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A data-driven complex network approach for aviation piston engine safety: critical causation analysis and predictive intervention

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Highlights

- Using complex networks, a framework called CN-TSCA is proposed for risk assessment.
- ICW-TOPSIS method is employed to assess the critical risk factors quantitatively.
- A hybrid metric integrating multiple aspects is designed for critical component analysis.
- An efficient searching algorithm is developed for critical risk path identification.
- Derived from CN-TSCA findings, multi-phase safety control strategies are proposed.

Abstract

Aviation piston engines (APEs), the primary propulsion systems in general aviation, are critical to flight safety. To understand the accident causation mechanism of APEs, this study proposes a data-driven methodology that integrates complex network (CN) theory with a three-step criticality analysis (TSCA). Maintenance records provide the data source for causal chain extraction and CN construction. In TSCA process, topology analysis using ICW-TOPSIS quantitatively identifies critical risk factors. Considering the uniqueness of component factors in physical systems, a hybrid metric integrating both objective and subjective dimensions is designed for accurate component evaluation. For critical risk path analysis, we develop an efficient path searching algorithm initiating from these prioritized components. The CN-TSCA findings enable the formulation of multi-phase safety control strategies. Leveraging historical maintenance records, this method effectively identifies risks in complex physical systems and provides a systematic framework for safety enhancement and preventive strategies.

Keywords

complex network, data-driven risk assessment, aviation piston engine, safety control strategy

1. Introduction

With the rapid expansion of the low-altitude economy in China, the flight safety of general aviation aircraft has become an increasingly critical concern. As the primary propulsion system in these aircraft, the operational safety of aviation piston engines (APEs) is now a top priority. As highlighted by Heinrich's theory [1], the occurrence of an accident is not an isolated event but rather the result of complex interactions among multiple factors. Due to the complex operations and environments, there are various kinds of hazardous factors that may lead to serious APE accidents, posing significant challenges to risk management for aviation companies. Analyzing critical factors and causal relationships in APE-related incidents can effectively support risk propagation interruption. Consequently, identifying critical risk patterns is crucial for developing targeted mitigation strategies to prevent hazardous outcomes and enhance aviation safety.

Accident causality-based methods constitute systematic analytical approaches that investigate incidents by examining the complex relationships among multiple contributing factors. There are many methods used for accident causation analysis.

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For example, the Systems Theoretic Accident Model and Process (STAMP) proposed by Nancy [2] has been developed and applied in many research areas, such as marine [3], aerospace [4,5] and industrial processes [6,7]. Due to the complex modes of operation in tiltrotor aircraft, Natalie et al. applied System Theoretic Process Analysis (STPA) to analyze human-machine interaction and identify hazards for tiltrotor aircraft before an accident occurs [8]. Given the significant impact of human factors in numerous accidents, the Human Factors Analysis and Classification System (HFACS) was developed to analyze their role in maritime traffic accidents [9] and Uncrewed Air Vehicle (UAV) accidents [10]. Yaniel et al. identified 31 influencing factors using AcciMap within the aerospace manufacturing system [11]. However, the aforementioned methods primarily emphasize human factors based on quality analysis, with limited attention given to quantitative analysis considering diverse factors. And the linear features of these classical models are inadequate for analyzing complex system accidents in large-scale datasets. As a result, scholars have increasingly adopted quantitative methodologies, such as Fault Tree Analysis (FTA), Failure Mode and Effect Analysis (FMEA) and Bayesian Networks (BNs), to more effectively quantify risk factors. Che et al. extended previous FTA methods by considering mental workload overload in risk analysis [12]. Yazdi et al. incorporated fuzzy logic into FMEA for the reliability analysis of aircraft landing system and results validated the priority of the proposed method [13]. In the context of risk management in various industries, Zhao et.al proposed a structured FRAM-BN mapping method for heavy goods vehicle fire accidents and demonstrated its effectiveness [14]. In recent studies on aircraft power systems, physical model-based [15] and machine learning-based [16] methods were adopted for safety analysis. However, the effectiveness of these quantitative analysis methods diminishes under the constraints of data quality. The challenges associated with such analyses can also escalate substantially with increasing complexity of the targeted systems, particularly when accurate characterization and assessment of multiple interacting factors are required.

Owing to their ability to quantify and visualize the characteristics of complex systems, complex network (CN)-based methods have garnered significant attention across diverse fields, including maritime [17,18,19], railway [20,21], energy systems [22,23] , and chemical industry [24]. CN theory offers significant advantages in addressing nonlinear dynamics and multi-factor coupling of complex systems. In aerospace, CNs have been widely applied to the study of UAVs [25]. While CN theory has been applied in related contexts [26], its use in aerospace accident investigation and aero-engine risk modeling remains limited. Causal networks are usually utilized in risk analysis to identify critical factors or events through topological analysis, followed by the provision of targeted risk management recommendations [27]. During the model construction process, the nodes of the network represent the risk factors and the edges represent causal relationships between nodes. Although risk factors in CNs were uniformly considered as the same type of nodes, in [28] and [29], nodes of risk factors can be roughly divided into two types of nodes: cause nodes and accident nodes. Some researchers tend to further subdivide the cause nodes. In [27] and [30], the cause nodes were divided into four types: human, object, environment and management. Moreover, for industrial accidents closely related to system components, Li et al. innovatively considered system component nodes, accident cause nodes, and accident consequence nodes when constructing accident chains of working fluid systems [31]. In the context of risk causation analysis of specific physical systems based on CNs, system component nodes usually serve as the initial points of causal chains and possess distinct physical properties. However, the authors did not further investigate the unique characteristics of system components in comparison to other node types.

To effectively identify critical risk factors in accident analysis, evaluating node importance is essential. At present, most researchers tend to assess the node importance in CNs using topological indicators. Panigrahi et al. adopted the degree, average path length, clustering coefficient and betweenness centrality for structural vulnerability analysis of power grid networks. Results showed the superiority of weighted networks in vulnerability assessment [32]. Miao et al. constructed a causation network model for roof accidents, and six basic network structural parameters were analyzed to obtain the key causal factors and important inter-causal relationships [33]. Qiao et al. also constructed a complex network for Chinese maritime accidents analysis and accident factors were quantitatively assessed in terms of activeness, connection strength and criticality based on the network topology indicators and the improved K-shell decomposition algorithm [34]. Since traditional indicators may inadequately characterize node importance, researchers have developed new network topology metrics [35,36]. However, most of current studies are based on the perspective of complex networks, adopting the same topological importance evaluation method for all types of nodes. Few researchers have explored the distinct role of system components, separating them from broader factor importance evaluation. They also fail to integrate objective metrics with subjective expert judgment for a holistic assessment of critical components. Moreover, existing research lacks a unified CN-based risk assessment for specific physical systems that bridges factor, component, and path analysis.

Overall, considering the application of CNs in complex physical systems, this paper proposes a Three-Step Criticality Analysis (TSCA) framework that assesses incident records through a unified criticality analysis of factors, components, and paths. And corresponding safety measures are designed to control risk sources, interrupt risk progression, and mitigate accident consequences. Specifically, the maintenance records of APEs provided by the flight school are initially adopted for causal chains extraction to develop a directed-weighted CN. Key nodes are evaluated and critical risk factors are identified using topological analysis. Recognizing the unique attributes of components in complex physical systems, this study proposes a critical component analysis that combines subjective and objective assessments. The subjective evaluation incorporates expert judgment based on engineering experience, while the objective assessment integrates both topological indicators and physics-related metrics. To systematically examine accident progression trends and outcome severity levels, we then employ critical risk path analysis for characterizing predominant accident scenarios. Finally, multi-stage safety control strategies are proposed based on the preceding analysis to effectively manage APE risks. The main contributions of this work include three aspects:

- Based on data mining of the maintenance records, a risk assessment methodology is proposed for APE scenarios. A directed-weighted CN is constructed and the corresponding analysis can be applied to other aerospace or industrial systems with distinct physical features.
- We further develop the CN analysis process and propose a three-step criticality analysis (TSCA) framework for complex physical systems. TSCA includes critical factor analysis, critical component analysis and critical path analysis. ICW-TOPSIS method is employed mainly from the integrated topological perspective for critical factor evaluation. Departing from existing studies, critical component analysis are separated from risk factor evaluation and a unified importance metric combining objective measures and subjective expertise is developed. Initiated from the identified critical components, an efficient critical path search is performed. A novel risk metric, called SFP, is introduced in this paper to evaluate the criticality of the risk propagation, which integrates cause frequency, accident severity, and accident chain occurrence probability.
- The effectiveness of critical factor analysis can be validated through network robustness assessment, whereas the selection of critical components and paths can be verified via global risk path ranking, particularly under small-scale network conditions. Building upon the findings from the TSCA, multi-stage safety control strategies are developed covering all identified risk dimensions.

This paper is outlined as follows. Firstly, the methodology with the combination of CN construction and TSCA process is introduced in Section 2. Then, the case study results of APEs are introduced in Section 3, followed by the verification results and discussions in Section 4. Section 5 proposes the risk prevention strategy. Finally, conclusions are drawn in Section 6.

2. Methods

The methodology proposed in this paper is illustrated in Fig. 1. It mainly includes five phases: data collection, complex network construction, TSCA process, result validations and safety control strategies. In order to construct the CN for APE safety research, maintenance records collected by the flight school staff are thoroughly analyzed. Risk factors and causal relationships between factors are extracted from the records to form causal chains. After that, the directed-weighted CN is built. During TSCA, system criticality is evaluated through three distinct aspects. Results of the analysis can be verified using robustness analysis and global path searching method. Finally, targeted safety control strategies are designed.

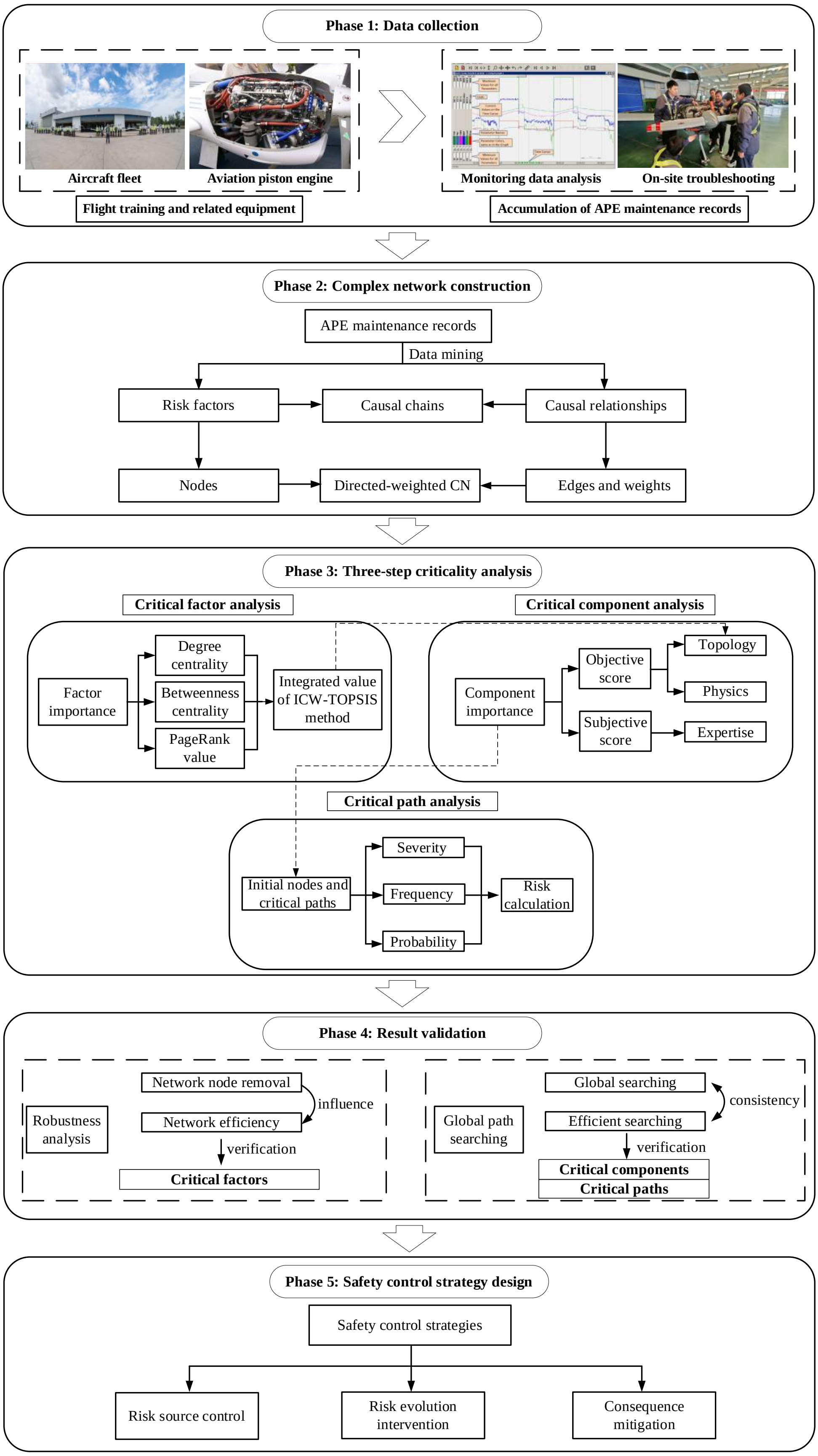

Figure 1. Analytical framework of this study.

2.1. Complex network construction

2.1.1. Data mining and causality extraction

This study employs the accident causation model as its theoretical foundation for safety analysis, providing both a systematic methodology for understanding safety phenomena and a comprehensive theoretical framework for accident investigation and prevention [37]. Building upon this causal principle, the study systematically reconstructs end-to-end accident sequences through comprehensive analysis of incident data. Specifically for APE-related accidents, the developmental process is structurally decomposed into three sequential phases: (1) initiating events (primary causation), (2) contributing events (escalation factors), and (3) culminating events (final consequences).

(1) Initiating Event: The primary trigger that establishes the accident sequence. In APE scenarios, such events stem from failures or function deviations of system components.

(2) Contributing Event: Intermediate factors that propagate the initiating event toward the final accident. These elements bridge the causal gap between the initial trigger and the ultimate outcome.

(3) Accident Event: The accident evolution process terminates in distinct accident types. Multiple accident event nodes may occur at the end of a causal chain, depending on the efficacy of implemented risk mitigation measures.

Three dominant risk categories can be summarized in complex physical system accidents: system components, risk factors, and accident consequences. Notably, system components are considered as a distinct category of risk factors and are therefore extracted for separate analysis. Through text mining techniques applied to historical incident records, comprehensive causal chains can be effectively reconstructed. During the causal analysis process, two fundamental hypotheses are also established to support accident chain reconstruction:

(1) Component Correlation Hypothesis: Multiple failed components identified within a single maintenance record are presumed to belong to the same accident causal chain. This conclusion is particularly valid for emergency landing records since cases without emergency responses, which were likely detected through routine inspections, typically exhibit weaker causal relationships between component failures.

(2) Propagation Direction Hypothesis: Fault progression within the causal chain is assumed to follow the dominant energy/information/material (EIM) flow direction characteristic within the APE system.

Furthermore, all reconstructed causal chains must satisfy an essential engineering consistency principle, ensuring alignment with established operational practices and physical system constraints.

2.1.2. Network modeling

In this study, a directed-weighted network is constructed based on identified risk factors and their causal relationships derived from prior analysis. In our network model for APE causal chain analysis, nodes correspond to the three risk event types (initial, contributing, and accident events), while directed edges represent causal relationships between these events, weighted by their connectivity strength [38]. As illustrated in Fig. 2, this framework generates a directed-weighted CN where multiple accident chains may share common nodes, resulting in duplicate edges. To optimize the network topology, we consolidate redundant edges by incrementing their weights, ultimately representing the refined structure through the weighted adjacency matrix presented in Fig. 2.

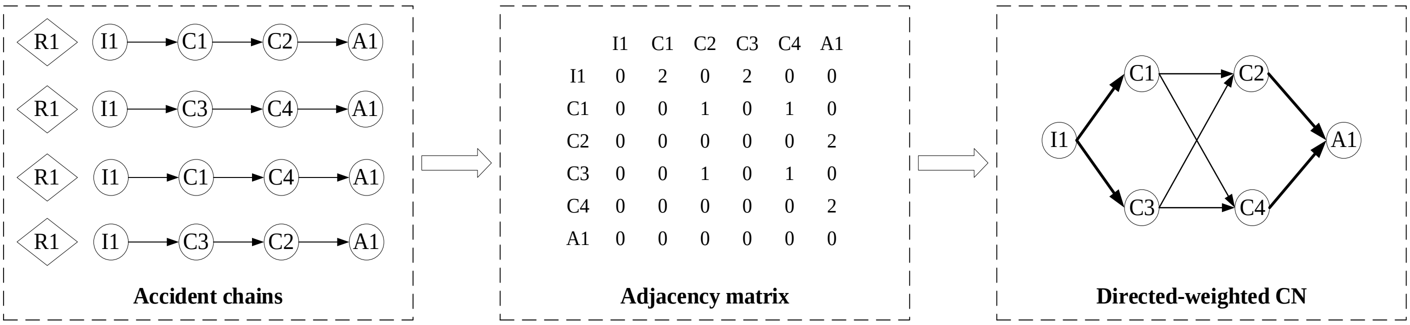

Figure 2. Schematic diagram of directed-weighted CN modeling process.

The directed-weighted CN can be established base on the $N \times N$ weighted adjacency matrix, where N is the sum of the CN nodes. The adjacency matrix can be expressed as follows:

$$AM = \begin{cases} w_{ij} & i \to j \in Edges \\ 0 & i \to j \notin Edges \end{cases} \tag{1}$$

where w_{ij} is the weight of the edge from node i to j, and *Edges* is the set of edges.

2.2. TSCA process

CNs have emerged as a fundamental framework in safety science and accident analysis, offering a systematic approach to understanding and mitigating risks in complex systems. This study employs directed-weighted CNs to model event sequences, combined with a novel TSCA methodology that identifies critical risk factors, key components, and high-impact propagation paths disproportionately affecting system safety.

2.2.1. Critical factor analysis

A. Single-metric approach

Network topology analysis provides an essential measure for determining nodal importance across CN structures. Key topological metrics can collectively quantify the system's risk propagation patterns and vulnerability distribution. Therefore, in this paper, the following topology indicators are utilized to quantitatively characterize the network model and identify critical factors for targeted incident prevention strategies in APE applications.

(1) Degree centrality

Degree centrality serves as a fundamental network metric, where higher node degrees indicate greater topological importance and stronger local connectivity. This parameter effectively captures both a node's structural significance and its interaction intensity within the network. Its calculation combines out-degree and in-degree connections, as shown in Eq. (2):

$$\begin{gathered} DC_{in}(i) = \sum_{j \in V}^{i \neq j} a_{ji} \\ DC_{out}(i) = \sum_{j \in V}^{i \neq j} a_{ij} \\ DC(i) = DC_{in}(i) + DC_{out}(i) \end{gathered} \tag{2}$$

where $DC_{in}(i)$ and $DC_{out}(i)$ denote the in-degree and out-degree of the node i; $DC(i)$ is the degree centrality of the node i; a_{ji} means the number of edges that point into i. V is the set of nodes.

Notably, when the degree distribution follows a power-law pattern, the network is classified as scale-free—a distinctive architecture where most nodes exhibit limited connectivity while a few critical hub nodes maintain extensive connections. Targeted removal of central nodes significantly disrupts network functionality, whereas peripheral node deletion induces negligible effects. Consequently, topological analysis of scale-free networks enables accurate identification of critical network vulnerabilities through their distinct connectivity patterns.

(2) Betweenness centrality

While node degree provides a basic measure of connectivity, it fails to identify strategically positioned nodes that serve as critical bridges between network communities. Betweenness centrality addresses this limitation by quantifying how frequently a node lies on the shortest paths between all other node pairs in the network. Nodes with elevated betweenness centrality demonstrate superior influence over network-wide connectivity, even if they possess a lower degree of centrality. The calculation method can be represented as follows:

$$BC(h) = \sum_{i \neq j \neq h \in V} \frac{\sigma_{ij}(h)}{\sigma_{ij}} \tag{3}$$

where the $BC(h)$ indicates the betweenness of the node h. σ_{ij} means the sum of shortest paths between node i and node j; $\sigma_{ij}(h)$ is the number of shortest paths from node i to node j through node h.

(3) PageRank value

The PageRank algorithm models node importance through a stochastic process on directed graphs. Based on random walk theory, it simulates the movement along the edges of the graph, randomly transitioning between nodes. The algorithm converges to a stationary distribution, where each node's visitation probability defines its PageRank score [19]. Higher PageRank values indicate greater nodal importance in the network. Mathematically, the PageRank of node i is:

$$PR(i) = \frac{1-\theta}{N} + \theta \sum_{j \neq i \in V} \frac{a_{ji} PR(j)}{DC_{out}(j)} \tag{4}$$

where $PR(i)$ indicates the PageRank value of the node i; θ is the damping factor, usually set as 0.85; N is the total number of network nodes.

(4) Network efficiency

Network efficiency quantifies network connectivity by averaging the reciprocal shortest-path lengths between all node pairs. Higher value of the network efficiency indicates a strong capacity for rapid and effective information transfer. Owing to this property, network efficiency is widely adopted as a key metric in robustness analysis, serving to validate the accuracy of topological parameters. The expression of the network efficiency is shown in Eq. (5):

$$Eff = \frac{1}{N(N-1)} \sum_{i \neq j \in V} \frac{1}{d_{ij}} \tag{5}$$

where d_{ij} counts edges on the shortest *i-j* path.

B. Integrated-metric approach

The aforementioned topological indicators characterize different dimensions of network properties, demonstrating the inherent constraints of single-metric approaches in node criticality evaluation. Consequently, a systematic integration of these parameters is essential for accurate risk assessment, which consists of two key aspects: (1) weight determination for individual indicators and (2) decision-making methodology selection.

(1) Weight determination method

A commonly used objective weighting method is the entropy-weighting (EW) approach, which applies information entropy theory to calculate indicator weights in multi-indicator evaluations. Its core principle involves assigning weights to each indicator by measuring their degree of variation across samples. Specifically, a higher information entropy value indicates lower variability among samples for that particular indicator, suggesting it contributes less to distinguishing results. The entropy value in the EW method is calculated as follows: Assuming there are *m* samples and *n* indicators, the decision matrix *X* is shown in Eq. (6):

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{6}$$

The standardized decision matrix *Y* can be constructed using Eq. (7):

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{7}$$

where x_{ij} and y_{ij} are the value and standardized value for the *j*-th indicator under sample *i*. $max(x_j)$ and $min(x_j)$ are the maximum and minimum values of the *j*-th indicator.

The entropic value of the *j*-th evaluation indicator E_j can be calculated as follows:

$$\beta_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{8}$$

$$E_j = -\frac{\sum_{i=1}^{m} \beta_{ij} \ln(\beta_{ij})}{\ln(m)} \tag{9}$$

The CRITIC-weighting (CW) method is another objective weighting approach demonstrating superior performance [39]. The final weights in the CW method are derived from two elements: contrast intensity and conflict. Their calculations are detailed as follows:

The standard deviation and correlation coefficient of each data can be calculated using Eq. (10) and (11):

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m} (y_{ij} - \bar{y}_j)^2}{m-1}} \tag{10}$$

$$r_{jt} = \frac{\sum_{i=1}^{m} (y_{ij} - \bar{y}_j)(y_{it} - \bar{y}_t)}{\sqrt{\sum_{i=1}^{m} (y_{ij} - \bar{y}_j)^2 \sum_{i=1}^{m} (y_{it} - \bar{y}_t)^2}} \tag{11}$$

where σ_j and $\bar{y}_j$ are the standard deviation and the average value of the *j*-th evaluation indicator. r_{jt} is the correlation coefficient between the *j*-th and *t*-th indicator.

The contrast intensity and conflict in the CW method are shown in Eq. (12) and (13):

$$S_j^{CW} = \sigma_j \tag{12}$$

$$A_j^{CW} = \sum_{t=1}^{n} (1 - r_{jt}) \tag{13}$$

where the S_j^{CW} and A_j^{CW} are the corresponding contrast intensity and conflict of the *j*-th evaluation indicator.

The improved CRITIC weighting (ICW) method advances the original CW approach in the following aspects: Firstly, the ICW method uses the mean deviation instead of the standard deviation employed in traditional CW method, as the latter tends to overestimate contrast intensity when outliers are present. This substitution yields more balanced weights that better represent each indicator's true variation. Secondly, since coefficients with the same absolute value indicate the same strength of correlation, using $|r_{jt}|$ in the ICW method is more appropriate to measure conflict between indicators than r_{jt} adopted in the CW method. Thirdly, while the CW method fails to account for data dispersion among indicators, the EW method quantifies information disorder through information entropy, effectively reflecting dispersion [40]. Thus, incorporating information entropy *E* into the ICW method refines weighting by quantifying the informational value of data dispersion. It complements the original CW approach, assigning higher weights to criteria with more uncertain or distributed data, thus improving objectivity and robustness in determining indicator importance. The formula of the ICW method is depicted in Eq. (14):

$$w_j^{ICW} = \frac{\left(E_j + S_j^{ICW}\right) A_j^{ICW}}{\sum_{j=1}^{n}\left(E_j + S_j^{ICW}\right) A_j^{ICW}} = \frac{\left(E_j + \frac{\sum_{i=1}^{m}\left|y_{ij} - \bar{y}_j\right|}{m}\right)\sum_{t=1}^{n}\left(1 - \left|r_{jt}\right|\right)}{\sum_{j=1}^{n}\left(E_j + \frac{\sum_{i=1}^{m}\left|y_{ij} - \bar{y}_j\right|}{m}\right)\sum_{t=1}^{n}\left(1 - \left|r_{jt}\right|\right)} \tag{14}$$

where w_j^{ICW} and A_j^{ICW} are the weight and the conflict of the j-th evaluation indicator calculated by the ICW method. S_j^{ICW} is the mean deviation of the j-th indicator.

(2) Decision-making method

Using the results obtained from the ICW method, the weighted decision matrix Z can be derived by multiplying the standardized decision matrix Y with the computed weight vector w_j^{ICW} ,which can be expressed in Eq. (15):

$$Z = W_j^{ICW} Y \tag{15}$$

For the decision-making methodology, the TOPSIS method is selected as the main solution in this study [41]. In this method, the positive ideal solution (A^+) and the negative ideal solution (A^-) are defined as shown in Eq. (16):

$$\begin{aligned} A^+ &= \left\{\max_i\left(z_{ij}\right)\right\} = \left\{z_1^+, z_2^+, \cdots, z_j^+, \cdots, z_n^+\right\} \\ A^- &= \left\{\min_i\left(z_{ij}\right)\right\} = \left\{z_1^-, z_2^-, \cdots, z_j^-, \cdots, z_n^-\right\} \end{aligned} \tag{16}$$

where z_j^+ and z_j^- are the maximum and minimum values for the weighted decision values of the j-th indicator among samples.

The formulas for calculating the distance measures between the i-th sample and the best (D_i^+)/ worst (D_i^-) solutions are presented below:

$$\begin{aligned} D_i^+ &= \sqrt{\sum_{j=1}^{n}\left(z_j^+ - z_{ij}\right)^2} \\ D_i^- &= \sqrt{\sum_{j=1}^{n}\left(z_{ij} - z_j^-\right)^2} \end{aligned} \tag{17}$$

In TOPSIS method, the final score of the i-th sample can be represented by the closeness to the ideal solution, which is depicted as follows:

$$T_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{18}$$

2.2.2. Critical component analysis

Typically, system components, as a special class of risk factors, can also be analyzed using the aforementioned topological evaluation method. However, for accident causation network research focused on critical risk event-path interactions, component analysis serves a specialized purpose in this study: enabling efficient identification of high-risk propagation pathways in complex physical systems, where critical components typically act as initiation points for high-risk cascades. It has to be emphasized that system components are particularly distinctive among CN nodes, not only because they predominantly serve as the initial nodes of causal chains, but also due to their more significant physical-related characteristics. Therefore, relying solely on the topological component analysis proves to be inadequate for component evaluation and high-risk path detection, as demonstrated in subsequent sections. To overcome this limitation, a multidimensional indicator integrating key evaluation criteria is necessary for improved component analysis.

Specifically, in this paper, a novel method for critical component analysis that employs a hybrid of subjective and objective indicators has been proposed. Objective indicators include the integrated topological score derived from the ICW-TOPSIS method and the failure rate performed as the physical-related indicator. Subjective score is mainly based on the engineering experience provided by experts. The expression of this method is shown in Eq. (19):

$$CII_i = \alpha \frac{TS_i}{max(TS)} + \delta \frac{FR_i}{max(FR)} + \varepsilon \frac{ES_i}{max(ES)} \tag{19}$$

where CII_i is the component importance indicator of the component i; TS is the topological score conducted by ICW-TOPSIS; FR is the failure rate score; ES is the maintenance expert score; α, δ and ε are weight coefficients given by the analysts, typically determined via methods like the analytic hierarchy process. In this study, all scores are are treated as equally important and are consequently assigned a uniform weight of $\frac{1}{3}$.

2.2.3. Critical path analysis

Following the identification of critical system components, the analysis proceeds to determine pivotal causal paths within APE risk networks, enabling comprehensive risk assessment. The path analysis proceeds with a localized search method applied to the APE risk network, originating from the identified critical components to ensure computational efficiency. When the propagation probabilities exist between nodes, all potential causal chains can be calculated. The probability of the risk evolution from node i to j is shown in Eq. (20):

$$P_{ij} = \frac{w_{ij}}{\sum_{i \neq j} w_{ij}} \tag{20}$$

Based on the SFP risk metric proposed in [27], the risk of a specific causal chain is composed of three aspects: causal chain frequency, consequence severity and the formation probability. Therefore, the risk outcome of a specific causal chain can be represented by following equation:

$$R_{cc} = F_a \times P_{cc} \times S_b \tag{21}$$

where the R_{cc} is the risk of the causal chain; F_a is the frequency of the causal chain, represented by the frequency of the initial node a in the causal chain. P_{cc} indicates the formation probability of the causal chain from the initial node a to accident node b, which can be calculated by Eq. (22). S_b is the consequence severity of the accident node b. In this paper, the APE data records are collected by the flight fleet used for training in flight school. F_a is set as the occurrences of initial component failure per year. Notably, due to the unique nature of flight training environments, maintenance records in flight school scenarios rarely contain casualty reports. In technical terms, these extracted causal chains are classified as accident precursors (APs) - truncated accident sequences as demonstrated in [42]. Since AP chains represent a specialized form of accident chains, this study defines AP severity through a quantitative metric: the proportion of records where emergency landings were implemented following the occurrence of a precursor node. As is shown in Table 1 and Fig. 3, the measurement of the severity can be divided into three stages: marginal severity, moderate severity and substantial severity. Leakage related consequences in APE records has the lowest severity and almost no emergency measures were taken due to the leakage. Power-related APs exhibit substantial severity, necessitating full emergency response (100% activation) in loss-of-control events.

$$P_{cc} = \prod_{i,j \in V_{cc}} P_{ij} \tag{22}$$

Table 1. The measurement of the severity of the accident consequences.

Consequence	Severity indicator
Marginal	5
Moderate	50
Substantial	100

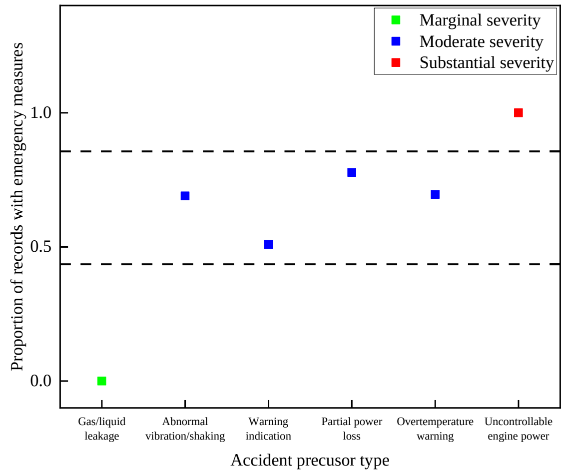

Figure 3. Severity of consequence defined for flight school APE records.

3. Results

3.1. Case introduction

The data for this study was obtained from CD-135 maintenance records systematically collected by the technical staff at Chaoyang Flight College, Civil Aviation University of China (CAUC). After excluding incomplete records and those irrelevant to APE, 1200 records from 2015 to 2023 are preliminarily selected as research samples, which are visualized in Fig. 4.

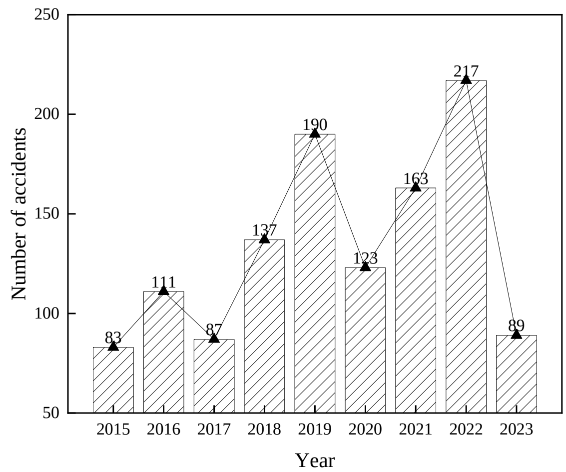

Figure 4. Time distribution of the APE records.

As illustrated in Fig. 4, the temporal distribution of APE maintenance records exhibits an overall fluctuating upward trend prior to 2022, culminating in a peak incidence of 217 cases during that year. In APE systems, AP records merit rigorous investigation due to their inherent transferability and portability characteristics [42]. It is noteworthy that records documenting emergency landing operations represent particularly severe events and directly satisfy the chain extraction criteria outlined in Hypothesis 1 (Section 2.1.1), thus warranting focused analysis. Therefore, to enable efficient extraction of critical risk patterns from these high-impact cases, 154 representative records are selected for CN model development.

3.2. CN construction for APEs

System components play a vital role in APE accident analysis. Fig. 5 displays the diagram of APE schematized as a single cylinder, annotating approximate locations of system components that appeared in the 154 selected records for clarity. As illustrated, the APE is a complex physical system that contains multiple kinds of flows, with arrows indicating the main directions. Risk propagation directions are assumed to exhibit significant alignment with the EIM flow directions, wherein upstream component failures may systematically propagate to downstream components, reflecting their inherent functional dependencies.

APE record analysis identifies four key risk domains: (i) precursor types, (ii) system components, (iii) equipment factors, and (iv) human factors, as shown in Table 2. Subsequent data mining revealed the inter-factor risk propagation mechanisms, with complete causal paths documented in Table 3. In this study, the extracted causal chains originate from system component nodes and terminate at precursor-type nodes. These causal chains can be long or short, and some may involve multiple components. The extraction process should satisfy the two key assumptions presented in Section 2.1.1. After the initial chain extraction by the authors, further discussions need to be conducted with maintenance staff in CAUC to ensure that the extracted causal chains are consistent with their engineering experience. Then the CN can be constructed on aforementioned basis for in-depth accident causation research of APEs.

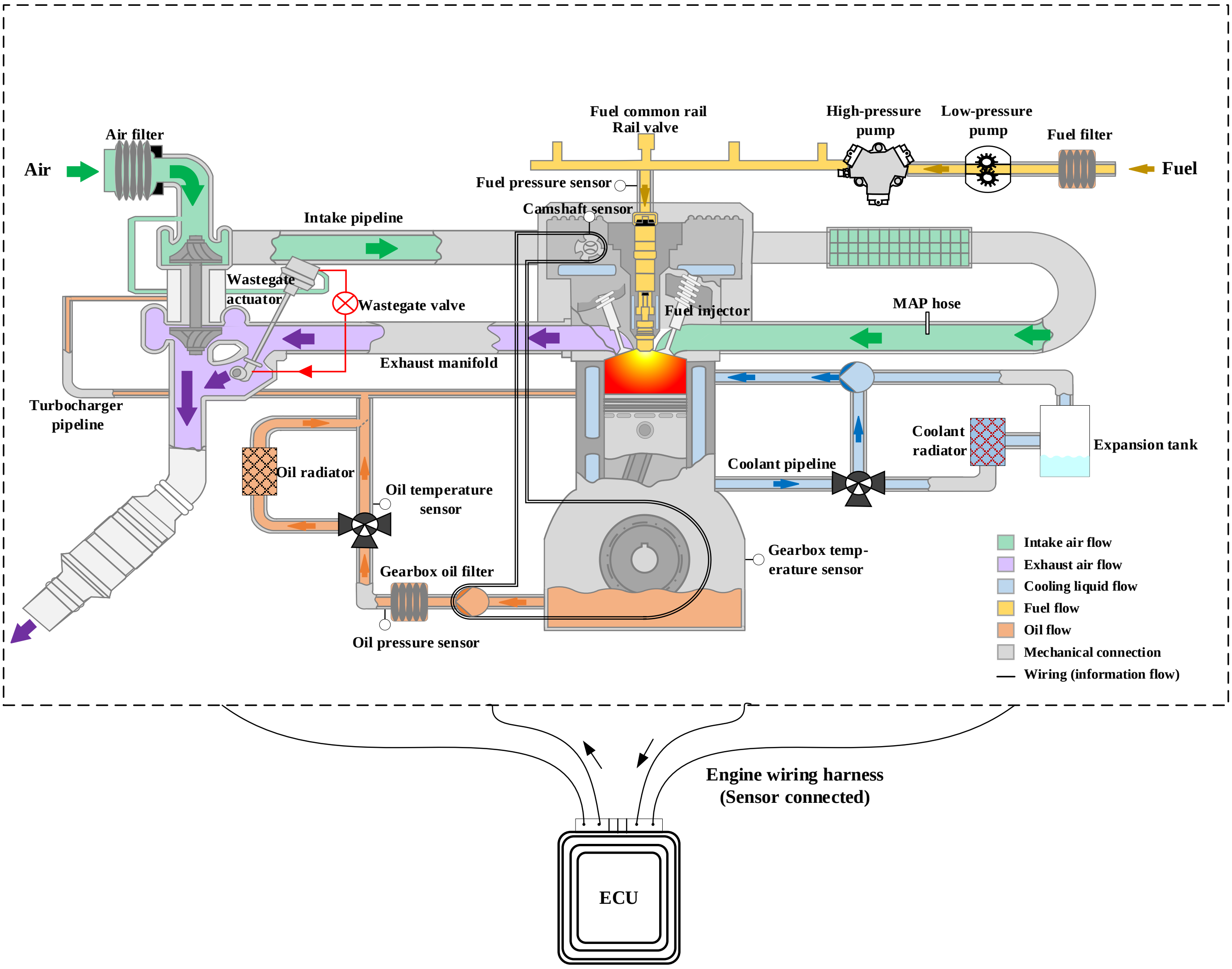

Figure 5. Schematic diagram of EIM flow direction in APEs.

Table 2. Identified risk factors in selected APE records.

No.	Label	Risk factors	Category	No.	Label	Risk factors	Category
1	A1	MAP hose	System component	26	B1	Blockage	Equipment factor
2	A2	Fuel common rail		27	B2	Vulnerability rupture	
3	A3	Camshaft sensor		28	B3	Pollution	
4	A4	Oil pressure sensor		29	B4	Sticking	
5	A5	Air filter		30	B5	Sealing failure	
6	A6	Rail valve		31	B6	Abnormal temperature	
7	A7	Electronic Control Unit (ECU)		32	B7	Abnormal pressure	
8	A8	Fuel injector		33	B8	Outdated software version	
9	A9	Intake pipeline		34	B9	Wiring failure	
10	A10	Coolant radiator		35	B10	Electronic failure	
11	A11	Gearbox temperature sensor		36	C1	Improper operation	Personnel factor
12	A12	Wastegate actuator		37	C2	Improper maintenance	
13	A13	Coolant pipeline		38	D1	Abnormal vibration/shaking	Precursor type
14	A14	Fuel pressure sensor		39	D2	Warning indication	
15	A15	Wastegate valve		40	D3	Gas/liquid leakage	
16	A16	Gearbox oil filter		41	D4	Partial power loss	
17	A17	Turbocharger pipeline		42	D5	Overtemperature warning	
18	A18	Engine wiring harness		43	D6	Uncontrollable engine power	
19	A19	Exhaust manifold					
20	A20	High-pressure pump					
21	A21	Fuel filter					
22	A22	Oil temperature sensor					
23	A23	Oil radiator					
24	A24	low-pressure pump					
25	A25	Expansion tank					

3.3. CN analysis results

Based on the CN theory, risk events in the process of accident evolution and terminations are considered as the network nodes and the evolution path from one node to another is the edge of the network. Therefore, the directed-weighted CN is generated from the systematic analysis of Table 3 data, and 507 distinct causal chains are adopted in the construction process. The CN is shown in Fig. 6, visualized by Gephi software. It has 43 nodes and 114 edges, while the weight of the edge represents the repeated chains and the edge thickness increases proportionally with the weight. Directional arrows denote risk evolution, and nodes belong to the same categories are plot using the same colors.

Table 3. Extracted causal chains using selected APE maintenance records.

No.	Extracted causal chain of APEs
1	A5→A9→B2→D3→D4
2	A10→B1→B6→D5
3	A1→B2→A7→B10→D2
...	...
153	A20→B5→D3→D1
154	A21→B1→D1

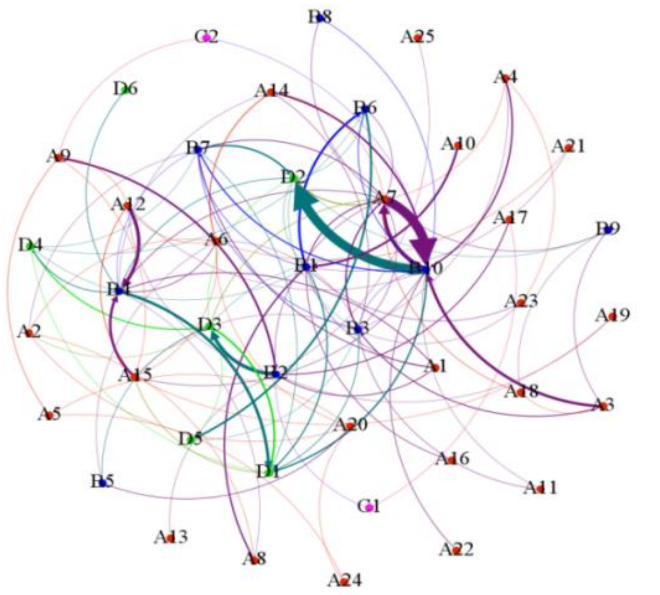

Figure 6. Directed-weighted CN for APE risk analysis.

3.3.1. Risk factor analysis

TEXT. The average path length of the APE network is 3.085, which means the network passes three times on average after an accident occurs. The average clustering coefficient of the network is 0.185. Compared with three random networks generated by Pajek software, the APE network possesses the higher clustering coefficients and smaller average path lengths, as shown in Table 4. Therefore, the network has the small-world characteristic. Small-world networks can exhibit accelerated information transmission due to their short path lengths and high clustering coefficients. This topology necessitates effective disruption to mitigate severe consequence.

Table 4. The small-word characteristic of the APE network.

	Average path length	Clustering coefficient
Our network	3.085	0.1850
Random network 1	3.554	0.0577
Random network 2	3.635	0.0596
Random network 3	3.702	0.0597

In degree analysis, the average degree of the network is 2.651, which means each node may cause accidents of about 2 other nodes. Fig. 7 illustrates the degree distribution of risk nodes, specifically highlighting those with degrees exceeding 3. Fig. 8 further demonstrates that the cumulative degree distribution follows a power-law pattern in log-log coordinates, confirming its scale-free topology with a fitted function of $y = 0.2473x^{-0.754}$ ($R^2 = 0.835$). For scale-free networks, most nodes demonstrating sparse connectivity while a limited subset of hub nodes maintain extensive edge connections. Notably, from the degree perspective, system component nodes with the top four degrees are A7 (ECU), A6 (common rail valve), A15 (wastegate valve) and A12 (wastegate actuator), while the top four equipment factors are B10 (electronic failure), B3 (pollution), B1 (blockage) and B4 (sticking). Consequently, targeted prevention and control of these high-degree nodes becomes paramount for effectively reducing their systemic influence and interrupting risk propagation.

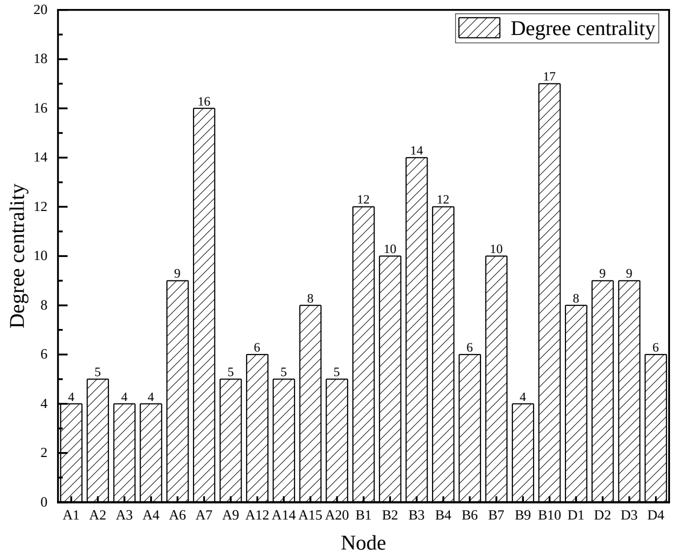

Figure 7. Degree of risk nodes (larger than 3).

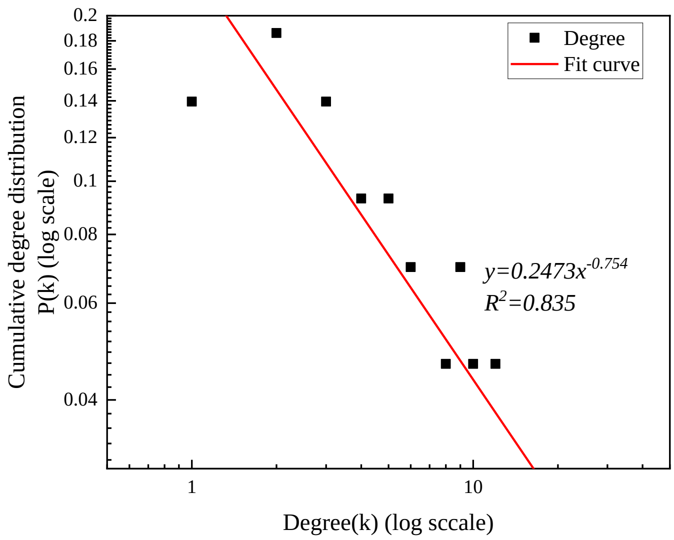

Figure 8. Cumulative degree distribution of the network.

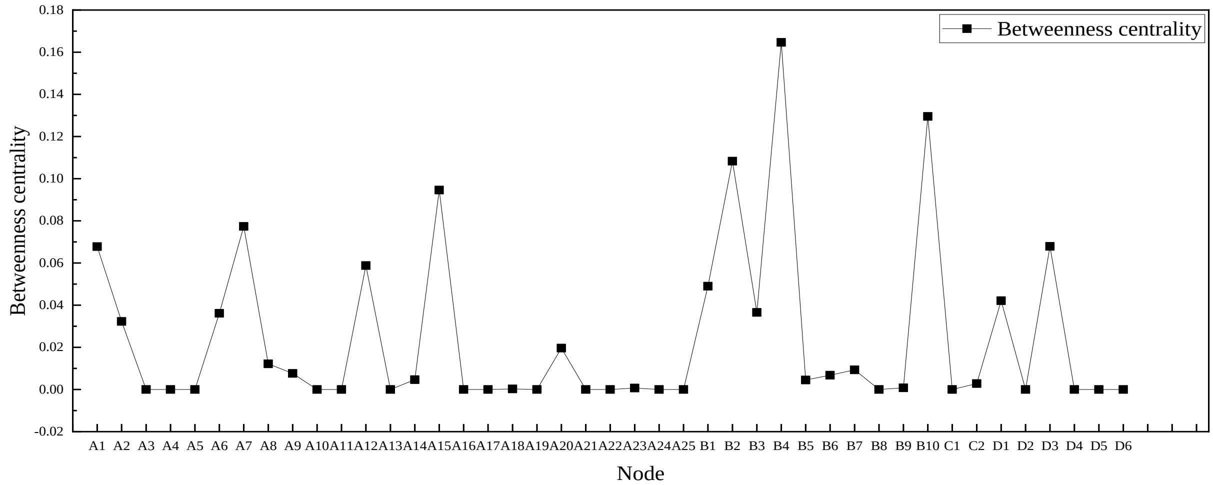

Figure 9. Betweenness centrality of the network.

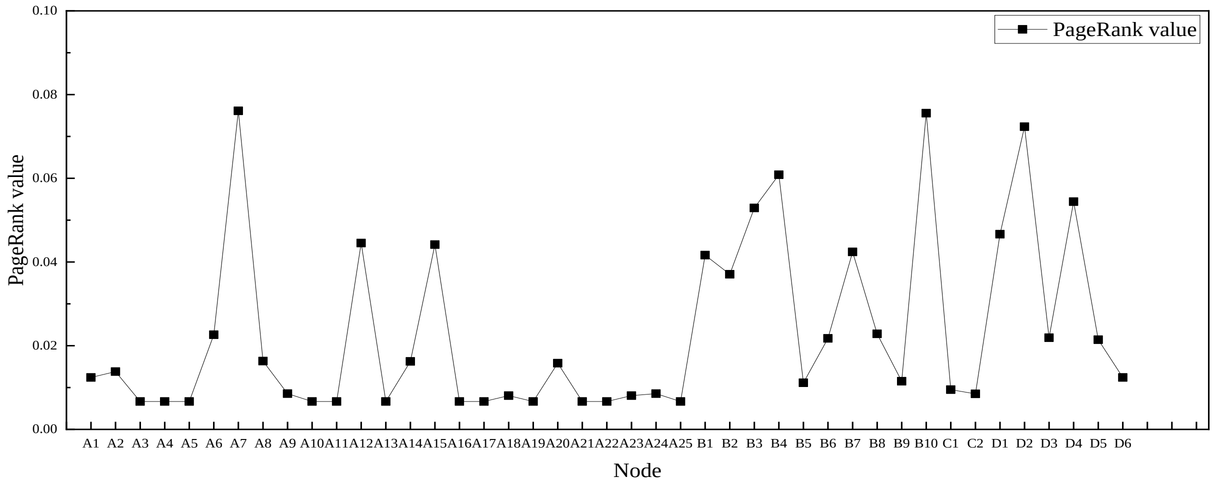

Figure 10. PageRank values of the network.

Nodes with high betweenness centrality, such as B4 and B10 shown in Fig. 9, serve as critical bridges in complex networks, controlling the majority of shortest paths between distant regions. This also suggests that these risk events can easily be evolved into other events in APE accidents. The betweenness centrality of B4 (sticking) is the largest, indicating that multiple shortest paths pass this node. Sticking of valves in APEs typically results from carbon deposits accumulating on valve stems, thermal distortion, inadequate lubrication, and mechanical wear. This malfunction initially causes noticeable power loss and rough engine operation. Ultimately, untreated valve sticking may progress to component damage or potentially total engine failure, which is particularly dangerous in aviation applications. Additionally, when considering the precursor type, the leakage betweenness centrality is the largest, indicating multiple shortest paths pointing to the leakage node. It also demonstrates that leakage events are more likely to occur, and, compared to other types of precursors, the possibility of passing fewer nodes during a leakage event is greater.

Using the PageRank algorithm, the PageRank values of each node is obtained and results are shown in Fig. 10. Compared to aforementioned metrics, nodes A7, B10, B4 and A15 are identified as important nodes by multiple methods. These nodes are crucial in APE networks, as proven by multiple analysis methods (degree, betweenness, and PageRank) that all identify them as highly connected hubs. Moreover, A7 (ECU) possess the highest PageRank values, exhibiting its significant transmission effect within the APE network. The predominance of ECU and electronic failures reveals a critical insight: even in thermal-mechanical systems, electronic device reliability demands greater attention in safety analysis. As a pivotal system component, ECU failure has a significant impact on APE risk monitoring and control. In reality, APE designers generally reduce the impact of ECU failure on system safety through redundant design, such as equipping two ECUs simultaneously. On the foundation of the topological analysis above, the ICW-

TOPSIS method is adopted to assess node importance by integrating three positively correlated centrality metrics: degree centrality, betweenness centrality, and PageRank values. The method innovatively integrates mean deviation with the information entropy in EW method to evaluate contrast intensity. Greater mean deviations and higher entropy values indicate more significant data spread and richer information content. Besides, the method also assesses conflict through the absolute correlation coefficient metric. The weight allocation follows an inverse relationship with the correlation coefficient, where weakly correlated indicators demonstrate greater conflict and consequently receive more weighting. Indicator weights derived from Eq. (14) and their 95% confidence intervals are shown in Table 5, reflecting the thorough consideration of the improved method. Betweenness centrality indicator has the highest mean deviation and conflict values, while the degree centrality has the largest information entropy value. The analysis reveals betweenness centrality as the most influential metric (highest weight), followed by PageRank, with degree centrality demonstrating the lowest weighting.

Table 5. Parameters after ICW-TOPSIS calculation.

	Mean deviation	Information entropy	Conflict	Weight (95% Confidence Interval)
Degree centrality	0.0761	0.9243	0.3831	0.2866 (0.2497~0.3525)
Betweenness centrality	0.1001	0.7062	0.6032	0.3637 (0.3085~0.4065)
PageRank value	0.0837	0.9062	0.4726	0.3498 (0.2828~0.4079)

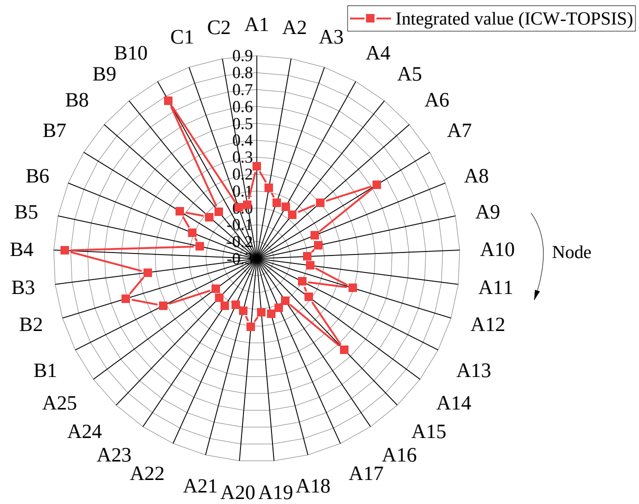

Figure 11. Integrated values derived from ICW-TOPSIS method.

The ICW-TOPSIS method indicating the integrated topological importance of risk nodes is adopted and the results are shown in Fig. 11. The AP nodes are not considered during this analysis. The presented results show that the risk nodes, such as B4 (sticking), B10 (electronic failure), A7 (ECU), B2 (vulnerability rupture), A15 (wastegate valve), and B3 (pollution), may have larger effect on the network from integrated topological perspective. The common cause for both sticking and pollution in APEs may be the contaminant deposition. These contaminants, primarily carbon deposits, can significantly degrade engine performance. They may reduce operational efficiency, leading to increased fuel consumption and, in severe cases, engine misfires or abnormal vibrations that may damage critical components. Furthermore, integrated results also underscore the importance of electronic components (e.g., ECU) in ensuring APE system safety. Finally, vulnerability rupture is another critical failure mode that may stem from casting defects, stress concentration, or material imperfections, necessitating targeted mitigation strategies in design and manufacturing to minimize such risks.

3.3.2. Risk initiation and evolution analysis

In order to incorporate the physical and subjective indicators into the critical component analysis, Eq. (19) is employed and the results of top-ranking components are shown in Table 6. By comparing the two composite indicators with the pure topological indicator, several observations can be described as follows. First, A7, A15, and A12 consistently rank among the top across all evaluation methods, confirming their critical importance for APE system safety. Second, A1 and A6 show high topological importance but demonstrate declining significance when incorporating other aspects into the evaluation. Relevant observation can also be seen on A20: A20 doesn't rank high in topology ranking, but as the physics-related parameter and expert experience are gradually added to the evaluation, its ranking is getting higher. The trends shown in A1, A6 and A20 indicate that relying solely on topological analysis is not enough, highlighting the importance of comprehensive scoring for critical component evaluation in complex physical systems. Third, despite minimal topological significance, A10 achieves top ranking when physical failure rates are incorporated. However, based on expert experience, the short-term failure of the coolant radiator may not have a significant impact on APE safety, resulting in a slight decrease in the final ranking. Furthermore, a sensitivity analysis is performed to investigate the effect of different weighting schemes, moving beyond the initial equal-weight assumption. The results, presented in Table 7, indicate that the overall determination of critical components is robust to small weight changes. Notably, specific rankings are more susceptible to adjustments in the weight of the physical aspect. Overall, as the evaluation process progressively incorporates physical-related parameters and expert insights, the ranking of critical components improves and stabilizes, yielding more practical and reliable results. The final critical component rankings will be further validated against high-ranking global risk paths by comparing their starting nodes, as presented in the Section 4.

Table 6. Component ranking comparison of different evaluation methods.

Indicators		Topology	Topology+Physics	**Topology+Physics+Expert**
Ranking	1	A7	A7	**A7**
	2	A15	A15	**A15**
	3	A12	A10	**A12**
	4	A1	A12	**A20**
	5	A6	A1	**A10**

Table 7. Component ranking comparison under different weighting schemes.

Indicators		**Topology:Physics:Expert**			
Weighting ratio		**1:1:1**	2:1:1	1:2:1	1:1:2
Ranking	1	**A7**	A7	A10	A7
	2	**A15**	A15	A7	A15
	3	**A12**	A12	A15	A12
	4	**A20**	A6	A12	A20
	5	**A10**	A20	A20	A6

In this study, critical paths denote high-risk propagation sequences requiring prioritized monitoring. Their detection becomes computationally intensive as network size increases. Since the system component performs as the initial node of the APE risk chain, an efficient searching method for critical risk paths is proposed in this study. The searching method is basically a local traversal approach, introduced as follows: select the previously obtained critical component nodes as initial nodes, explore possible causal chains based on directed edges between nodes, and stop the extension of the specific chain whenever it encounters the end node. Unlike global algorithms that require traversing all nodes as starting points, our method only initiates from a node subset, significantly improving efficiency. The efficiency of this method can be further validated through the following algorithm complexity analysis: If a global traversal algorithm such as the Floyd-Warshall algorithm is employed, its time complexity is $O(V^3)$. In contrast, by applying a greedy algorithm like Dijkstra algorithm to the selected critical components in our method, the time complexity becomes $O\big((V+e)\,log\,V\big)$, where e denotes the number of edges. This clearly shows that when the network scale is large enough, our proposed method effectively reduces the time cost.

Table 8 displays high-risk propagation paths starting from critical components. Among these results, A10→B1→B6→D5, A12→B4→D1 and A7→B10→D2 are identified as the top 3 critical causal chains with the highest risk level, representing the most hazardous event evolution process of APE systems. These high-risk chains tend to be short, as longer causal chains typically have lower formation probabilities and consequently reduced overall risk. Coolant radiator is not a rank 1 critical component, but it serves as the initial node of the highest-risk path due to its exceptionally high failure rate. Blockage is the main failure mode of the coolant radiator, which can directly lead to abnormal temperature changes, cooling efficiency loss and hydraulic degradation, potentially shortening component lifespan. For wastegate components, sticking is the failure mode that require special attention. It can lead to the abnormal vibration/shaking of the APE, which is a critical precursor to severe engine failure requiring special attention. Additionally, considering the top 1 critical component ranking of ECU, associated high-risk ECU failure path further illustrates the dominant position of this device in APE safety management.

Table 8. Risk values of causal propagation from critical components.

Causal chain	Risk value	Ranking of risk
A10→B1→B6→D5	3.259	1
A7→B10→D2	0.806	3
A20→B5→D3→D1	0.788	4
A12→B4→D1	1.407	2
A12→B4→D6	0.528	6
A12→B4→D1→D4	0.469	7
A15→B4→D1	0.735	5
A15→B4→D6	0.275	8

4. Result validations

This study systematically examines the outcomes generated through the TSCA process. Specifically, the criticality of identified factors can be validated through node removal operations, demonstrating the efficacy of the integrated evaluation method proposed for critical factor analysis (Section 4.1). For the verification of critical components and paths, the global risk path search method serves as a viable approach, particularly suitable for small-scale networks (Section 4.2).

4.1. Network robustness analysis

For safety personnel, the selection of effective measures for safety enhancement can be a challenging decision-making task. Analysis of the incident-causation network enables dual understanding: the forward process examines patterns of incident occurrence, while the reverse process investigates preventive measures [43]. Topological analysis of the steady-state network demonstrates that targeted removal of critical incident nodes significantly reduces overall connectivity [44], indicating that focused interventions on these critical nodes can disproportionately enhance safety. Therefore, robustness analysis of the accident causation network is essential for systematically mitigating APE-related safety risks.

This study systematically investigates network robustness by analyzing how seven distinct attack strategies influence network efficiency. While more in-depth intervention simulations would be preferable, further elaboration on them is reserved for subsequent studies due to space limitations. The attack strategies introduced in this study include random attacks and six deliberate targeting methods. Random attacks are implemented through stochastic node removal with results averaged across multiple simulations to ensure statistical reliability, while the other deliberate strategies follow a node removal based on descending order of their respective importance metrics. Due to the scale-free characteristics of the APE network, most nodes exhibit low degree values with limited edge connections. Consequently, low-importance nodes with fewer connections are statistically more vulnerable to initial attacks. As illustrated in Fig. 12, the network efficiency demonstrates significantly slower degradation under random attacks compared to other strategies.

For the deliberate attack, we explore the robustness of the APE network by comparing the common deliberate attack methods based on single metrics with the intentional attack strategies based on integrated importance metrics. As depicted in Fig. 12, except for the PageRank value attack, the other deliberate attack strategies have relatively similar decreasing trends in network efficiency. Overall, three deliberate attack strategies based on comprehensive values are better than strategies based on single metrics. And when the number of removed nodes is 3 and 6, networks subjected to attacks using the CW-TOPSIS and ICW-TOPSIS methods demonstrate significantly lower efficiency metrics compared to those attacked via the EW-TOPSIS approach. This observation indicates that CW-based attack strategies perform relatively better than the attack strategy based on EW-TOPSIS. When the number of removed nodes is 7, the network under the CW-TOPSIS-based attack has the lower network efficiency than the network under the ICW-TOPSIS-based attack; but when the number of removed nodes is 9, the ICW-TOPSIS-based attack strategy performs better. Therefore, it is difficult to determine the superiority of the two CW-based methods. As a result, this comparative robustness analysis offers critical insights for developing targeted protection strategies in safety-critical networks. The ICW-TOPSIS method, adopted as the main approach for topological evaluation, is confirmed to be a viable and effective technique for the risk assessment of network nodes.

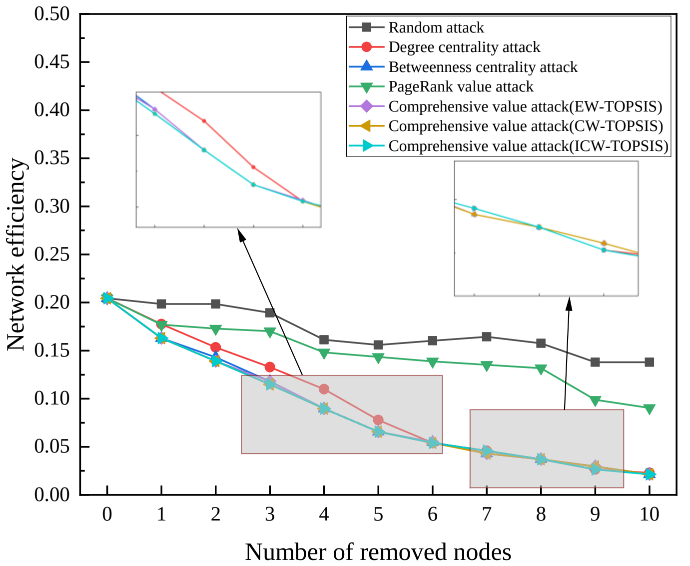

Figure 12. Network efficiency of the APE network under different attack modes.

4.2. Global searching verification

This section presents the validation of an efficient critical path detection algorithm originating from top-ranked critical components. The primary rationale stems from the observation that paths initialized from purely topology-ranked components may not represent globally high-risk scenarios. To enable more precise assessment of component criticality in complex physical systems and optimal identification of high-risk propagation paths, the component analysis method and the path-search algorithm is improved in this study. To illustrate the superiority of this methodology, for small-scale CNs such as the APE network discussed in this study, global searching method can be applied with acceptable computation cost and performed as the viable tool for validation. While the global search method identifies potential high-risk paths, subsequent filtering is necessary to eliminate physically implausible pathways from consideration. The final results are shown in Table 9. Results confirm that our component evaluation methodology successfully predicts all high-risk path origin nodes in the APE network, outperforming conventional topological metrics. Overall, global search validation demonstrates the algorithm's superior capability to maintain computational efficiency while effectively identifying critical risk paths, making it ideally suited for component-path joint analysis in CN applications.

Table 9. Risk values of causal propagation from global view.

High-risk path (Global view)	Risk value	Ranking
A10→B1→B6→D5	3.259	1
A12→B4→D1	1.407	2
A7→B10→D2	0.806	3
A20→B5→D3→D1	0.788	4
A15→B4→D1	0.735	5

5. Safety control strategies

Leveraging TSCA results, targeted risk control measures can be implemented to enhance APE system safety. Building upon established principles of accident risk prevention and control [18] and incorporating our findings on critical events and propagation paths, Fig. 13 systematically presents both the risk evolution process and corresponding intervention strategies. This framework proposes targeted safety measures addressing three critical aspects: (1) risk source containment, (2) propagation-path interruption, and (3) consequence mitigation, implementing sequential safety barriers for comprehensive risk management.

(1) As demonstrated in earlier sections, system components constitute the main source of APE risk. Among them, A7 (ECU), A15 (wastegate valve), A12 (wastegate actuator), A20 (high-pressure pump) and A10 (coolant radiator) are the critical components as well as the initial nodes of high-risk critical paths.

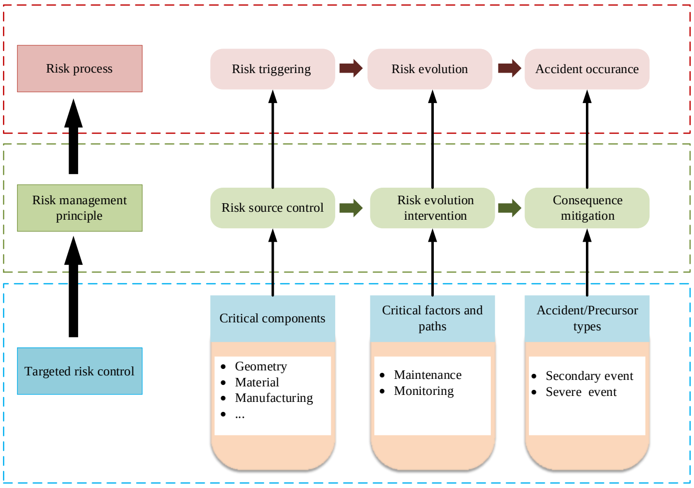

Figure 13. Risk evolution and risk intervention process.

The ECU serves as the critical brain of modern APEs, precisely regulating fuel injection, ignition timing, and air-fuel ratio to optimize performance, efficiency, and emissions. To enhance ECU reliability, redundant design for software and hardware is a common approach. Moreover, regular software updates and conformal coatings are both effective means of ECU improvement.

For wastegate valve and actuator, the primary cause of the failure is the B4 (sticking). Key solutions include optimizing component clearances and geometries to prevent sticking, upgrading to advanced high-temperature materials and coatings for enhanced durability, and implementing precision manufacturing techniques to ensure optimal surface finishes. These technical improvements guarantee wastegate component durability at the design phase.

For high-pressure pump in APEs, the failure mode is mainly of the sealing failure, leading to the leakage during the fuel transmission process. Therefore, to reduce this type of pump failure, solutions include: optimizing valve seat geometry and interference fit specifications; upgrading to composite seals with superior creep resistance; or applying coatings on surfaces to reduce wear.

(2) For complex physical systems like APEs, the intervention of risk propagation primarily relies on the real-time condition monitoring and regular maintenance. Real-time condition monitoring is the prerequisite of the predictive maintenance. Using the data obtained by multiple sensors, fault precursors can be accurately

identified and staff can take timely response measures. Regular maintenance also plays a crucial role in risk interruption. During this process, staff should pay more attention to the identified critical factors and paths. For example, maintenance staff should pay more attention to the coolant radiator, which belongs to the critical components. As A10→B1→B6→D5 represents the highest-risk propagation path originating from the coolant radiator, staff should also monitor its risk evolution while performing enhanced cleaning procedures. Moreover, given the observed high failure rate, maintenance strategies for the coolant radiator should integrate both service life optimization and increased replacement frequency to ensure sustained operational reliability.

(3) Severe accident consequences must be rigorously prevented. From a consequence mitigation perspective, immediate intervention is required upon initial incident detection to prevent escalation into more severe outcomes. In this study, initial type of APs in APEs are D1 and D3. These types of events may lead to secondary accidents. Especially the Gas/liquid leakage event (D3), it may cause D1, D2, D4 and D5 depending on the corresponding failure component and risk evolution path. To effectively mitigate leakage risks, maintenance personnel should prioritize immediate containment through residual fluid recovery or controlled ventilation to prevent hazardous accumulation. Temporary sealing compounds rated for aerospace applications can provide interim protection against further leakage propagation. For long-term risk reduction, engineering solutions should focus on advanced sealing technologies coupled with real-time monitoring systems to enable proactive leak detection.

Notably, while D6 (uncontrollable engine power) incidents exhibit relatively low frequency in APE accident data, their extreme severity—manifested by a 100% emergency landing rate—demands rigorous measures from both pilots and maintenance personnel. CN analysis reveals that these accidents are predominantly associated with wastegate component failures. Since emergency landing might constitute the only effective mitigation strategy for such accidents, this underscores the critical need for stringent safety design standards of wastegate components and targeted maintenance plans to ensure continuous operational integrity of the APE system.

6. Conclusions

In this paper, a systematic methodology is proposed for analyzing APE maintenance records based on CN theory. The CN-TSCA framework is presented to investigate accident causation mechanisms in APEs, aiming to provide a basis for aviation professionals to enhance safety management through data-driven risk identification and mitigation. The main conclusions of this paper are as follows:

1) The analysis of flight school APE documentation yields 43 risk events and enables the establishment of 154 representative causal chains. After that, a directed weighted APE network consisting of 43 causative nodes and 114 edges is constructed.
2) A TSCA framework is proposed, which is suitable for CN analysis on complex physical systems. The TSCA process systematically identifies critical risk factors, components, and propagation paths through three sequential steps. Topological analysis confirms the APE network exhibits characteristic features of both scale-free and small-world networks. B4 (sticking), B10 (electronic failure), B2 (vulnerability rupture) and B3 (pollution) are identified as the key causative factors using the integrated ICW-TOPSIS method. A unified metric combining objective measures and subjective expertise is introduced for component importance evaluation. A7 (ECU), A15 (wastegate valve) and A12 (wastegate actuator) are the three most critical components that warrant attention. An efficient critical path detection algorithm originating from top-ranked critical components is proposed and SFP metric is defined for the path risk calculation.
3) Network robustness analysis is adopted and multiple topological indicators are compared. Results show that the integrated indicator derived from the ICW-TOPSIS method is suitable for critical factor analysis. The global search method enables global high-risk path identification, simultaneously validating the effectiveness of our high-efficiency algorithm for joint

component-path analysis.

4) Multi-stage safety control strategies are developed for APEs, addressing risk source containment, propagation-path interruption, and consequence mitigation. For APE risk source control, safety personnel can improve the system components from geometry, material and manufacturing process aspects. Regular maintenance and condition monitoring play a vital role in risk evolution interruption. In order to avoid severe consequences, leakage is a type pf APs that should be early treated to avoid further accident. Uncontrollable engine power represents a high-severity failure event, with wastegate components identified as critical contributing factors requiring prioritized safety intervention.

The CN-TSCA framework proposed in this study offers valuable methodological insights for applying network science to safety analysis across different physical systems. In future work, detailed comparisons with traditional methods and their in-depth integration will be undertaken to refine the framework. Notably, several considerations must be addressed when applying it: First, the relative importance of various causal factors can differ significantly between systems, which will accordingly influence the analytical focus and the design of safety strategies. Second, in complex systems where internal risk propagation cannot be fully monitored, a portion of the causal paths remain opaque. This challenge is particularly pronounced in tightly-coupled systems like aero-engines. Thus, the analysis must extend beyond directly observed data to incorporate expert judgment and plausible assumptions. It also underscores the need for advanced condition monitoring and fault detection technologies in future research. Finally, when designing the evaluation metric for critical components in physical systems, it’s crucial to recognize that design principles of the metric are intrinsically linked to how risk is defined within propagation paths. Consequently, the framework's analytical process and conclusions are inherently shaped by the underlying definition of risk.

Acknowledgment

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