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*Research Article*

# Risk and Reliability Assessment of Metal Lathe Machining Operation with DBN-FFTA Hybrid Approach

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A metal lathe is a high-performance tool used in the field of metalworking to remove excess material and shape metal parts. However, engaging in metal turning operations carries risks that can lead to serious accidents and physical harm. It is crucial to ensure that these systems are functioning correctly, as any malfunction or flaw can lead to dangerous situations. To maintain safety in industrial environments, it is important to assess the risks and reliability of the equipment. A study was conducted using a method called fuzzy fault tree analysis (FFTA), combined with fuzzy logic, to determine the probability of basic events. Bayesian networks (BNs) were utilized to update probabilities and overcome limitations of the fault tree (FT). A Dynamic Bayesian Network (DBN) was employed to estimate the reliability of a metal lathe in a specific scenario. The FT identified 57 root events and estimated the probability of workpiece FLY-OUTS as 0.03174329 using the FT method and 0.031505849 using the BN method. Based on the predictions of the DBN, system reliability decreased by 19.89% after 24 months. The FT diagram comprehensively captured all the factors associated with FLY-OUTS, highlighting that improper closing of the part on the tool was a significant contributing factor. The study concludes by proposing safety measures for turning operations based on the identified critical events.

## 1. Introduction

A metal lathe is a high-performance tool used in the field of metalworking to remove excess material and shape metal parts. However, engaging in metal turning operations carries risks that can result in serious accidents and physical harm. One of the primary hazards when operating a metal lathe is the potential for contact with sharp components and moving machinery. Failing to take the necessary precautions can expose workers to the risk of severe injuries to their hands and fingers. Additionally, if flammable and explosive substances are present in the work area, there is a possibility of fire and explosion hazards [1].

The data reveal that accidents involving metal lathe machines occur frequently and can present significant risks to the involved workers. Machinists make up a substantial part of the industrial workforce in the United States. Nonvehicle machinery accounts for over 10% of total annual work-related injuries. It is estimated that ∼3,400 metal lathe operators in the US suffer work-related injuries resulting in time off each year. These incidents encompass a range of injuries, including cuts, fractures, wounds, and bruises, with some instances potentially leading to fatalities [2].

A study conducted on a small electrical equipment and parts manufacturing plant revealed that lathe accidents ranked fifth in terms of frequency, following accidents involving woodworking machines, metal cutting saws, electric presses, and drilling machines [3].

With the emergence of new technologies and the increasing complexity of modern manufacturing systems, it has become imperative to establish reliable and effective maintenance programs. These programs play a crucial role in ensuring high levels of productivity and availability, while also minimizing costs and unexpected shutdowns [4, 5]. In order to facilitate decision-making in maintenance activities within process-oriented systems, researchers have concentrated on risk-based and reliability-based approaches. These methods have been widely utilized to identify areas of concern, address problems, and continuously monitor systems. Both data-based and knowledge-based techniques have been employed in this context. Knowledge-based methods are highly valuable when combined with data-based techniques, as they enhance the evaluation of risk and reliability, facilitate fault diagnosis, and support maintenance decision-making [6, 7]. These approaches prove to be particularly useful when confronted with incomplete or inaccurate data pertaining to equipment failure, environmental factors, and human activities [8–10]. Numerous knowledge-based methods are available, primarily focusing on risk and reliability analysis. Some examples include failure mode and effect analysis (FMEA), hazard analysis critical control points (HACCP), hazard and operability study (HAZOP), event tree analysis (ETA), fault tree analysis (FTA), among others [8, 11–15]. FTA is regarded as a powerful diagnostic tool and has been one of the most significant knowledge-based methods since the twentieth century. It is recognized as a comparative technique used to identify combinations of system and human errors [6, 16].

FTA analyses are typically categorized into two levels: qualitative and quantitative. Qualitative analysis involves transforming tree networks into minimal cut sets (MCS), which consist of the smallest combinations of basic events (BE) necessary to establish the top event (TE). In quantitative analysis, mathematical calculations are employed to determine the probability of occurrence for the top event (TE) and other indicators that possess similar importance criteria [17, 18]. Once the FTA structure has been created, the results can provide valuable insights into the reliability of the system. By identifying the units of the system that are at immediate risk, the analyst can swiftly implement corrective measures to address any critical units in jeopardy.

Indeed, this analysis method illustrates how the failure of individual units, human error, or environmental factors can lead to a system-wide failure [19, 20]. The FTA technique has found diverse applications in numerous industrial systems and is extensively utilized. For instance, it is employed in system safety assessments for nuclear reactors and gas distribution systems [20, 21]. Risk and reliability analysis have been employed in various sectors including automotive, chemical, and petrochemical industries [22–24]. Electronic components, pipelines, and aerospace systems are subjected to failure diagnosis [25, 26]. Suryoputro et al. [27] employed several techniques, including the Systematic Human Action Reliability Procedure (SHARP), Hazard Identification and Risk Assessment (HIRA), FTA, and FMEA, to investigate human reliability and lathe safety. Oriola et al. [28] conducted a study on lathe functionality using FTA, and their findings indicated that the most probable type of accident would involve occurrences of FLY-OUT.

While the classic FTA technique offers several advantages and has been associated with successful outcomes, it also possesses various drawbacks and limitations. These include the necessity to simplify models due to system complexity and gaps in knowledge regarding system behavior, the potential for human error during fault tree (FT) construction, and the presence of unforeseen failures. Such uncertainties can not only affect the accuracy of expected analysis results but also impact decision-making and the implementation of corrective measures. Consequently, there is a need to address these uncertainties in order to enhance the validity of FTA findings [6, 16]. To address uncertainties and complement classical FTA calculations, researchers often propose utilizing computational knowledge and decision tree network techniques or theories. One technique frequently referenced in this context is the fuzzy sets theory (FST), which was introduced by Zadeh [29] in 1965 to address uncertainty issues associated with FTA. The FST is utilized to handle both data and ambiguous knowledge that is difficult to express or analyze using precise numerical values.

The system is designed to better align with how humans process information and has the capability to mathematically process qualitative language used by experts in a specific field [30]. Due to the significant level of uncertainty commonly found in data and information related to accident analysis and risk assessment, FST has been extensively utilized in these fields for various applications. Numerous investigations have been conducted across various fields utilizing FST to tackle the uncertainties and data deficiencies inherent in traditional FTA. Recently, Aghaei et al. [31] developed a model called Fuzzy Fault Tree Analysis (FFTA) to assess safety risks associated with the implementation of shopping mall construction projects. The objective of this model is to identify the sources of potential risks and recommend appropriate strategies for their management. In another study, Yazdi et al. [32] developed the FFTA model by incorporating expert input to determine event probability. Furthermore, they employed an importance measurement technique to reduce the probability of TEs occurring with respect to three factors: safety consequences, cost, and profit. Based on the findings, this method proves to be highly effective in determining the probability of reliability.

While the utilization of this theory can reduce ambiguity, its composition remains unchanged and lacks the ability for comparative reasoning. In recent years, several efforts have been made to address these issues by incorporating novel and dynamic approaches such as Bayesian networks (BNs), evidence theory, Monte Carlo models, and Marco's method [33]. Among the mentioned techniques, the BN methodology stands out for its distinct attributes in evaluating hazards and analyzing incidents. This specific method was employed by Barua et al. [34], Li et al. [35], Guo et al. [36], and Mohammadi et al. [37]. The utilization of BNs is widespread in various engineering fields, including reliability engineering and risk evaluation [38]. However, the limitation of BNs lies in the absence of a causal feedback loop, which can complicate receiving network feedback. Nevertheless, this challenge is overcome by utilizing dynamic Bayesian networks (DBNs) as an alternative for time series data. DBN can replicate time lags in the data and construct loop networks, contrary to BN which relies on static data. Instead, DBN employs time series data to establish causal relationships between random variables [39]. Moreover, certain studies have utilized DBN to examine the cascading effects in chemical processing infrastructure [40].

Cai et al. [41] introduced a technique to assess comprehensive safety levels by employing DBN. In another study, researchers modeled the outcomes of incidents occurring in metal turning machining operations using a Bayesian Belief Network (BBN) [42].

The main objective of this study was to develop a strategy for evaluating and analyzing the risk and reliability of metal lathe machining operations under uncertain conditions. To achieve this, the researchers utilized the FT approach to identify the root causes of machine failure. Additionally, they employed fuzzy theory along with expert opinion to estimate the probability of these events occurring. As standard BNs have limitations in capturing the dynamic nature of FTs, this research utilized a DBN model to evaluate the reliability of lathe machining operations over time. By adopting this approach, it becomes possible to identify critical factors contributing to low reliability and formulate effective strategies for preventing machine failure.

## 2. Materials and Methods

The research employed the FT method, along with fuzzy theory and DBN, to assess risks, analyze data, and ascertain the reliability of lathe machining operations. The cognitive diagram used in the research is shown in Figure 1, and a detailed explanation of each step can be found below.

### *2.1. FT Approach*

*2.1.1. Comprehending the Metal Lathe's Design and Functionality, as well as Selecting the Primary Event.* At the outset, a comprehensive gathering of detailed information and specific details pertaining to all components of the system, as well as the physical and functional relationships between these parts associated with the metal lathe, was conducted. All technical and functional documents related to the metal lathe, including its operation during turning processes, as well as other documents pertaining to its activity, were acquired and thoroughly examined. By reviewing available resources and consulting with experts in the field, it was possible to categorize the lathe into four subsystems: structural, mechanical, electrical, and functional features, along with safety measures. This approach facilitated a comprehensive understanding of errors, malfunctions, and defects that occurred within the lathe.

*2.1.2. FT Development.* The FT technique is a widely recognized and systematic approach used to identify the potential causes behind an undesired event or a significant occurrence that can lead to adverse safety and financial consequences [43]. This method entails organizing the potential sources of failure into a hierarchical structure or logic tree, with the most general causes at the top and the specific causes at the bottom. The resulting structure is subsequently analyzed to assess the probability of the final outcome, either through subjective assessment or numerical analysis [44]. The research employed the FT technique to identify the basic events that influence the primary hazard and determine its probability of occurring.

*2.1.3. FT Validation.* Content validity demonstrates the extent to which a tool adequately measures all dimensions of the intended concept. There are various approaches to evaluate validity, with content validity being the most prevalent. It is determined by calculating the content validity ratio (CVR) and the Content Validity Index (CVI). This research utilized both of these criteria to evaluate the significance and essentiality of basic events, intermediate events, and types of gates. For this research, a team of five specialists was selected from universities and workshops. The team comprises two HSE experts, one senior mechanical expert, and two university experts. The role of the team was to address any uncertainties in the initial FT structure, and a brainstorming approach was employed to gather their insights. The validation process of the FT is shown in Figure 2, based on the feedback provided by this specialized team. The CVR is a technique used to assess the validity of an instrument. This methodology was developed by Lawshe [45]. To calculate this ratio, expert opinions from the relevant field are sought. The experts are informed about the objectives of the assessment and provided with operational definitions pertaining to the content of the questions. Each question is rated on a scale of 1–3, with 1 indicating that it is not necessary and 3 indicating that it is essential. Equation (1) is then utilized to compute the CVR value.

$$\mathrm{CVR} = \frac{n_E - \frac{N}{2}}{\frac{N}{2}}. \tag{1}$$

The CVR equation incorporates two variables: "$n_E$" representing the number of experts who considered a specific question necessary; and "$N$," which denotes the total number of experts.

Referring to the Lawshe table, it was determined that for a panel comprising 11 experts, the minimum acceptable CVR value is 0.59. Any value below this threshold is deemed unacceptable in terms of content validity. The validity of the questionnaire can be evaluated using a tool known as the CVI [46]. Experts are requested to assess each component using a 4-point Likert scale, where 1 denotes it as not relevant and 4 signifies it as highly relevant. The number of experts who select option 3 or 4 is divided by the total number of experts to compute the CVI score. If the resulting score is below 0.7, the component is eliminated; if it falls within the range of 0.7–0.79, it necessitates revision; and if the score surpasses 0.79, it is deemed acceptable.

### *2.2. FST*

*2.2.1. The Use of FST to Determine the Probability of Basic Event.* Due to the unavailability of data for the identified basic events in this study, the probability of the TE was

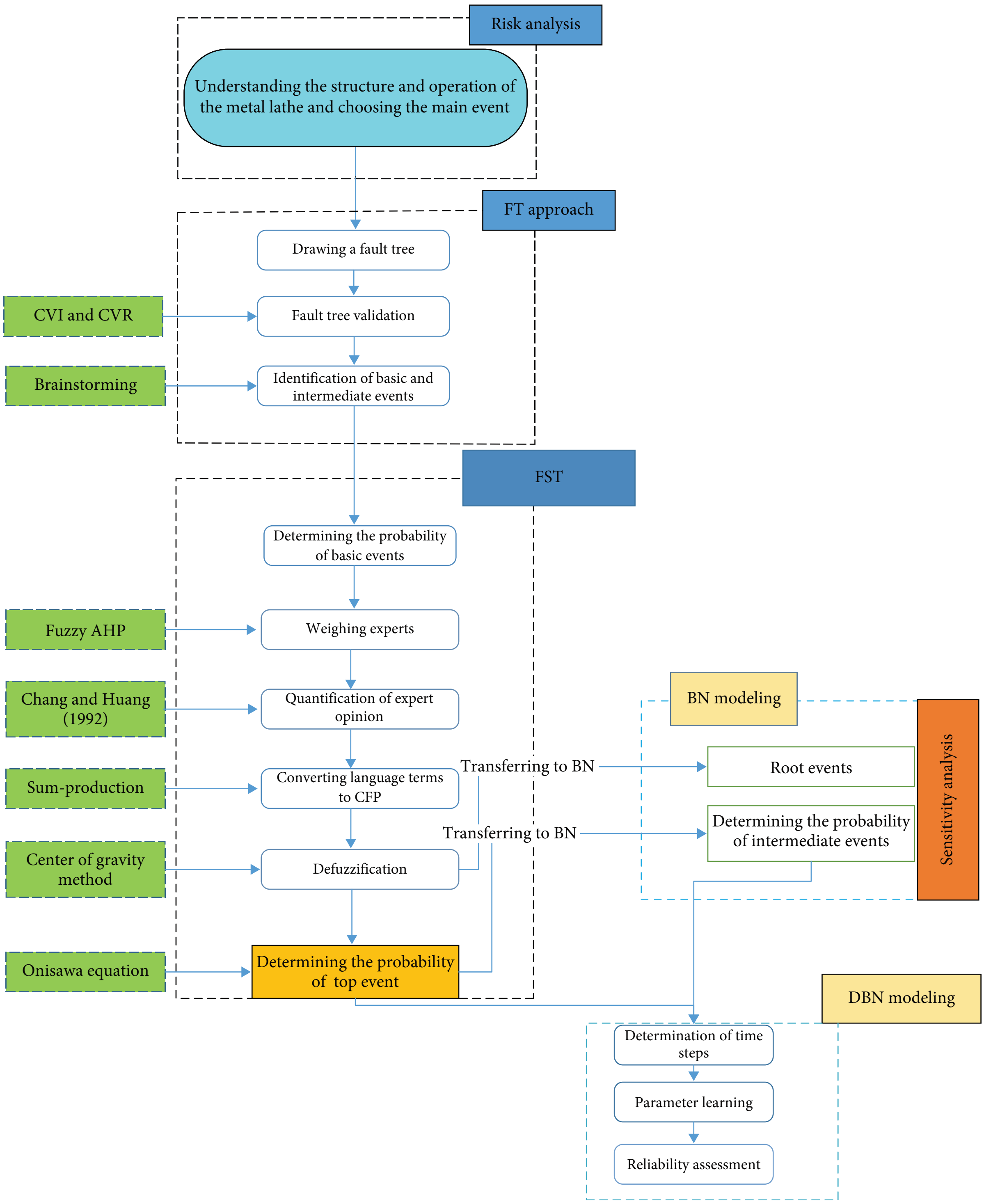


Figure 1: Research method.

estimated using FST and expert opinions. To evaluate the probability of basic events, a combination of FST and expert input was employed. Many research studies have utilized FST to gather expert opinions and address potential uncertainties in failure data. The primary focus of FST lies in measuring the quality index [37, 47]. The following steps outline the procedure for utilizing this theory to ascertain the probability of basic events.

Step 1: to commence, a panel of experts was asked to express their assessment of failure using linguistic expressions. The five-term linguistic scale proposed by Chen and Hwang [48] was utilized to gauge the significance of expert opinions and ascertain their influence on the probability of basic event failures. Several studies, such as Zarei et al. [49] and Omidvari et al. [50], have

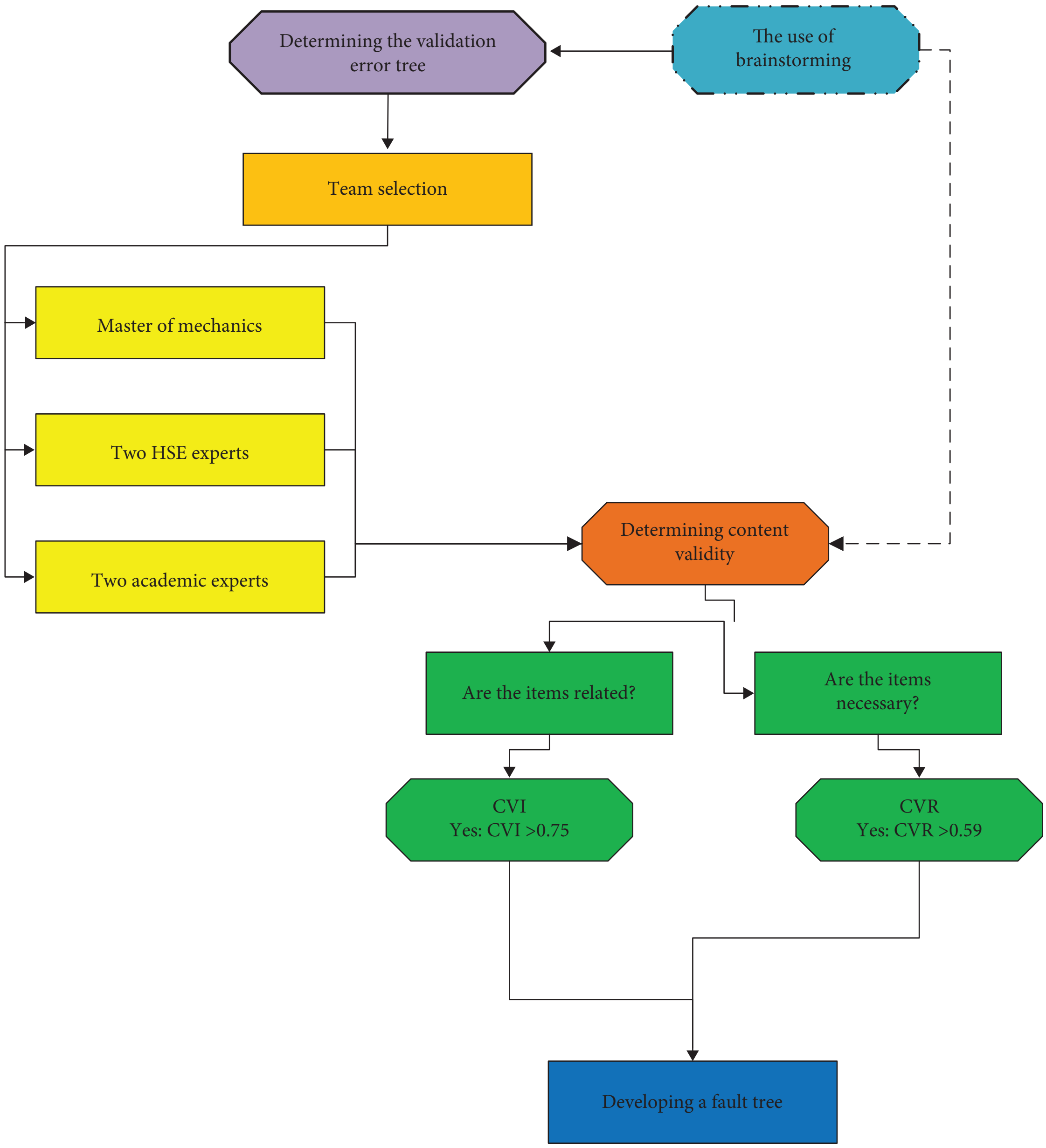


FIGURE 2: Fault tree validation process.

previously employed this approach. The scale comprises five categories: very low (0, 0, 0.1, 0.2), low (0.1, 0.25, 0.25, 0.4), medium (0.3, 0.5, 0.5, 0.7), high (0.6, 0.75, 0.75, 0.9), and too high (0.8, 0.9, 1, 1).

Step 2: in the subsequent phase, it becomes necessary to calculate the level of consensus between each pair of experts. This is achieved by computing the dissimilarity between the perspectives of two experts, $R_u = A$ $(a_1, a_2, a_3)$, and $R_v = B$ $(b_1, b_2, b_3)$, using Equation (2).

$$d\left(\widetilde{A}, \widetilde{B}\right) = \frac{1}{J = 3 \text{ or } 4} \sum_{i=1}^{3 \text{ or } 4} |ai - bi|. \tag{2}$$

In Equation (2), $a_i$ corresponds to the matching components of $A$, and $b_i$ represents the matching components of $B$. The variable $J$ is set to 3 for triangular fuzzy numbers and 4 for trapezoidal fuzzy numbers. The degree of agreement between the two experts is subsequently determined by applying Equation (3).

$$S_{uv}\left(\widetilde{R}_u - \widetilde{R}_v\right) = S\left(\widetilde{A}, \widetilde{B}\right) = 1 - d\left(\widetilde{A}, \widetilde{B}\right). \tag{3}$$

Here, $S_{uv}\left(\tilde{R}_u - \tilde{R}_v\right)$ refers to the level of concurrence between experts $u$ and $v$.

Step 3: by utilizing the consensus levels determined for each pair of experts, Equation (4) is employed to calculate the average agreement (AA) score for each expert.

$$\mathrm{AA}(E_u) = \frac{1}{m-1} \sum_{u \neq 1}^{3} \left( \widetilde{R}_u - \widetilde{R}_v \right), \tag{4}$$

$\mathrm{AA}(E_u)$ represents the average level of agreement for expert $u$.

Step 4: Equation (5) is utilized to determine the relative agreement (RA), which is calculated based on the average agreement computed for all experts.

$$\mathrm{RA}(E_u) = \frac{\mathrm{AA}(E_u)}{\sum_{u=1}^{m} \mathrm{AA}(E_u)}, \tag{5}$$

$\mathrm{RA}(E_u)$ denotes the level of relative agreement on the viewpoint provided by expert u, and $\sum_{u=1}^{m} \mathrm{AA}(E_u)$ is equals 1.

Step 5: Equation (6) is used to determine the overall agreement among all experts, considering the degrees of agreement established for each pair of experts.

$$\mathrm{CC}(E_u) = \beta \cdot W(E_u) + (1 - \beta) \cdot \mathrm{RA}(E_u), \tag{6}$$

$\mathrm{CC}(E_u)$ is determined based on the expert opinion of "$u$," with "$W$" representing the weight assigned to expert "$u$," and "$\beta$" denoting a relaxation factor that indicates the significance of "$W$" in relation to RA. The value of $\beta$ can range from zero to one. A greater value of $\beta$ implies a heightened emphasis on "$W$" as opposed to RA. When a homogeneous group of experts provides their opinions, $\beta$ equals zero. This indicates that when all experts have an equal weight, $\beta$ must be regarded as zero.

Step 6: weighting experts with the Fuzzy Hierarchy Analysis Process (FAHP) approach

Selecting experts is considered a technique for assessing the probability of events. This approach is seen as a way to deal with uncertainties and insufficient data, providing valuable insights for risk evaluation [51]. In this study, a diverse group of experts was recruited, and the FAHP method was employed to assign weights to these experts. While the Analytic Hierarchy Process (AHP) is often used to choose a preferred option from multiple alternatives, in this case, pairwise comparisons were made at each level to achieve the desired result [52]. The traditional AHP technique has several limitations. It is primarily suitable for simple decisions, heavily relies on subjective judgments, and does not account for the inherent uncertainties in individual evaluations. Here is my attempt at paraphrasing the text: the rankings produced using this method may lack accuracy due to the subjective nature of evaluations and decisions made by decision-makers. The outcomes of AHP are heavily influenced by an individual's preferences, judgments, and subjective assessments of quality indicators, which inherently contain ambiguity. The traditional AHP method may not fully meet the specific criteria set by decision-makers. To address the ambiguity and vagueness in human preferences, FST can be incorporated with pairwise comparisons to enhance the AHP approach. This integrated approach provides a more comprehensive understanding of the decision-making process [51, 53]. The method used in this study to calculate the weights of the experts was based on Buckley's technique, following the approach described by Yazdi et al. [54].

Step 7: the next step involved synthesizing the experts' opinions using Equation (7) as described in the study.

$$\widetilde{R}_{AG} = \sum_{i=1}^{m} CC(E_i).\widetilde{R}_i \tag{7}$$

Step 8: in this specific stage, the $R_{AG}$ computed in the previous step is transformed into a fuzzy set $\tilde{R}_{AG}$. To obtain a single value known as the Fuzzy Probability Score (FPS), which represents the probability of BEs, a defuzzing method needs to be applied. Defuzzing involves converting fuzzy sets into precise values [30]. Several techniques can be employed for defuzzing, including maximum first, fuzzy average, area bisector, center of gravity (COA), center of area, extended center, and fuzzy clustering. In this study, the COA method, developed by Onisawa [55] and described in Equation (8), was utilized for the fuzzification process. The result of this stage was adopted as the failure rate associated with the root causes.

$$X^* = \frac{\int u_i(x) x dx}{\int u_i(x) dx}. \tag{8}$$

In this context, $X^*$ represents the explicit output, while $\mu(x)$ refers to the combined membership function, with $x$ representing the output variable. Equation (9) is used to represent the formula for a triangular fuzzy number $A$ $(a_1, a_2, a_3)$.

$$X^* = \frac{\int_{a}^{a_2} \frac{x-a_1}{a_2-a_1} x dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} x dx}{\int u_i(x) dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} dx} = \frac{1}{3}(a_1 + a_2 + a_3). \tag{9}$$

To denote the formula for a trapezoidal fuzzy number $A$ $(a_1, a_2, a_3)$, Equation (10) can be expressed.

$$X^* = \frac{\int_a^{a_2} \frac{x-a_1}{a_2-a_1} x dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} x dx}{\int u_i(x) dx + \int_{a_2}^{a_3} \frac{a_3-x}{a_3-a_2} dx} = \frac{1}{3} \times \frac{(a_4+a_3)^2 - a_4 a_3 - (a_1+a_2)^2 + a_1 a_2}{(a_4+a_3-a_1-a_2)}. \tag{10}$$

Step 9: TE and failure probability (FP): during the defuzzing stage, a number represented as CFP is obtained for each event. The derived number needs to be transformed from possibility to probability, which can be achieved using Equations (11) and (12). These equations play a crucial role in computing the FP associated with the events [56].

$$\mathrm{FP} = \begin{cases} \frac{1}{10^K} \rightarrow \mathrm{CFP} \neq 0 \\ 0 \rightarrow \mathrm{CFP} = 0 \end{cases}, \tag{11}$$

$$K = \left[\frac{1-\mathrm{CFP}}{\mathrm{CFP}}\right]^{\frac{1}{3}} \times 2.301. \tag{12}$$

The process involves several variables, including FP, which represents the FP. Additionally, there is CFP, which stands for conditional FP obtained during defuzzification, and $K$, an intermediary variable that depends on CFP.

Step 10: to determine the probability of the occurrence of MCS and TE, Equations (13)–(15) are employed to estimate the probability of intermediate events linked to the main event. The calculations performed using these equations are generally influenced by the type of gate utilized.

$$P_{\mathrm{or}} = 1 - \prod_{i=1}^{n} (1 - P_i), \tag{13}$$

$$P_{\mathrm{and}} = \prod_{i=1}^{n} P_i, \tag{14}$$

$$P(\mathrm{TE}) = 1 - \prod_{j=1}^{K} \left(1 - P\left(\mathrm{MCS}_j\right)\right). \tag{15}$$

In this scenario, $P_i$ represents the probability associated with basic event $i$, while $P\left(\mathrm{MCS}_j\right)$ denotes the probability of main cut set $j$. Similarly, $P(\mathrm{TE})$ indicates the probability of TE occurrence.

*2.3. BN Modeling.* The BN methodology is a graphical model that illustrates the connections among various target variables. The network comprises qualitative and quantitative components. In the qualitative segment, the structural model depicts the relationships between the variables and incorporates a continuous probability distribution that applies to all variables. The quantitative aspect of the BN strategy provides a series of localized probability descriptions that are vital for determining probabilities and numerically evaluating variables or groups of variables. It is important to note that BN is a directed graph without any cycles [57]. BNs rely on the Bayesian theory for probability revision and possess a remarkably versatile and adaptable characteristic for modeling various event scenarios in real time. These networks calculate the joint probability distribution by utilizing a range of variables [58, 59].

During this investigation, the basic, intermediate, and TE identified in the FT model are considered as the root, intermediate, and TEs in BN [60]. Jensen and Nielsen [58] have noted that the BN probability distribution includes a set of variables due to conditional dependence and chain rules, as depicted in Equation (16).

$$P(U) = \prod_{i=1}^{n-1} P(X_i | X_{i+1}, \ldots, X_n|). \tag{16}$$

Here, $U = \{X_1, X_2, \ldots, X_n)$ and $X_{i+1}, \ldots, X_n$ are its parents.

The ability to perform both inductive and deductive reasoning is regarded as one of the most significant features of BNs. Inductive reasoning involves predicting and estimating the probability of events and their outcomes. While the FT model can also engage in this type of reasoning, it may generate inaccurate estimations of incident scenario probabilities and consequently, final consequence probabilities due to the outlined limitations [61, 62]. The capacity for deductive reasoning is a noteworthy attribute of BNs, proving to be highly advantageous in dynamic risk assessment. This characteristic makes the network structure highly flexible and allows for the updating of the probability of basic event occurrence by considering data on precursor events. Conducting a risk analysis enables the identification of the key basic event that contributes substantially to the occurrence of the main event through the updating of the probability of basic event occurrence [63]. This study has applied this logic to revise the probability of basic events.

*2.3.1. Sensitivity Analysis in BNs.* In BNs, the conventional interpretations of significance criteria such as rate of variation (ROV) and Birnbaum importance measure (BIM) are expanded through the use of probability regulations. Furthermore, by employing newly established definitions within the BN structure, FT boundaries can be assessed, and critical events can be identified. Equation (17) was employed to compare the prior and posterior probabilities of basic events and determine the most critical one. The ROV measure was utilized for this purpose [63].

$$\mathrm{ROV}(\mathrm{BE}_i) = \frac{\pi(\mathrm{BE}_i) - \theta(\mathrm{BE}_i)}{\theta(\mathrm{BE}_i)}, \tag{17}$$

where $\pi(\mathrm{BE}_i)$ refers to the probability of the basic event after being updated $\mathrm{BE}_i$. The $\theta(\mathrm{BE}_i)$ denotes the probability of the basic event before being updated $BE_i$.

*2.3.2. BIM Criterion.* By employing this approach, the key components of the system are identified by assessing the degree to which the probability of failure or health for a component aligns with the probability of failure or health for the entire system. Put simply, we evaluate the importance of a component's probability in relation to the overall functioning of the system. Equation (18) is employed to compute this metric [57].

$$\mathrm{BIM}(\mathrm{BE}_i) = P(\mathrm{TE}|\mathrm{BE}_i = \mathrm{True}) - P(\mathrm{TE}|\mathrm{BE}_i = \mathrm{False}). \tag{18}$$

In the text mentioned earlier, $P(\mathrm{TE}|\mathrm{BE}_i = \mathrm{True})$ refers to the probability of the TE happening when the base event $\mathrm{BE}_i$ is true in the base node of the BN. $P(\mathrm{TE}|\mathrm{BE}_i = \mathrm{False})$ statement can be rephrased as the probability of the TE occurring when the base event in the base node BN is false.

*2.4. Fussell–Vesely Criteria to Determine the Importance and Classification of Basic Events.* After calculating the overall occurrence rate, the Fussell–Vesely equation (Equation (19)) is utilized to assess the significance of the MCS in relation to the obtained value. Following that, these MCS are categorized according to their level of importance [64].

$$\mathrm{FVI}(i) = \frac{\mathrm{MCS}_i}{\mathrm{TE}}. \tag{19}$$

The value of TE is determined using Equation (15).

*2.5. Reliability Estimation.* In order to assess the reliability of a turning operation, it can be assumed that if the operation is functioning smoothly at the beginning (time zero), its dependability would be the probability of it continuing to operate without any failure within a specific timeframe and under normal conditions. This study has utilized DBNs to evaluate the dependability of lathe turning operations.

*2.5.1. DBNs Modeling.* DBNs are an extension of BNs that serve two primary purposes. First, they can detect cyclic interdependence over time, similar to the Markov model. Second, they function as a continuous process that repeats within a defined timeframe. The variables in a DBN are interconnected, and there is no need to disregard causal relationships with consistent time intervals. This allows each relationship to form a cycle. A DBN model operates as a Markov process that maintains stability over time, even when influenced by various factors and changes. DBNs are specifically designed to accommodate modifications in incomplete structures, enhancing their analytical capabilities by accounting for the uncertainty that governs the model. DBNs serve as extensions of BNs, enabling effective modeling of probability distributions for random variables. To define a DBN, a format involving two variables $(B_1, B\rightarrow)$ is utilized. The term "$B_1$" is used to describe a BN that sets the initial probability of $Z_1$, and another variable $(B_1, B\rightarrow)$ involved. Using a loop-free graph represented by Equation (18), a Two Times Bayesian Network structure (2TBN) is employed to determine the probability distribution $P(Z_t|Z_{t-1})$ [65].

$$P(Z_t|Z_{t-1}) = \prod_{i=1}^{N} P(Z_t^i|P_a(Z_t^i)), \tag{20}$$

where $Z_t^i$ is the $i$th node at time $t$; and $P_a(Z_t^i)$ is the parent of $Z_t^i$ in the graph.

## 3. Results

### 3.1. FT Approach

*3.1.1. Understanding the Structure and Operation of the Metal Lathe and Determining the TE.* Based on an analysis of multiple reports, this study aims to examine occurrences in which the workpiece is ejected during a turning operation and optimize the said operation. These ejections may encompass situations where the tool exits during the machining process, instances where the workpiece is expelled, and cases where the removal of swarf affects the turning or shaping processes. Through their research, Oriola et al. [28] discovered that the most probable accident to transpire within a metal lathe machining system is the phenomenon known as FLY-OUTS.

*3.1.2. Drawing the FT and its Validation.* An expert panel, comprises relevant specialists and operational staff, constructed the FT pertaining to FLY-OUTS during a turning operation (see Figure 3). Subsequently, a team of experts evaluated the accuracy of the content concerning the basic events in relation to their location and gate type using CVI and CVR. Corrections were implemented based on their assessments. For instance, the gate connecting the basic events associated with the IE2 intermediate event was designated as "or". The internal corrosion event of the grip chuck was excluded from the FT due to low CVI and CVR values, whereas the final base events exhibited high values. Detailed descriptions of the 57 identified basic events and 28 final events are shown in Tables 1 and 2, respectively.

### 3.2. FST

*3.2.1. Determining Probability of Basic Event Using FST.* Before determining the probability of a root event failing, it is crucial to establish its failure rate. A technique that involves five scales, based on the indicators from the Ishikawa et al. [66] study, was used to calculate the probability of basic events occurring. Initially, a team comprising five experts with different roles was chosen to evaluate the probability of these events. The team consisted of a chief mechanical engineer, unit supervisor, mechanical expert, unit technician, and lathe operator. To assess the significance of

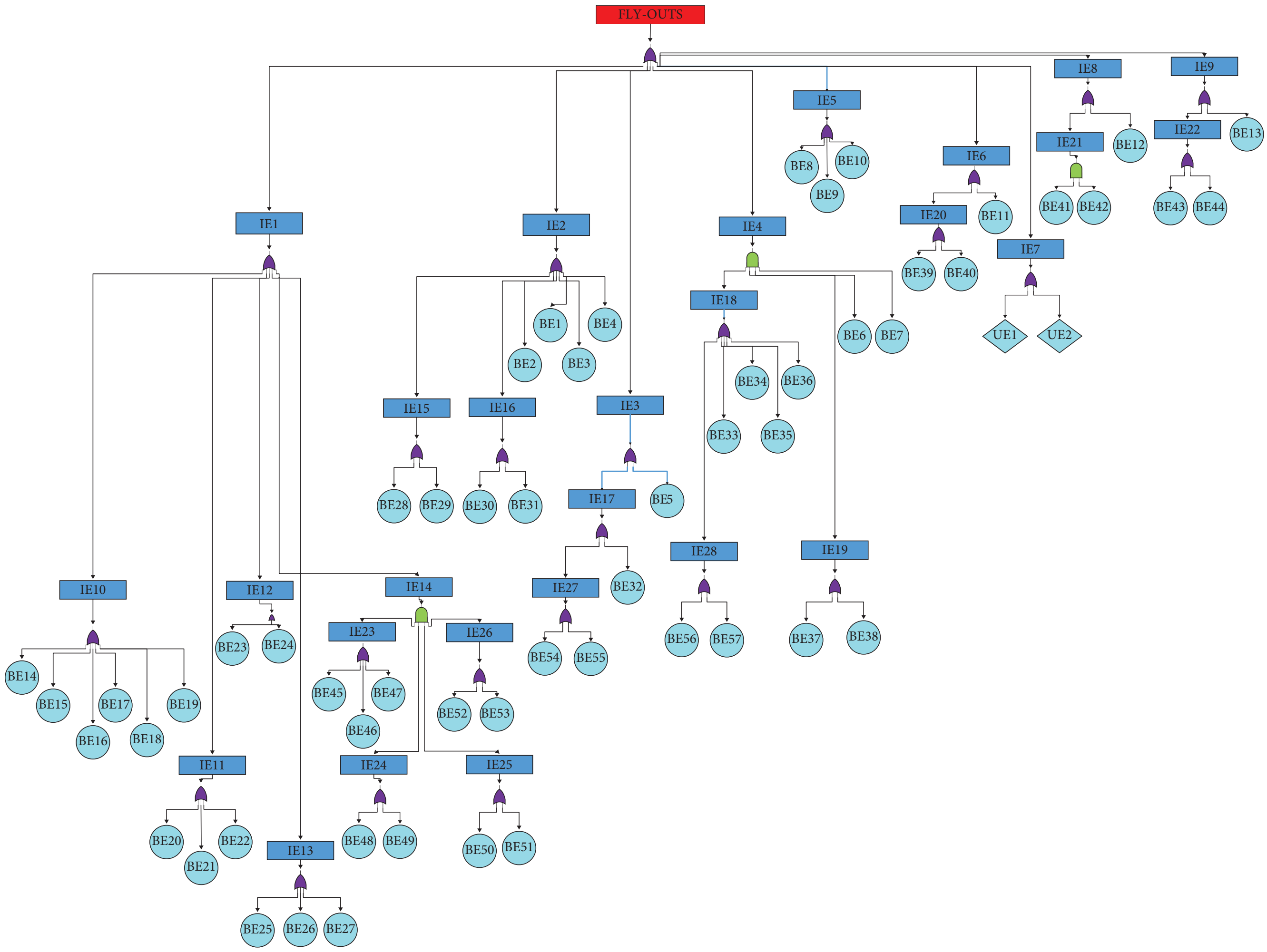


Figure 3: FT diagram of the FLY-OUTS.

Table 1: Description of intermediate events in metal lathes relevant failure.

| Symbol | Intermediate event | Symbol | Intermediate event |
|---|---|---|---|
| IE1 | Deficiency of grip chuck | IE15 | Gathering of flouncy in grip chuck |
| IE2 | Failure to hold the workpiece | IE16 | Loose connections and screws of the upper jaw |
| IE3 | Tool post defect | IE17 | Functional defect of the cutting tool |
| IE4 | Defective cooling system | IE18 | Defective coolant outlet |
| IE5 | Installation and assembly error of machine components | IE19 | Defective cooling pump motor |
| IE6 | Inappropriate performance speed | IE20 | Speed control malfunction |
| IE7 | Safety guard error | IE21 | Shaking |
| IE8 | Improper feeding rate | IE22 | Lock lever not working properly |
| IE9 | Tail stock | IE23 | Spindle heating |
| IE10 | Workpiece vibration | IE24 | High noise of the spindle |
| IE11 | Insufficient rotation and movement | IE25 | Spindle cutting stop |
| IE12 | Not moving supports or Vernier's | IE26 | Incorrect spindle orientation |
| IE13 | Malfunction of the grip chuck key | IE27 | Corrosion and tearing of the grater or tool post |
| IE14 | Spindle defect | IE28 | Low coolant level |

Table 2: Description of basic events.

| Symbol | Basic event | Symbol | Basic event |
|---|---|---|---|
| BE1 | Changing the shape of the upper jaw and not being in the center of the workpiece | BE30 | Wear and tear of cutting tools |
| BE2 | Deformation of the workpiece due to high gripping force | BE31 | The workpiece is not properly closed on the cutting tool |
| BE3 | Improper shaping of the upper jaw | BE32 | Head stock screw defect |
| BE4 | The inadequacy of the three systems and the fact that they are too far away | BE33 | Poor coolant flow |
| BE5 | Malfunction of the ratchet wrench or tool holder | BE34 | Damage or blockage of the coolant valve hole |
| BE6 | Shutting off the cooling system and cutting off the liquid | BE35 | Inlet or outlet hose blockage |
| BE7 | Failure of the pump body | BE36 | Coolant nozzle blockage |
| BE8 | Human error in installation | BE37 | Engine bearing failure |
| BE9 | Lack of integrity of equipment | BE38 | Not receiving voltage |
| BE10 | Unavailability of installation industrial map | BE39 | Electrical circuit fault |
| BE11 | Variable operating speed | BE40 | Speed change lever error |
| BE12 | The presence of chips and pleats | BE41 | The workpiece is not placed correctly in the cutting tool |
| BE13 | Not having enough strength against the incoming force | BE42 | Variable spindle speed and excessive feeding |
| BE14 | The cutting part is not aligned with the fixed bird tool | BE43 | Not setting the supports |
| BE15 | Insufficient rotation and movement | BE44 | Improper maintenance |
| BE16 | Not moving the supports | BE45 | Absence or lack of lubricating fluid |
| BE17 | Excessive cutting force | BE46 | High cutting force exceeding the tolerance of the spindle |
| BE18 | The diameter of the supports is not suitable with the diameter of the workpiece | BE47 | Bearing wear |
| BE19 | Lack of grip strength | BE48 | Bearing and gear damage |
| BE20 | The presence of chips and pleats inside the cutting tool | BE49 | Weakness of the dynamic balance of the spindle assembly |
| BE21 | Loose supports or jaws | BE50 | The gearbox belt is worn |
| BE22 | The inappropriateness of the three systems | BE51 | The transmission belt is loose |
| BE23 | Corrosion and wear of support tools | BE52 | Spindle taper position is not adjusted |
| BE24 | Support gearbox not working | BE53 | Conical spindle looseness |
| BE25 | Not having the output of three systems | BE54 | Feeding speed too low |
| BE26 | Defect of toothed part or wrench operator | BE55 | Cutting speed too high |
| BE27 | The size of the three-system wrench is not suitable | BE56 | Damage to the liquid level float sensor |
| BE28 | Lack of periodic cleaning | BE57 | Sensor error related to liquid level indicator |
| BE29 | Hard access to the feeding area | | |

their evaluations, the fuzzy AHP method was employed. The weighting profile of these five experts is shown in Table 3.

The next step involved determining the fuzzy numbers that corresponded to the individual assessments provided by each expert. These fuzzy numbers were then converted into specific values, allowing us to determine the probability of each basic event. The results of this analysis are shown in Table 4. According to this table, BE31 had the highest impact rate, followed by BE29 and BE28. On the other hand, among the contributing factors, BE36 was found to have the least influence.

After establishing the probability of the basic events, we proceeded to calculate the probability of the TE using the FT method. This included analyzing the type of gate between the events. The resulting probability value from this analysis was determined to be 0.03174329.

Table 3: Weight profile of experts.

| Experts | Job filed | Education level | Work experience (year) | Age (year) | Weighted score of each experts |
|---|---|---|---|---|---|
| Expert 1 | Department's supervisor | Bachelor | 20–30 | 40–50 | 0.296 |
| Expert 2 | Lathe operator | Associate degree | <6 | 30–39 | 0.084 |
| Expert 3 | Department's technician | Diploma | 10–19 | 40–50 | 0.152 |
| Expert 4 | Mechanical engineer | Bachelor | 10–19 | 30–39 | 0.166 |
| Expert 5 | Senior Engineer | Master | 20–30 | 40–50 | 0.302 |

Table 4: Expert opinions and fuzzy probability of basic events.

| Basic events | E1, E2, E3, E4, and E5 | | | | | Fuzzy corresponding number | | | | $d$ | $K$ | Fuzzy probability |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | VL | VL | VL | L | L | 0.047 | 0.117 | 0.17 | 0.293 | 0.302 | 3.042 | 0.00090782 |
| 2 | M | L | L | M | H | 0.342 | 0.515 | 0.515 | 0.687 | 0.236 | 3.404 | 0.00039446 |
| 3 | M | L | L | L | L | 0.158 | 0.322 | 0.322 | 0.486 | 0.217 | 3.529 | 0.0002958 |
| 4 | VL | L | L | L | H | 0.221 | 0.327 | 0.356 | 0.491 | 0.289 | 3.106 | 0.00078343 |
| 5 | H | H | H | H | VH | 0.658 | 0.792 | 0.823 | 0.927 | 0.336 | 2.888 | 0.0012942 |
| 6 | VH | L | L | H | H | 0.538 | 0.673 | 0.702 | 0.808 | 0.32 | 2.958 | 0.00110154 |
| 7 | H | L | L | H | H | 0.538 | 0.673 | 0.702 | 0.808 | 0.32 | 2.958 | 0.00110154 |
| 8 | L | L | L | L | L | 0.1 | 0.249 | 0.249 | 0.398 | 0.233 | 3.423 | 0.00037757 |
| 9 | VL | VL | VL | VL | VL | 0 | 0 | 0.1 | 0.199 | 0.364 | 2.771 | 0.00169434 |
| 10 | VL | VL | VL | VL | VL | 0 | 0 | 0.1 | 0.199 | 0.364 | 2.771 | 0.00169434 |
| 11 | VH | VL | VL | M | H | 0.465 | 0.572 | 0.625 | 0.727 | 0.324 | 2.94 | 0.00114815 |
| 12 | M | M | M | H | H | 0.439 | 0.615 | 0.615 | 0.791 | 0.248 | 3.33 | 0.00046774 |
| 13 | L | L | L | M | H | 0.284 | 0.442 | 0.442 | 0.599 | 0.248 | 3.33 | 0.00046774 |
| 14 | H | M | M | H | H | 0.527 | 0.688 | 0.688 | 0.849 | 0.283 | 3.137 | 0.00072946 |
| 15 | M | M | M | L | M | 0.266 | 0.457 | 0.457 | 0.647 | 0.195 | 3.691 | 0.0002037 |
| 16 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 17 | M | L | L | M | L | 0.191 | 0.364 | 0.364 | 0.536 | 0.209 | 3.586 | 0.00025942 |
| 18 | VH | H | H | H | H | 0.656 | 0.791 | 0.82 | 0.926 | 0.335 | 2.892 | 0.00128233 |
| 19 | H | M | M | H | H | 0.527 | 0.688 | 0.688 | 0.849 | 0.283 | 3.137 | 0.00072946 |
| 20 | M | M | M | M | H | 0.389 | 0.574 | 0.574 | 0.758 | 0.227 | 3.462 | 0.00034514 |
| 21 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 22 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 23 | M | H | M | H | H | 0.464 | 0.636 | 0.636 | 0.808 | 0.258 | 3.272 | 0.00053456 |
| 24 | H | H | H | H | VH | 0.658 | 0.792 | 0.823 | 0.927 | 0.336 | 2.888 | 0.0012942 |
| 25 | L | L | L | L | VL | 0.04 | 0.101 | 0.16 | 0.28 | 0.31 | 3.004 | 0.00099083 |
| 26 | VL | L | L | L | L | 0.07 | 0.176 | 0.205 | 0.34 | 0.271 | 3.2 | 0.00063096 |
| 27 | L | L | L | L | M | 0.16 | 0.325 | 0.325 | 0.489 | 0.217 | 3.529 | 0.0002958 |
| 28 | VL | VL | VL | VL | VL | 0 | 0 | 0.1 | 0.199 | 0.364 | 2.771 | 0.00169434 |
| 29 | VL | VL | VL | VL | VL | 0 | 0 | 0.1 | 0.199 | 0.364 | 2.771 | 0.00169434 |
| 30 | M | H | H | H | VH | 0.57 | 0.719 | 0.75 | 0.868 | 0.306 | 3.023 | 0.00094842 |
| 31 | VH | VH | VH | VH | VH | 0.797 | 0.896 | 0.996 | 0.996 | 0.389 | 2.675 | 0.00211349 |
| 32 | M | M | M | M | H | 0.389 | 0.574 | 0.574 | 0.758 | 0.227 | 3.462 | 0.00034514 |
| 33 | M | L | L | M | H | 0.342 | 0.515 | 0.515 | 0.687 | 0.236 | 3.404 | 0.00039446 |
| 34 | M | M | M | H | H | 0.439 | 0.615 | 0.615 | 0.791 | 0.248 | 3.33 | 0.00046774 |
| 35 | M | M | M | H | H | 0.439 | 0.615 | 0.615 | 0.791 | 0.248 | 3.33 | 0.00046774 |
| 36 | M | M | M | M | M | 0.299 | 0.498 | 0.498 | 0.697 | 0.189 | 3.739 | 0.00018239 |
| 37 | L | L | L | M | M | 0.193 | 0.366 | 0.366 | 0.539 | 0.209 | 3.586 | 0.00025942 |
| 38 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 39 | M | M | M | M | H | 0.389 | 0.574 | 0.574 | 0.758 | 0.227 | 3.462 | 0.00034514 |
| 40 | M | M | M | M | H | 0.389 | 0.574 | 0.574 | 0.758 | 0.227 | 3.462 | 0.00034514 |
| 41 | VH | H | H | H | H | 0.656 | 0.791 | 0.82 | 0.926 | 0.335 | 2.892 | 0.00128233 |
| 42 | M | M | M | M | H | 0.389 | 0.574 | 0.574 | 0.758 | 0.227 | 3.462 | 0.00034514 |

TABLE 4: Continued.

| Basic events | E1, E2, E3, E4, and E5 | | | | | Fuzzy corresponding number | | | | $d$ | $K$ | Fuzzy probability |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 43 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 44 | L | L | L | M | M | 0.193 | 0.366 | 0.366 | 0.539 | 0.209 | 3.586 | 0.00025942 |
| 45 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 46 | M | M | M | M | L | 0.238 | 0.423 | 0.423 | 0.607 | 0.198 | 3.668 | 0.00021478 |
| 47 | H | H | H | M | H | 0.548 | 0.706 | 0.706 | 0.863 | 0.291 | 3.096 | 0.00080168 |
| 48 | H | H | H | VH | VH | 0.691 | 0.817 | 0.864 | 0.943 | 0.35 | 2.828 | 0.00148594 |
| 49 | H | H | H | VH | VH | 0.691 | 0.817 | 0.864 | 0.943 | 0.35 | 2.828 | 0.00148594 |
| 50 | M | M | M | M | H | 0.389 | 0.574 | 0.574 | 0.758 | 0.227 | 3.462 | 0.00034514 |
| 51 | M | M | M | M | H | 0.389 | 0.574 | 0.574 | 0.758 | 0.227 | 3.462 | 0.00034514 |
| 52 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 53 | H | H | H | H | H | 0.598 | 0.747 | 0.747 | 0.896 | 0.309 | 3.009 | 0.00097949 |
| 54 | M | M | M | M | M | 0.299 | 0.498 | 0.498 | 0.697 | 0.189 | 3.739 | 0.00018239 |
| 55 | M | M | M | M | M | 0.299 | 0.498 | 0.498 | 0.697 | 0.189 | 3.739 | 0.00018239 |
| 56 | M | M | M | H | H | 0.439 | 0.615 | 0.615 | 0.791 | 0.248 | 3.33 | 0.00046774 |
| 57 | M | M | M | H | H | 0.439 | 0.615 | 0.615 | 0.791 | 0.248 | 3.33 | 0.00046774 |

### *3.3. Bayesian Modeling and Analysis*

*3.3.1. Determination of Basic Event Using FBN.* The results obtained from the methodology presented in this study were inputted into the GeNIe software (version 4.00) after determining the probability of basic events using FST. The prior and posterior probabilities were then calculated using BN update, and these values are shown in Table 5. A total of 57 basic events related to FLY-OUTS were identified during lathe turning operations. The FT approach was utilized, revealing that BE (36) and BE (33) had the lowest probability of failure based on the obtained results. By estimating the rate of main event failure using the FT model, a value of 0.031505849 was derived. However, according to the findings of the BN analysis, the rate of TE is lower than this value. Figure 4 shows the modeling of the FT in the BN.

*3.3.2. Deductive and Inductive Reasoning.* Both the FT and BN methods employ inductive reasoning, as evident from their respective results shown in columns 3 and 6 of Table 5. The FT approach estimates the probability of the TE to be 0.03174329, while the BN approach, in the previous state, yields a slightly lower probability of 0.031505849. The BN method possesses a distinctive attribute of analogical reasoning, which allows it to update basic events by incorporating information on events and quasi-events, thus rendering the model dynamic.

The outcomes of deductive reasoning can be observed in the fourth and eighth columns of Table 5, representing the revised probabilities of basic events calculated using GeNIe software. The updated probability values disclose that BE (31), BE (29), and BE (28) exert the greatest influence on the occurrence of TE, whereas BE (33), BE (57), and BE (38) have the least impact on the primary event. This characteristic of BNs facilitates the identification of the most significant basic event.

*3.3.3. Sensitivity Analysis.* In this study, the BIM and ROV methods were utilized in combination with the Fussell–Vesely criteria to assess the sensitivity of BNs and determine the most critical basic event. The results of the sensitivity analysis, shown in Figure 5, unveiled that among the 38 basic events, BE31 and BE29 held the highest significance.

### *3.4. Reliability Estimation*

*3.4.1. DBN Modeling.* Due to the fixed structure of traditional BNs, the DBN method was employed in assessing the failure rate of lathe machining procedures. Figure 6 depicts the DBN model created for simulating the lathe machining process. The simulation spanned 24 months using GeNie software, with each time step representing 1 month.

Using the FBN method, the initial probability of the lathe's failure state was estimated to be 0.031505849 ($\text{year}^{-1}$) [67]. The maintenance unit in the industry provided a repair rate of 0.235 ($\text{hr}^{-1}$). The transition probabilities were determined utilizing the parameter learning method, and Table 6 was utilized to establish the relationship between adjacent nodes at time $t$.

The results of the reliability simulation for the 24-month duration of the lathe machining process are shown in Figure 7.

The impact of eliminating each critical basic event was assessed, and the results, indicating the probability of the primary occurrence under existing conditions and in the absence of certain significant events, are shown in Figure 8.

## 4. Discussion

Nowadays, machineries are used for a wide range of applications in most industries. The metal lathe machinery is one the most commonly used machines in industries. The use of machinery has been associated with some serious accidents, leading in the death of the operator or amputation. Therefore, it is of pivotal importance to assess the safety of the machine and related operations to find out ways by which they can go out of control, resulting in undesired events. Although there are several tools to assess the safety of such

Table 5: Prior and posterior probability in FT and BN models.

| Basic event | Prior probability (FT) | Prior probability (BN) | Posterior probability (BN) | Basic event | Prior probability (FT) | Prior probability (BN) | Posterior probability (BN) |
|---|---|---|---|---|---|---|---|
| 1 | 0.00090782 | 0.00090782 | 0.028814332 | 30 | 0.00094842 | 0.00094842 | 0.030102981 |
| 2 | 0.00039446 | 0.00039446 | 0.012520215 | 31 | 0.00211349 | 0.00211349 | 0.067082464 |
| 3 | 0.0002958 | 0.0002958 | 0.0093887327 | 32 | 0.00034514 | 0.00034514 | 0.010954791 |
| 4 | 0.00078343 | 0.00078343 | 0.024866176 | 33 | 0.00039446 | 0.00039446 | 0.00039446002 |
| 5 | 0.0012942 | 0.0012942 | 0.041078086 | 34 | 0.00046774 | 0.00046774 | 0.00046774002 |
| 6 | 0.00110154 | 0.00110154 | 0.0011015401 | 35 | 0.00046774 | 0.00046774 | 0.00046774002 |
| 7 | 0.00110154 | 0.00110154 | 0.0011015401 | 36 | 0.00018239 | 0.00018239 | 0.00018239001 |
| 8 | 0.00037757 | 0.00037757 | 0.011984124 | 37 | 0.00025942 | 0.00025942 | 0.00025942002 |
| 9 | 0.00169434 | 0.00169434 | 0.053778585 | 38 | 0.00097949 | 0.00097949 | 0.00097949009 |
| 10 | 0.00169434 | 0.00169434 | 0.053778585 | 39 | 0.00034514 | 0.00034514 | 0.010954791 |
| 11 | 0.00114815 | 0.00114815 | 0.036442439 | 40 | 0.00034514 | 0.00034514 | 0.010954791 |
| 12 | 0.00046774 | 0.00046774 | 0.014846132 | 41 | 0.00128233 | 0.00128233 | 0.0012959176 |
| 13 | 0.00046774 | 0.00046774 | 0.014846132 | 42 | 0.00034514 | 0.00034514 | 0.00035874038 |
| 14 | 0.00072946 | 0.00072946 | 0.023153161 | 43 | 0.00097949 | 0.00097949 | 0.031089148 |
| 15 | 0.0002037 | 0.0002037 | 0.0064654661 | 44 | 0.00025942 | 0.00025942 | 0.0082340265 |
| 16 | 0.00097949 | 0.00097949 | 0.031089148 | 45 | 0.00097949 | 0.00097949 | 0.00097949012 |
| 17 | 0.00025942 | 0.00025942 | 0.0082340265 | 46 | 0.00021478 | 0.00021478 | 0.00021478003 |
| 18 | 0.00128233 | 0.00128233 | 0.040701331 | 47 | 0.00080168 | 0.00080168 | 0.0008016801 |
| 19 | 0.00072946 | 0.00072946 | 0.023153161 | 48 | 0.00148594 | 0.00148594 | 0.0014859401 |
| 20 | 0.00034514 | 0.00034514 | 0.0031740138 | 49 | 0.00148594 | 0.00148594 | 0.0014859401 |
| 21 | 0.00097949 | 0.00097949 | 0.031089148 | 50 | 0.00034514 | 0.00034514 | 0.00034514012 |
| 22 | 0.00097949 | 0.00097949 | 0.031089148 | 51 | 0.00034514 | 0.00034514 | 0.00034514012 |
| 23 | 0.00053456 | 0.00053456 | 0.016967008 | 52 | 0.00097949 | 0.00097949 | 0.00097949012 |
| 24 | 0.0012942 | 0.0012942 | 0.041078086 | 53 | 0.00097949 | 0.00097949 | 0.00097949012 |
| 25 | 0.00099083 | 0.00099083 | 0.031449081 | 54 | 0.00018239 | 0.00018239 | 0.0057890837 |
| 26 | 0.00063096 | 0.00063096 | 0.020026757 | 55 | 0.00018239 | 0.00018239 | 0.0057890837 |
| 27 | 0.0002958 | 0.0002958 | 0.0093887327 | 56 | 0.00046774 | 0.00046774 | 0.00046774002 |
| 28 | 0.00169434 | 0.00169434 | 0.053778585 | 57 | 0.00046774 | 0.00046774 | 0.00046774002 |
| 29 | 0.00169434 | 0.00169434 | 0.053778585 | TE | | | 1 |

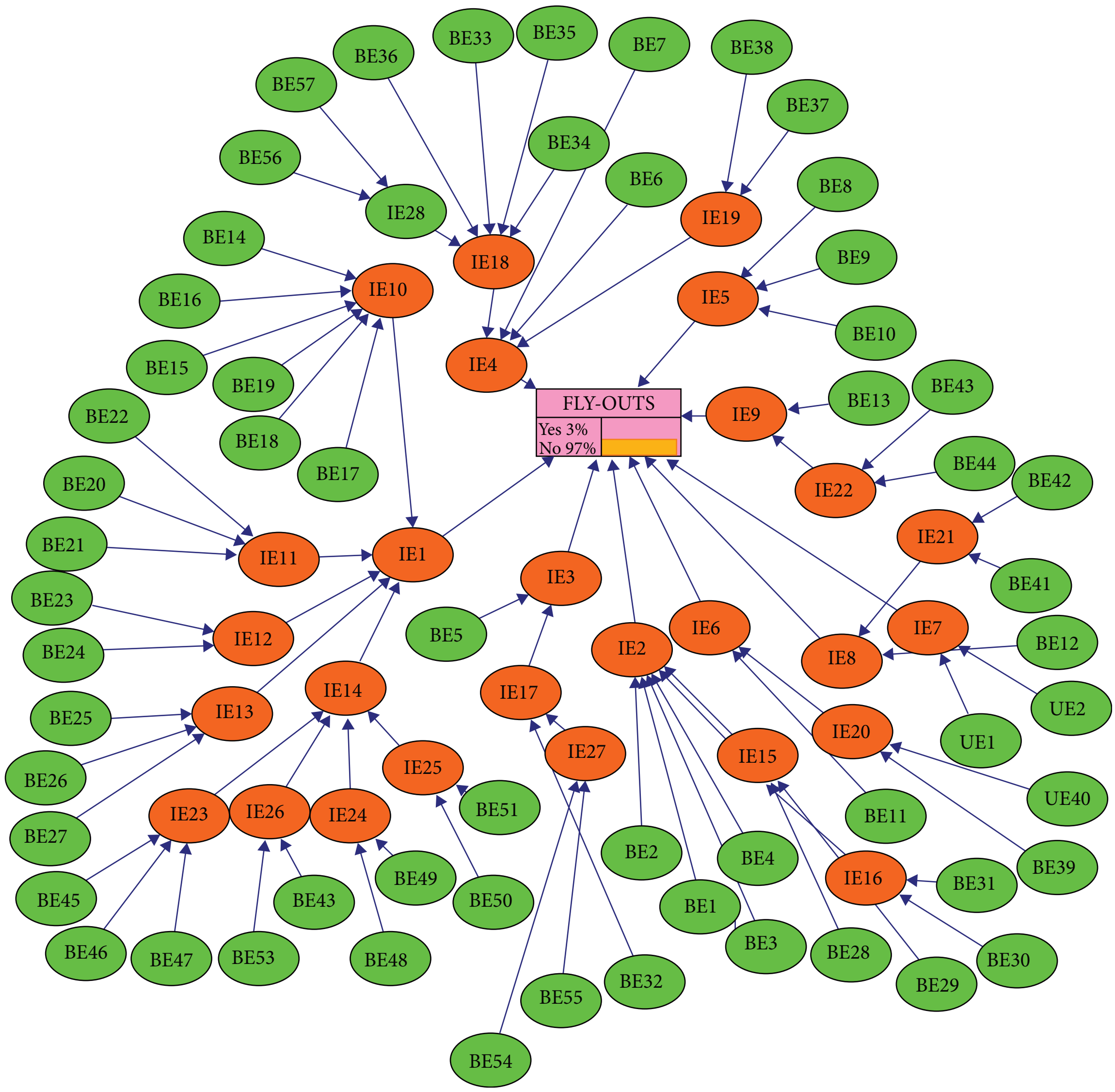


Figure 4: The structure of Bayesian networks based on the fault tree method.

machineries, recent studies have shown that BN is a preferable approach in this regard. However, the use of this approach is associated with some challenges.

In developing countries, the absence of a database for basic event failure rates makes it impossible to compute their probabilities. To manage this uncertainty, fuzzy logic can be utilized [68]. There are two approaches to estimating event probabilities. The first method involves classical techniques that stem from deterministic mathematics. This methodology necessitates precise and quantitative information, which results in rigid mathematical models with reduced accuracy. The second method involves referring to a database of events, even though such data may be irrelevant or incongruent and may not represent actual event data in the country under consideration. The classical approach to probability estimation assumes uncertainty about future events and determines parameters deterministically. Conventional models are limited in their ability to accurately represent reality. On the other hand, fuzzy logic can assess parameters within a specific range of study and present a more accurate depiction of the scenario [69]. The probability of basic events was estimated in this research using a diverse team of experts and fuzzy logic. This method has the potential to increase system dependability, reduce expenses, and minimize uncertainties and ambiguities. The method utilized in this study aligns with the approach used in the research conducted by Mohammadi et al. [37] and Soltanali et al. [70]. Yazdi et al. [71] utilized Buckley's approach in their research method was used for expert weighting, and the COA method developed by Onisawa [55] was used for defuzzing. The disparity between this research and Soltanali et al.'s [12, 70] study is the employment of the COA technique in determining the probability of basic events.

Ghasemi et al. [72] employed two methods, namely the sum–product method and the COA method, to defuzz the data in order to achieve consensus among experts, The methods described above align with the approach taken in the current study. Yazdi and Zarei [9] carried out a study where

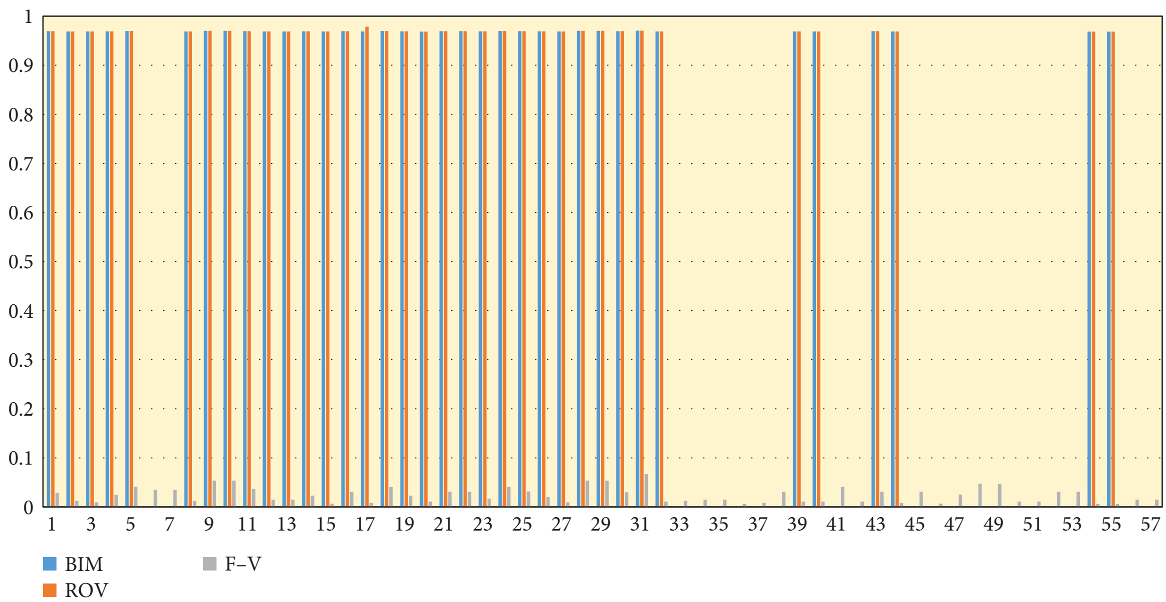


Figure 5: Results of sensitivity analysis by BIM, ROV, F–V method.

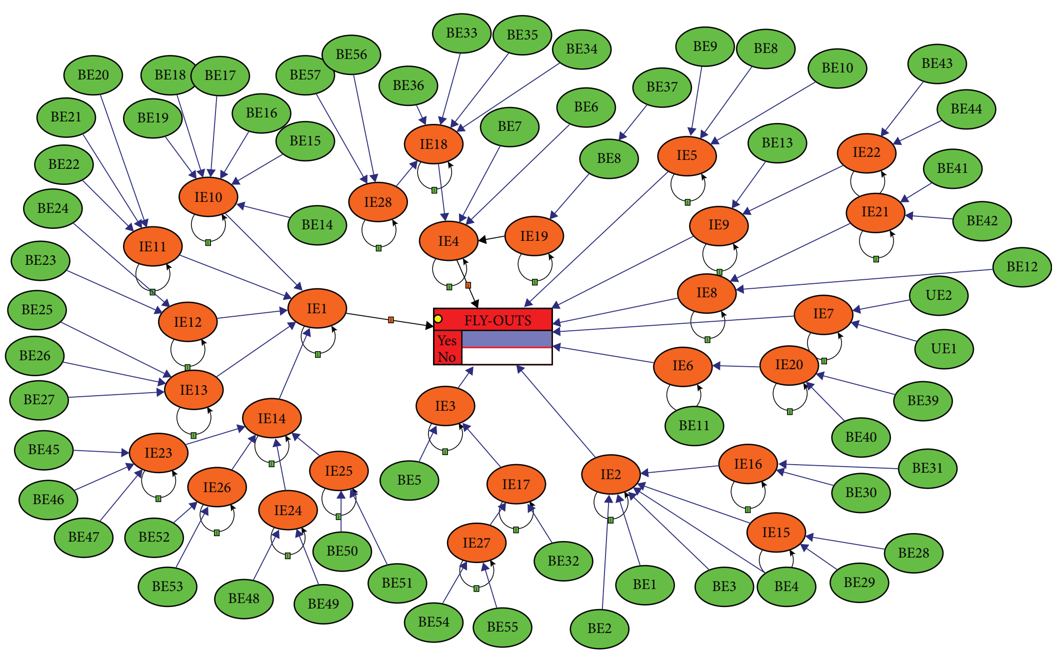


Figure 6: Reliability of lathe machining operations in a 24-month period.

Table 6: Transition probability between nodes.

| $t$ | $t+\Delta t$ | |
|---|---|---|
| | Failure-free operation in the lathe | Lathe failure |
| Failure-free operation in the lathe | $e^{-\lambda\Delta t}$ | $1-e^{-\lambda\Delta t}$ |
| Lathe failure | $1-e^{-\mu\Delta t}$ | $e^{-\mu\Delta t}$ |

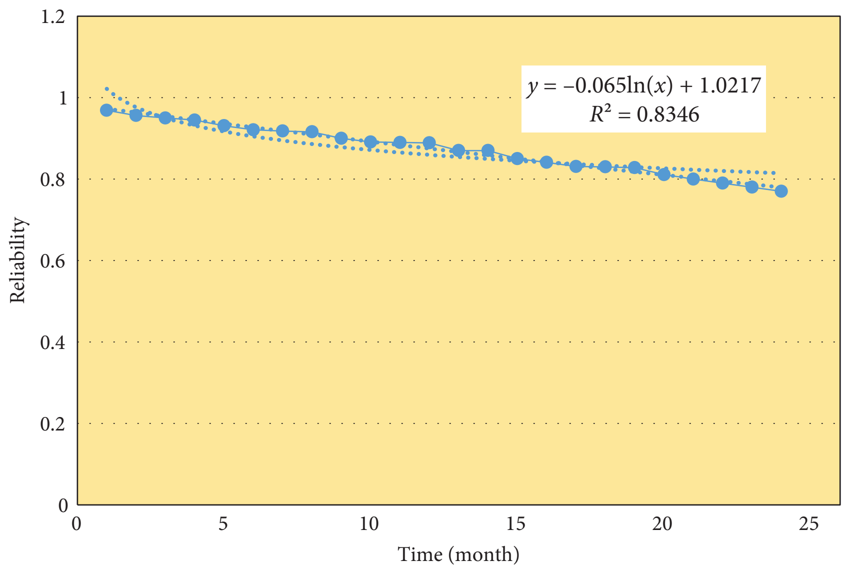


FIGURE 7: The results of the reliability simulation of lathe machining operations in a 24-month period.

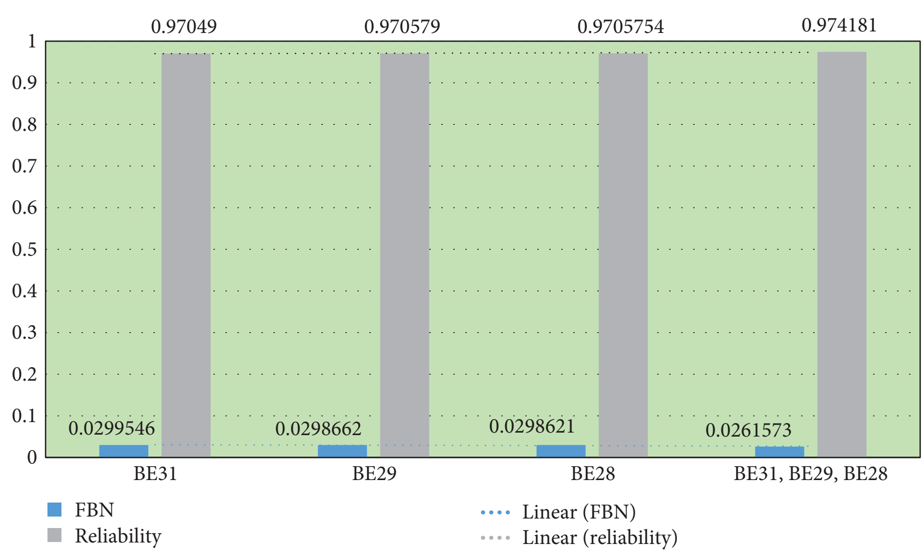


FIGURE 8: Effectiveness results of removing the most important MCSs.

they compared the Sum–product/COA approach with the sum–product/max–min approach within the context of fuzzy theory. The aim was to assess the probability of both base events and main event. According to their results, the sum–product/COA method appears to be a viable, reliable, and clear-cut approach for assessing safety in intricate systems [47]. The sum–product/COA method was utilized in this research to approximate the probability of both primary events and the main event (FLY-OUTS).

To verify the accuracy of the FT, a group consisting of experts in the relevant field was assembled [73]. To confirm the initial segment of the FT structure, the CVI and CVR indices were employed in this investigation. Using the aforementioned criteria, a group of specialists from academic and practical backgrounds evaluated the correlation, importance, and positioning of primary events, along with the type of gates linking them. Figure 3 demonstrates that the qualitative FT diagram was successful in identifying a total of 85 causes or faults (comprising 57 basic events and 28 intermediate events) to be eliminated. By employing the fuzzy error tree, a probability of 0.03174329 was calculated for FLY-OUTS during the turning operation. Conversely, the BN method produced a lower estimated value of 0.031505849 for the same event. The difference in the results obtained from these two methods can be explained by the inclusion of conditional interdependence between the root and middle events, particularly with respect to shared causes. Since the FT approach does not consider such interdependencies, it is unable to acknowledge the statistical correlation between certain events. As per the BN model, some events are found to be correlated with each other.

A crucial element in developing preventative measures is identifying the primary events that have the most influence on the main event. To determine the most critical event, the BN method uses the technique of increased values of updated probabilities. However, this approach may generate inaccurate information for risk analysts. This could result in inadequate control and preventative measures being proposed to manage the primary event, ultimately leading to inefficiencies in dynamic risk analysis studies.

Therefore, in this research, three distinct criteria—BIM, ROV, and Fussell–Vesely—were employed to determine the crucial events that hold the greatest significance in causing the main event.

These criteria have been extensively utilized to prioritize and rank basic events that are linked to the incidence of the main event, as well as in conducting sensitivity analyses [74]. As per Figure 5, the events BE31 and BE29, followed by BE10 and BE9, exhibit the highest value. This result is valid because the probability of system failure when these events are not in a failure mode state is relatively low compared to other events. As a result, when these variables are present, there is a more significant decrease in system reliability. In improving safety and reliability of the lathe machine, the priority should be given to these basic events, as their improvement would reduce the probability of accidents significantly.

This investigation utilized DBN modeling to approximate the reliability of lathe turning operations for a period of 2 years. As shown in Figure 7, the DBN model predicted a decline in system reliability over time, with its value decreasing by 19.89% at the end of 24 months. The observed decrease in system reliability can be attributed to the presence of several significant basic events, including BE31, BE29, and BE28. These events tend to exhibit high variability over time and contribute significantly to reducing the probability of system failure. It is necessary to design and implement appropriate preventive maintenance programs to prevent this declining trend of reliability. Moreover, training employees regarding the hazards of lathe machine can be useful in enhancing safety of the machine.

## 5. Conclusion

The research introduces a methodology for evaluating and assessing risks, as well as forecasting the reliability of turning operations, by employing DBN and fuzzy FTs. Initially, a team of experts from both industry and academia was assembled to validate the FT structure. Subsequently, fuzzy theory was utilized to determine the probability of failure rates for root events. Following this, most of the BNs were constructed based on the fuzzy FT, and the system's reliability was computed over a 24-month period using DBN analysis.

The study employed DBN to perform a time-varying assessment of system reliability. DBN is a versatile method widely used for estimating system reliability. The findings obtained using this method demonstrated a decrease in the system's reliability over time. Although this study specifically focused on evaluating and analyzing the risk related to lathe turning operations with respect to FLY-OUTS, the methodology can be applied to assess reliability in various other potential scenarios. Ultimately, the DBN approach enables conducting reliability analyses across multiple scenarios for the entire system.

## Data Availability

No data is available for this study.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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