Circuit Board Assembly Workshop Operational Risk Management and Assessment

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Abstract. The article presents a method for managing and evaluating operational risks in manufacturing production sites for circuit board assembly, addressing the uncertainties, diversities, and dynamic changes in influencing factors. This approach, employing Fuzzy Dynamic Bayesian Network (FDBN), establishes a risk assessment framework from five perspectives: personnel, machinery, materials, methods, and environment. It constructs a Fault Tree Analysis (FTA) model and maps the fault tree to a Dynamic Bayesian Network model (DBN). Node probabilities are quantified using fuzzy theory and expert scoring method. Through bidirectional inference of dynamic Bayesian reasoning, the method evaluates safety risks for on-site operation personnel in manufacturing production, deriving time-sequential dynamic curves of safety risk changes and reverse inferring key influencing factors. The research conclusions offer new insights for operational safety regulations.

Keywords: Operational Risk Management, 5M1E, Fault Analysis (FTA), Dynamic Bayesian (DBN), Fuzzy Set Theory

1 INTRODUCTION

In the electronics manufacturing industry, the surface mount assembly workshop for circuit boards is a crucial and highly automated part of the production line, involving precision equipment and a variety of chemical materials. Despite the significant improvement in production efficiency and product quality brought about by modern assembly technology, the safety risks during the operation process have also increased, posing a potential threat to the safety of operation personnel. Therefore, conducting a systematic risk assessment of personnel operation safety in the circuit board assembly workshop is not only a regulatory requirement but also a necessary measure to ensure the health and safety of employees.

The purpose of safety risk assessment is to identify and evaluate potential risks in operations, determine the severity of risks and their likelihood of occurrence, and propose corresponding risk control measures. Iing Pamungkas[1] integrated Failure Mode, Effects, and Criticality Analysis (FMECA) with Fishbone Diagram to analyze quality issues in the fishing boat manufacturing process, aiming to achieve quality improvement. Wang Weizhong[2] et al. conducted an evaluation of workshop safety conditions

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by analyzing the coupling of risk factors, establishing evaluation indicators, and constructing a coupling coordination model. Wang Yuqian[3] used data statistical analysis to identify risk factors and conducted weighted risk level division for occupational risk assessment. Naji Khalid K [4] Using the Delphi method, integrating conceptual and performance evaluation methods with fuzzy logic-structural equation modeling, effectively detecting and mitigating factors contributing to disputes before the construction phase. Zhang Qi[5] obtained a risk prediction line chart model through questionnaire surveys and statistical analysis. The line chart model constructed by logistic regression intuitively displays the effects of multiple influencing factors. Although the above analysis methods can effectively analyze risks, they lack comprehensive analysis of risk sources and dynamic changes in risks.

This paper focuses on the analysis of safety risks for operation personnel. It constructs a risk model using the similarity aggregation method introduced in fuzzy theory. Finally, dynamic Bayesian reasoning is employed for both forward and backward risk inference to identify potential safety hazards and propose corresponding improvement suggestions. This ensures that the operating environment of the assembly workshop meets the highest safety standards and provides employees with a safe and healthy workplace.

2 DESIGN OF RISK MANAGEMENT PROCESS BASED ON DYNAMIC BAYESIAN NETWORK

2.1 Risk Identification (Establishment of Risk Indicator System)

The electronic assembly process is complex, and in SMT automated production, there are many sophisticated instruments and equipment that pose risks to personnel. In the DIP process, the working environment of personnel and raw materials can also cause safety issues. This paper analyzes operational safety issues based on five aspects: personnel, equipment, environment, management, and materials. Personnel and equipment events are combined into A1, while environment and materials are combined into A2, and methods into A3. The operational safety risk of workshop personnel is defined as the top event (T), and fault tree analysis is used for branching description, as shown in Figure 1 below:

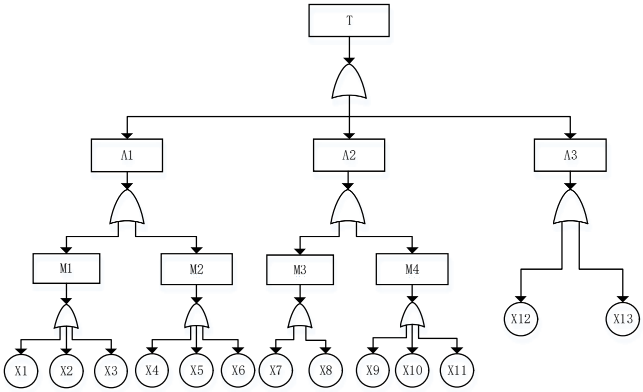

Fig. 1. Operator Risk Fault Tree Model

The meanings of the codes for various levels of risk events in the diagram are as follows: Work fatigue(X1)、Lack of operation training or experience(X2)、Personal health issues(X3)、Improper operation of high-temperature and high-pressure electrical equipment(X4)、Risk of mechanical injuries such as clamping or cutting(X5)、Inadequate safety protection measures(X6)、Collision injuries caused by layout issues(X7)、Bodily injuries caused by high temperatures, noise, etc.(X8)、Chemical burns(X9)、Inhalation of toxic gases or dust(X10)、Electric shock injuries caused by improper handling(X11)、Accidents caused by improper operation(X12)、Unreasonable operational processes(X13)、Personnel issues(M1)、Equipment issues(M2)、Environmental issues(M3)、Material issues(M4).

2.2 Constructing the Structure of the DBN Model

Mapping the fault tree to a dynamic Bayesian network, analyzing potential risks in the system through parameter estimation and adjustment. In the constructed DBN network, the states of each node are determined based on the Boolean algebra states of various events in the fault tree. Among them, X1, X2, X10, and X13 serve as transition nodes, dividing the states of each node into binary variables (represented by "yes/no" or "0/1"). Investigative analysis is conducted on risk events, and finally, the network model is drawn using GeNIe Academic software.

2.3 Determining the Parameters of the DBN Model

Expert Assessment Language Fuzzy Conversion. Using the method of expert assessment and fuzzy set transformation to obtain node probability values. This paper adopts a 7-level linguistic scale as the standard for expert judgment of the likelihood of basic event occurrences. Combined with fuzzy set theory, the qualitative language of experts is transformed into fuzzy intervals to obtain the values of event occurrences. The fuzzy intervals corresponding to the 7-level linguistic scale and their membership functions are shown in Table 1 below:

Table 1. Language variables and corresponding trapezoidal fuzzy numbers

Linguistic quantity value	Fuzzy Interval			
	a	b	c	d
Very Low （VL）	0	0	0.1	0.2
Low （L）	0.1	0.2	0.2	0.3
Medium Low （ML）	0.2	0.3	0.4	0.5
Medium （M）	0.4	0.5	0.5	0.6
Medium High （MH）	0.5	0.6	0.7	0.8
High （H）	0.7	0.8	0.8	0.9
Very High （VH）	0.8	0.9	1	1

Aggregation of Expert Opinions. The paper employs an improved similarity aggregation method to aggregate similar viewpoints, reducing bias and better handling the heterogeneity and complexity of expert opinions. Assuming there are N experts Ei (i=1, 2, ..., n), each expert provides fuzzy semantic values for all factors to be evaluated, and these fuzzy semantic values are converted into fuzzy intervals. The aggregation of expert opinions is carried out according to the following steps:

(1) Expert weights determination

According to the evaluation criteria and grading scores, determine the weight score for each expert, and compare it with the weight scores of all experts to determine the weight value for each expert. The expert grouping and rating criteria are shown in Table 2:

Table 2. Expert Classification and Scoring Standards

Standard	classification	Scores
Professional title	Manager	10
	Production Supervisor	8
	Researcher	6
Working years	≥20years	10
	15-19years	8
	10-14years	6
	≤9years	4
Academic qualifications	Doctor degree	10
	Master degree	8
	Bachelor degree	6
Ages	≥50	10
	40-29	8
	≤29	6

(2) Consistency between opinions of every two experts

$$S(A_i, A_j) = 1 - \frac{1}{4} | A_i - A_j | \tag{1}$$

The two experts opinions' similarity function is $S(A_i, A_j) \in [0,1]$, A_i, A_j are standard fuzzy numbers, $A_i = (a_i, b_i, c_i, d_i)$, $A_j = (a_j, b_j, c_j, d_j)$ are two trapezoidal fuzzy numbers.

(3) Average consistency measure of expert opinions $A(E_i)$

$$A(E_i) = \frac{1}{n-1} \sum_{\substack{j=1 \\ i \neq j}}^{n} S_{ij}(A_i, A_j) \tag{2}$$

(4) Expert opinions E_i relative consistency $f_{RAD,i}$

$$f_{RAD,i} = \frac{A(E_i)}{\sum_{i=1}^{n} A(E_i)} \tag{3}$$

(5) Consistency coefficient of expert opinions W_i

$$W_i = f_{EID,i} \times \alpha + (1-\alpha) \times f_{RAD,i} \tag{4}$$

$f_{EID,i}$ is the weight of each expert $(0 \le f_{EID,i} \le 1, \sum f_{EID,i} = 1)$, α is relaxation factor $(0 \le \alpha \le 1)$, α =0.5, determine the importance of $f_{RAD,i}$ and $f_{EID,i}$ to W_i according to the specific situation of the research question.

(6) Summary of expert opinions (overall fuzzy number)

$$P_j = \sum_{i=1}^{n} w_i \otimes p_{ij} \tag{5}$$

P_j is the aggregated fuzzy number representing the combined expert opinions on the basic events, n represents the number of lower-level events in the system, p_{ij} represents the expert judgment opinions of E_i on the basic events, W_i is the aggregated weight coefficient of expert E_i .

Node Parameters Determination. Due to the linguistic description ambiguity of product failure probability, we need to clarify the fuzzy possibility values and convert them into single Fuzzy Possibility Scores (FPS) to represent the likelihood of events occurring. The process uses the centroid method for defuzzification as shown in Equation (6):

$$S_{FP} = \frac{\int_a^b \frac{x-a}{x-b} x dx + \int_b^c x dx + \int_c^d \frac{d-x}{d-c} x dx}{\int_a^b \frac{x-a}{b-a} dx + \int_b^c dx + \int_c^d \frac{d-x}{d-c} dx}$$

$$= \frac{1}{3} \frac{(c+d)^2 - cd - (a+b)^2 + ab}{c+d-a-b} \tag{6}$$

Use a Markov transition matrix to represent the transition probabilities of the DBN, and the transition probabilities of the nodes are obtained using the calculation method in the following equation:

$$P = \left[p_{ij} \right] = \begin{pmatrix} p_{00} & \cdots & p_{0n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{pmatrix} \tag{7}$$

P represents the transition matrix, ij represents two adjacent states, p_{ij} represents the transition probability, $p_{ij} \geq 0$, $\sum_{j \in [0,n]} p_{ij} = 1$ 。

2.4 Dynamic Risk Inference

First, forward inference is performed on the DBN model to predict the likelihood of risk accidents occurring. Then, through backward inference, the key influencing factors causing the risk are identified. Assuming the state of the leaf node is X, backward inference is conducted to obtain the posterior probabilities of each child node. The relative change values (ROV) between them are calculated, and the child nodes are sorted accordingly.

$$V_{RO}(X_i) = \frac{\pi(X_i) - \theta(X_i)}{\theta(X_i)} \tag{8}$$

V_{RO} is the relative change value of X_i, denoted as ROV , X_i represents the root, $\pi(X_i)$ represents the posterior probability, and $\theta(X_i)$ represents the prior probability.

3 EMPIRICAL STUDY ON JOB RISKS

3.1 Job Overview

Analyzing based on the actual production environment of two SMT and DIP production lines, as well as the health conditions of 52 employees, to conduct a risk assessment of personnel operation safety in the circuit board assembly workshop.

3.2 Determining Model Parameters

Firstly, four experts from relevant fields (heterogeneous) are invited to assess the project, ensuring that their subjective opinions do not interfere with each other during the scoring process. After detailed analysis of quality data and production conditions, the experts provide evaluation opinions. The weights of expert information are as shown in Table 3:

Table 3. Expert Information and Weights

Expert	Job title	Working years	Academic qualification	Ages	Weighted score	Weight value
1	manager	≥20years	Doctor	≥50	40	0.313
2	Production supervisor	15to19years	Docter	40-29	36	0.281
3	Reseacher1	10to14years	master	40-29	30	0.234
4	Reseacher2	≤9years	bachelor	≤29	22	0.172

processing all the data, and the prior probability of the child nodes is obtained as:

Table 4. Evaluation opinions and prior probabilities of sub nodes

Nodes	Expert1	Expert2	Expert3	Expert4	FPS
X1	L	ML	ML	ML	0.297
X2	VL	VL	L	L	0.134
X3	VL	VL	VL	L	0.103
X4	VL	VL	VL	VL	0.078
X5	VL	L	VL	VL	0.110
X6	VL	VL	L	L	0.134
X7	VL	VL	L	VL	0.108
X8	VL	L	L	L	0.167
X9	L	VL	VL	ML	0.171
X10	L	ML	L	VL	0.214
X11	VL	VL	VL	VL	0.078
X12	ML	ML	L	VL	0.176
X13	L	VL	L	VL	0.143

According to Equation (7), the transition probabilities of dynamic nodes are determined. Taking the process monitoring inadequacy of node X10 as an example, its transition probability matrix is shown below, where states 0 and 1 correspond to "poor" and "good" respectively.

$$P_{ij} = \begin{bmatrix} P_{00} & P_{01} \\ P_{10} & P_{11} \end{bmatrix} = \begin{bmatrix} 0.863 & 0.171 \\ 0.137 & 0.829 \end{bmatrix}$$

3.3 Risk Analysis

Forward Inference. Dynamic Bayesian networks are a probabilistic inference method based on Bayesian theory, used to handle data and models that change over time. They consider the dynamic nature of time series data and can predict future state data, facilitating accurate pre-emptive decision-making. A dynamic Bayesian network consists of an initial network and a transition network, encompassing a finite number of time slices. Each time slice is composed of a directed acyclic graph and a conditional probability table. Input the probability values of the nodes into the DBN model to obtain the FDBN model without evidence input (Figure 2), as shown in the figure, the risk probabilities of work fatigue (X1) and inhalation of toxic gases and dust (X10) are relatively high, with noticeable variations. Moreover, with the passage of time, the risks show a positive correlation trend, indicating that prolonged exposure to poor working environments and intensity of work pose significant hazards to the workers.

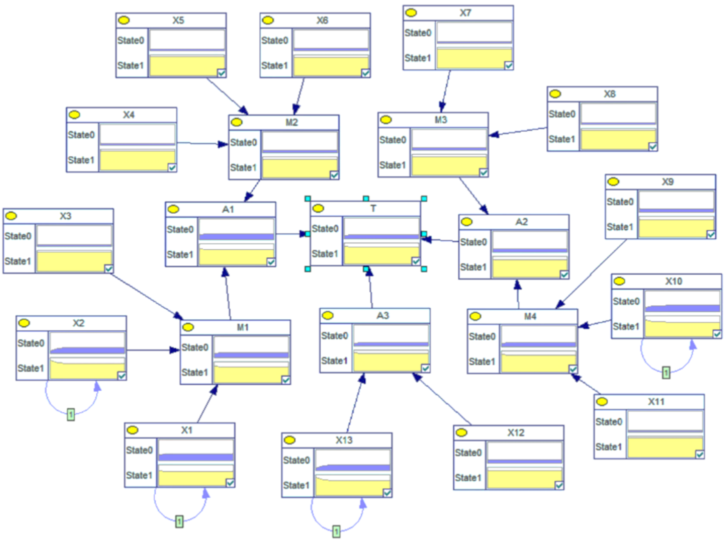

Fig. 2. FDBN model without evidence input

Backward Inference. Assuming that there will definitely be safety risks for operation personnel in the assembly scene, backward inference is performed to obtain the posterior probabilities and ROV values of each sub-node and various types of overall influencing factors, as shown in Table 5 and Table 6 below:

Table 5. Ranking of posterior probabilities and ROV values of sub nodes

Nodes	Prior probability	Posterior probability	ROV
X1	0.297	0.327	9.17%
X2	0.134	0.135	0.74%
X3	0.103	0.114	9.65%
X4	0.078	0.084	7.14%
X5	0.110	0.132	16.67%
X6	0.134	0.136	1.47%
X7	0.108	0.112	3.57%
X8	0.167	0.184	9.24%
X9	0.171	0.193	11.40%
X10	0.214	0.219	2.28%
X11	0.078	0.082	4.88%
X12	0.176	0.180	2.22%
X13	0.143	0.144	0.69%

Table 6. Posteriori probability of various risk factors

Risk categories	Posterior probability	Ranks
A1	0.446	2
A2	0.503	1
A3	0.319	3

From Table 5, it can be observed that after fitting using the posterior probabilities, work fatigue (X1), inhalation of toxic gases and dust (X10), and chemical burns (X9) reflect the importance of personnel safety risks, with relatively high occurrence probabilities. Therefore, prevention and control measures should be strengthened during the operation process.

From Table 6, it is evident that A2 > A1 > A3, indicating that the risks are mainly concentrated in the control of materials and environment. The factory should improve the control and handling of materials and carry out environmental hygiene improvement according to 6S management to avoid long-term pollution causing harm to the physical and mental health of employees.

4 CONCLUSION

In the management and assessment of operational risks for personnel in circuit board assembly workshops, the approach involves initial analysis using fault trees. Subsequently, employing the trapezoidal fuzzy set theory, expert weighting and scoring of influencing factors are conducted to avoid conflicts arising from subjective opinions. A mass matrix is then constructed using membership functions to further quantify the impact of each factor objectively. Finally, dynamic Bayesian reasoning is applied for both forward and reverse inference to validate the model's adaptability and identify potential sources and trends of risk evolution.

This comprehensive approach helps enterprises conduct comprehensive risk monitoring, timely identification, and effective prevention and control, thereby minimizing potential operational risks and enhancing personnel safety management. However, this method relies on high-quality historical data and expert knowledge. Difficulties in data acquisition or poor data quality may affect the accuracy of the results. Therefore, in the calculation process, conflicts of subjective opinions are minimized through weighting and specific scoring methods. In the future, data integration and big data analysis technology can be used to improve data quality and model accuracy. This method is not only applicable to circuit board assembly workshops but can also be extended to other manufacturing industries and high-risk sectors, enhancing safety management across various domains. It enables real-time monitoring of operational risks and dynamic adjustments, improving the ability to respond to sudden risks.

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