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Research on Multi-factor Coupling Analysis and Risk Warning of Operation Activity in Petrochemical Enterprises

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The Operation activity has always been the biggest threat to the safety of petrochemical enterprises. There is continuous dynamic interaction at operation area among operators/supervisors, machine and tools, hazard materials and the environment. Abnormal changes in any factor may lead to accidents. However, failure sequence of operation risk prevention measures is disordered in the evolution of operation accident. Thus, traditional static or sequential risk assessment methods are not suitable for this field, which restricts the assessment and control of operation risk. Therefore, this paper uses System Dynamics to construct a multi factor coupling feedback model for operation risk identification firstly, and describes the coupling and interaction relationship within the subsystems and between subsystems. Secondly, key indicators and corresponding monitoring techniques are determined, i.e., operators' unsafe behaviors, gas leakage and so on. Finally, Bayesian theory is adopted to fuse multi-source information collected by the monitoring techniques, and then assessment operational risk. What's more, a hierarchical early warning rule is built to determine the priority of risk control. This method can guide the realization of operation risk intelligent management and control.

Keywords: operation risk, system coupling analysis, multi-information fusion, monitoring and early warning.

1. Introduction

Operation activity has always been the biggest threat to the safety of petrochemical enterprises . The operation area of petrochemical enterprises is a dynamic intersection system of material, energy, and information, involving various potential risk factors such as personnel behavior, equipment and facilities, and operating environment. Any abnormal change in the system may cause system failures, presenting complex characteristics such as integrity, nonlinearity, and uncertainty, which makes it difficulty in risk control. Feng (2022).

The high coupling between risk factors makes it difficult to characterize the mechanism of accident occurrence. What's worse, operators may have uncertain actions which is affected by personal physical and mental condition and the work environment. And, failure sequence of risk prevention measures like safety belt and helmet, is disordered in the evolution of accident. Li et al.(2018), Skogdalen et al. (2011). Thus traditional sequential risk assessment methods, such as logical tree analysis, are unsuitable for this field.

In addition, the changes in personnel behavior and environmental conditions are difficult to perceive and quantify in real time, and the analysis process relies on the subjective experience of experts, resulting in large deviations in the analysis results. There is a continuous dynamic interaction process in the operation area, and static and qualitative risk analysis methods such as job safety analysis and fuzzy comprehensive evaluation cannot describe the above dynamic changes, which further restricts the accurate measurement and control of job risks.

Therefore, when evaluating operation risks, it is not only necessary to measure traditional, static, and shallow indicator such as “operation content” and "number of workers" in the site, but also to measure dynamic, deep-seated indicator oriented towards information networks such as "operators’ behavior" and "effectiveness of protective measures". Only through comprehensive collection and measurement of these indicators can we discover and grasp the evolution laws of operational risks, thereby curbing the occurrence of major accidents.

System dynamics was founded by Jay W. Forrester to study the changes of system morphology by constructing a causal loop feedback model.Zhang et al. (2023) Since the 1990s, it has been widely used in project management, coal mine safety, water resources safety, traffic safety and other fields. You et al. (2020) Huang, et al. (2020). The Bayesian theory is demonstrated as the best choice for accident modeling and quantitative risk assessment due to its updating and experience learning mechanisms, especially dealing with multiple states and uncertain problems. Villa et al.(2016)

Therefore, the authors tried to break through traditional static, scattered and subjective analysis approach by combining system dynamics and Bayesian theory and realize warning of operation risk. The operation area is compared to a big system with dynamic intersection among factors and adopt the system dynamics to analysis their interactions. With the development of intelligence, state changes of factors can be obtained by monitoring techniques, like video analysis. And then, Bayesian theory can be used to fuse these multi-source information and assess the operational risk. Chrysaitis and Seriès (2023)

2. Construction of Operation Risk Identification Feedback Model

2.1. *Risk Identification of Operation Risk*

According to the energy release theory and the theory of two kinds of hazard sources, human control energy and provide certain limitations and constraints to enable it to function within the expected range. An accident is essentially an uncontrolled energy that accidentally influences the human, machine, environment, etc. The source of primary hazard refers to energy or hazardous materials that may be accidentally released. The source of secondary hazard refers to various unsafe factors that lead to the failure or destruction of restraint and energy limiting measures, such as operators’ unsafe behaviors.

Operation risks mainly come from the frequent interaction between operators, materials and tools involved in the activities, and the surrounding environment. We can abstract operators who engage in unsafe behaviors, hazardous materials, unsafe tools, and the surrounding environment with risk factors as hazardous energy carriers. The accidental release of energy often occurs at the interaction interface of the energy carriers, meaning that risks always exist at the contact interface of human, materials, tools, and the environment.

There is continuous energy and material exchange among those carriers in operation activities. The exchange implies the existence of contact interface, which can lead to risk.

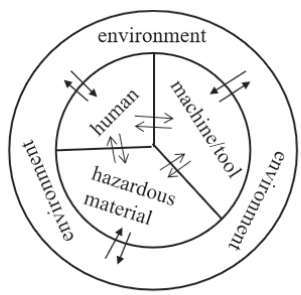

Fig.1 contact interface & energy exchange among factors

Management factors like sound laws and regulations have an important impact on the operation safety. However, they are difficult to be measured objectively, and will not be included in the analysis of this paper for the time being.

Based on the above analysis, as well as results of accident statistic and literature research, the operation risk factors can be summarized into 4 categories and 9 subcategories of operation/ supervisory personnel, environment, tools and hazardous materials, with a total of 35 factors, as shown in Figure 2.

The above four categories are defined as *P*-subsystem, *E*-subsystem, *T*-subsystem and *M*-subsystem, respectively. There is an impact correlation relationship between these independent subsystems. That is, the negative change in risk factors in anyone subsystem may lead to an accident, and the coupling influence of risk factors between different subsystems may also lead to an accident.

2.2. *Analysis on the Coupling Influence of Risk Factors*

With the help of Vensim PLM dynamic simulation software, the coupling influence of operation risk is analyzed. The interaction between different risk factors in a subsystem is defined as homogeneous factor coupling (HoC). Factors within the same system are relatively concentrated and their coupling frequency is high. Similarly, the interaction of risk factors between different subsystems is defined as heterogeneous factor coupling (HeC). There is a potential influence relationship between these factors, as well as a long transmission/influence distance, which may easy to cause major accidents once coupled. Nabi, et al. (2020).

2.2.1. *Homogeneous Factor Analysis*

Taking the *P*-subsystem as an example, it can be seen from Figure 3 that other risk factors have a direct influence on human behavior, or an indirect influence by HoC, where "→" represents the transmission / influence path between risk factors, "+" and "-" respectively represent the positive and negative influence between factors. For example, training effect→—man′ insecure behavior, which means that the training effect will affect the probability of occurrence of insecure behaviors. The better the training effect, the lower the probability of insecure behaviors.

A detailed description of some influence paths follows. poor psychological quality / physiological status will be manifested in carelessness, incompetence and slow response during operation, which will directly cause illegal / irregular behaviors such as misoperation. Lack of sense of responsibility easy to weaken the safe production awareness, which indirectly leads to absence without permission or other illegal behaviors; The above factors all have a direct and negative influence on operation skills, and will result in insecure behaviors finally.

Besides, negative psychological / physiological conditions or poor awareness of safety may promote personnel gathering. Once an explosion occurs, this gathering may causing stampede or expands the number of casualties.

2.2.2. *Heterogeneous Factor Analysis*

There are six coupling forms of heterogeneous factors between any two subsystems, namely *P-E*, *P-T*, *P-M*, *E-T*, *E-M*, *T-M*. The coupling among risk factors in three or more subsystems can be seen as the joint influence of multiple pairwise subsystems, which will not be analyzed in detail here.

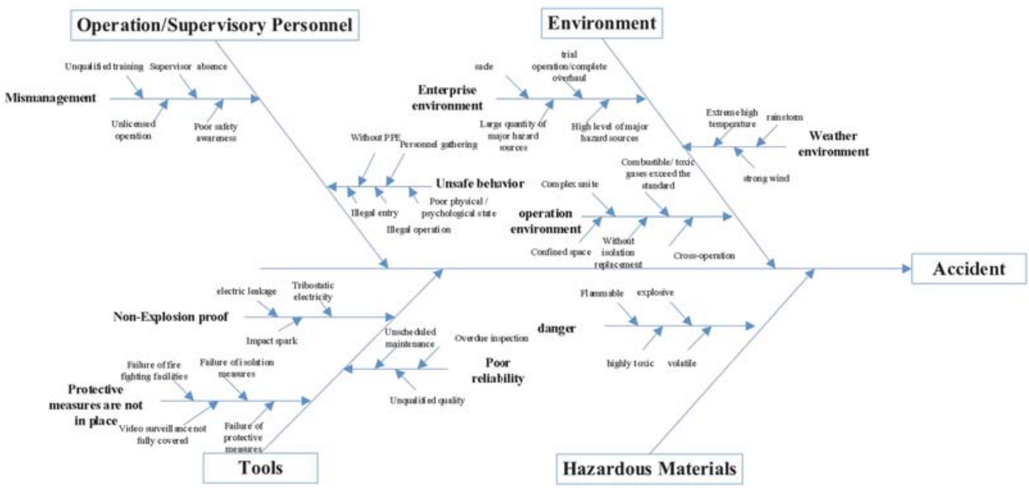

Fig. 2 Fish bone for operation risk identification

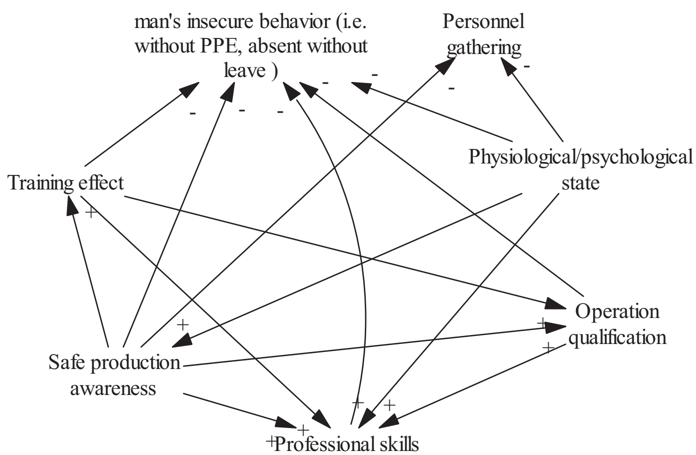

Fig.3 Coupling relationship of homogeneous factors in *P*-subsystem

Take the HeC between *P-E* subsystems as an example, as shown in Figure 4. The black arrows indicate the coupling relationship within the subsystem, and the blue arrow indicates the coupling relationship between subsystems. Work at heights in scorching weather may cause employees to have bad emotions such as anxiety and tension, and will increase the risk of unsafe behaviors. If the concentration of harmful gas in the operation area exceeds the standard, it will directly lead to poisoning and suffocation of operators; When operators' awareness of safety is weak, they may blindly pursue the construction progress, which may indirectly lead to adjacent cross operations and increase the possibility of accidents.

2.3. *Feedback Model for Operation Risk Identification*

Based on the above analysis, a feedback model for operation risk identification is constructed, as shown in Figure 5.

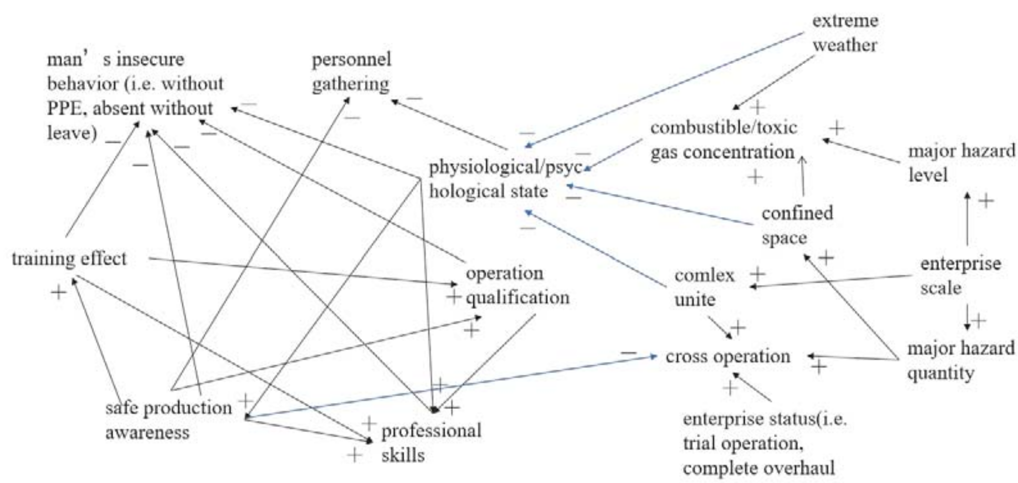

Fig. 4 Heterogeneous factor coupling between *P-E* subsystems

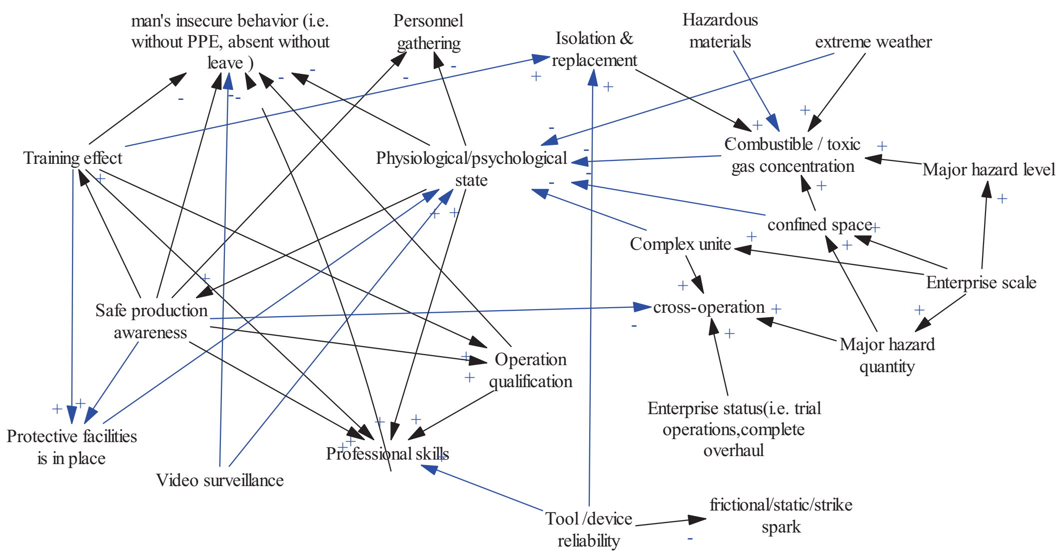

Fig. 5 Feedback model for operation risk identification

3. Dynamic Monitoring And Warning Of Operation Risks

In the operation sites, human have the widest range of activities and are more likely to interact with other risk factors. Therefore, the weight of the *P*-subsystem is relatively large, and its coupling with other subsystems is mostly strong.

As is described above, the stronger the coupling, the higher the risk. The facts do indicate that most operation accidents are caused by unsafe behaviors of people, such as illegal entry into confined spaces, failure to wear protective measures, inadequate monitoring personnel, unauthorized departure, illegal operations, etc.

Therefore, it is necessary to focus on controlling the key factors in the *P*-subsystem, while real-time monitoring the concentration of harmful gases in the *E*-subsystem, the presence of ignition sources, and other key factors that may lead to serious casualties such as explosion, poisoning and suffocation.

The petrochemical enterprises are trying to use information and intelligent techniques for operation supervision, such as permit to work system (PWS), intelligence video analysis (IVA), personnel location system (PLS), gas leakage detection system (GLDS), etc. Therefore, the authors provide a feasible way for dynamic monitoring and warning of operation risks. Bayesian theory is used to integrate the multiple risk information obtained from the processional systems to achieve comprehensive judgment. The causal relationship between dynamic operation risk factors is represented in Figure 6. The data source of input are shown in Table 1.

Tab.1 Data source for the dynamic operation risk assessment model

No.	Input	Data source
1	hot work	PWS
2	working location	
3	supervision	
4	ignition source	IVA
5	security measures	
6	fire-fighting measures	
7	unsafe behavior	IVA/PLS/PWS
8	combustible gas concentration	GLDS
9	toxic /harmful gas concentration	

Dynamic operation risk is denoted as R_o , which can be calculated based on the Eq. (1).

$$R_0 = \delta_i R_B \tag{1}$$

Where, n_i presents the number of personnel in an operation point; δ_i is a correction coefficient, which is given based on the distribution of *ni*. (See Tab.2). R_B presents the risk of "casualties" calculated by Bayesian theory. The prior probabilities of nodes are presented in Appendix A, which are obtained from statistics and experts' experience.

Intelligent techniques are used to real-time monitor the status of nodes in the table 1. We developed an operational risk control system to collect these multi-source states and convert them into probability values using computer language and input to the Bayesian network.

For example, if the IVA catches someone is working without helmet, the status of "unsafe behavior" is judged as TRUE, which means its probability value turns into 1. And then, the system will input a new evidence to the network and recalculate the R_B.

Tab.2 The values of δ_i based on n_i

i	n_i	δ_i
1	$n_i<3$	1
2	$3\le n_i\le 9$	10
3	$n_i\ge 10$	10^2

Tab.3 The risk ranking based on risk values

Risk value	Level of risk
$<1\times10^{-5}$	Low
1×10^{-5}~1×10^{-4}	General
1×10^{-4}~1×10^{-3}	Great
$\ge 1\times10^{-3}$	Major

The risk ranking based on risk values is shown in Tab.3, which is derived from as low as reasonably practice (ALARP). The regulators with different staffing level will receive corresponding warning information for different risk levels. For example, if it's assessed as major risk, the warning information will be sent to the workshop supervisor, the production manager, and the company leadership. While if it's general risk, the information will be sent to the workshop supervisor only. When the risk level undergoes an upward mutation, an alarm will be triggered and warning information will be send simultaneously.

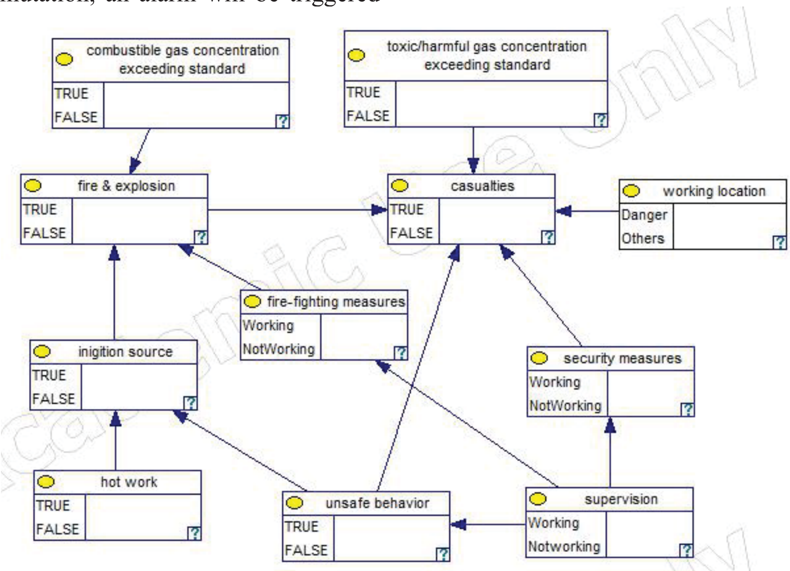

Fig.6 Dynamic operation risk assessment model

5. Conclusion

The petrochemical enterprises is susceptible to operation accidents due to the dynamic interaction of operation personnel, tools, hazardous materials and the complex environment. From the perspective of system dynamics, this paper identified the above four types of risk factors and analyzed the HoC and HeC relationship among them. What's more, an integrated operation risk warning technology is developed based on Bayesian theory by fusing multi-source information provided by professional systems. A hierarchical warning rule is made to improve the efficiency of risk handling. This paper provides a feasible way to assist petrochemical enterprises in achieving intelligent monitoring and early warning of operation risks, which would promptly contain security accidents.

Acknowledgement

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Appendix A. The prior probability of nodes

NO.	Nodes	Status	*P*
1	Hot work	True False	0.5115 0.4885
2	Supervision	Not working working	0.01 0.99
3	Working location	Danger Others	0.7483 0.2517
4	Combustible gas concentration exceeding standard	True False	0.0001 0.9999
5	Toxic/harmful gas concentration exceeding standard	True False	0.0001 0.9999

References

Chrysaitis, N.A. and Seriès, P.. (2023). 10 Years of Bayesian Theories of Autism: a Comprehensive Review. *Neuroscience & Biobehavioral Reviews. 145*.105022.

Feng C.S.. (2022). Discussion on Safety Standardization Management of High-Risk Operations in Refining and Chemical Enterprises. *Chemical Management*.(*27*), 86-88.

Huang,Y., Hu, S. and Yao, S.M..(2020). System Dynamics Analysis and Safety Risk of Building Tower Crane. *Journal of Safety and Environment*. *20*(*06*)*,*2060-2068.

Li W., Cao Q., Min H. and Sun, Y.B.. (2018). Industrial Non-Routine Operation Process Risk Assessment Using Job Safety Analysis (JSA) and a Revised Petri Net. *Process Safety and Environmental Protection*, *117*, 533-538.

Li W., Sun Y., Cao Q., He M. and Cui, Y.Q.. (2019). A Proactive Process Risk Assessment Approach Based on Job Hazard Analysis and Resilient Engineering. *Journal of Loss Prevention in the Process Industries*.*59*,54-62.

Nabi, M. A., El-Adaway, I.H. and Dagli, C..(2020). A System Dynamics Model for Construction Safety Behavior. *Procedia Computer Science*.*168,*249-256.

Skogdalen, J.E. and Vinnem, J.E.. (2011). Quantitative Risk Analysis Offshore--Human and Organizational Factors. *Reliability Engineering &System Safety*. *96*(*4*),468-479.

Villa, V., Paltrinieri, N., Khan, F., and Cozzani, V.. (2016). Towards Dynamic Risk Analysis: a Review of The Risk Assessment Approach and Its Limitations in The Chemical Process Industry. *Safety Science*, *89*, 77-93.

You M., Li S., Li D., Cao Q.R. and Xu, F.. (2020). Evolutionary Game Analysis Of Coal-Mine Enterprise Internal Safety Inspection System in China Based on System Dynamics. *Resources Policy*, *67*,101673.

Zhang, Y., Wang, S. X., Yao, J.T. and Tong, R.P.. (2023). The Impact of Behavior Safety Management System on Coal Mine Work Safety: a System Dynamics Model of Quadripartite Evolutionary Game. *Resources Policy*. *82*, 103497.