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A safety investment optimization model for power grid enterprises based on System Dynamics and Bayesian network theory

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ABSTRACT

In recent years, frequent large-scale power grid accidents have caused serious economic losses and bad social impact, which has drawn great attention from power grid enterprises. As one of the key elements of production, safety investment plays an important role in improving the safety level and reducing accident loss. In this paper, System dynamics (SD) and Bayesian network (BN) are integrated to develop a novel safety investment optimization model for power grid enterprises, which takes into account the impact of safety investment factors on accidents and the interactions between them. Based on sensitivity analysis, critical safety investment factors are determined to form the subsystem of the SD model. Subsequently, the optimal safety investment strategy is determined by a three-step simulation. The simulation results show that there are barrel effects and a diminishing marginal utility in safety investment. The proposed safety investment optimization model is practical to provide technical supports and guidance for determining an effective safety investment strategy in power grid enterprises.

1. Introduction

Although the reliability and flexibility of the power grid have been greatly improved, it still faces many new challenges and problems, such as the increasing risk of large-scale power outages due to the uncoordinated network sources, and the strengthening of the chain reaction caused by the failure of one component [1]. Both traditional and new risk factors from inside or outside of the grid pose more serious threats to the power system than ever before [2,3]. Disruptive grid accidents like blackout of the United States and Mexico in 2011, led to the 4300 MW generator out of operation, indirectly caused the traffic completely paralyzed in San Diego and border, nearly 4 million liters to sewage dumped into the sea directly, residents affected by the blackout accident total exceeds 5 million [4]. The Central China Power Regulation Sub-center of the State Grid analyzed more than 50 typical accidents from 2011 to 2015, characterized by a rapid chain reaction, wide coverage, and huge economic losses [1]. As is known to all, safety investment is an effective way for enterprises to avoid accidents and reduce economic losses [5-7]. Thus, the development of a scientific and reasonable safety investment strategy is the key step to ensure the safe production of power grid enterprises.

Safety investment is risk-oriented, slow-rewarded and invisible [8]. Since companies often face limited safety budgets, the economic issues of risk play an indispensable role in safety investment decisions [9]. There have been many studies on safety investment optimization in the past decades. With the gradual maturity of safety economics theory, the researches on investment optimization decisions have focused on reducing accident risks and minimizing investment costs. Bayesian network (BN) is proven as an effective tool to calculate the probability of accident risk, and can be extended to a limited memory influence diagram to select the most cost-effective safety measures [10]. The Bayesian decision-making network was used to multi-attribute decision analysis in the fields of real estate, chemical industry, construction, public health, etc., which can illustrate the causal connection of relevant factors [11,12]. Kim et al. [13] proposed a system state transition modeling method combining dynamic Bayesian network and functional modeling to improve the ability of risk-informed decision-making. For enterprises, under limited resources, how to save safety costs and determine the minimum value of safety investment is of great significance to sustainable development. Abrahamsen et al. [14] indicated the decision-making process of safety investment usually includes risk assessment and cost-benefit analysis. And they discussed the

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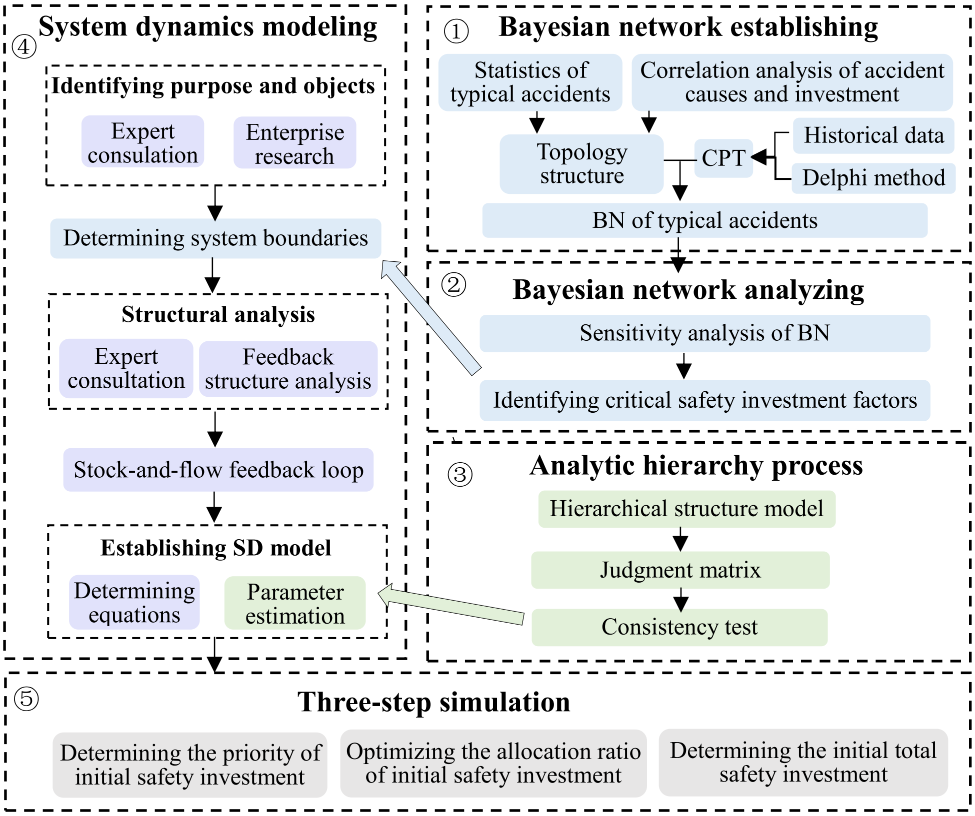

Fig. 1. The framework of the model

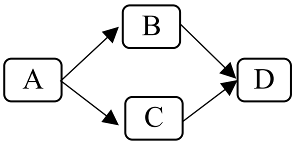

Fig. 2. A simple Bayesian network.

effectiveness of a framework for prioritizing safety measures based on the return of safety investment. Linear programming and analytic hierarchy process (AHP) are combined by Sato [15] to quantify accident risk and determine the minimum safety investment budget planning. The framework of the traditional AHP is optimized by Abrahamsen et al. [16] to guide the chemical safety investment to realize a better allocation of resources. Due to the uncertainty of the risk of the power grid, the safety investment for the power grid is indirect, slow-rewarded, complex and dynamic with nonlinear feedback. The above methods can't take into account the integrity of the safety investment system and the correlation between the various safety investment factors, so they could not well achieve the optimization of power grid safety investment.

The System dynamics (SD) method is suitable for high-order, nonlinear, and multi-feedback time-varying dynamic systems, is attractive to solve the abovementioned defects of complex safety investment problems. SD originated in 1956, early used in industrial enterprise management to solve the problem of a dynamic information feedback system [17]. SD can provide an effective modeling platform for

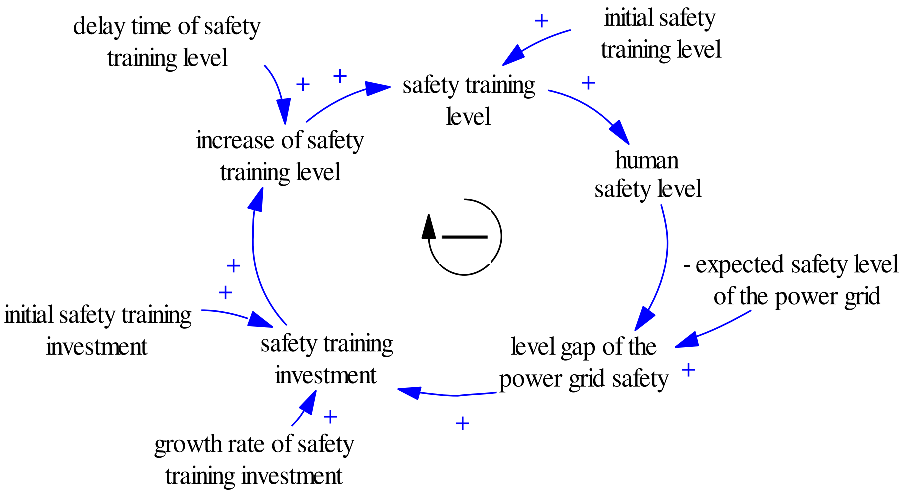

Fig. 3. The causal-loop diagram of safety training investment.

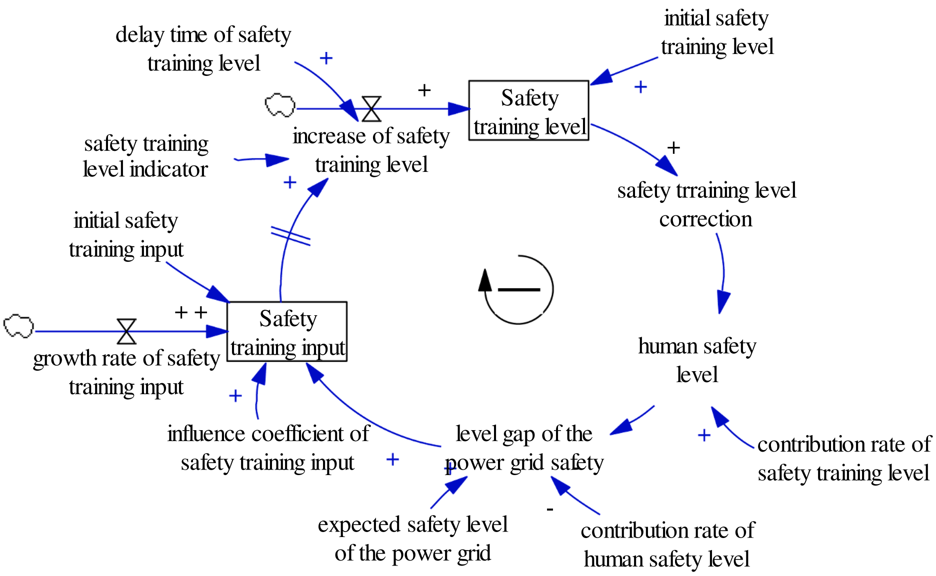

Fig. 4. The stock-and-flow diagram of safety training investment.

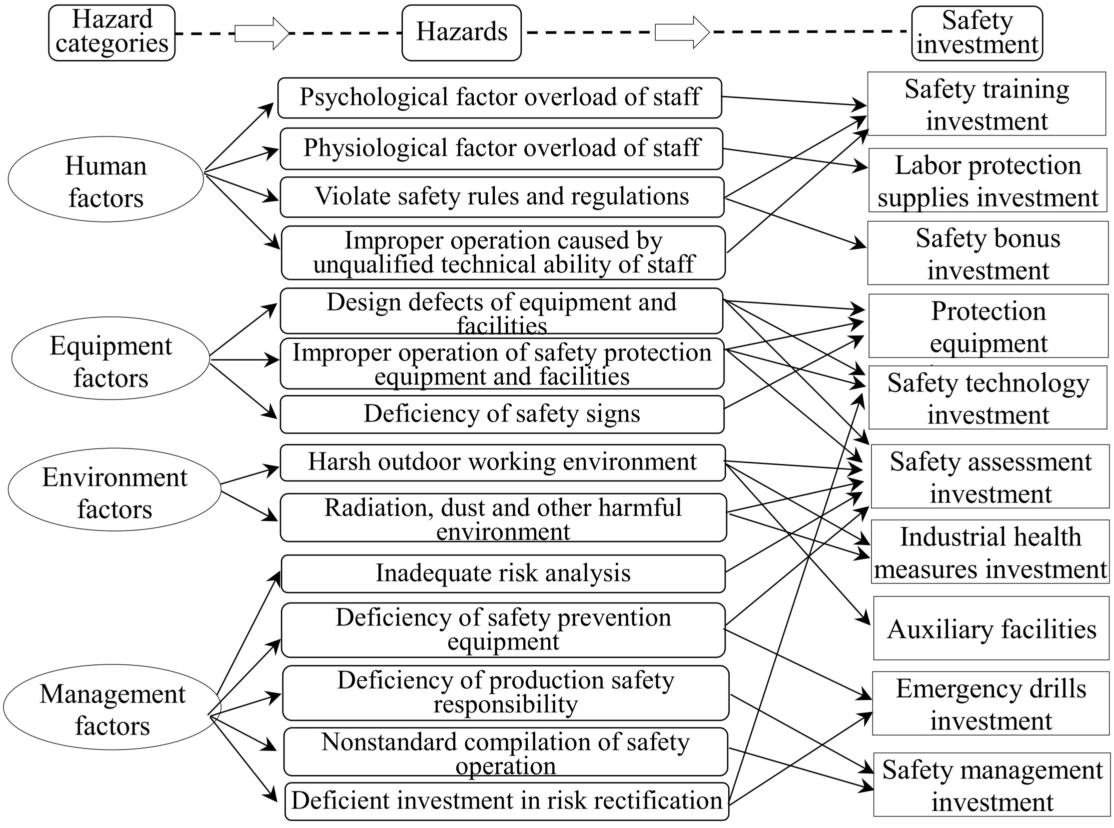

Fig. 5. The correlation of accident cause and safety investment

the analysis of safety investment decisions. With the development of SD theory, it has been gradually used in the research of power industry investment strategy. He et al. [18] pointed out that investment optimization is an effective way to match power grid resources and investment demand. With the emerging of renewable energy generation, some scholars have studied the impact of different incentive policies on the investment in power expansion planning [19-21]. In addition, based on the SD method of different scenarios, some scholars analyze the reasonable investment of electric power enterprises with different market environments [22, 23]. Some of these SD models aimed to simulate the effects of different investment strategies under specific influencing factors, and some were more suitable for investment analysis of specific systems. Overall, there is still a lack of a dynamic investment analysis model which allows addressing the safety problems of power grid system to improve the overall safety level. Hence, it is essential to develop an integrated investment optimization method to identify the critical investment factors and determine the optimal investment strategy according to the specific expectation.

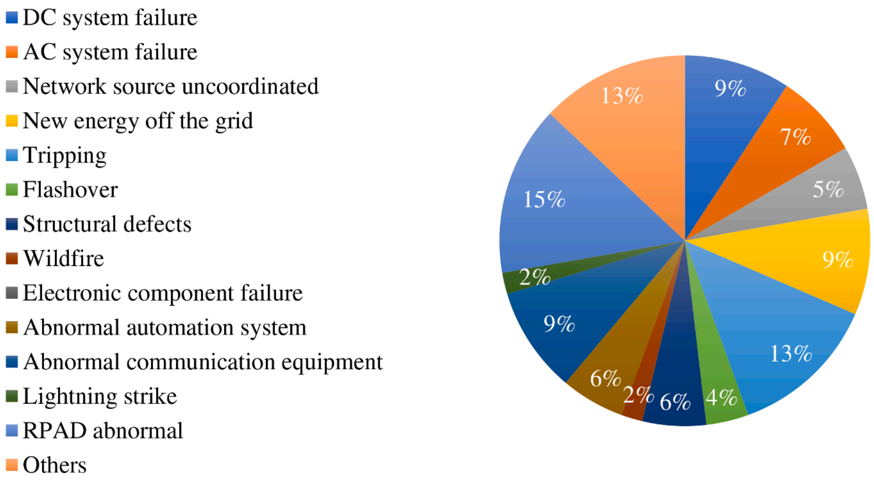

Fig. 6. Classified statistics of typical power grid accidents

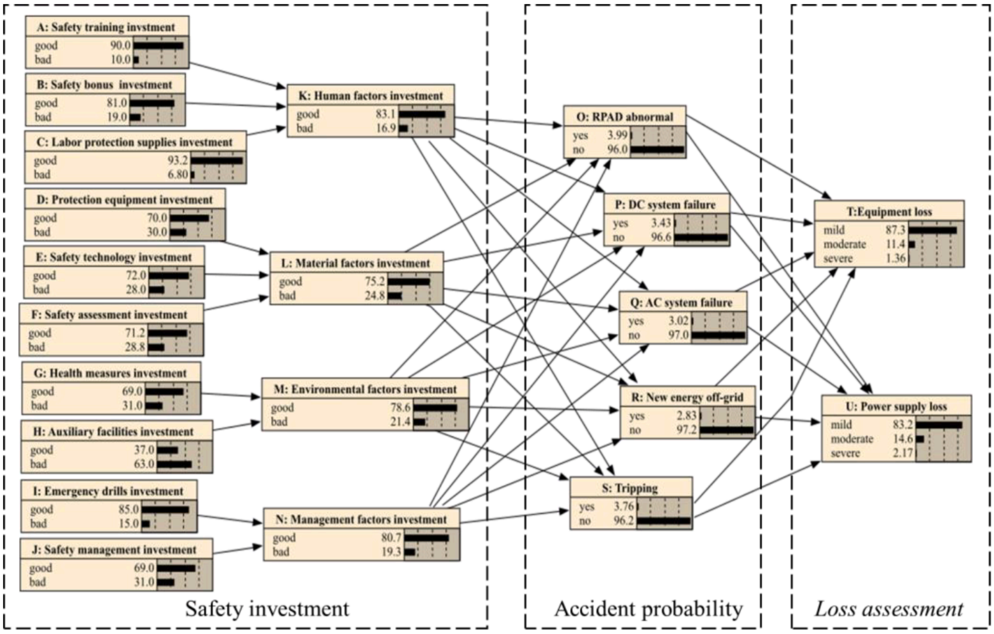

Fig. 7. BN of typical accidents in the power grid

Integrating BN, SD, and AHP, this paper establishes a safety investment optimization model for power grid enterprises. Section 2 briefly introduces technical framework of this paper and the methodology. Section 3 applying BN to identify the critical safety investment factors to determine subsystems of SD. Section 4 establishes the SD model for safety investment optimization. Section 5 determines the optimal safety investment strategy according to a three-step simulation framework and summarizes the simulation results. The final section presents the conclusion and outlook.

2. Methodology

The safety investment optimization model of the power grid integrates BN, SD, and AHP. The model can identify the critical factors of accidents and simulate the operation of the safety investment based on five steps, as shown in Fig. 1: (1) Through statistics and the correlation analysis of accident causes and safety investments, the topology structure, prior probabilities, and conditional probability tables (CPTs) of BN are determined to form the BN. (2) Appling sensitivity analysis (SA) to identify the critical factors of the BN to determine key safety investment factors of the subsystem of SD. (3) The analytic hierarchy process (AHP) is applied to determine the uncertain parameters of the stock-and-flow feedback loop of SD. (4) the complete SD model of the power grid safety investment can be obtained by inputting the corresponding equations and parameters into the stock-and-flow diagram. (5) After setting the initial values of the SD model, the optimal safety investment strategy can be determined by a three-step simulation.

2.1. Bayesian network

The economic system of the power grid is a complex and large system that includes various factors of the human-material-environment-management. Therefore, higher requirements are put forward for the establishment of scientific and rigorous models. If too many factors are taken into account, the model will be redundant and the boundary demarcation is not clear. But if the model is too general, there will be a large deviation from reality, which makes it difficult to ensure the scientific and rigor of the simulation results. Having a scientific and strict demarcation of system boundaries is the primary task of SD modeling. To overcome these issues, the BN is employed to determine the system

Table 1
Node definitions

Nodes	Node definitions
A: Safety training investment	It is the cost to improve the safety knowledge, skills, and quality of staff, including pre-job safety training for employees, safety education for operators, safety training for special types of work, and so on.
B: Safety bonus investment	It refers to the research fund provided for researchers to improve the safety and reliability of enterprise systems and the safety bonus paid to motivate employees' safety behaviors.
C: Labor protection supplies investment	The expenditure for purchasing insulating clothing, insulating cap, insulating gloves, and other protective supplies.
D: Protection equipment investment	It refers to the investment in the improvement, renovation, and maintenance of safety protection equipment and facilities.
E: Safety technology investment	It includes improvement of process, adoption of new technology and new products, reduction of labor intensity and improvement of productivity, etc.
F: Safety assessment investment	The cost of assessment and inspection by experts hired to ensure the normal operation of safety production and identify the weak links (defect and aging of power grid equipment).
G: Health measures investment	It refers to the cost of all measures taken to prevent environmental pollution (radiation, radioactivity, etc.), such as mufflers, radioactive source shielding, and other equipment and facilities.
H: Auxiliary facilities Investment	Investment of equipment and facilities such as heating rooms, fire prevention, and flood control for open work in extreme circumstances.
I: Emergency drills investment	For avoiding unexpected accidents, the expenses incurred for emergency drills including emergency rescue materials and special tools reserved.
J: Safety management Investment	The cost of compiling safety regulations, information warnings, and other measures for behavior control and the salary of full-time safety management personnel.
T: Equipment loss	The equipment loss caused by the accident below 10 million yuan is defined as "mild"; Above 10 million yuan and below 50 million yuan is defined as "moderate"; More than 50 million yuan is defined as "severe".
U: Power supply loss	The power supply loss caused by the accident below 10 million yuan is defined as "mild"; Above 10 million yuan and below 50 million yuan is defined as "moderate"; More than 50 million yuan is defined as "severe".

boundaries to support SD modeling. With a flexible structure and the ability to dynamically update probability, BN is widely used in the modeling of complex systems [24-26]. This paper makes full use of the backward diagnosis function of the BN and identifies critical safety investment factors for typical grid accidents by SA.

BN is known as a belief network, which is a kind of directed acyclic graph, consists of nodes, directed arcs, and conditional probability tables [27]. The nodes are divided into parent and child nodes according to causality [28,29], and the conditional probability table (CPT) is used to determine the probabilistic correlation of the variables, which is generally obtained from expert experience and literature data [30]. Fig. 2 shows a simple BN consisting of four nodes. The principle of the BN is the Bayesian theorem and probability theory, so it has a powerful probabilistic inference function [31]. Bayes' theorem formula is shown as Eq. (1).

$$P(AB)=\frac{P(B|A)P(A)}{P(B)} \tag{1}$$

Where $P(A/B)$ is the posterior probability of A under the observed data B, $P(A)$ Is the prior probability, and $P(B)$ is the Marginal likelihood. BN enables us to update the prior probability of variables and generate the posterior probability when new information or evidence is observed [32]. Because of the conditional independence of node variables, the conditional probability distribution of node variables can be obtained, which is shown as Eq. (2). Where $P(X_1, X_2, \ldots\ldots X_n)$ represents a set of variables (nodes of BN). Based on the joint probability formula, the marginal and conditional probabilities of each variable can be calculated.

$$P(X_1,X_2,\ldots\ldots X_n)=\prod_{1}^{n}P\left(\frac{X_i}{Parent(X_i)}\right),\ i=1,2,\ldots,n \tag{2}$$

2.2. System dynamics

The concept of SD comes from the industrial dynamics which arose from Forrester at the Massachusetts Institute of Technology, and he pointed out that this method could be used for long-term decision modeling [33]. SD holds that the behavior characteristics and patterns of a system mainly depend on its internal feedback mechanism and dynamic structure, and emphasizes dynamics, system, feedback [34,35]. For decades, SD theory has been widely applied in ecology, management, economics, and other fields [36-38]. In recent years, some scholars have used SD theory to improve the reliability of power systems. Senkel et al. [39] used SD to simulate and evaluate the resilience of the energy system, which can measure the effectiveness of modification with quantified the resilience benefit. Liu et al. [40] applied the SD method to explore the dependence among the performance shaping factors in the risk-human reliability analysis of nuclear power plants. The main concept of SD is to fully understand the feedback and dynamic characteristics of the system and to establish the structural pattern of its system according to certain steps [41]. SD includes a causal-loop diagram and a stock-and-flow diagram, as shown in Fig. 3 and Fig. 4, which illustrate how the safety training investment influenced the safety level of the power grid. The former can qualitatively describe the relationship between variables, while the latter quantifies variables with formulas

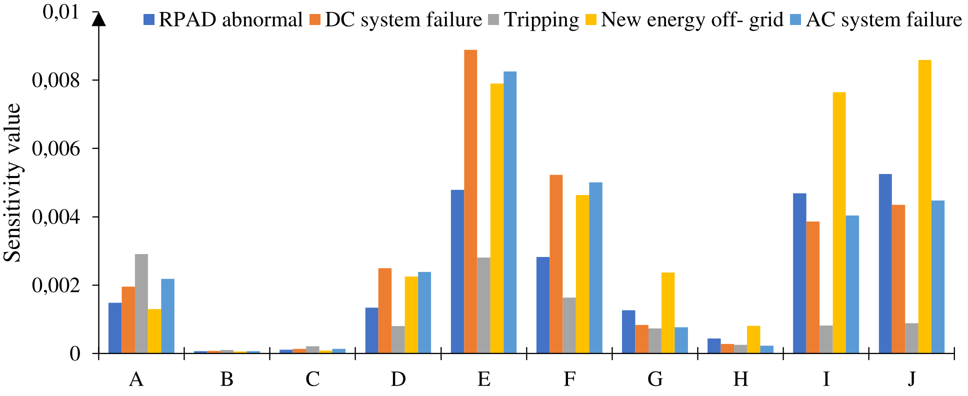

Fig. 8. Sensitivity analysis of typical accidents in the power grid

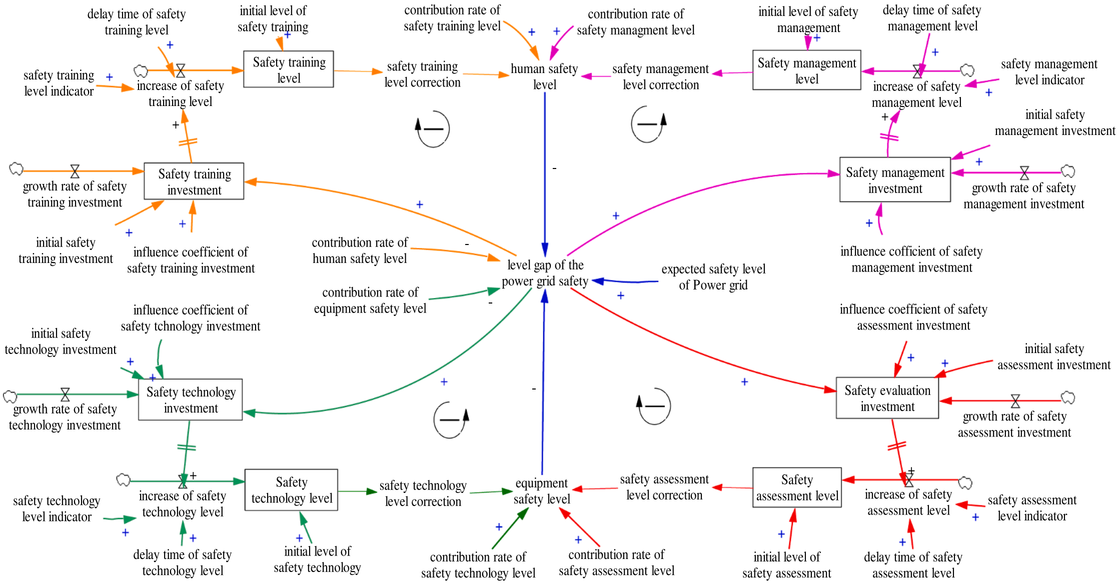

Fig. 9. Stock-and-flow diagram of power grid safety economy system

[17]. Therefore, it is a system modeling method that can achieve quantitative processing of qualitative information.

The causal chain is composed of arrows and polarities, indicating the transmission and feedback of information, while the positive and negative signs indicate that the effect between two elements is enhanced or weakened, i.e. positive feedback or negative feedback. The stock-and-flow diagram is further refined based on the causal-loop diagram. The variables are divided into four variables (horizontal variable, rate variable, auxiliary variable, and constant), and the corresponding equations and values are input through Vensim software (Dss8.1, Ventana Systems, Inc.) to form a complete SD model. There may be an equal sign along the causal chain to indicate that the actual information transmission is delay-rewarded.

3. Identification of critical safety investment factors

Based on the connection between accident occurrence and the status of safety investment, a BN of typical accidents in the power grid was established. Based on the posterior probability of the BN, the critical safety investment factors were identified by sensitivity analysis.

3.1. Safety investment factors analysis

The probability and severity of accidents can be effectively reduced by conducting safety investments based on the causes of typical accidents [42]. Thus, three safety managers, one safety engineer of power grid enterprises and a researcher were invited as consulting experts to conduct an in-depth analysis of the accident causes and summarize the relevant measures. In Fig. 5, the hazards were divided into human factors, equipment factors, environmental factors, and management factors. Possible abnormal situations were identified as “hazards”, and corresponding safety investment measures are put forward to avoid the situation.

3.2. Establishment of Bayesian network

Based on the statistics of typical grid accidents, 54 typical grid accidents that occurred from 2011 to 2015 were divided into 10 categories, as shown in Fig. 6 [1]. Among them, five typical accidents (each account for more than 9%) were selected as targets of the safety investment system (Fig. 7), including Relay protection and automatic device (RPAD) abnormal, DC system failure, AC system failure, new energy off-grid, and tripping.

The correlation diagram of accident causes and safety investment in Section 3.1 (Fig. 5) can be further mapped to the topology structure of BN. As shown in Fig. 7, based on the modeling framework of “safety investment-accident probability-loss assessment”, a four-level BN of typical power grid accidents was constructed. Ten safety investment factors of the power grid were determined as the parent nodes. Five typical power grid accidents determined by statistics in recent years were regarded as the sub-nodes of investment. Finally, the nodes of loss assessment were taken as the consequence nodes of BN, including equipment loss and power loss. The prior probability and CPT were obtained based on literature research and the Delphi method. The experts who participated in scoring included three safety managers and one safety engineer of power grid enterprises, and a researcher on safety management. All expert opinions were collected and further checked by calculating Cronbach’s Alpha (Eq.(3), Eq.(4)) to measure consistency (if so, the average of the five experts was used as CPT; If not, go back to the second step until the consistency is reached). There are some node definitions in Table 1.

3.3. Sensitivity analysis (SA)

The SA of BN can test the influence of the change of one variable to other variables [43]. Therefore, the SA of typical accidents can effectively identify the key safety investment factors that have a greater impact on typical accidents, to support the later system dynamics modeling. The sensitivity of grid safety investment factors to five accident nodes of RPAD anomaly, DC system fault, AC system fault, new energy off-grid, and tripping were respectively studied, as shown in Fig. 8. The two most sensitive safety investment factors to each typical accident were selected as subsystems of the SD model. For example, the investment factors with a greater impact on new energy off-grid accidents were safety technology investment (E) and safety management investment (J), which meant by improving the level of safety technology and safety management can effectively reduce the occurrence probability of new energy off-grid accidents. Therefore, safety training investment (A), safety management investment (J), safety technology investment (E), and safety assessment investment (F) were determined as the critical investment factors with a higher influence on the typical accidents in the power grid (Fig. 8).

Table 2
Model variable interpretations

Variable name	VariableType	Definition
Safety level of Subsystem *i*	Level	It includes the safety levels of training, management, technology, and assessment.
Safety investment of Subsystem *i*	Level	It includes four investment aspects: safety training, safety management, safety technology, and safety assessment.
Safety level increment of subsystem *i*	Rate	The growth rate of subsystems safety level.
Safety investment growth rate of subsystem *i*	Rate	The safety investment elements increase at a steady growth rate every month.
Influence coefficient of safety investment	Constant	It represents the relationship between the level gap of the power grid and the safety investment.
Safety level indicator	Constant	It illustrates the influence of increasing safety investment on the improvement of safety levels.
Delay time of safety training level	Constant	There is a time lag between increasing safety investment and safety level improvement.
Contribution rate of safety training level	Constant	The contribution of safety training level to the human safety level.
Contribution rate of safety management level	Constant	The contribution of safety management level to human safety level
Contribution rate of safety technology level	Constant	The contribution of safety technology level to equipment safety level
Contribution rate of safety assessment level	Constant	The contribution of safety assessment level to equipment safety level
Contribution rate of human safety level	Constant	The contribution of safety management level to human safety level
Contribution rate of equipment safety level	Constant	The contribution of safety management level to human safety level
Expected safety level of the Power grid	Constant	It is the power grid's desired target value of safety level.
Initial safety level	Constant	The initial safety level of the power grid without an initial investment.
Safety level correction of subsystem i	Auxiliary	Safety level correction is to limit the subsystem safety level according to the actual grid value.
Safety level gap of the Power grid	Auxiliary	The difference between the actual safety level and the expected safety level.
Equipment safety level	Auxiliary	It is a component of the power grid safety level, including the safety level of technology and assessment.
Human safety level	Auxiliary	It is a component of the power grid safety level, including the safety level of training and management.

4. Safety investment optimization model

The SA of BN was used to obtain the four critical safety investment factors that had the greatest impact on five typical power grid accidents. Taking the identified critical safety investment factors as the subsystems of the SD model. Then, the SD model of power grid safety investment optimization including four subsystems was established based on three steps: establishment of the stock-and-flow diagram, parameter estimation, and equation determination.

4.1. *Establishment of the stock-and-flow diagram*

As determined by SA, safety training investment, safety management investment, safety technology investment, and safety assessment investment were the four critical factors of typical accidents, which constitute the power grid safety economic system. To deeply reveal the complex relationship between the investment factors and the safety level, the stock-and-flow diagram of the power grid safety economic system was constructed, as shown in Fig. 9, which contained four sub-loops that are negative. By taking safety training subsystem as an example, the feedback loop can be described as Level gap of the power grid (+)→Safety training investment (+)→Increase of safety training

Table 4
Equations of the SD model.

Variable name	Variable type	Equation
Safety level of Subsystem *i*	Level	INTEG (increase the safety level of subsystem *i*, initial safety level value of subsystem *i*)
Safety investment of Subsystem *i*	Level	INTEG (growth rate safety investment of subsystem *i**influence coefficient of subsystem *i* *level gap of Power grid safety, initial safety investment of subsystem *i*)
Increase safety level of subsystem *i*	Rate	SMOOTH {safety investment of subsystem *i**safety level indicator of subsystem *i*, delay time of safety level}
Growth rate of subsystem i	Rate	0.2
Safety level correction of subsystem i	Auxiliary	IF THEN ELSE(100<=Safety training level, 100,Safety training level)
Human safety level	Auxiliary	WITH LOOKUP (contribution rate of safety management level*safety management level correction + contribution rate of safety training level*safety training level correction, [(60,60)-(90,100)], (60,63), (65,67), (70,73), (75,76), (78,80), (80,82), (82,83), (84,86), (86,87), (88,89), (90,90))
Equipment safety level	Auxiliary	WITH LOOKUP (contribution rate of safety assessment level*safety assessment level correction + contribution rate of safety technology level*safety technology level correction, [(60,60)-(90,90)], (60,60), (65,61), (68,65), (70,72), (75,78), (78,81), (80,86), (83,87), (85,88), (87,89), (90,90))
Level gap of power grid safety	Auxiliary	IF THEN ELSE (0>=expected safety level of the Power grid-(contribution rate of equipment safety level*equipment safety level + human safety level*contribution rate of human safety level), 0, expected safety level of the Power grid- (contribution rate of equipment safety level*equipment safety level + human safety level*contribution rate of human safety level))

Table 3
Weight distributions of power grid safety level contribution rate

Target layer	Contribution rate for Power grid safety level		Contribution rate forHuman safety level		Contribution rate forEquipment safety level	
Safety level	Human	Equipment	Safety training	Safety management	Safety technology	Safety assessment
Expert.1	0.167	0.833	0.25	0.75	0.875	0.125
Expert.2	0.25	0.75	0.125	0.875	0.875	0.125
Expert.3	0.167	0.833	0.25	0.75	0.833	0.167
Expert.4	0.25	0.75	1	1	0.9	0.1
Expert.5	0.125	0.875	1	1	0.833	0.167
Weights	0.1867	0.8133	0.3789	0.6211	0.865	0.135

Table 5
Safety investment from 2012 to 2017.

Safety investment (10,000 CNY)	Safety training	Safety management	Safety technology	Safety assessment
2012	3202	12042.6	2819.2	104.4
2013	3474.7	13068.1	3059.2	113.3
2014	4322.6	16256.8	3059.3	140.9
2015	4585.7	17246.8	3805.8	149.5
2016	5460	20534.5	4037.5	178
2017	5471.7	20579.1	4817.2	178.4

1CNY=0.1545USD
1CNY=0.1302EUR

level (+)→Safety training level (+)→Human safety level (+)→Level gap of the power grid (-). A plus sign indicated an increase in the effect, while a minus sign indicated a decrease in the effect. The greater the power grid safety gap, the more safety training investment is needed, which led to a higher level of safety training, and the improvement of the safety training level led to the improvement of human safety level, thereby reducing the level gap of the power grid safety level. There were 50 variables in the stock-flow diagram, and the description of all variables is introduced in Table 2. detailed.

4.2. Parameter determination

There are four types of variables in the stock-and-flow diagram, which are horizontal variables, rate variables, auxiliary variables, and constants. To simulate the SD model, it is necessary to determine the variables and equations of the stock-and-flow diagram. In addition to the constant variables, the other three variables can be determined by mathematical logic relations. Some constants can be obtained from the real power grid (such as delay time of safety level, the expected safety level of the power grid, etc.). However, some variables are uncertain constants, which are difficult to be quantified (such as contribution rate of safety level, impact coefficient of safety investment, safety level indicator, etc.). To solve this issue, parameter estimation is applied.

In this paper, Analytic hierarchy process (AHP) was adopted to determine the contribution rate of safety levels. AHP was first proposed in the mid-1970s by Thomas Saaty [44]. In general, AHP follows four basic steps: modeling, scoring, prioritizing, and synthesizing [45]. We invited three safety managers and one safety engineer of power grid enterprises, and a researcher on safety management to score the contribution rate of safety level (Table 3). To determine the consistency of all experts' scoring opinions, we use the variation coefficient and Cronbach's alpha, as shown in Eq. (3) and Eq. (4). If the Cronbach's alpha is greater than 0.8, the expert opinion is considered consistent; otherwise, the grading should be repeated until the Cronbach's alpha is greater than 0.8.

$$V_i = \frac{\delta_i}{\overline{X}_i} \tag{3}$$

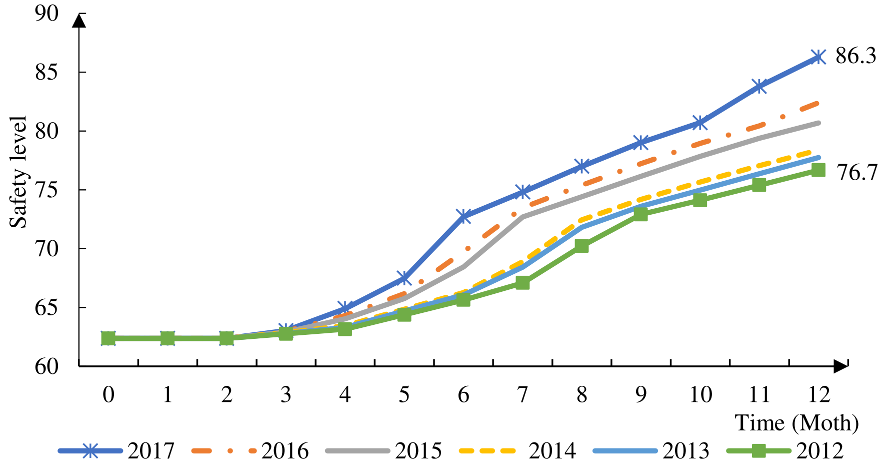

Fig. 10. Predicted Power grid safety level from 2012 to 2017

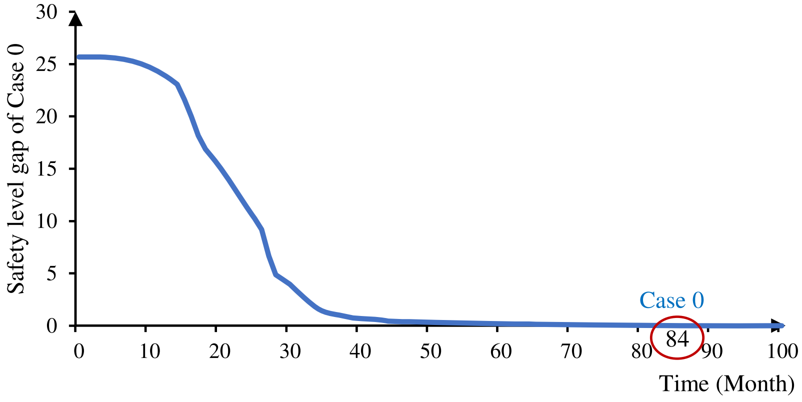

Fig. 11. Power grid safety level gap without an initial investment

Table 7
Single initial safety investment allocation strategy

Cases	Safety investment (10,000 CNY)			
	Safety training	Safety management	Safety technology	Safety assessment
Case 1	10	0	0	0
Case 2	0	10	0	0
Case 3	0	0	10	0
Case 4	0	0	0	10

1CNY=0.1545USD
1CNY=0.1302EUR

$$\alpha = \frac{K}{K-1}\left(1-\frac{\sum_{i=1}^{k}\sigma^2 Y}{\sigma^2 X}\right) \tag{4}$$

Where, "V_i" and "δ_i" represent the variation coefficient and standard deviation of problem "i" respectively. "$\sigma^2 X$" represents the variance of all expert scores, "$\sigma^2 Y$" represents the variance of scores for specific problems, "k" represents the number of problems, if "α" is greater than 0.8, experts are considered to agree. Then the square root method was used to determine the weight. Eq. (5) showed the square root method and the results were shown in Table 3.

$$W_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{\frac{1}{n}}}, \quad i = 1, 2, \ldots\ldots, n \tag{5}$$

Since the contribution rate of each subsystem is positively correlated with the influence coefficient of safety investment, 2/3 of the contribution rate is taken as the value of them. The safety level indicator and initial safety level are estimated by the Delphi method and Cronbach's alpha was used for the consistency test.

4.3. Equation determination

Based on the stock-and-flow diagram and parameter estimation, a complete SD model was established according to corresponding mathematical formulas for horizontal variables, rate variables, and auxiliary variables. The main SD model equations of the power grid safety economic system were shown in Table 4.

4.4. Model validation

As a large state-owned key enterprise, the organization structure of State Grid Corporation of China includes three levels, which are the State Grid headquarters, provincial subsidiaries, and prefecture subsidiaries. In this study, we have collected the safety investment data from 2012 to 2017 of one provincial subsidiary for model verification. According to the classification of safety production cost of the provincial subsidiary, it mainly includes four parts, i.e. safety education and training investment, safety management expenditure, safety equipment and new technology cost, hazard identification and safety assessment cost. After statistical analysis of the given data, the provincial subsidiary's safety investment status from 2012 to 2017 are summarized in Table 5.

The run of SD-BN safety investment optimization model requires initial parameter settings. According to the given safety investment data of provincial subsidiary (see Table 5), the initial parameters are set as follows. (1) Whole simulation lasts for 12 months; (2) Every simulation step lasts for 1 month; (3) The growth rate of the safety investment is 0.1; (4) The initial safety level is 62; (5) The target safety level is 90. In other words, there is no need to increase safety investment after the safety level reaches 90. The simulation results are shown in Fig. 10.

The model simulation results (see Fig. 10) showed that the safety level of the provincial subsidiary increased year by year with the increase of the total safety investment from 2012 to 2017, which qualitatively and quantitatively verify the model's prediction reasonability of safety investment. Furthermore, from the real decreasing accident economic loss and casualty of the provincial subsidiary from 2012 to2017, it also reflects the simulation safety performance results are consistent

Table 8
Safety investment allocation strategy

Cases	Safety investment (1,000,000 CNY)			
	Safety training	Safety management	Safety technology	Safety assessment
Case 5	30%	40%	10%	20%
Case 6	25%	45%	10%	20%
Case 7	35%	40%	5%	20%
Case 8	25%	40%	15%	20%
Case 9	35%	40%	10%	15%
Case 10	30%	45%	5%	20%
Case 11	30%	35%	15%	20%
Case 12	30%	45%	10%	15%
Case 13	30%	35%	10%	25%
Case 14	30%	40%	5%	25%

1CNY=0.1545USD
1CNY=0.1302EUR

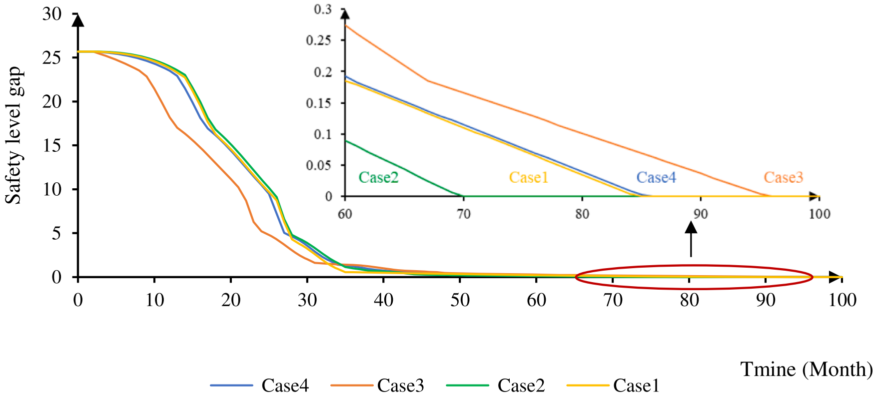

Fig. 12. Safety level gap of single initial safety investment

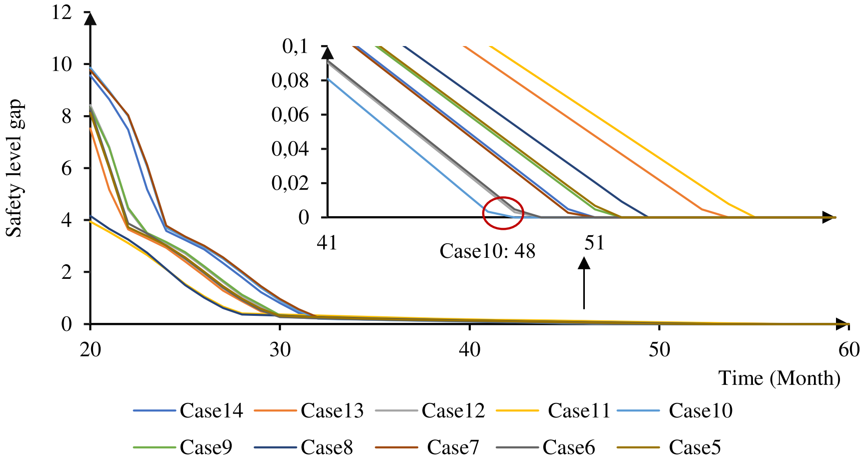

Fig. 13. Power grid safety level gap of different allocation strategies

Table 9
The initial total safety investment strategy

Cases	Safety investment (100,000 CNY)				
	Initial total safety investment	Safety training	Safety management	Safety technology	Safety assessment
Case 15	60	18	27	3	12
Case 16	100	30	45	5	20
Case 17	140	42	63	7	28
Case 18	180	54	81	9	36
Case 19	220	66	99	11	44
Case 20	260	78	117	13	52
Case 21	300	90	135	15	60
Case 22	340	102	153	17	68
Case 23	380	114	171	19	76
Case 24	420	126	189	21	84
Case 25	460	138	207	23	92
Case 26	500	150	225	25	100
Case 27	540	162	243	27	108
Case 28	580	174	261	29	116
Case 29	620	196	279	31	124
Case 30	660	198	297	33	132

1CNY=0.1545USD
1CNY=0.1302EUR

with the actual safety situation records, which further demonstrates the model is reasonable.

5. Case study

The SD model can simulate different safety investment strategies and obtain safety performance. The decision-maker may change the allocation proportion of safety resources or increasing the initial safety investment to reach the expected safety level. Thus, the SD model take initial safety investment as the independent variable and the gap of power grid safety level as the dependent variable. When the simulation result reaches the expected safety level of the power grid enterprise, the gap of the power grid safety level is 0. In the past few years, the safety operation of small-scale Power Grid enterprises (i.e. prefecture subsidiaries of State Power Grid) have drawn more attention. Therefore, next taking a prefecture subsidiary of State Grid as an example to derive the optimal safety investment strategy with three-step simulation.

As a reference, case 0 takes 84 months to reach the expected safety level without any initial safety investment (seen in Fig. 11). The three-step simulation scheme is presented as follows. Step 1: determine the priority of initial safety investment factors. Step 2: optimize the allocation ratio of initial safety investment. Step 3: determine the initial total safety investment. Through the three-step simulation, the minimum initial total investment and the optimal investment allocation strategy can be obtained. Initial parameters: (1) Whole simulation lasts for 100 months. (2) Every simulation step lasts for 1 month. (3) The growth rate of the safety investment is 0.2. (4) The criterion of the top safety level is 90. When the gap between the safety level of the power grid is 0 in the simulation results, it means that the safety level of the power grid reaches the expected safety level of 90. In other words, there is no need to increase investment in this case.

5.1. *Determine the priority of initial safety investment factors*

In step 1, when the total initial safety investment is constant, the ranking of investment allocation is obtained according to the simulation results of a single initial safety investment. Table 7. lists four investment scenarios. From cases 1 to 4, only one safety investment factor is selected, and the rest investment factors are all 0. Fig. 12 shows the simulation results, the ordinate is the gap of the expected safety level of the power grid, and the abscissa is the time. It is obvious that the shorter the time to reach the expected safety level, the more important the safety investment is to the safety level of the power grid.

Invest all the initial investment of 100,000 CNY in one element. The simulation results (Fig.12) show that the investment in safety management is the first to reach the expected safety level, indicating that safety management is the most important investment factor, followed by safety training, safety assessment, and safety technology.

By comparing the results in Fig.12 (case 1-4) and Fig.11 (case 0), it is found that the time reaching the expected safety level when the initial investment is zero is similar to that when investing in one single target. This indicates that the improvement of the safety level of the power grid is the result of the synthesis of the improvement of the four sub-systems safety level, and the improvement of a single item's safety level cannot shorten the time for the power grid to reach the expected safety level. Therefore, the safety investment of the power grid should pay attention

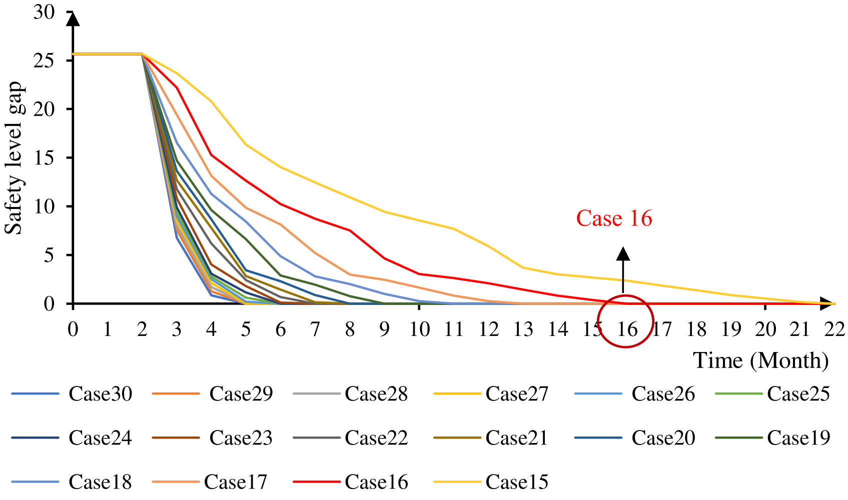

Fig. 14. Safety level gap under different initial total safety investment

to comprehensiveness, from both human and equipment aspects promoting the improvement of power grid safety level jointly.

5.2. *Optimizing allocation ratio of initial safety investment*

In step 2, the investment allocation ratios are refined based on step 1 to determine the relatively optimal investment strategy. The simulation results of step 1 only determine the importance of each safety investment element, but can’t get a specific safety investment plan. Make a preliminary investment allocation to the initial total investment (1,000,000 CNY) in case 5, which is 40%, 30%, 20%, and 10% according to the degree of importance. To refine the allocation proportion of safety investment, the total initial investment amount remains unchanged based on Case 5, and the simulations are conducted from case 6 to case 14, as Table 8. shows.

The simulation results are shown in Fig. 13, when the total initial safety investment is constant, the allocation proportion of case 10 can make the power grid reach the expected safety level in the shortest time. Thus, the allocation investment proportion of case 10 is the best, that is, the proportion of safety investment in training, management, technology, and assessment is 30%, 45%, 5%, and 20% respectively.

5.3. *Determine the initial total safety investment*

In step 3, different initial total safety investment is set and simulated with the optimal investment allocation ratio, then the minimum initial total safety investment meeting the expected time of the grid can be determined. According to the simulation analysis in Section 5.2, the optimal allocation proportion was obtained for a certain initial total safety investment. To achieve the expected safety level within 16 months, it is necessary to increase the initial total safety investment. Therefore, 16 cases of different initial total investments are proposed in this section (Table 9). The difference of initial total investment between adjacent cases is 4 million yuan, which is allocated according to the optimal investment ratio of case 10.

The simulation results are shown in Fig. 14. When the initial total investment is 10,000,000 CNY, the grid can achieve the expected safety level in 16 months. So, it can be concluded that when the grid expects 16 months to achieved safety level, the optimal investment strategy is 3,000,000 CNY for initial safety training, 4,500,000 CNY for safety management, 500,000 CNY for safety technology, and 2,000,000 CNY for safety assessment.

To analyze the simulation results (Fig. 14), the more initial safety investment, the shorter the power grid reaches the expected safety level. When the total amount of investment is small, the grid safety level ascending faster as increasing the initial safety investment. While the power grid safety level has reached a certain criterion, the investment will be less effective than before. For example, the initial safety investment increased by 44,000,000 CNY from cases 19 to cases 30, however, there are only five months shortened to reach the expected safety level. Besides, there is a step phenomenon in the simulation, which indicates that there is a time delay from the increasing investment to the safety level improved. Therefore, even if the initial safety investment is infinite, the safety level will remain stable in the first 2-3 months.

6. Conclusion

In this paper, a safety investment optimization model for power grid enterprises based on System Dynamics and Bayesian network is developed, and also a three-step simulation framework was proposed to obtain the optimal investment strategy. The reasonable results showed that the proposed safety investment optimization model is an effective tool for safety investment decision-making of power grid enterprises. The main conclusions are presented as follows:

(a) The proposed BN-SD integrated model and simulation schemes can dynamically update according to the new-coming data from power grid enterprises, which is effective to predict the effects of safety investment and examine the safety performance of the power grid enterprises.
(b) According to the sensitivity analysis of BN, it is found that safety training, safety management, safety technology, and safety assessment are the critical safety investment factors for power grid enterprises. These critical investment factors are used to build the structure of the SD model.
(c) When comparing the simulation results of single initial safety investment strategies, it indicates that there is a significant barrel effect. Thus, to improve the safety level of the whole power grid system, the level of all subsystems must be improved.
(d) Based on the three-step simulation analysis, it is found that the time to reach the expected safety level will be shortened by two-thirds if the initial safety investment is increased by ten times. Moreover, there was a phenomenon of diminishing marginal utility in this process, as the initial safety investment increases, the improvement extent of the safety level will decrease.

Overall, the BN-SD integrated safety investment optimization model for power grid enterprises complements the safety investment decision-making method. The optimal safety investment strategy can be determined through the BN-SD integrated model and the three-step simulation scheme, which can prevent typical power grid accidents and save safety resources. Meanwhile, the proposed safety investment optimization model allows being updated and improved by collecting more actual data from power grid enterprises in the future.

CRediT authorship contribution statement

Jiansong Wu: Conceptualization, Methodology, Writing – original draft, Funding acquisition, Supervision. **Linlin Zhang:** Software, Writing – original draft. **Yiping Bai:** Visualization, Writing – original draft. **Genserik Reniers:** Formal analysis, Writing – review & editing.

Declaration of Competing Interest

The authors declared that they have no conflicts of interest to this work

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