

## Research Article

# Research on the Prediction Model of Mine Subsidence Based on Object-Oriented and Probability Integration Method

Zhongyuan Gu,<sup>1</sup> Yanlin Zhao ,<sup>2</sup> Rugao Gao ,<sup>2</sup> and Lewen Wu<sup>3</sup>

<sup>1</sup>Changchun Institute of Technology, Changchun, Jilin 130021, China

<sup>2</sup>School of Resource and Environment and Safety Engineering, Hunan University of Science and Technology, Xiangtan, Hunan 411201, China

<sup>3</sup>School of Resource and Safety Engineering, Central South University, Changsha, Hunan 410083, China

Correspondence should be addressed to Rugao Gao; gaorgcsu@163.com

Received 17 May 2022; Revised 21 June 2022; Accepted 28 June 2022; Published 16 August 2022

Academic Editor: Hao Wu

Copyright © 2022 Zhongyuan Gu et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The movement of rock formations caused by mining eventually leads to the mining subsidence damage of the surface. In order to accurately and efficiently predict the surface subsidence caused by mining, an object-oriented method combined with the classical probability integration method is introduced in this paper, and an object-oriented probability integration prediction model framework is established. MATLAB2019 is used to develop the application program of the prediction model, the reliability of the prediction model is tested by engineering cases, and the main influencing factors of mining subsidence are analyzed at the same time. The results show that the predicted results of the model are basically consistent with the case. The prediction model developed in this paper using the object-oriented method combined with the probability integration method is reliable. It is feasible to apply the object-oriented method to mining subsidence prediction.

## 1. Introduction

Surface subsidence caused by mining leads to the destruction of surface land resources, collapse of buildings, and destruction of roads and induces geological disasters and soil erosion, which seriously threatens the ecological environment and infrastructure safety of mining areas [1]. A series of secondary problems, such as vegetation and water environment pollution and land resource destruction caused by mining, have seriously affected the sustainable development of the mining industry [2, 3]. A large number of scholars have studied the prediction of mining subsidence, and by anticipating the basic information of surface subsidence in advance, it can not only guide mine production and disaster prevention but also reduce the environmental and resource

damage caused by mining subsidence through optimizing the mining plan and treatment countermeasures in advance [4, 5]. The study of mining subsidence has been a hot research topic in the mining industry, and the common research methods mainly include similar simulation and numerical simulation [6–8]. Accurate prediction and assessment of mining subsidence is an important prerequisite for reducing mining damage and subsidence disasters, as well as protecting ecological environment [9]. Simulation-based methods have strong versatility and can adapt to a large number of complex engineering application requirements. Similar models have high costs and are difficult to analyze a large number of changing model parameters. The reliability of numerical models is closely related to the professional background and engineering experience of the modeler [10,

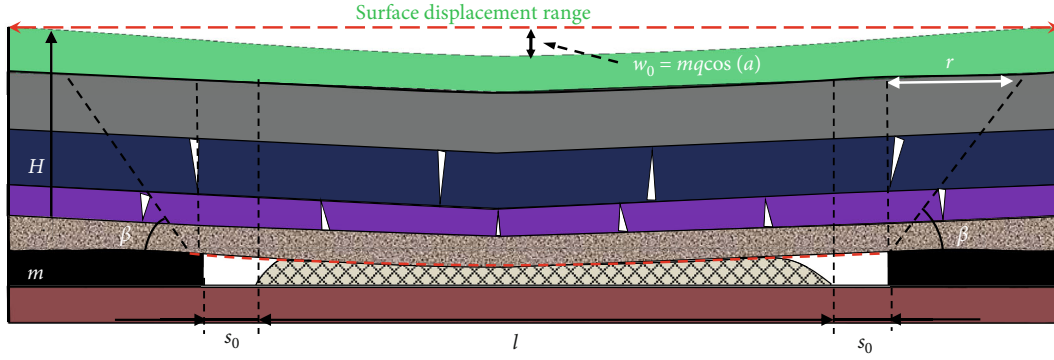


FIGURE 1: Mining subsidence model diagram.

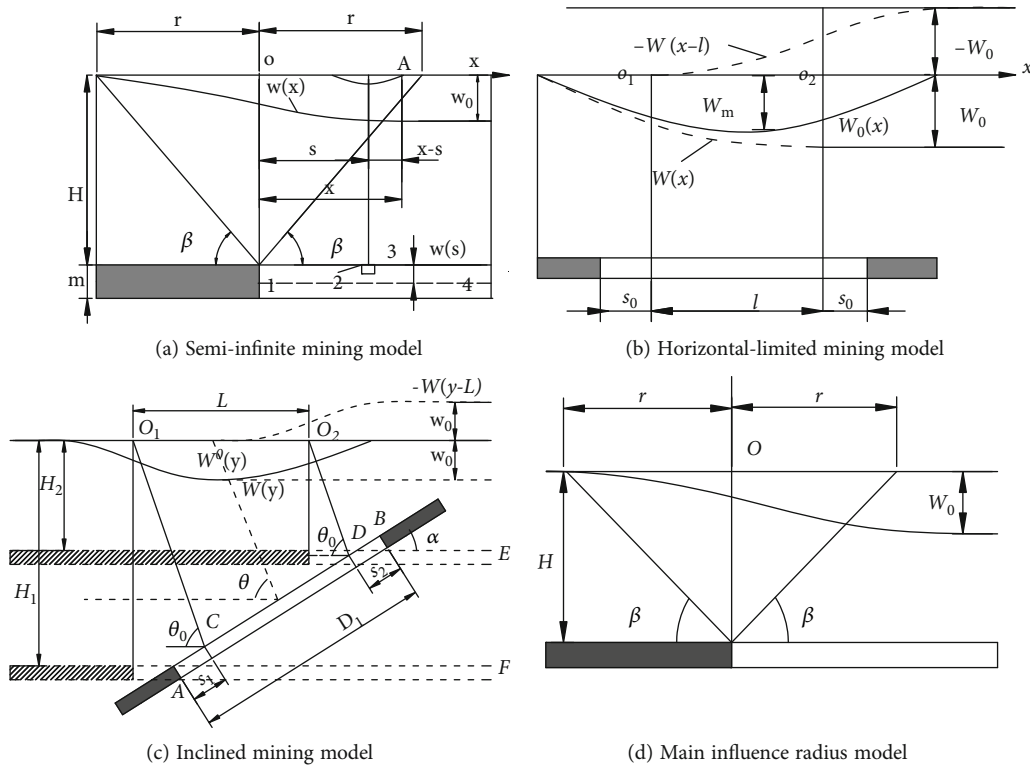


FIGURE 2: Basic model of mining subsidence probability integration method.

11]. In recent years, with the development of AI technology, mining scientists and technicians have introduced AI models into the field of mining subsidence prediction and obtained certain research results [12–14]. The research on mining subsidence prediction has achieved many research results, and each method has its own advantages and disadvantages. Artificial intelligence, machine learning, and other methods are mainly good at mining and analyzing the non-relationship between data labels and features from a large amount of data. Linear relationship often has higher requirements and dependence on the quality of data [15]. At present, the main prediction method for mining subsidence research and engineering practice in China is the probability

integration method, which is widely employed due to its rich theory and convenient calculation [16]. There are many methods for predicting mining subsidence, and each has certain characteristics; however, in most cases, decision makers are more concerned with the reliability and applicability of the prediction model, rather than a particular research method or model, since each has its own advantages and drawbacks. Therefore, those with simpler algorithm principles, easier development procedures, higher reliability, and easier way of implementation have better application value in engineering practice, program design, and decision support. The rapid development of computer technology has provided an important basis for the design and development

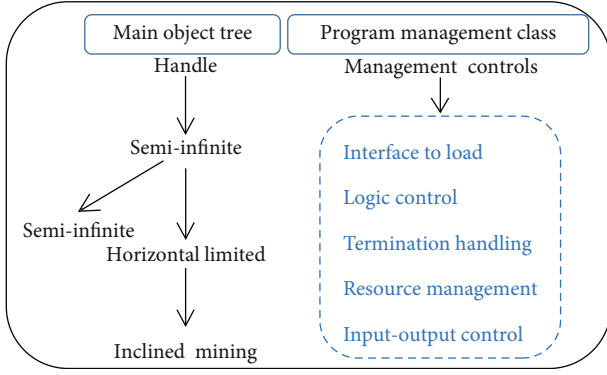


FIGURE 3: Object tree of the prediction model.

of complex models and mathematical principles, especially in the complex prediction process of mining subsidence. To take full advantage of the computing performance can effectively promote the progress of mining subsidence research. Instead of consuming a lot of energy to study the program development and algorithm design, researchers are more likely to study the performance and improvement strategies of the predicted model [17]. In view of the above analysis, this paper combines the classical object-oriented methodology with the probability integration method of mining subsidence to design the framework of the object-oriented probability integration prediction model, develop the prediction procedure of the combined model, and also verify the correctness and feasibility of the developed model through engineering cases. Meanwhile, the main factors affecting mining subsidence were analyzed to provide scientific guidance for mining subsidence management decisions.

## 2. Object-Oriented Probability Integration Model

**2.1. Mining Subsidence Model.** After extraction of the ore body, the roof collapses and breaks with the expansion of the goaf. Mining activities have an influence in the upward direction, causing a series of complex activities such as fracture penetration, bending, delamination, and dislocation in the overlying rock layer, which eventually lead to violent mining subsidence on the surface [18, 19]. After scientific research and field practice by a large number of scholars, a variety of methods and models for surface subsidence prediction have been developed, mainly including numerical simulation, physics experiment, mechanical model, probability integration method, and nonlinear model [20, 21]. The probability integration method is one of the most widely used mining subsidence prediction methods in China due to its high accuracy and convenience with fewer parameters [22]. The mining subsidence model is shown in Figure 1, where  $H$  denotes the burial depth of the ore body,  $m$  the thickness of the ore body,  $s_0$ , the inflection point offset,  $r$  the radius of influence,  $w_0$ , the maximum subsidence value, and  $q$  the subsidence coefficient.

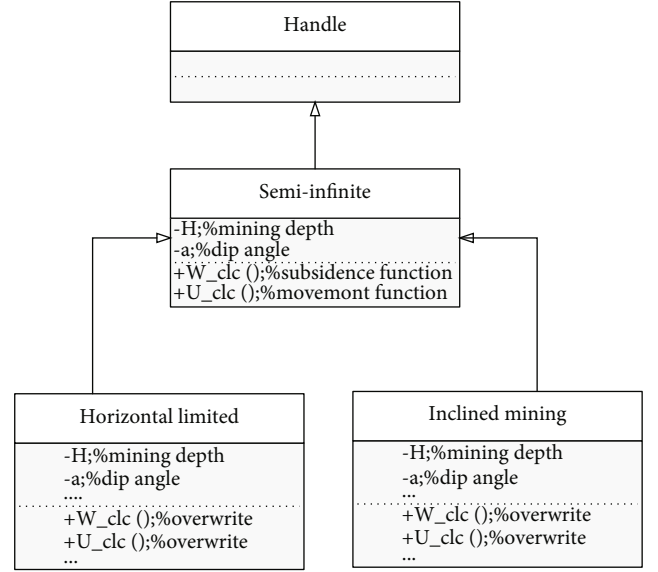


FIGURE 4: The UML model of the main classes in the prediction model.

**2.2. Basic Principles of Probability Integration Method.** The probability integration method based on the random medium theory has become relatively mature and most widely applied prediction theory in China [23], named due to the fact that the movement and deformation prediction formula used contains probability integration. With rigorous mathematical derivation and a large amount of domestic field practice data for theoretical improvement and correction, the method has been fully applied and improved in mining subsidence prediction, guiding a large number of field engineering practice, and a typical probability integration theory model is shown in Figure 2 [24], in which (a) is semi-infinite mining model, (b) is horizontal-limited mining model, (c) is inclined mining model, and (d) is main influence radius model.

The basic mining model of surface subsidence caused by mining of the ore body is mainly depicted in Figure 2. In order to facilitate the program development of the model, on the basis of previous research, this paper organizes the calculation formulas of the probability integral method predicted by the subsidence model and organizes the main subsidence calculations and horizontal movement calculations with other formulas [25]. The basic mathematical models of mining subsidence values, horizontal movement, inclination, deformation, and other indicators involved in the probability integration method are shown in the following equations [26, 27].

$$\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_0^x e^{-t^2} dt,$$

$$W(x) = \frac{W_0}{2} \left[ \text{erf} \left( \sqrt{\pi} \frac{x}{r} \right) + 1 \right],$$

$$U(x) = U_0 \left( -\frac{x}{r} \right) e^{-\pi(x/r)^2},$$

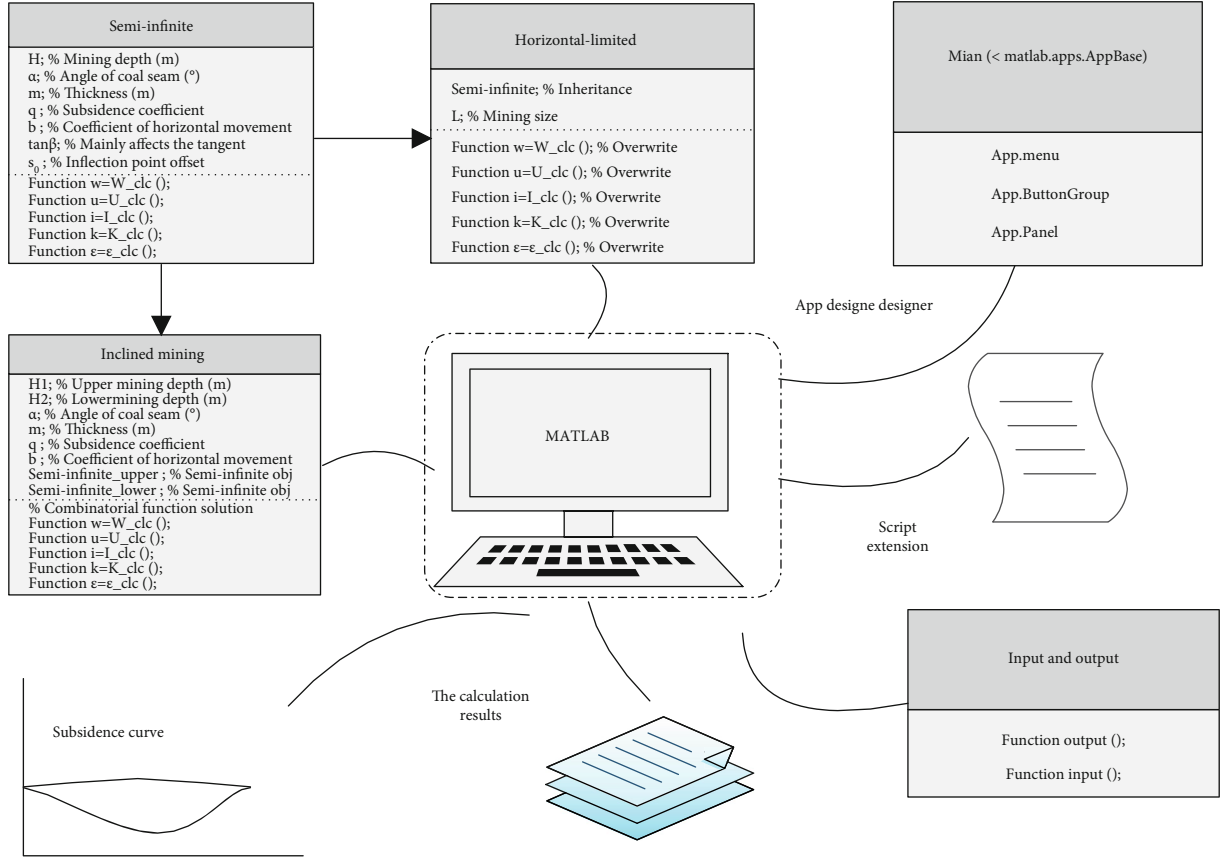


FIGURE 5: Research framework of object-oriented probability integration model.

$$\begin{aligned}
 W_0 &= mq \cos \alpha, \\
 U_0 &= bW_0, \\
 \tan \beta &= \frac{H}{r}, \\
 i(x) &= i_0 e^{-\pi(x/r)^2}, \\
 K(x) &= 4.13K_0 \left( -\frac{x}{r} \right) e^{-\pi(x/r)^2}, \\
 \varepsilon(x) &= 4.13\varepsilon_0 \left( -\frac{x}{r} \right) e^{-\pi(x/r)^2}.
 \end{aligned} \tag{1}$$

In the equations,  $\text{erf}(x)$  – is error function,  $m$  is the thickness of the ore body,  $\alpha$  is the dip angle of the ore body ( $^\circ$ ),  $q$  is the subsidence coefficient,  $b$  is the horizontal movement coefficient,  $H$  is the burial depth of the ore body,  $r$  is the influence radius,  $\tan \beta$  is the main influence tangent,  $W$  is the subsidence value,  $U$  is the horizontal movement value,  $K$  is the curvature,  $i$  is the inclination, and  $\varepsilon$  is the horizontal deformation.

**2.3. Basic Principles of Object-Oriented Method.** The objective world is a mixed system composed of a large number of various complex entities interacting and linking with each other, and each entity has its own internal state and activity mechanism, so the system of the objective world is also a complex giant system formed by the combination of a large

number of subsystems. Object-oriented methodology provides a unified method and framework for analyzing, designing, and implementing systems by simulating human way of thinking, decomposing the solution problem layer by layer, and realizing the mapping isomorphism of problem space and solution space. Object-oriented technology shows great potential and advantages in dealing with large and complex problems [28, 29], which is essentially a method of analyzing, designing, and developing software systems using techniques such as objects, classes, encapsulation, and inheritance [30]. After continuous research and improvement, it has been widely employed in scientific research and engineering cases in various industries and has achieved many practical results [31–33]. Compared with the traditional process-oriented analysis methods, object-oriented technology is object-centered and message-driven and simulates the properties and behaviors of objective entities through object-encapsulated data and methods, which improves the stability and cohesiveness of programs, reduces coupling, and provides greater convenience for the analysis and program development of complex problems [34]. In this work, parameters are calculated by object-encapsulated probability integration method to define subsidence and horizontal movement calculation methods, and model calculation in complex limited and inclined situation is achieved through polymorphic techniques with basic semi-infinite mining as a base class. Combining the probability integration method model with the object-oriented

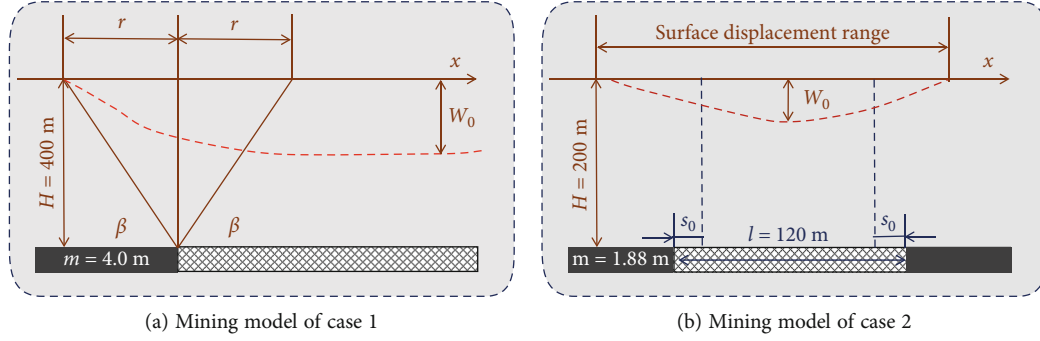


FIGURE 6: Case verification models.

technology, the object-oriented probability integration model is developed and designed, and the object tree of the model is also established as to the inheritance system of the main classes and the needs of management control, etc., as shown in Figure 3.

According to the object tree structure of the model, we established the abstract design and organizational relationship of the main classes used in the prediction model through UML as shown in Figure 4. All user-defined classes inherit from the handle class of MATLAB and define common variables such as mining depth ( $H$ ), dip angle ( $\alpha$ ), and function methods for calculating subsidence and horizontal movement in the semi-infinite mining class value. Horizontal finite mining and inclined mining are inherited from the semi-infinite mining model. By adding unique variables and rewriting related function methods, code reuse and mining subsidence prediction functions of different models are realized.

**2.4. Research on Object-Oriented Probability Integral Subsidence Prediction Framework.** The broken ore pillar extraction subsidence model based on probability integration theory is difficult to achieve efficient, fast, and repeated adjustment operations through manual calculation due to its large number of prediction parameters and large variation in the selection of empirical values of parameters. The use of object-oriented programming technology to establish a common program script can realize fast calculation and efficient adjustment of parameters, thus contributing to model solving. A high-cohesion, low-coupling object-oriented probability integration model based on MATLAB2019 was established by combining object-oriented abstract analysis and probability integration model and using object-oriented encapsulation, inheritance, polymorphism, and other technical features, the framework of which is shown in Figure 5. The framework includes the encapsulation and abstraction of semi-infinite mining, finite mining, and inclined mining models. The main parameters involved in the probability integration method are defined as variables, and the calculations such as subsidence and horizontal movement are defined as function interfaces. The subsidence visualization module and the data input and output interface are developed to enhance the interactivity of the model, improve the user experience, and improve the computing efficiency [35, 36].

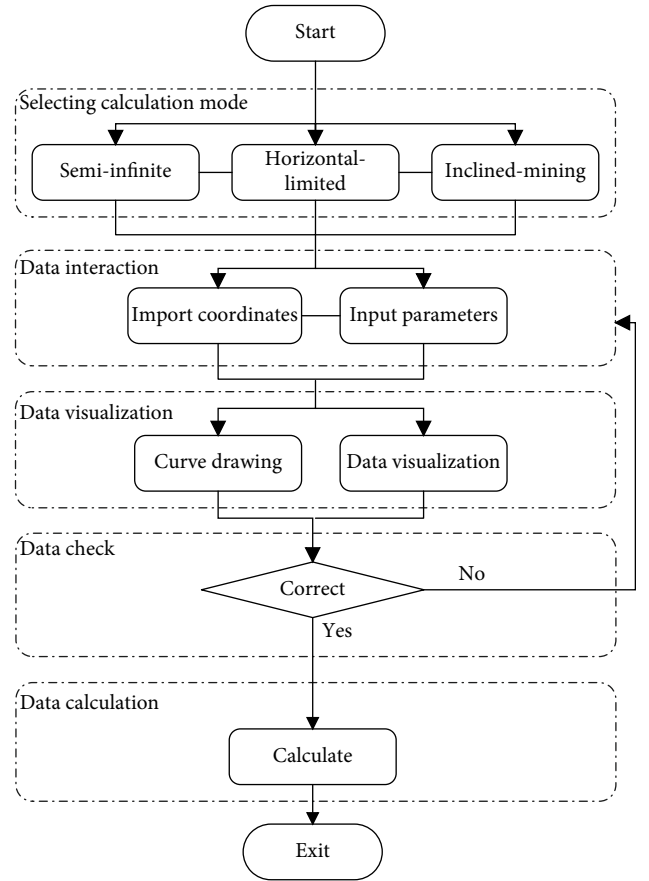


FIGURE 7: Model calculation flow chart.

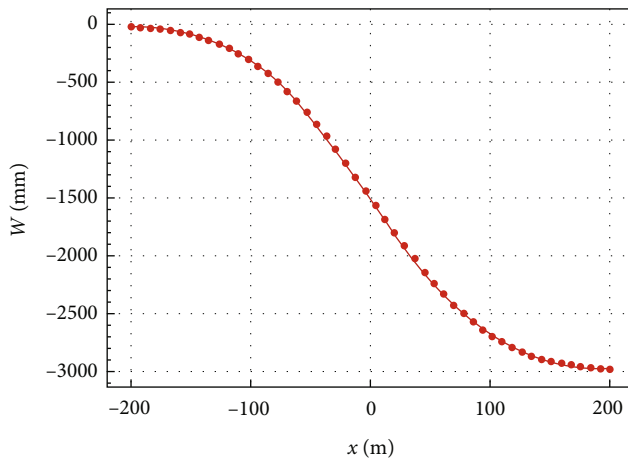
### 3. Case Verification

In order to test the object-oriented probability integration model, the combinatorial model is validated in the paper using a practical case studied by previous scholars [27], as shown in Figure 6, where (a) is a semi-infinite mining model while (b) is a limited one.

The computational flow of the combinatorial model employing the combined probability integration method with object-oriented technology is presented in Figure 7.

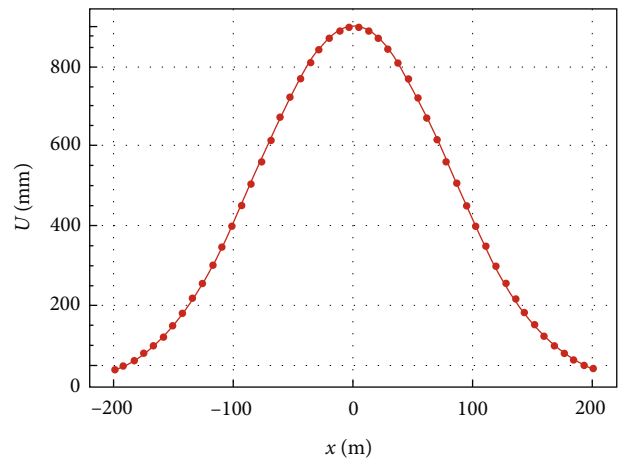
TABLE 1: Calculation results of case (a).

$x/m$	$W$ (mm)	$U$ (mm)	$i$ (mm/m)	$k$ (mm/m <sup>2</sup> )	$\varepsilon$ (mm/m)
-200	18.28332	38.89253	0.648209	0.020366	1.221941
-160	67.39606	120.5151	2.008586	0.050485	3.029115
-120	198.8809	290.4471	4.840785	0.091254	5.47523
-80	474.0437	544.4303	9.073838	0.114034	6.842052
-40	924.2129	793.7202	13.22867	0.083125	4.987484
0	1500	900	15	0	0
40	2075.787	793.7202	13.22867	-0.08312	-4.98748
80	2525.956	544.4303	9.073838	-0.11403	-6.84205
120	2801.119	290.4471	4.840785	-0.09125	-5.47523
160	2932.604	120.5151	2.008586	-0.05049	-3.02911
200	2981.717	38.89253	0.648209	-0.02037	-1.22194



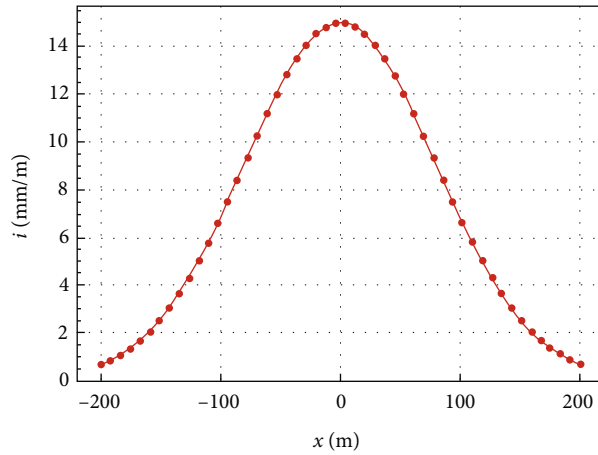
—•— Subsidence

(a) Calculate result of subsidence



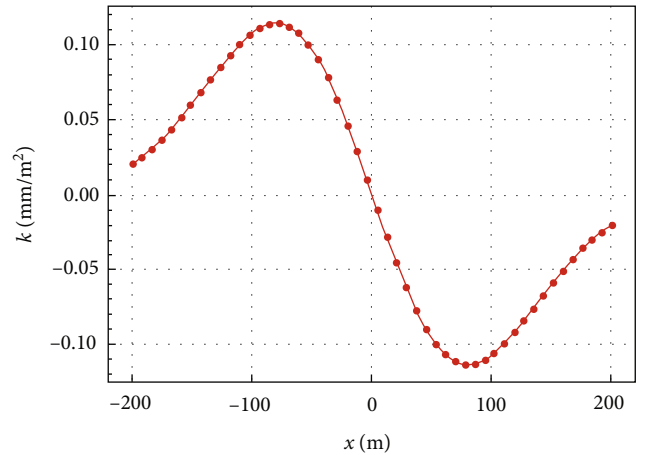
—•— Horizontal movement

(b) Calculate result of horizontal movement



—•— Inclination

(c) Calculating result of inclination

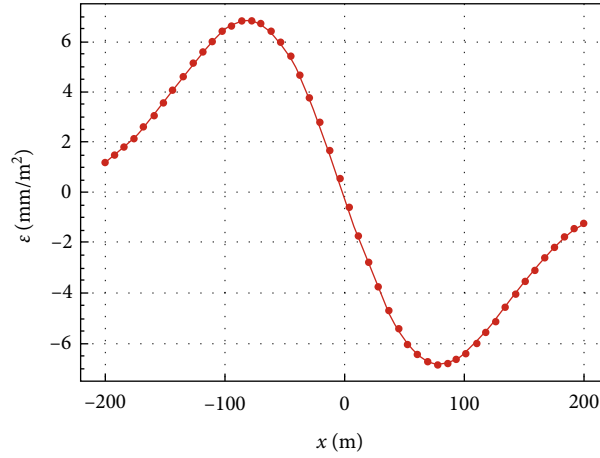


—•— Curvature

(d) Calculating result of curvature

FIGURE 8: Continued.





—●— Horizontal deformation

(e) Calculating result of horizontal deformation

FIGURE 8: Calculation curve diagram of case (a).

TABLE 2: Calculation results of case (b).

$x$ (m)	$W$ (mm)	$U$ (mm)	$i$ (mm/m)	$k$ (mm/m <sup>2</sup> )	$\epsilon$ (mm/m)
-60	59.63406	80.61439	3.224575	0.141728	3.543191
-30	237.316	226.6547	9.066188	0.225875	5.646873
0	598.7774	355.971	14.23884	0.068359	1.708963
30	1006.873	281.2501	11.25001	-0.26793	-6.69831
60	1188.023	0	0	-0.43089	-10.7723
90	1006.873	-281.25	-11.25	-0.26793	-6.69831
120	598.7774	-355.971	-14.2388	0.068359	1.708963
140	339.1057	-281.537	-11.2615	0.207617	5.190415

The calculated results of movement and deformation on the main section in case (a), Figure 6, are shown in Table 1, which are basically consistent with the conclusions of the case. The subsidence and horizontal movement curves of the semi-infinite mining towards the main section are demonstrated in Figure 8. The curve change law in Figure 8 suggests that in the case of semi-infinite mining, the mining subsidence gradually changes from 0 to a relatively fixed range and then reaches stability. The horizontal movement gradually grows to the peak and then starts to decrease. Under the semi-infinite mining conditions, certain strategies should be adopted to reduce the subsidence value, so as to control mining damage.

The calculation results of case (b) in Figure 6 are shown in Table 2, which basically match with the case, indicating that the object-oriented probability integration model for calculating mining subsidence is feasible. The movement deformation law of the finite mining case is presented in Figure 9, implying that the subsidence value of the center of the mining area is the largest in the limited mining case, the overlying rock body shows movement towards the center

of the mining area, the monitoring of the subsidence above the mining area should be strengthened under the limited mining conditions, and the mining-induced subsidence damage can be prevented by optimizing the mining pillar or improving the mining method.

#### 4. Sensitivity Analysis

When mining subsidence is predicted using the probability integration method, the application of the prediction model is significantly affected by different actual geological occurrence conditions, selection of prediction parameters, and the need for accuracy and safety. According to the actual engineering experience on site, the mining thickness of the ore body is an important factor that directly causes mining. Generally, the larger the mining thickness, the more severe the subsidence and the more serious the surface damage. The existence of the dip angle of the ore body leads to the reduction of the equivalent mining thickness, which can alleviate the subsidence damage caused by mining to a certain extent. Generally, as the dip angle of the coal seam increases,

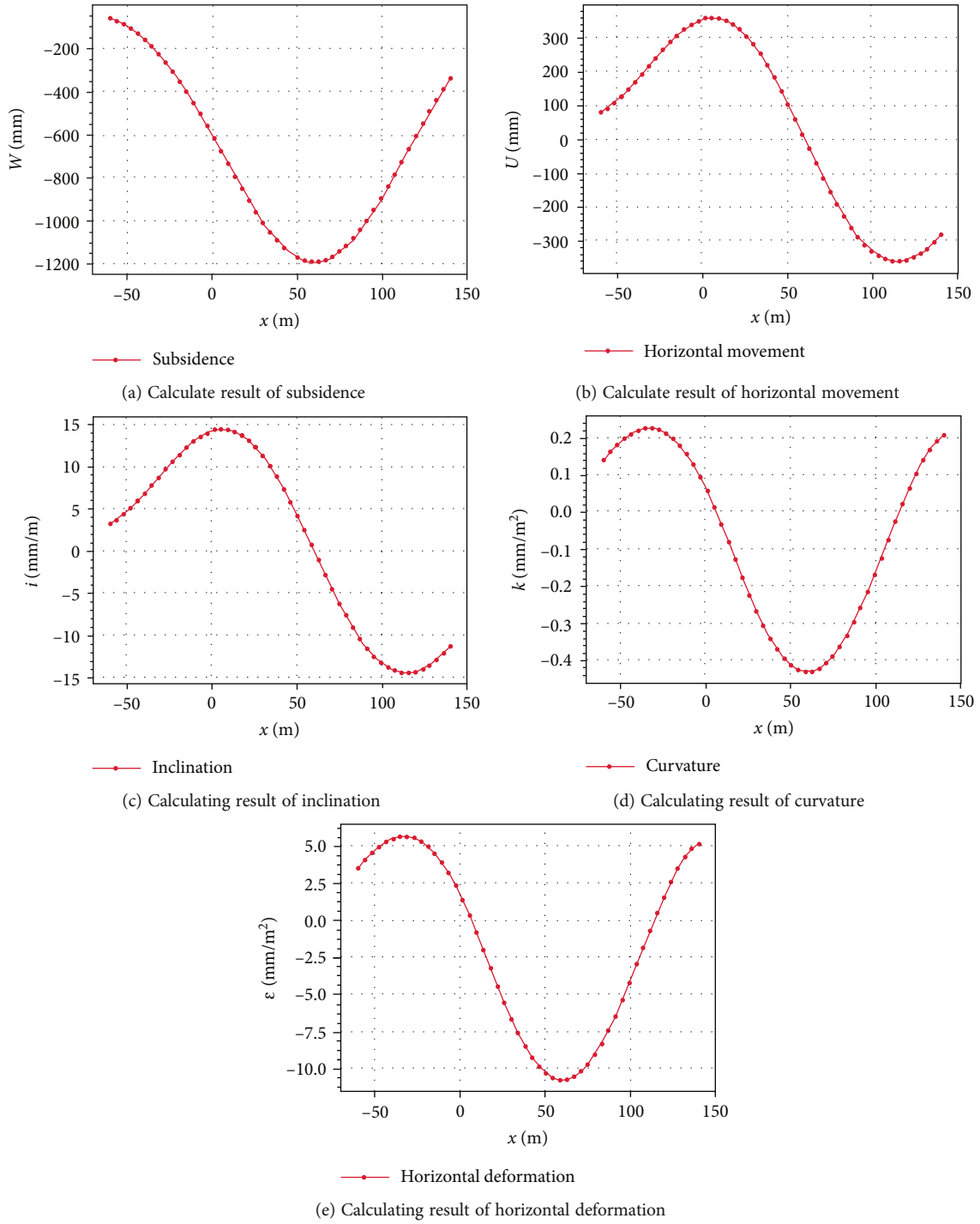
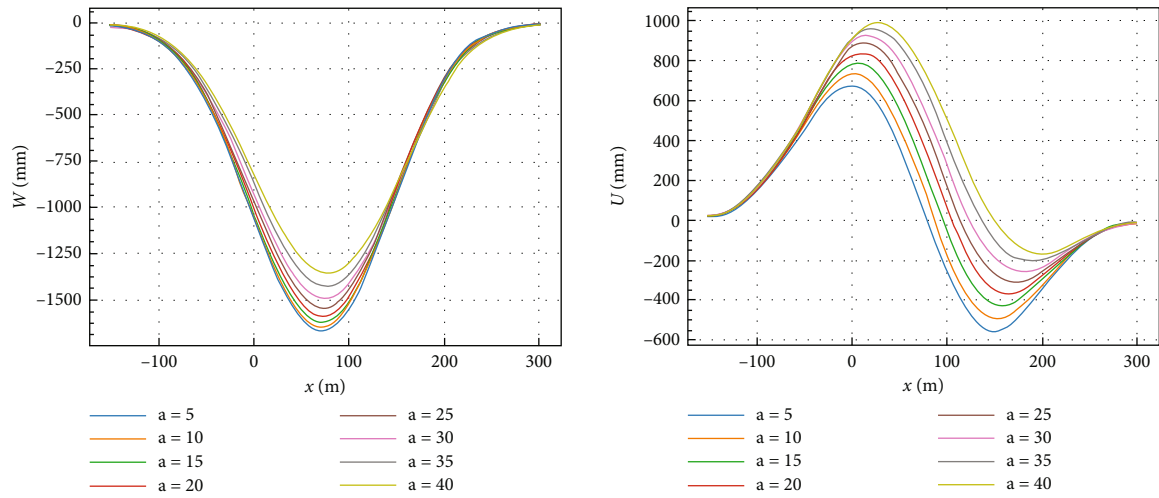
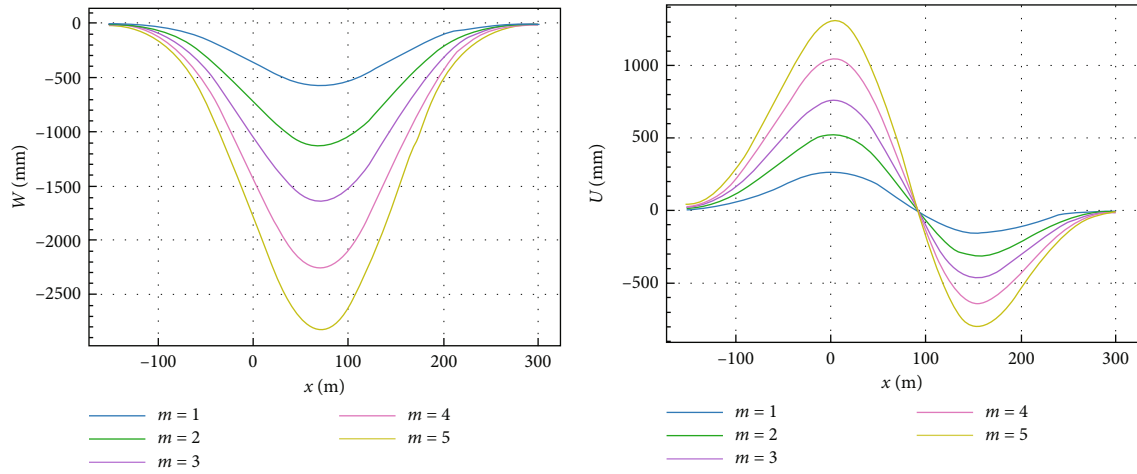


FIGURE 9: Calculation curve diagram of case (b).

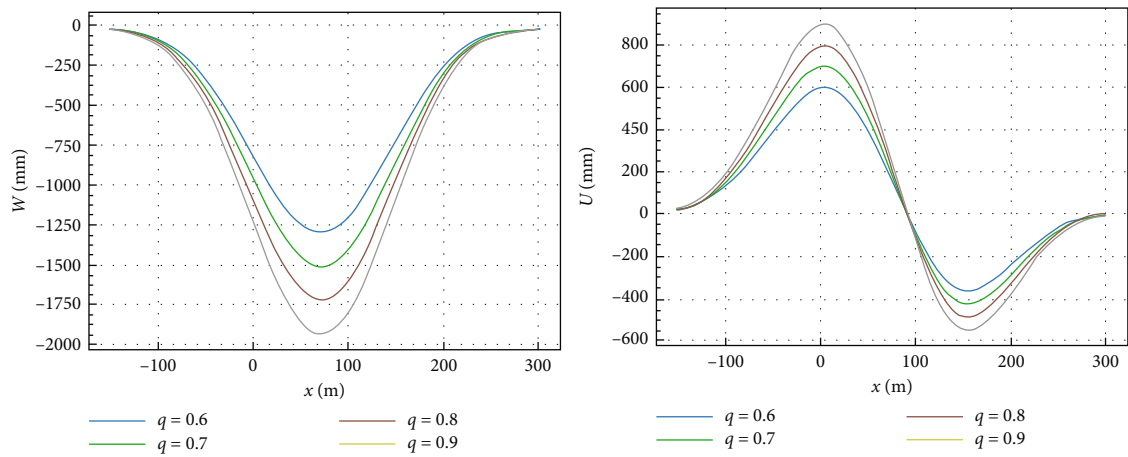




(a) Coal seam dip angle



(b) Coal seam thickness



(c) Subsidence coefficient

FIGURE 10: Sensitivity analysis diagram.

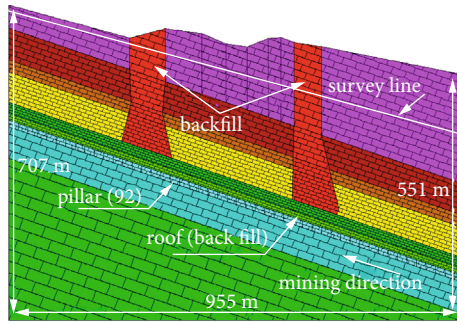


FIGURE 11: Mining model of No. 92 pillar.

the subsidence caused by mining decreases. After increasing to a certain extent, the accuracy of the model will decrease. The selection of mining subsidence coefficient is mainly used to quantitatively describe comprehensive geological conditions. In practical applications, methods such as engineering analogy are mainly used for determination, and its selectivity has certain subjective factors, which have a great impact on the accuracy of model prediction. To this end, based on previous research, we selected indicators such as dip angle ( $\alpha$ ), thickness ( $m$ ), and subsidence coefficient ( $q$ ) to study the sensitivity of the object-oriented probability integration model [37–38], which is shown in Figure 10.

As shown in Figure 10(a), as the dip angle increases, the maximum subsidence value tends to weaken, indicating that the mining subsidence caused by the horizontal ore body mining may be more severe than the mining subsidence caused by the inclined ore body mining. The reduction of mining thickness improves the subsidence damage caused by mining [39]. Due to the influence of the dip angle, the peak value of the horizontal movement will increase after mining. The main reason is the existence of the dip angle of the ore body, the change in the shape of the gob, and the overlying strata, in addition to the horizontal movement pointing to the center of the gob, which is easier to send along the gob. Shear movement depends on the dip of the ore body. Therefore, attention should be paid to horizontal movement deformation during the mining of high-dip ore bodies to prevent secondary disasters caused by rock shear dislocation [40]. Figure 10(b) suggests that both subsidence and horizontal movement value increase with the growing of the thickness of the ore body, and the magnitude of increase is more than obvious, which indicates that the mining thickness is an important factor to cause subsidence. When the mining thickness is large, the filling method can be considered to deal with the gob to reduce the mining thickness of the ore body, so as to reduce the impact of mining and control the surface subsidence [41–43]. As shown in Figure 10(c), selection of subsidence coefficient also has a significant effect on the prediction of mining subsidence, which is mainly related to overlying lithology and treatment method of the gob. When the lithology is poor and the gob is large, the subsidence is more violent. In the actual prediction, the selection should be made by analogy with the actual engineering geological conditions or similar engineering

cases, so as to improve the prediction accuracy of the model and the reliability of the conclusion.

## 5. Engineering Application

Guangxi Tongkeng Mine has complex geological conditions and poor ore body occurrence conditions. In order to study the impact of pillar mining on the surface, the prediction model established in this paper is used to predict the mining subsidence of No. 92 pillar of the mine. At the same time, the predicted results are compared with those predicted by discrete element numerical model. The average thickness of No. 92 pillar in Tongkeng Mine  $m = 15$  m, the average dip angle  $\alpha = 20^\circ$ , the surface dip angle of  $10^\circ$ , and the ore body occurrence structure are shown in Figure 11.

The predicted mining subsidence results adopting the combined model established in the paper are demonstrated in Figure 11. It can be seen that the central area of the gob has the most severe subsidence, the maximum subsidence value is about 11.5 m, the maximum horizontal movement is about 2.5 m, the maximum subsidence is less than the mining thickness of the ore body, and the maximum subsidence value appears in the center of the gob. The subsidence curve is similar to the common coal mine stope subsidence law. It can be seen from the figure that after the ore body is mined, the overlying strata subside, and a subsidence basin is likely to appear near the center of the gob. At the same time, due to the influence of the inclination angle of the ore body and the mining direction, the overlying rock mass does not completely move towards the center of the gob. After the model is excavated, the overall model is inclined and deformed, which hinders the migration characteristics of the lower rock mass to the gob, while the upper rock mass increases the tendency to migrate to the gob along the inclined direction, so the horizontal shift curve offset occurs. This is also consistent with the actual mining rock movement law.

In the paper, the discrete element numerical simulation technique was applied to construct the mining model of No. 92 pillar and analyze the surface subsidence and deformation law during the backfilling process, shown in Figure 12.

As seen in Figure 13, with the mining of the ore pillar, the top plate breaks and collapses, the overlying rock layer bends and deforms, the surface subsidence gradually increases, and the mining impact area expands. Due to the influence of the dip angle of the ore body, after the ore body is extracted, the overlying rock body has a tendency to move to the center of the mining area in addition to the overall dip deformation of the mining model, which limits the horizontal movement of the overlying rock body to the mining area. The numerical simulation results imply that subsidence is the most intense in the center of the gob, the value of which reaches about 12 meters, basically consistent with the theoretical calculation conclusion. The horizontal movement is approximately 2 meters, which is smaller compared with the theoretical calculation. The main reason may be that the overall inclined deformation of the model causes the overlying rock body in the gob to have a tendency to move

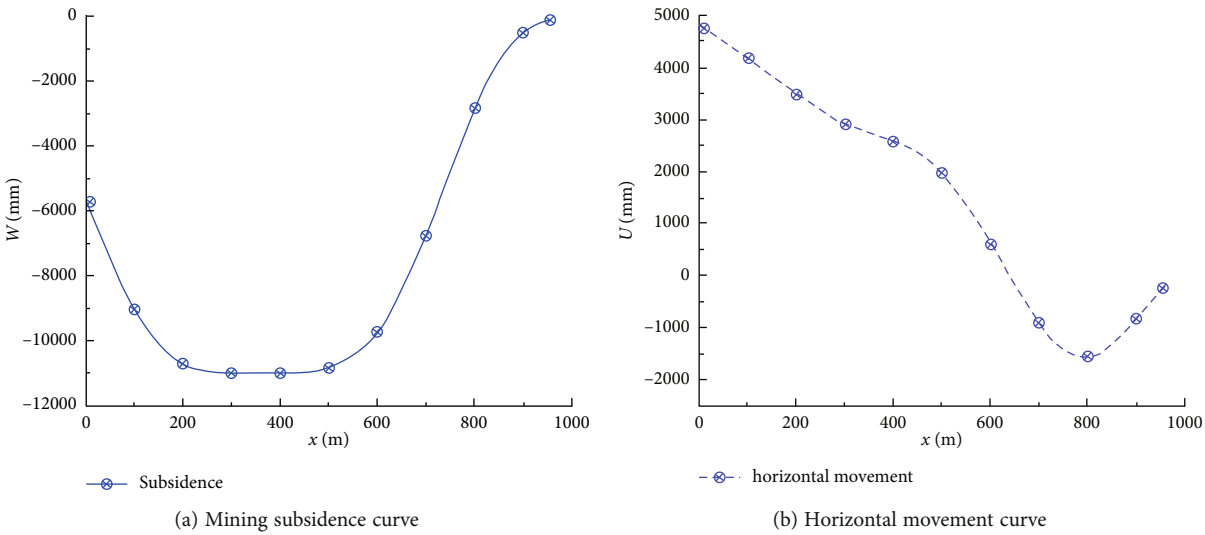


FIGURE 12: Numerical model of No. 92 pillar backfilling.

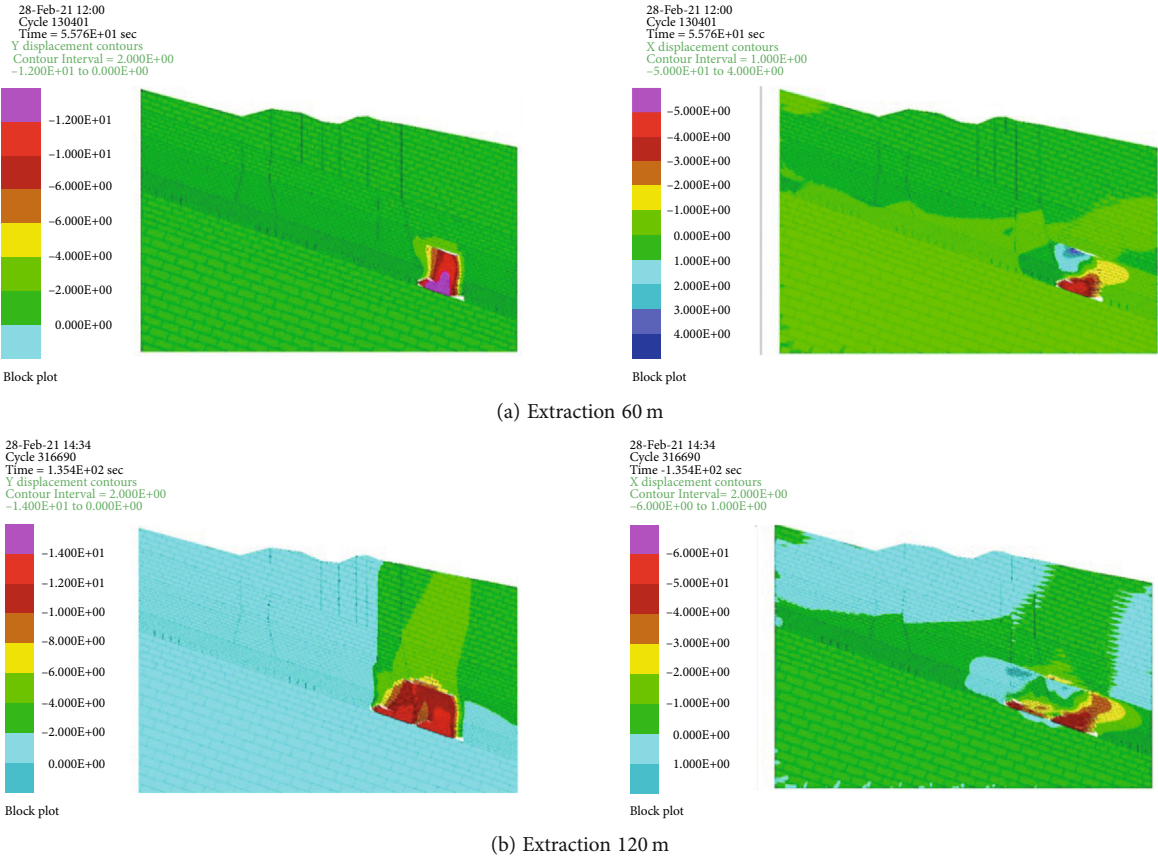


FIGURE 13: Continued.

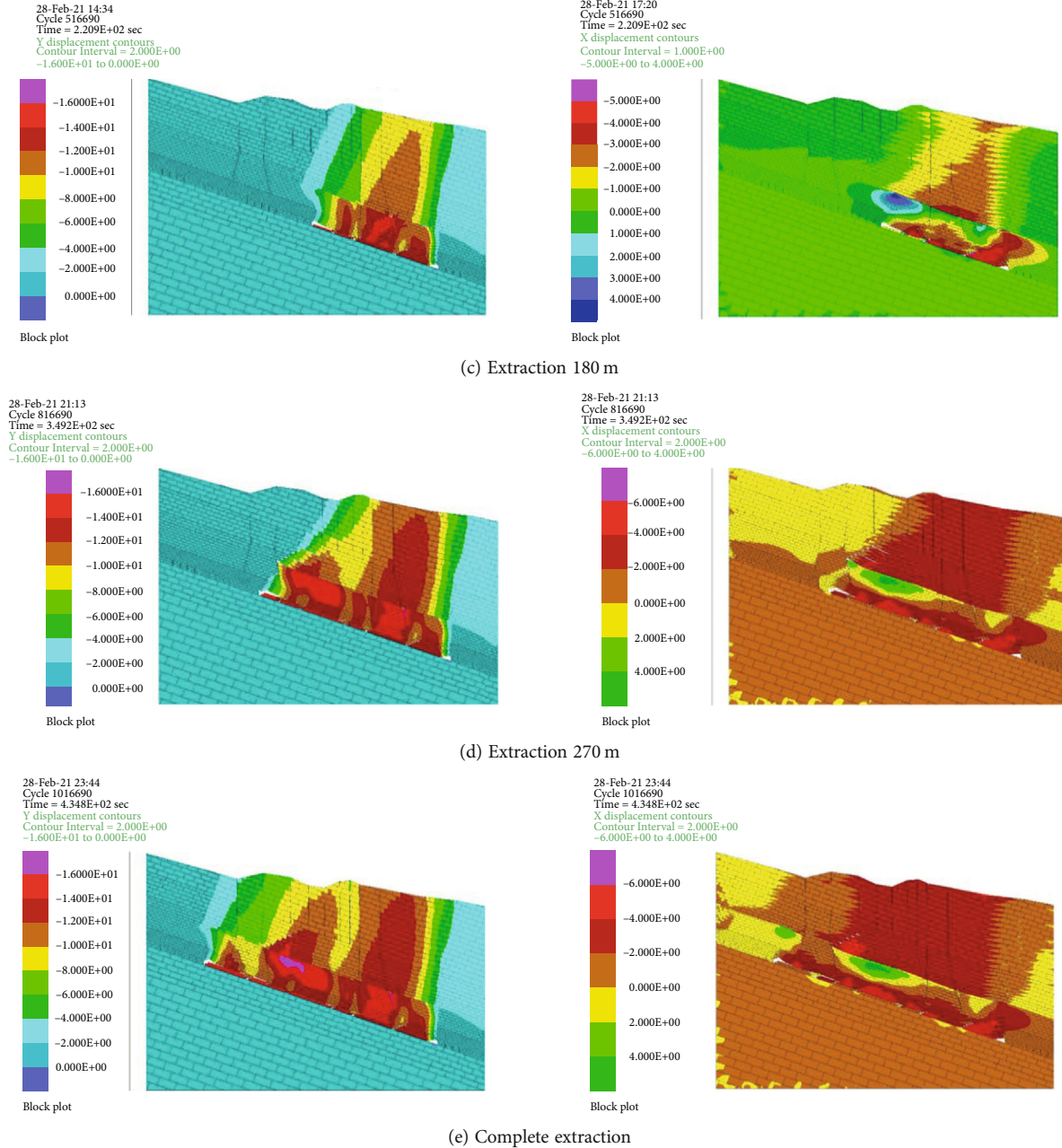


FIGURE 13: Numerical simulation results of No. 92 pillar backfilling.

towards the center of the mining area but also superimposes the movement along the inclined direction, reducing the horizontal movement of the overlying rock body towards the center of the goaf. The numerical simulation is basically consistent with the conclusion of theoretical predicted mining subsidence.

## 6. Conclusion

By analyzing the occurrence and mining conditions of ore pillars, a mining subsidence predicted model applicable to the principle of random media was established by applying the principle of equivalent mining, and a visualized and

interactive graphical prediction system was developed with the help of the MATLAB object-oriented programming technology. After analyzing the influence of commonly used empirical parameters in China, the theoretical projection was carried out with reference to similar engineering cases, while a numerical model of mining pillar mining was established employing discrete element numerical simulation technology for comparison and verification, and the main conclusions were obtained as follows.

- (1) In this study, object-oriented technology combined with traditional probability integral method is applied to the prediction of mining subsidence. The



multivariate and complex calculation formulas involved in the abstract prediction model are abstracted by the object method as the internal attributes and methods, and an object-oriented development framework and application interface are constructed to improve the solution efficiency of the model and reduce the development and maintenance costs. It can quickly provide reasonable and reliable prediction results for designers and related departments. The correctness of the mining subsidence prediction model was verified through case tests, which proved that it is feasible to adopt the object-oriented technology to combine the probability integration method to build a model for mining subsidence prediction

- (2) Sensitivity analysis was conducted on the main factors affecting mining subsidence, namely, dip angle, thickness, and subsidence coefficient. The mining thickness of the ore body has the most drastic effect on mining subsidence, and the dip angle can reduce the maximum subsidence peak caused by mining to a certain extent. The selection of the subsidence coefficient has a significant impact on the accuracy of the mining subsidence prediction and should be selected in conjunction with similar engineering cases in application. The case test proves that it is feasible to use the object-oriented method combined with the probability integration method to abstract the complex multivariate and nonlinear prediction methods and to construct a combined prediction model for mining subsidence prediction
- (3) It is difficult to analyze the dynamic mining process and the structural support effect formed by overlying damage for the prediction of mining subsidence by the probability integration method, so the factors affecting the accuracy and reliability of the mining subsidence are more complicated in the process of metal mining. In the future, the mechanical properties of the overlying structure of the mining stope and the influence of the dynamic mining process, as well as more geological and mining influence factors, could be considered to improve the effectiveness of the model in the actual mining subsidence prediction

## Data Availability

The data used by the researchers are for scientific research purposes rather than commercial purposes. Most of the data generated or analyzed during this study are included in this manuscript, and all of the data are available from the corresponding author on reasonable request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

The authors gratefully acknowledge the financial support by the Natural Sciences Foundation of China (No. 51774323).

## References

- [1] J. Rošer, D. Potočnik, and M. Vulić, "Analysis of dynamic surface subsidence at the underground coal mining site in Velenje, Slovenia through modified sigmoidal function," *Minerals*, vol. 8, no. 2, p. 74, 2018.
- [2] Y. Zhao, W. Zheng, W. Xiao, S. Zhang, X. Lv, and J. Zhang, "Rapid monitoring of reclaimed farmland effects in coal mining subsidence area using a multi-spectral UAV platform," *Environmental Monitoring and Assessment*, vol. 192, no. 7, p. 474, 2020.
- [3] L. C. Sui, F. Ma, and N. Chen, "Mining subsidence prediction by combining support vector machine regression and interferometric synthetic aperture radar data," *ISPRS International Journal of Geo-Information*, vol. 9, no. 6, p. 390, 2020.
- [4] X. Li, D. Wang, C. Li, and Z. Liu, "Numerical simulation of surface subsidence and backfill material movement induced by underground mining," *Advances in Civil Engineering*, vol. 2019, 17 pages, 2019.
- [5] J. Ma, D. Yin, N. Jiang, S. Wang, and D. Yao, "Application of a superposition model to evaluate surface asymmetric settlement in a mining area with thick bedrock and thin loose layer," *Journal of Cleaner Production*, vol. 314, p. 128075, 2021.
- [6] J. Tang, Z. Dai, Y. Wang, and L. Zhang, "Fracture failure of consequent bedding rock slopes after underground mining in mountainous area," *Rock Mechanics and Rock Engineering*, vol. 52, no. 8, pp. 2853–2870, 2019.
- [7] G. Li, Z. Hu, P. Li et al., "Innovation for sustainable mining: integrated planning of underground coal mining and mine reclamation," *Journal of Cleaner Production*, vol. 351, p. 131522, 2022.
- [8] X. Zhu, W. Zhang, Z. Wang, C. Wang, W. Li, and C. Wang, "Simulation analysis of influencing factors of subsidence based on mining under huge loose strata: a case study of Heze mining area, China," *Geofluids*, vol. 2020, 17 pages, 2020.
- [9] C. Q. Ma, H. Z. Li, and P. P. Zhang, "Subsidence prediction method of solid backfilling mining with different filling ratios under thick unconsolidated layers," *Arabian Journal of Geosciences*, vol. 10, no. 23, p. 12, 2017.
- [10] Z. L. Du and M. T. Yi, "Numerical simulation of deep mining subsidence prediction based on FLAC3D," *Surveying and Mapping and Spatial Geographic Information*, vol. 44, no. 7, p. 4, 2021.
- [11] H. Z. Li, J. F. Zha, and G. L. Guo, "A new dynamic prediction method for surface subsidence based on numerical model parameter sensitivity," *Journal of Cleaner Production*, vol. 233, pp. 1418–1424, 2019.
- [12] M. Mohammady, H. R. Pourghasemi, M. Amiri, and J. P. Tiefenbacher, "Spatial modeling of susceptibility to subsidence using machine learning techniques," *Stochastic Environmental Research and Risk Assessment*, vol. 35, no. 8, pp. 1689–1700, 2021.
- [13] A. Arabameri, S. Saha, J. Roy et al., "A novel ensemble computational intelligence approach for the spatial prediction of land subsidence susceptibility," *Science of the Total Environment*, vol. 726, p. 138595, 2020.

- [14] L. Wang, Z. Shangjun, J. Chuang et al., "Research on 3D laser scanning monitoring method for mining subsidence based on the auxiliary for probability integral method," *KSCE Journal of Civil Engineering*, vol. 25, no. 11, pp. 4403–4416, 2021.
- [15] G. J. Zhang, W. Yan, and K. G. Jiang, "Inversion method of mining subsidence prediction parameters based on variable weight PB combination prediction model," *Chinese Journal of Mining and Rock Formation Control Engineering*, vol. 3, no. 1, p. 9, 2021.
- [16] Z. Zhang, H. Qin, Y. Liu et al., "Wind speed forecasting based on quantile regression minimal gated memory network and kernel density estimation," *Energy Conversion and Management*, vol. 196, pp. 1395–1409, 2019.
- [17] T. Yi and C. Fang, "A complexity metric for object-oriented software," *International Journal of Computers and Applications*, vol. 42, no. 6, pp. 544–549, 2020.
- [18] W. Yan, J. Chen, Y. Tan, W. Zhang, and L. Cai, "Theoretical analysis of mining induced overburden subsidence boundary with the horizontal coal seam mining," *Advances in Civil Engineering*, vol. 2021, Article ID 6657738, 7 pages, 2021.
- [19] C. He and J. Xu, "Subsidence prediction of overburden strata and surface based on the voussoir beam structure theory," *Advances in Civil Engineering*, vol. 2018, Article ID 2606108, 13 pages, 2018.
- [20] T. Tan, Z. Yang, F. Chang, and Zhao, "Prediction of the first weighting from the working face roof in a coal mine based on a GA-BP neural network," *Applied Sciences*, vol. 9, no. 19, p. 4159, 2019.
- [21] W. Liu, L. Pang, B. Xu, and X. Sun, "Study on overburden failure characteristics in deep thick loose seam and thick coal seam mining," *Geomatics, Natural Hazards and Risk*, vol. 11, no. 1, pp. 632–653, 2020.
- [22] Y. Wu, R. Gao, and J. Yang, "Prediction of coal and gas outburst: a method based on the BP neural network optimized by GASA," *Process Safety and Environmental Protection*, vol. 133, pp. 64–72, 2020.
- [23] Y. Yuan, H. Li, H. Zhang, Y. Zhang, and X. Zhang, "Improving reliability of prediction results of mine surface subsidence of Northern Pei County for reusing land resources," *Applied Sciences*, vol. 10, no. 23, p. 8385, 2020.
- [24] Z. Yang, Z. Li, J. Zhu, Y. Wang, and L. Wu, "Use of SAR/InSAR in mining deformation monitoring, parameter inversion, and forward predictions: a review," *IEEE Geoscience and Remote Sensing Magazine*, vol. 8, no. 1, pp. 71–90, 2020.
- [25] H. J. Li, L. Zhu, G. X. Guo et al., "Land subsidence due to groundwater pumping: hazard probability assessment through the combination of Bayesian model and fuzzy set theory," *Natural Hazards and Earth System Sciences*, vol. 21, no. 2, pp. 823–835, 2021.
- [26] G. Q. He, *Mining Subsidence Science*, China University of Mining and Technology Press, 1991.
- [27] K. Z. Deng, Z. Tan, Y. Jiang, H. Dai, Y. Shi, and L. J. Xu, *Deformation monitoring and subsidence engineering*, China University of Mining and Technology Press, Xuzhou, China, 2014.
- [28] A. B. Rauzy and C. Haskins, "Foundations for model-based systems engineering and model-based safety assessment," *Systems Engineering*, vol. 22, no. 2, pp. 146–155, 2019.
- [29] G. Chen, X. Rui, J. Gu, X. Zeng, and X. Liu, "Development of an object-oriented framework for the vibration characteristic computation of multibody systems," *Advances in Engineering Software*, vol. 148, p. 102874, 2020.
- [30] M. Laaziri, S. Khouliji, K. Benmoussa, and K. M. Larbi, "Information system for the governance of university cooperation," *Engineering, Technology & Applied Science Research*, vol. 8, no. 5, pp. 3355–3359, 2018.
- [31] K. Qin, B. Li, and Z. Pei, "Attribute reduction and rule acquisition of formal decision context based on object (property) oriented concept lattices," *International Journal of Machine Learning and Cybernetics*, vol. 10, no. 10, pp. 2837–2850, 2019.
- [32] Y. Xiaoyan, L. I. U. Wenlu, L. I. Long, C. H. E. N. Longqian, and C. H. E. N. Longgao, "Object-oriented land use/cover classification in coastal area," *Bulletin of Surveying and Mapping*, no. 6, p. 89, 2019.
- [33] W. Lee, M. Kim, and D. H. Cho, "Deep cooperative sensing: cooperative spectrum sensing based on convolutional neural networks," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 3, pp. 3005–3009, 2019.
- [34] H. Fathizad, M. A. H. Ardakani, R. T. Mehrjardi, and H. Sodaiezhadeh, "Evaluating desertification using remote sensing technique and object-oriented classification algorithm in the Iranian central desert," *Journal of African Earth Sciences*, vol. 145, pp. 115–130, 2018.
- [35] L. Yu, C. Ximin, R. He, and L. Chunyi, "Automatic realization of surface subsidence prediction based on Matlab," *Coal Technology*, vol. 37, no. 9, pp. 147–149, 2018.
- [36] C. Wu, *Interactive visual analysis system for mining subsidence prediction based on Matlab*, China University of Geosciences, Beijing, 2015.
- [37] P. R. Sheorey, J. P. Loui, K. B. Singh, and S. K. Singh, "Ground subsidence observations and a modified influence function method for complete subsidence prediction," *International Journal of Rock Mechanics and Mining Sciences*, vol. 37, no. 5, pp. 801–818, 2000.
- [38] Z. Zhang, L. Ye, H. Qin et al., "Wind speed prediction method using shared weight long short-term memory network and Gaussian process regression," *Applied Energy*, vol. 247, pp. 270–284, 2019.
- [39] Y. J. Sun, J. P. Zuo, M. Karakus, L. Liu, H. Zhou, and M. Yu, "A new theoretical method to predict strata movement and surface subsidence due to inclined coal seam mining," *Rock Mechanics and Rock Engineering*, vol. 54, no. 6, pp. 2723–2740, 2021.
- [40] C. Lailiang, *Research on an Integrated Prediction Model of Mining Subsidence Suitable for Changes in Dip Angle*, China University of Mining and Technology, 2011.
- [41] Q. Guo, *Characteristics and Prevention Measures of Surface Subsidence Disasters in Thick Coal Seam Slicing and Fully Mechanized Caving Mining in Chenjiagou Coal Mine*, Xi'an University of Science and Technology, 2018.
- [42] L. Meng, *Research on the mechanical behavior of gangue filling materials and the mechanism of controlling rock movement*, China University of Mining and Technology, 2018.
- [43] C. Xie, H. Nguyen, X. N. Bui, V. T. Nguyen, and J. Zhou, "Predicting roof displacement of roadways in underground coal mines using adaptive neuro-fuzzy inference system optimized by various physics-based optimization algorithms," *Journal of Rock Mechanics and Geotechnical Engineering*, vol. 13, no. 6, pp. 1452–1465, 2021.