 10.1007/978-3-030-57453-6_15

3. Битюков, В. К. Обобщенная математическая модель сетевой системы управления с конкурирующим методом доступа / В. К. Битюков, А. Е. Емельянов // Вестн. Тамб. гос. техн. ун-та. – 2012. – Т. 18, № 2 – С. 319 – 326.

4. Метод моделирования многосвязной цифровой системы управления процессом синтеза аммиака / В. С. Кудряшов [и др.] // Вестн. Тамб. гос. техн. ун-та. – 2017. – Т. 23, № 4. – С. 572 – 580. doi: 10.17277/vestnik.2017.04.pp.572-580

5. Попов, Н. С. К методике конструирования экспертной системы оценки промышленной безопасности / Н. С. Попов, Н. В. Лузгачева, М. Т. Чан // Вестн. Тамб. гос. техн. ун-та. – 2013. – Т. 19, № 1. – С. 43 – 51.

6. Серов, А. Ю. Действующая компьютерная модель производственного предприятия / А. Ю. Серов, А. В. Сморгонский // Экономика и математические методы. – 2009. – Т. 45, № 3. – С. 40 – 47.

7. Дмитриевский, Б. С. Бизнес-модель управления планированием на наукоемком предприятии / Б. С. Дмитриевский // Приборы и Системы. Управление, Контроль, Диагностика. – 2007. – № 5. – С. 66 – 68.

8. Математические модели многосвязных объектов управления / М. Н. М. Саиф, В. Г. Матвейкин, Б. С. Дмитриевский, А. В. Башкатова, А. А. Мамонтов // Вестн. Тамб. гос. техн. ун-та. – 2019. – Т. 25, № 1. – С. 53 – 62. doi: 10.17277/vestnik.2019.01.pp.053-062

9. Панченко, И. С. Математическое моделирование и алгоритмизация организационно-технологических систем, производящих инновационную продукцию : автореф. дис. … канд. техн. наук : 05.13.06 / И. С. Панченко. – Тамбов, 2012. – 16 с.

10. Джамбеков, А. М. Оптимальное управление процессом каталитического риформинга бензиновых фракций / А. М. Джамбеков, И. А. Щербатов // Вестн. Тамб. гос. техн. ун-та. – 2017. – Т. 23, № 4. – С. 557 – 571. doi: 10.17277/vestnik.2017.04.pp.557-571

11. Управление объектами с взаимосвязанными величинами / М. Н. М. Саиф, В. Г. Матвейкин, Б. С. Дмитриевский, А. В. Башкатова, А. А. Мамонтов // Вестн. Тамб. гос. техн. ун-та. – 2019. – Т. 25, № 2. – С. 206 – 218. doi: 10.17277/vestnik.2019.02.pp.206-218

12. Матвейкин, В. Г. Проектирование системы управления инновационно-производственной системой / В. Г. Матвейкин, Б. С. Дмитриевский, И. С. Панченко // Вестн. Тамб. гос. техн. ун-та. – 2011. – Т. 17, № 2. – С. 289 – 296.

13. Jiang, X.-C. Application of Weighted Markov SCGM(1,1)c Model to Predict Drought Crop Area / X.-C. Jiang, S.-F. Chen // Systems Engineering – Theory & Practice. – 2009. – Vol. 29, No. 9. – P. 179 – 185, doi: 10.1016/S1874-8651(10)60072-5

14. The research of the application of grey Markov SCGM (1,1) model in the prediction of source water quality / J. Wang, D. Liang, Y. Xu [et al.] // Proc. 2nd International Conference on Applied Mathematics, Modelling, and Intelligent Computing (CAMMIC 2022). – 2022. – Vol. 12259. doi: 10.1117/12.2641081.

15. Azadeh, A. A simulated-based neural network algorithm for forecasting electrical energy consumption in Iran / A. Azadeh, S.F. Ghaderi, S. Sohrabkhani // Energy Policy. – 2008. – Vol. 36, No. 7. – P. 2637 – 2644, doi: 10.1016/j.enpol.2008.02.035

Mathematisches Modell zur Vorhersage von Fehlern autonomer Selbstretter

Zusammenfassung: Einer der gefährlichsten Industriezweige der Welt ist der Bergbau. Es gibt verschiedene Sicherheitsausrüstungen zum Schutz der unter Tage arbeitenden Bergleute, von denen der autonome Selbstretter hervorgehoben werden sollte. Das Gray-Markov- und SCGM-Modell ist zur Vorhersage des Versagens von Scars aufgrund von menschlichem Versagen verwendet. Es wird berücksichtigt, dass SCSR-Ausfälle dynamischer Natur sind, und das Modell wird angepasst, um die Genauigkeit zu verbessern. Das Zustandstrennungskriterium ist ermittelt und die Zustandsübergangswahrscheinlichkeitsmatrix ist angegeben. Die Genauigkeit des vorgeschlagenen Modells ist überprüft. Es ist vorgeschlagen, intelligente und automatisierte Selbstrettungsgeräte zu entwickeln und einzusetzen, die Fehler selbst diagnostizieren und Bergleute bei der Evakuierung unterstützen können.

Modèle mathématique de la prédiction de l'échec de l'auto-sauveteur autonome

Résumé: Une des industries les plus dangereuses de la planète est l'exploitation minière. Il existe différents moyens de sécurité pour protéger les mineurs travaillant sous terre, parmi lesquels il convient de souligner l'auto-sauveteur autonome. Sont utilisés le modèle caché de Gray Markov et le modèle de la formation des clasters pour prédire l'échec de Scars en raison d'une erreur humaine. Attendu que les défaillances SCSR sont dynamiques et que le modèle est ajusté pour améliorer la précision. Est obtenu le critère de la séparation des états; est donnée la matrice de probabilité de transition des états. Est vérifiée la précision du modèle proposé. Il est supposé qu'il est nécessaire de développer et d'utiliser des auto-sauveteurs intelligents et automatisés capables de diagnostiquer eux-mêmes les dysfonctionnements et d'aider les mineurs pendant l'évacuation.

Авторы: ***Матвейкин Валерий Григорьевич*** – доктор технических наук, профессор, заведующий кафедрой «Информационные процессы и управление»; ***Правин Правин Кумар*** – аспирант кафедры «Информационные процессы и управление», ***Дмитриевский Борис Сергеевич*** – доктор технических наук, профессор кафедры «Информационные процессы и управление»; ***Терехова Анастасия Андреевна*** **–** аспирант кафедры «Информационные процессы и управление», ФГБОУ ВО «ТГТУ», Тамбов, Россия.