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System Dynamics Modeling: A Prototype Technical-Economic Analyzation Tool for Supporting Sustainable Development in Operational Metal Mines

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ABSTRACT Technical-economic analyzation is critical to increasing a mine's economic benefits and saving mineral resources for its sustainable development. However, since the mining system has many technical-economic indicators that are connected and that respond to each other, it is not easy to determine mining production and operation performance when an indicator changes or when multiple indicators change. Thus, the complicated system of operational metal mining cannot be easily solved in a general way. In this paper, system dynamics (SD), an alternative approach that can qualitatively and quantitatively assess mining production and operation from a system analysis perspective, is employed. Taking the Sanshandao gold mine in China as the industrial research context, we built an SD model based on an integrated stock and flow diagram, which is derived from the identification of technical-economic parameters and the system conceptualization of causal loop diagrams, including four subsystems of geology, mining production, mineral processing, and financial. After establishing the equations and testing the model based on historical data, the SD model simulated with the PLE 6.3 software can be used as a decision support tool to calculate the simulation results in many scenarios. Monte Carlo simulation is also introduced to consider uncertainties in the assessment. In the future, development of the prototype SD model will continue, and it will be verified by many more case studies to be a useful alternative tool for decision-making to improve the actual processes and to support the sustainable development of metal mine production and operation.

INDEX TERMS Modeling, sustainable development, mining industry, operational level, and system dynamics.

I. INTRODUCTION

Currently, mineral metal resources have become a vital material basis for determining the development of a country's economy, science, technology, and national defense. Metals are also a critical strategic resource for enhancing a country's comprehensive strength and safeguarding its national security. However, because mineral resources are finite and nonrenewable, after years of exploitation and utilization, both the quantity and quality of metal resources will decrease. Then, with the rapid expansion of the social economy, the contradiction between the shortage of metal resources and the needs of national economic development becomes increasingly prominent. In such circumstances, studies on supporting sustainable development in operational metal mines to improve the efficiency of production and operation and to rationalize metal resource utilization are receiving more and more attention.

As a part of such undertakings, the majority of existing literature has mainly focused on the optimization of technical and economic indicators during the industrial processes that begin with geological resources and end with concentrates

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because indicators such as cut-off grade, head grade, production rate, and production cost are considered to be critical parameters that can be artificially adjusted to control the production of mines, thus affecting the operational efficiency of mining enterprises.

For instance, Azimi and Osanloo [1] established an optimization model taking the maximum net present value as the objective and the cut-off grade as the decision variable. The calculation results show that this model would undoubtedly provide the ability to consider managerial and technical flexibilities and incorporate more real mining conditions to improve the goal of mine projects. Additionally, similar research, including studies by Rahimi and Ghasemzadeh [2], Ahmadi and Shahabi [3], Rahimi et al. [4], has focused on optimizing the cut-off grade strategy. Taking Lane's algorithm as a basis, Asad and Topal [5] demonstrated the combined impact of introducing economic parameters, escalation and stockpiling options into the cut-off grade optimization model. Consistent with the research of Asad and Topal [5], Narrei and Osanloo [6] provided a model for the determination of cut-off grades in open-pit mines. In addition to the costs associated with the management and reclamation of waste dumps, tailing dams, and pits, possible incomes from reclamation are also considered in this model. Regarding environmental and technical considerations and operating costs, Rahimi and Akbari [7] proposed a method with a higher efficiency in optimizing the cut-off grades of processing methods using the Karush-Kuhn-Tucker theorem. In other work, He et al. [8] set up an optimization model with the objective function of economic benefit, two constraints consisting of the resource utilization rate and the output of concentrate, along with head grade and dressing grade as the decision variables. The case study validates that this method can effectively increase the resource utilization rate and concentrate volume and significantly increase the net present value of mine enterprises. Rahimi et al. [9] proposed a logical mathematical algorithm that considers important designing parameters and the mining economy to provide the maximum benefit by calculating the destination of ores. Yu et al. [10] presented a nonlinear multi-objective programming model for mineral processing production planning to optimize five production indexes, including concentrate grade, metal recovery, concentrate volume, concentration ratio, and production cost. Wang et al. [11] proposed a data-driven multi-objective optimization model to optimize the concentrate grade and concentrate volume of the mineral process.

As a whole, progress has been made in the optimization of the technical and economic indicators of mine production mentioned above, and some results have been achieved in practice. However, it should be noted that the studies mentioned above mostly focus on a single or a few technical-economic indicators, and seldom examine the whole mining system.

In fact, for operational metal mines that consider concentrates as the final product, formulating the mining production and operating systems is quite a complicated process because there exist numerous technical-economic indicators that can be organized as a series of data collection, reflecting the geological resource, ore quality, the efficiency of mining and mineral processing, and the operation results. Simultaneously, these indicators are closely linked and mutually restrained; any changes to one indicator will provoke a series of unexpected reactions to the others, which in return gives rise to a new situation to the whole system. Moreover, given the uncertainties of geological resources, the ups and downs of the market economy, and the progress of production technology, some key indicators should be flexible rather than static to adjust and optimize the operation results in time.

The above characteristics of the complex system of mining production and operation prevent most traditional methodologies, such as dynamic marginal analysis [12] and the fuzzy comprehensive evaluation method [13], from comprehending the system behavior well. Therefore, a holistic modeling method from a system analysis perspective is required to observe, analyze, and model the whole system, considering complex feedback mechanisms among technical-economic indicators of operational metal mines.

System dynamics (SD), as a powerful method to implement systems thinking, is an appropriate method for addressing this problem. SD is a computer-aided method for modeling complex systems to understand the patterns of behavior of different stages over time. More specifically, SD provides a holistic modeling method, because it reduces a system to multiple small, individual pieces, which enables the system to be investigated, and it considers causal relationships in a dynamic, uncertain and multidimensional manner [14]. Since the first reference to SD was made by Forrester [15], SD has been employed in several areas. Nassery et al. [16] built a system dynamics model for water management in semiarid regions. Wen and Bai [17] constructed an system dynamics model for simulating the impact of different strategies on the energy consumption and carbon emissions of urban traffic. Fitch et al. [18] presented a system dynamics valuation model to promote public initiatives, encourage private participation and enhance the economic sustainability of public-private partnerships.

Within the field of mining engineering, Cooke [19] established an SD model to analyze mining safety management given the complicated relationship between various factors. Lagnika et al. [20] proposed an integration of environmental management tools based on system dynamic simulations for mining. Sontamino and Drebenstedt [21] developed an SD model of mining cost estimation by using equations and a unit cost database from chapter 2 of the book "Open Pit Mine Planning and Design" by Hustrulid and Kuchta [22]. Subsequently, Sontamino and Drebenstedt [23] developed a prototype dynamic decision-making model of mining feasibility on investment.

However, apart from some of the papers referred to above and to the best of our knowledge, the application of SD in mining enterprises is limited, as is the development of holistic

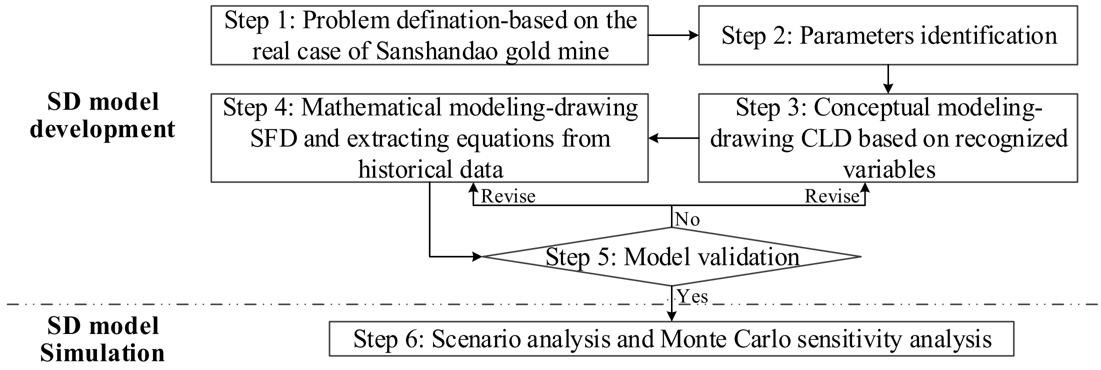

FIGURE 1. Research framework.

SD models for technical-economic analyzation in operational metal mines including the entire geological, mining, and mineral processing processes. As a response to the knowledge gaps identified in the literature, the objectives of this paper are to develop a deeper and broader technical-economic analyzation tool from a systems analysis perspective and to provide an in-depth sustainability assessment for mining production and operation through system dynamics modeling.

The Sanshandao gold mine is one of the most representative underground gold mines in China. It is characterized by a large size, simple shape, stable attitude, considerable continuity of mineralization, and richness in low-grade resources. Also, it consists of all the production processes including mining, concentrating, and refining. After over 30 years of extraction, the high-grade ores have almost been depleted. Faced with an ever-decreasing ore grade, it is essential to seek sustainable ways to utilize low-grade metal resources through technical-economic systems analysis and to ensure both technical feasibility and economic justification. This is substantially consistent with the macro objectives of this paper.

Therefore, the Sanshandao gold mine in China is used as the industrial context in this paper. After a systematic analysis of the feedback mechanisms in mining production and operation systems and its influencing technical-economic indicators, the SD model adapted to the actual production and operation outputs generated from the Sanshandao gold mine is constructed to analyze system behaviors quantitatively. Additionally, Monte Carlo simulation was introduced to analyze probabilities and effectively deal with uncertainties. This research is a vital attempt toward systematically and comprehensively balancing technical performance and economic performance during the sustainable development of operational metal mines. The modeling methods and research ideas proposed in this paper can provide a reference for decision-making to improve actual processes and to support the sustainable development of operational metal mines.

II. RESEARCH FRAMEWORK

System dynamics is used as the primary modeling methodology in this study. Generally, system dynamics modeling takes on two complementary forms: qualitative modeling, with the end goal of developing causal loop diagrams (CLDs) that represent the interactions of dynamic factors and improve the conceptual system understanding, and quantitative modeling, with the end goal of developing stock-and-flow diagrams (SFDs) that simulate the dynamic effects of factors and their interactions [24]. Within an SFD, a stock characterizes the state of any system variable at a specific time, and a flow is responsible for causing the stock to change via inflows or outflows over time. In many cases, qualitative modeling, serves as a conceptual framework of the interactions of recognized parameters and is used to inform subsequent quantitative modeling and simulations with quantitative modeling tools such as STELLA or VENSIM [25], [26].

Overall, an SFD can be considered as an algebraic representation of a CLD. Then, to develop a quantitative SFD from a qualitative CLD, it is vital to numerically define each of the model parameters through formulas or direct numerical values. Because the quantitative relationships among various technical-economic indicators might be different due to the distinctive features of different operational metal mines, such as the geological conditions, mining, and mineral processing methods, it is necessary to extract adaptive equations from historical production data of the real case.

Figure 1 presents the main steps of this study based on the SD methodology. At the first step, the main problem is articulated. Then, technical-economic parameters are selected and described. Third, a conceptual framework is clarified through the CLDs based on recognized variables. Fourth, actual historical data for the system's variables are gathered from the real case of the Sanshandao gold mine, and formulas between any pair of variables are set to explain the SFDs. After modeling the CLDs and SFDs, the system is simulated for a reasonable period, considering the initial baseline values of the past data in step five. Then, the simulation results are validated to determine if the SD model represents the actual behavior of the system by comparing the output with past data. Finally, once the SD model is validated, simulation runs of scenario analysis and Monte Carlo sensitivity analysis can be made to analyze and forecast system behavior. Moreover, this method can provide scientific guidance for the sustainable development of other operational metal mines.

To simulate the SD model, computer support is also needed. This paper built the SD model using the Vensim PLE 6.3 software, which is a simulation software for improving the performance of real systems. Vensim enables the causal tracing of structure and behavior and provides a user-friendly interactive interface with wide-ranging mathematical functions. Further, it has Monte Carlo sensitivity, optimization, and subscripting capabilities [27].

III. SYSTEM DYNAMICS MODEL DEVELOPMENT

A. PARAMETERS IDENTIFICATION

Before the construction of the CLDs, some key parameters that could affect the mining production and operation systems are summarized in the form of the expert investigation method, as shown in Table 4 in Appendix A, along with their symbols, units, categories, and types. The categories of these parameters, including geology, mining production, mineral processing, and financial, are chosen to enable a concise description of the processes in mining production and operation. The types of these parameters are classified as levels, rates, auxiliaries, and constants to prepare for the quantitative explanation of the influence mechanisms among these parameters. When the parameters only change over time and their values depend on other variables, they are classified as levels; when changes of the parameters cause direct changes to the levels, the parameters are classified as rates; auxiliaries are the parameters that determine the rate values over time; and constants are the parameters that change minimally during simulations. The experts who participated in this task have a professional background, a wealth of experience, and a good understanding of production and operation management in metal mines, which ensures that the parameters used in the SD model are scientific.

B. SYSTEM CONCEPTUALIZATION

System conceptualization can be explained with the CLDs and a brief description of each causal loop, which gives a graphical explanation of the system structure and its dynamic complexity. After identification of the parameters used in modeling, the blueprint of the SD model for technical-economic analysis supporting sustainable development in operational metal mines is presented in Figure 2, including significant subsystems and associated indicators among each subsystem.

The CLDs of four subsystems, as shown in Figure 3, are then used to analyze the causal loop relationships among the parameters in more detail. In each CLD, a positive link means that two variables change in the same direction, as denoted with a "+"; and a negative link means that two variables change in the opposite direction, as denoted with a "-". Further, a positive reinforcement loop, labeled by ⊕, has an even number of negative links, whereas a negative feedback loop, labeled by ⊖, has an uneven number of negative links.

A brief description of each subsystem and the associated casual loops is provided below.

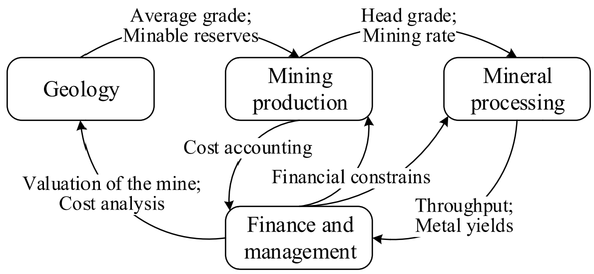

FIGURE 2. Blueprint of the SD model for technical-economic analysis in a working metal mine.

➢ Geology subsystem

Geological resources act as a "raw-material provider" in mining production and directly affects the survival and development of mining enterprises. Therefore, the parameters in the geology subsystem, such as the average grade, mineral reserves and mineable reserves, should reflect geological resources. Figure 3(a) presents the CLD of the geology subsystem. Although the most salient feature of an orebody lies in its inherent natural characteristics, there still exists some parametric uncertainty due to the option of the cut-off grade, as seen in Figure 3(a). For example, a lower cut-off grade will extend the ore boundary and increase mineral reserves, subsequently increasing the mineable reserves, mining rate and contained metal tonnage. Conversely, the average grade will as the cut-off grade decreases, leading to reduction of the contained metal tonnage.

➢Mining production subsystem

Losses and dilution are essential parameters to reflect the utilization of geological resources. Traditional technical-economic analysis often deems them as constants, which ignores the managerial flexibilities of geological resources. Therefore, in this paper, the influence of the cut-off grade on losses and dilution is incorporated to develop the CLD of the mining production subsystem. As shown in Figure 3(b), decreasing of the cut-off grade will improve the continuity of the orebody, which makes it feasible to improve the mining production strategy, reduce losses and dilution and increase the mineral reserves, mineable reserves and mining rate. Additionally, the mining rate is also constrained by the mining capacity.

The mined ore grade is a complicated situation. On the one hand, the average grade of an ore will decline as the cut-off grade decreases, which in turn will lead to a decline in the mined ore grade. On the other hand, an improved continuity of the orebody followed by the lower cut-off grade will reduce waste mixing and dilution as mentioned, and the mined ore grade will be improved.

➢Mineral processing subsystem

Figure 3(c) depicts the relationships among the parameters in the mineral processing subsystem. It is well documented that processing recovery is positively related to head grade. Considering the positive links between the cut-off grade and the mined ore grade and the assumption that head grade is equal to mined ore grade, a higher cut-off grade will cause

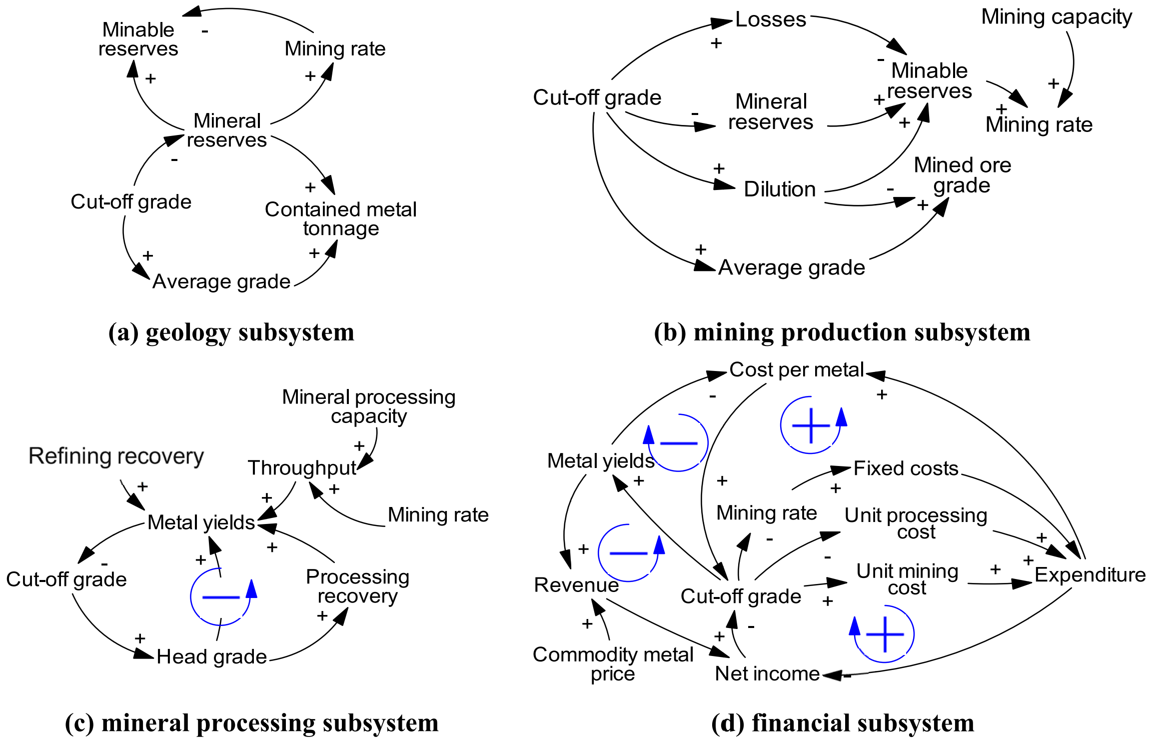

FIGURE 3. CLDs of four subsystems: (a) geology; (b) mining production; (c) mineral processing; and (d) financial.

an increase in processing recovery, which will further add the amounts of metal yields because it is the production of head grade, recovery, and throughput. Again, the increase of metal yields will promote the utilization of low-grade ores according to the detailed analysis of the following financial subsystem. Therefore, a negative feedback loop can be found in Figure 3(c).

➢Financial subsystem

The three subsystems mentioned above are integrated into the financial subsystem, as shown in Figure 3(d). This subsystem provides a comprehensive description of the performance and the combinatorial complexity of the causal interrelationships in mining production and operation systems. What can be found in Figure 3(d), there are two main positive reinforcement loops and six negative feedback loops, which are simplified as follows:

(1) Cut-off grade → (+) Unit mining cost → (+) Expenditure→(-) Net income→(-) Cut-off grade (⊕);

(2) Cut-off grade → (+) Unit mining cost → (+) Expenditure→ (+) Cost per metal→ (+) Cut-off grade (⊕);

(3) Cut-off grade →(-) Unit processing cost → (+) Expenditure→(-) Net income→(-) Cut-off grade (⊖);

(4) Cut-off grade →(-) Unit processing cost → (+) Expenditure→ (+) Cost per metal→ (+) Cut-off grade (⊖);

(5) Cut-off grade →(-) Mining rate → (+) Fixed costs→ (+) Expenditure→(-) Net income→(-) Cut-off grade (⊖);

(6) Cut-off grade→(-) Mining rate→ (+) Fixed costs→ (+) Expenditure→ (+) Cost per metal→ (+) Cut-off grade (⊖);

(7) Cut-off grade → (+) Metal yields → (+) Revenue→ (+) Net income→(-) Cut-off grade (⊖);

(8) Cut-off grade → (+) Metal yields →(-) Cost per metal→ (+) Cut-off grade (⊖).

C. QUANTITATIVE SYSTEM MODELING

Although the CLDs can describe the basic structure of feedback relationships, they cannot distinguish the differences among various parameters. Therefore, taking the CLDs of the four subsystems presented and explained above as a structural guide, an SFD, as shown in Figure 4, is constructed with the Vensim software to illustrate the accumulated reactions for different variables. Due to the size and complexity of this SFD, we have demarcated the model into two subsystems called production and operation management, respectively.

As SFD models are inherently quantitative, it was necessary to numerically define each of the model parameters through formulas or direct numerical values as following. It should be explicitly stated that all these parameters are quantified based on data generated from the actual production of the Sanshandao gold mine.

➢Equations in the production subsystem

$$Q = -1566.987g^2 + 2329.584g + 2616.236 \quad (1)$$

$$g_k = 0.682g^2 - 1.12g + 2.462 \quad (2)$$

A specific cut-off grade can yield the mineral reserves and average grade. This process can be easily implemented and regressed according to reporting data generated from the block model. Since 2010, the Sanshandao gold mine has

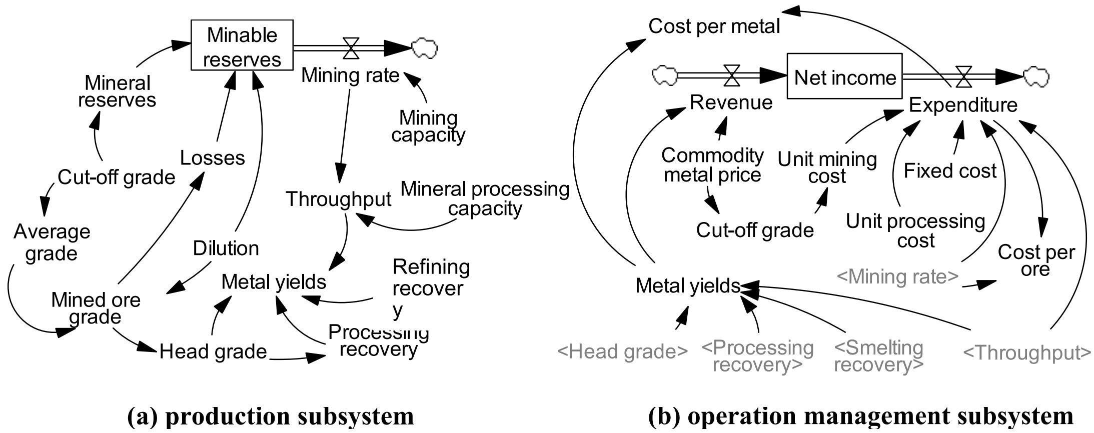

FIGURE 4. SFDs of the SD model for technical-economic analysis of the Sanshandao gold mine: (a) production; (b) operation management.

established a refined block model using 3D mining software, and this block model has played a useful role in guiding actual production. Therefore, Equations 1-2 are directly employed according to the reporting data of the block model used in the Sanshandao gold mine.

$$Q_d = \text{INTEG}(-M, Q \times (1 - \varphi * 0.01)/(1 - \rho \times 0.01)) \quad (3)$$

In Equation 3, the parameter of mineable reserves serves as one of the level variables. The mineral reserves, losses, and dilution can determine its initial value; if there is no new exploration project, the mineable reserves will decrease continuously at the speed of the mining rate until the reserves are depleted.

$$M = Q_m \quad (4)$$
$$g_m = g_k \times (1 - \rho \times 0.01) \quad (5)$$
$$\varphi = 1.669 g_m^2 + 0.682 g_m + 1.29 \quad (6)$$

Equation 6 is a regression equation ($R^2 = 0.784$) based on monthly data (2014-2016) generated from the actual production of the Sanshandao gold mine, which explains the mathematical relationship between the mined ore grade and losses.

$$g_h = g_m = g_k \times (1 - \rho \times 0.01) \quad (7)$$
$$H = \text{IF THEN ELSE}\,(M > Q_h, Q_h, M) \quad (8)$$

The relationship between the head grade and processing recovery is defined by regression analysis ($R^2 = 0.931$), as shown in Equation 9, based on monthly data (2014-2016) generated from the actual production of the Sanshandao gold mine.

$$r_h = -1.032 g_h^2 + 4.976 g_h + 88.483 \quad (9)$$

➢Equations in the operation management subsystem

$$C_m = 2.458 \times e^{1.753 \times g_m} \quad (10)$$

The variable of unit mining cost is estimated by Equation 10, which is resolved by a fitting analysis for the dates from 2015 to 2016, and the correlation (R^2) is 0.752.

$$C = M \times C_m + H \times C_h + F \quad (11)$$
$$G = g_h \times 10^{-3} \times H \times r_h \times r_S \quad (12)$$
$$R = G \times P/10 \quad (13)$$
$$N = \text{INTEG}\,(R - C, 0) \quad (14)$$
$$C_g = C/G \quad (15)$$
$$C_O = C/H \quad (16)$$

As mentioned in 3.2, an increase in metal yields will give rise to revenue and net income. Whereas, the net income and revenue are critically dependent on the metal commodity price in the context of a relatively stable production capacity in a working mine. Then, correlation and regression analysis are performed between the commodity metal price and the cut-off grade. Equation 17 shows the regression model, and the R^2 is 0.758.

$$g = 9.4961 \times e^{-0.0081 \times P} + 0.35 \quad (17)$$

Additionally, the constant values of the variables in the SD model, as summarized in Table 4 in Appendix A, are listed in Table 1. It can be seen that the dilution and unit processing cost change to be constant values although they are theoretically influenced by the cut-off grade because after statistical analysis of the monthly data (2014-2016) generated from the actual production of the Sanshandao gold mine, both dilution and the unit processing cost have always fluctuated at 4.45% and 54.03 ¥/t, respectively.

D. MODEL VALIDATION

Before one can analyze or use the results of a simulation model, it should be verified and validated. As Barlas [28] suggested, the ultimate goal in system dynamics model validation is to establish the validity of the structure of the model. The accuracy with which a model can reproduce real behavior is also evaluated, but this is meaningful only if

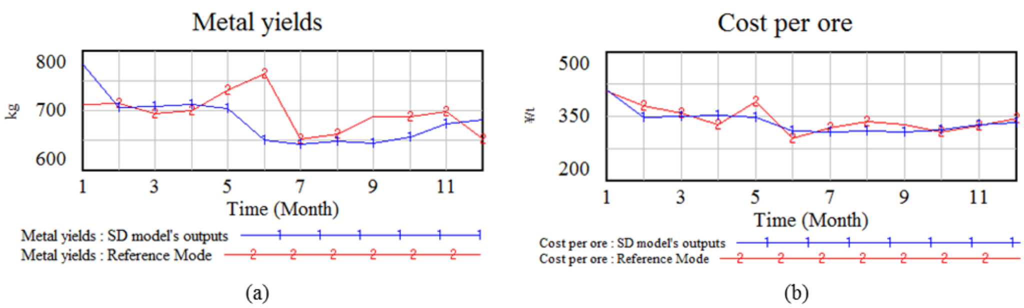

FIGURE 5. Comparisons of the SD model's outputs and reference modes: (a) Metal yields, (b) Cost per ore.

TABLE 1. Initial values of the relevant technical-economic variables of the Sanshandao gold mine.

Variables	Symbols	Units	Value
Mining capacity	Q_m	10^4t/month	34
Mineral processing capacity	Q_h	10^4t/month	34
Dilution	ρ	%	4.40
Unit processing cost	C_h	¥/t	54.03
Refining recovery	r_s	%	97.60
Fixed costs	F	10^4¥/month	5712.91

TABLE 2. Commodity gold price (¥/g) fluctuations in 2016.

Month	Commodity price	Month	Commodity price
1	236.31	7	285.75
2	256.72	8	282.63
3	256.1	9	284.79
4	255.05	10	278.81
5	256.96	11	267.58
6	281.72	12	264.34

we already have sufficient confidence in the structure of the model. Therefore, two types of model validation methods are used in this paper to validate the developed model, namely, structure testing and behavior testing.

➢Structure testing

To verify the validity of the model structure, the model is validated using a parameter confirmation test, a structure verification test, and a dimensional consistency test. For the parameter confirmation test and the structure verification test, the parameters included in the model and the structure of all cause-and-effect chains of the CLDs in Figure 3 are based on expert opinions and a comprehensive analysis of empirical data, respectively. While for the dimensional consistency test, the model is verified using the Vensim software because it has a function to automatically verify the dimensions after defining the measurement units of all parameters. To summarize, the structure of the model developed in this paper is logical and closely represents the actual systems in operational metal mines.

➢Behavior testing

As the core validation test, a proper behavioral validation, that is, a behavioral reproduction test for a reference mode with a thorough statistical analysis, is used here to prove that the model's behavior is statistically correct. In this validation test, monthly metal yields and the cost per ore of the Sanshandao gold mine during 2016 are utilized as reference modes to test the capability of the SD model to precisely simulate the reality of mining production and operation. Simultaneously, the commodity gold price acquired from the SHANGHAI GOLD EXCHANGE is regarded as the initial input data and shown in Table 2.

Simulate the presented model in discrete time with a one-month time step, and the SD model's outputs of metal yields and cost per ore are compared with the reference modes.

As seen in Figure 5, there is good agreement between the simulation data and the actual cost per ore, and there are some differences between the simulation data and actual metal yields. Since there are many ways to statistically validate the significance of any differences between two datasets. Referring to Qudrat-Ullah and Seong [29], we choose the R-square (R^2) and the root mean square percentage error (RMSPE) as statistical validity indicators because they have more significant advantages in reliability, sensitivity, and other protection than the others. With regard to metal yields, the values of R^2 and RMSPE are 0.94 and 5.96%, respectively, whereas the values of R^2 and RMSPE are 0.95 and 5.07%, respectively, for the cost per ore. Overall, it can be concluded that there is remarkable consistency between the model simulations and the actual situation for the SD model presented in this paper.

IV. MODEL SIMULATION AND ANALYSIS

An application of the proposed SD model is simulated in this section. The objective of this part is to understand how the dynamics of concern are generated in the production and operation of the Sanshandao gold mine and to then search for policies to support the sustainable development of the mine. Scenario analysis and stochastic analysis are used. Considering that the cut-off grade and the throughput are

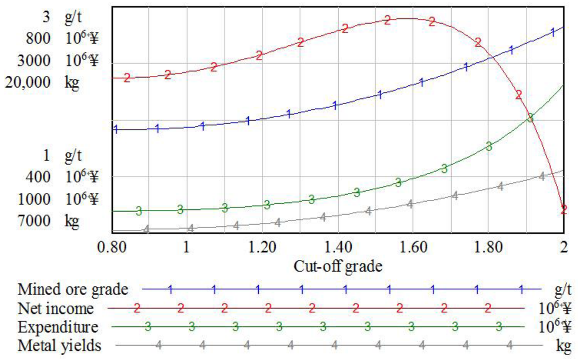

FIGURE 6. Simulation results of some key indicators under scenarios of different cut-off grades.

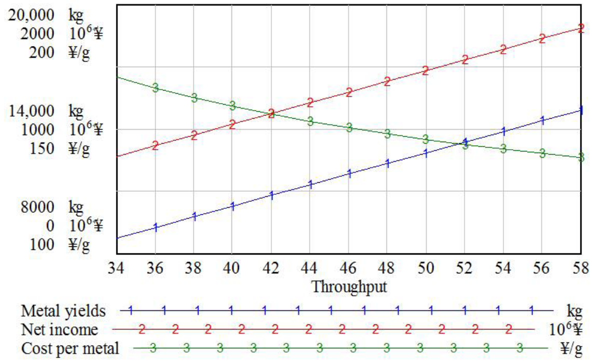

FIGURE 7. Simulation results of some key indicators under scenarios of different throughputs.

the key parameters affecting the performance of production and operation in an operational mine without considering market risk factors, there are two main types of scenarios in the scenario analysis. One type includes scenarios of different cut-off grades, and the other type includes scenarios of different throughputs. In addition, because the commodity gold price is the critical market factor affecting the economic benefits of a mine, stochastic analysis based on Monte Carlo simulation is also incorporated to clarify the uncertainty of the commodity gold price and its effects on the performance of mining production and operation. It is worth mentioning that simulation experiments need to be limited, and in order to isolate the consequences from the applied strategy, only a few parameters were changed while the other parameters were not manipulated.

A. SCENARIO ANALYSIS

➢Simulation results and analysis under scenarios of different cut-off grades

At present, the commodity gold price is nearly 260¥ /g. If the Sanshandao gold mine continues to operate on the scale of 34×10^4t per month, the simulation results under scenarios of different cut-off grades are exported by the proposed SD model. Some key indicators, such as the mined ore grade, metal yields, expenditure, and net income, which demonstrate the performance of mining production and operation, are selected and shown in Figure 6.

Three observations can be made from Figure 6:

(a) Overall, the mined ore grade, metal yields and expenditures will increase as the cut-off grade increases, which is consistent with the description of the CLDs in the system conceptualization. Therefore, in the case of a constant production scale, when the company needs to increase metal yields in order to achieve production goal, the cut-off grade needs to be increased correspondingly.

(b) There is a complicated development trend for net income along with the increase of the cut-off grade; namely, it will reach a peak value of 865.048 million yuan when the cut-off grade is equal to 1.61g/t, and then gradually decline. That is because net income is the difference between revenue and expenditure. In the case of constant commodity gold prices, revenue will also increase as the cut-off grade increases, considering the positive relationship between metal yields and the cut-off grade. Then, the net income will increase when the rate of revenue increase is larger than the rate of expenditure increase, and conversely, it will decrease. Based on the above considerations and under current market conditions, it estimated that when the cut-off grade is adjusted to 1.61g/t, Sanshandao gold mine will obtain a yearly maximum net income of 865.048 million yuan.

(c) According to the actual investigation, the current production and operation target of the Sanshandao gold mine is 8300kg of metal yields, with an annual profit of 7.68 billion yuan. Thus, under the condition of guaranteeing the realization of production and operation target, when the cut-off grade is set to 1.50g/t, Sanshandao gold mine can better realize the effective use of resources and support the sustainable development compared with the optimum cut-off grade mentioned in (b).

➢Simulation results and analysis under scenarios of different throughputs

In the case of a relatively constant commodity gold price, mining enterprises need enough metal yields to ensure higher profits. However, apart from adjusting the cut-off grade strategy, the throughput serves as another key variable to raise metal yields. Moreover, with the continuous progress of technology, the throughput can be increased to a certain extent under the existing production layout. According to the actual investigation, the throughput of the Sanshandao gold mine can be increased up to 58×10^4t per month. Simulate the proposed SD model with a commodity gold price of 260¥/g and an optimum cut-off grade of 1.61g/t, as derived from the simulation results under scenarios of different cut-off grades, Figure 7 presents the simulation results of the critical indicators and illustrate mining production and operating performance under scenarios of different throughputs.

From Figure 7, we can see that with the expansion of throughput, metal yields and the net income will gradually increase, whereas the cost per metal will correspondingly decrease. Therefore, to improve economic benefits, it is of

TABLE 3. Monte Carlo simulation of the commodity metal price and the corresponding variation ranges of the simulated results.

Group	Variation ranges of commodity metal price (¥/g)	Variation ranges of simulated results		Frequency
		Metal yields (kg)	Net income (10^6 ¥)	
1	235-240	9387.72-9135.93	503.91-578.79	10.87%
2	240-245	9135.93-8907.88	578.79-639.91	10.20%
3	245-250	8907.88-8701.74	639.91-691.01	11.80%
4	250-255	8701.74-8515.77	691.01-734.84	9.13%
5	255-260	8515.77-8348.34	734.84-773.41	9.27%
6	260-265	8348.34-8197.94	773.41-808.23	10.00%
7	265-270	8197.94-8063.13	808.23-840.42	10.47%
8	270-275	8063.13-7942.59	840.42-870.83	10.33%
9	275-280	7942.59-7835.10	870.83-900.09	9.20%
10	280-285	7835.10-7739.51	900.09-928.69	8.73%

great significance to realize economies of scale by enlarging the production scale. In addition, since simulation results under scenarios of different throughputs, as seen in Figure 7, have far exceeded the production and operation target mentioned above, it is possible for the Sanshandao gold mine to enlarge its throughput to exploit and utilize lower grade mineral resources and, thus, to improve the efficiency of resource utilization and to support sustainable development under the premise of guaranteeing the realization of the production and operation target.

B. STOCHASTIC ANALYSIS

The commodity metal price is also a critical parameter that affects technical-economic analyzation in the Sanshandao gold mine. It is necessary to analyze the variation ranges of the simulated results of the system to determine the effects of the commodity metal price. Since it is also influenced by factors such as supply and demand, monetary policy, and inflation outside the mining production and operation system described in this paper, a Monte Carlo simulation is conducted to study how the mining production and operation performance is affected by the uncertainty of the commodity metal price. We randomly generate 1500 inputs of individual commodity metal prices as their possible potential values changed from 235￥/g to 285￥/g for a set throughput of 34×10^4t per month. The results obtained from the stochastic analysis, as shown in Table 3, show that an increase in the commodity metal price will lead to a reduction of metal yields and a growth of net income, which is consistent with the description of the CLDs in the system conceptualization. Moreover, the expectation of metal yields and the corresponding net income are nearly 8427.45kg and 754.05 million yuan, respectively. That is, when the commodity metal price reaches approximately 255-260￥/g, the Sanshandao gold mine will achieve the operating goal under the current production strategy. If the commodity metal price rises or falls, the production strategy of cut-off grade and throughput should be adjusted accordingly based on an analyzation of the above simulated scenarios to achieve the production and operation target of Sanshandao gold mine.

V. CONCLUSION

In this article, we have introduced an system dynamics model for technical-economic analysis of operational metal mines. Taking the Sanshandao gold mine in China as an illustrative example, an SD model that is in line with the actual production of the mine is built, including qualitative modeling of the CLDs and quantitative modeling of the SFDs. The CLDs, which consist of four subsystems of geology, mining production, mineral processing and financial, can be used to analyze the causal relationships between the identified parameters. The SFDs are integrated based on four subsystems of the CLD, and their mathematical equations are excavated from historical data generated from the actual production of the Sanshandao gold mine. After the SD model is developed, it is validated with the actual trends of metal yields and cost per ore observed in 2016. The R^2 and RMSPE for metal yields are 0.94 and 5.96%, respectively, whereas the R^2 and RMSPE for the cost per ore are 0.95 and 5.07% respectively, illustrating the validation of the proposed model.

The focus of the paper is to show how the SD model can be used for decision-making to achieve the sustainable development of a mine while ensuring economic benefits. The modeling methods and research ideas proposed in this paper can provide a reference for decision-making to improve actual processes and to support the sustainable development of operational metal mines. The practical use of the SD model was illustrated with simulations under different scenarios. The scenario analysis showed the effects of the cut-off grade and throughput on mining production and operation performance. In addition, the Monte Carlo simulation makes dynamic stochastic assessment possible, clarifying the uncertainty of the commodity gold price and its effects on mining production and operation performance. Thus, production strategies, including the determination of the cut-off grade and throughput, can be formulated according to the

TABLE 4. Identification of key model parameters.

Symbols	Parameters	Units	Categories	Types
g	Cut-off grade	g/t	Geology	Auxiliaries
g_k	Average grade	g/t		Auxiliaries
Q	Mineral reserves	10^4t		Auxiliaries
Q_d	Minable reserves	10^4t		Levels
K	Contained metal tonnage			Auxiliaries
φ	Losses	%	Mining production	Auxiliaries
ρ	Dilution	%		Auxiliaries
g_m	Mined ore grade	g/t		Auxiliaries
M	Mining Rate	10^4t		Rates
Q_m	Mining Capacity	10^4t		Constants
g_h	Head grade	g/t	Mineral processing	Auxiliaries
H	Throughput	10^4t		Auxiliaries
Q_h	Mineral processing capacity	10^4t		Constants
r_h	Processing recovery	%		Auxiliaries
r_s	Refining recovery	%		Constants
G	Metal yields	Kg		Auxiliaries
C_m	Unit mining cost	¥/t	Financial	Auxiliaries
C_h	Unit processing cost	¥/t		Auxiliaries
F	Fixed costs	10^4¥		Constants
C	Expenditure	10^4¥		Rates
R	Revenue	10^4¥		Rates
P	Commodity metal price	¥/g		Auxiliaries
N	Net income	10^4¥		Levels
C_g	Cost per metal	¥/t		Auxiliaries
C_o	Cost per ore	¥/t		Auxiliaries

simulation results. To summarize, our approach is useful for improving the accuracy of technical-economic analysis for operational metal mines and enabling decision-makers to make more scientific production decisions.

Despite the value of our method, it has several limitations. On the one hand, the quantitative relationships among the technical-economic indicators might be different in different mining projects. In this case, the equations of the SD model should be carefully adapted. On the other hand, the uncertainty of geological resources considering prospecting projects is not discussed in this paper. To address this issue, we require an appropriate optimization model and a more complicated SD model, which are areas for future research.

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APPENDIX A

See Table 4.

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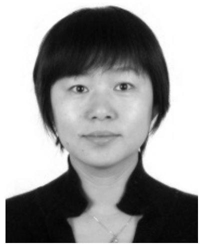

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