# Bayesian Belief Network Modeling of Accident Occurrence in Metal Lathe Machining Operations

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Date received: September 9, 2020
Revision accepted: July 25, 2022

## Abstract

*Accidents occurrence in metal lathe machining operations in industrial workshops often cost organizations billions of dollars while injured workers and families are faced with financial and emotional burdens. Studies revealed that the fly-out accident is the most probable accident that occurs during metal lathe machining operations. The uncertainty surrounding its occurrence is rarely reported. This study, therefore, modeled the uncertainty surrounding the occurrence of a fly-out accident during metal lathe machining operations and its corresponding consequences using the Bayesian belief network (BBN). Fly-out accident causal factors were identified representing the parent nodes with two states each. Two child-node scenarios were modeled on Bayesian belief influence diagrams, namely the fly-out accident with two states (yes and no) and the consequences of the fly-out accident with three states (fatal, serious and minor). Seven causal factors of the fly-out accident were identified (chuck-related fault, tool-post failure, workpiece holding fault, coolant fault, wrong operating speed, safety-related guards fault and wrong feed rate). Bayesian causal inference of fly-out accident was 0.708 and the fatal fly-out accident was 0.263. Bayesian diagnostic inference showed that chuck association fault and improper feed rate were significant causal factors influencing the occurrence of a fly-out accident, fatal fly-out accident and serious fly-out accident, while the occurrence of a minor fly-out accident was affected by coolant fault during machining operations. The study identified areas of safety concerns that may be used for the development of Machine Workshop Safety Management Systems toward sustainable, safe, and effective machine workshop operations.*

***Keywords:*** Bayesian belief network, causal factors, diagnostic inference, fly-out, probabilistic risk assessment

## 1. Introduction

Human beings by default are at risk of making mistakes and neglecting certain safety regulations and policies, which may have a negative effect on them, the company's employees and its machinery, and the environment, can potentially lose their lives, assets and license. However, human errors are only components of protection as system, equipment and other variables often function as ties to a safe machining process. The exponential introduction of modern technologies has radically altered the activities of machining operations in many industrial sectors. Based on this notion, there is a need for a strong balance of technological and human subsystems (Kletz, 1999). This is premised on the general concept of systems theory emphasizing that a failure of an element can jeopardize the whole system. Such systemic failure can lead to significant risks not just to those in the organization but also to the general populace. Similarly, accidents arising from lathe machining operations have often turned out to be particularly complex and more severe in most cases.

Safety is a critical issue for lathe machinists alike. In Nigeria, the lathe machines in small and medium enterprises offer approximately 8% job opportunity and they contribute to the occurrence of workplace injuries and accidents. Similarly, in the United States, the lathe machine is the source of approximately 10% of workplace injuries and accidents (Etherton *et al*., 1981). In big production facilities, sudden changes in accidents and safety offer an exceptional threat to the existence of an organization in terms of protecting its greatly revered assets like properties and lives. A few studies investigated the lathe machining safety and the occurrence of lathe accidents. Suryoputro *et al*. (2017) employed the systematic human action reliability procedure (SHARP), hazard identification and risk assessment (HIRA), fault tree analysis (FTA) and failure mode and effect analysis (FMEA) methods to analyze human reliability and understand lathe machine safety. Based on the analysis, two causal factors (machine and human factors) were modeled on the fault tree diagram while HIRA and FMEA only considered three events (power transmission parts, moving section and operating point section) and were analyzed on the lathe machine during operation. A major aspect missing in the said study was the systemic analysis of lathe machining system, which culminated in identifying only two causal factors of the lathe accidents. To bridge this gap, the current study explored the lathe machining system with a specific focus on the most probable lathe accident, which is the fly-out accident.

Sachdeva *et al.* (2011) also employed fuzzy logic methodology to predict the level of musculoskeletal disorders (MDs) among lathe machine workers. The study centered only on the health state of the lathe machine worker. The simulation of the fuzzy logic model helped in improving the health of workers and reducing absenteeism caused by prevalent MDs. Over four decades ago, Etherton *et al*. (1981) used three methods (review of injury reports, human factors analysis and fault tree procedures) to determine the effective injury control for metal cutting lathe machine operators and interestingly, the results are still relevant today. The analysis of results showed that workpiece, chips and workholding devices were major sources of injury while secondary tasks (setting up, loading/unloading, measuring, fitting/deburring, polishing and cleaning/clearing) were found to be more hazardous than they were generally recognized. A major similarity of this study with the current one is the identification of causal factors of injuries during lathe machining, modeling the causal factors on a fault tree diagram and identifying safety measures. A key difference is that the fault tree developed was not used to evaluate the probability of occurrence of the lathe injury/accident.

Furthermore, Akinyemi *et al*. (2015) identified the most probable accident during lathe machining operation as the fly-out accident. FTA was used to determine the likelihood of fly-out accident occurrence. In using FTA, the probability of the top event or of any intermediate event corresponding to the logical structure was calculated on the basis of the failure probabilities that were associated with the failure events of the basic components (Amrin *et al*., 2018). Meanwhile, Jorgensen (2016) stated that accident occurrence modeling consists of three major elements, namely description of causes, activities of causes leading to the accident and the consequences or damages of such accident. FTA used by Akinyemi *et al.* (2015) successfully described the causes of fly-out accidents and activities of causes leading to the accidents' occurrence, but it was unable to model the consequences or damages caused by the said accidents.

Bayesian belief network (BBN) is a way of modeling accidents and their corresponding consequences or damages (Akinyemi and Adebiyi, 2016). In Bayesian modeling, uncertainty or "degree of belief" is quantified utilizing probability. Data observed are employed to update the prior information or beliefs to obtain posterior information or beliefs. Engineers often have to analyze accident data to estimate the level of safety at different socio-technical systems to identify hazardous (unsafe) conditions and evaluate the effectiveness of safety countermeasures. BBN has greatly found usefulness in engineering specifically in the analysis of accident data of socio-technical systems. BBN was previously used to predict occupational accident statistics (Marcoulaki *et al.*, 2012), analyzed the causation of road accidents (Zou and Yue, 2017), examined nuclear reactor severe accidents (Zheng *et al.*, 2017) and modeled the probability of occurrence and consequence of runway accidents (Akinyemi and Adebiyi, 2016).

Similarly, Akinyemi *et al*. (2019) employed BBN to model the occurrence of a road traffic accident in Southwest Nigeria and predict the probability of its occurrence and its corresponding consequences. Interestingly, Delen *et al.* (2019) developed a BBN-driven probabilistic model which successfully predicted the risk of individual students' attrition from a higher learning institution. Miraballes *et al.* (2019) also used BBN to assess the possibility of a farm becoming infested with cattle disease known as *Rhipicephalus microplus*, which is caused by the introduction of tick-infested cattle. Jitwasinkul *et al*. (2016) noted that BBN has the capability to model expected consequences of uncertainty in the Thai construction industry; this was adopted to evaluate the safe work behaviors in the said industry. Also, Washington *et al*. (2019) developed a framework based on BBN, which provided an approach for capturing the uncertainty in the potential consequential outcomes of an identified failure in remotely piloted aircraft systems. Other researchers who worked on the application of BBN to risk evaluation of various facets of life include Krynski and Tenenbaum (2007), Fenton and Neil (2011), Li *et al.* (2012), Wang *et al*. (2015), Hadikusumo *et al*. (2017), Liao *et al.* (2018), Azar and Dolatabad (2019) and Zhang *et al.* (2019).

The similarity of this present study with these past and related works is the use of BBN to evaluate accidents and risk in socio-technical systems. However, previous work on the use of BBN for the safety modeling of lathe machine operations is scarce or rarely reported. While statistical analysis of accidents has become suggestive in quantifying accidents due to the uniqueness of every event leading to accidents and lack of available information (Zarikas *et al.*, 2013), the BBN technique is used for quantifying uncertainties that require a combination of data and experts' judgment in addition to developing models from the information enabling the factoring of casual relationships and interdependencies. This research, therefore, used BBN to model a combination of interdependencies of causal factors and experts' judgment to evaluate the probability of occurrence of a fly-out accident during lathe machining operation and the probability of occurrence of its corresponding consequences or damages.

## 2. Methodology

The BBN had the following steps as shown in Figure 1 below. Before the construction of the BBN diagram, understanding of the system was sacrosanct. This enabled the identification of Bayesian variables (and their states) that depicted the system. The BBN diagram, called the influence diagram, was the directed acyclic graph that showed the causal relationship between the child nodes and the parent nodes. The parent nodes were the Bayesian variables (causal factors) that determined the values of the child node (accident and or consequences of accident). An excellent understanding of the system to be modeled was necessary to develop an influence diagram that represented the system.

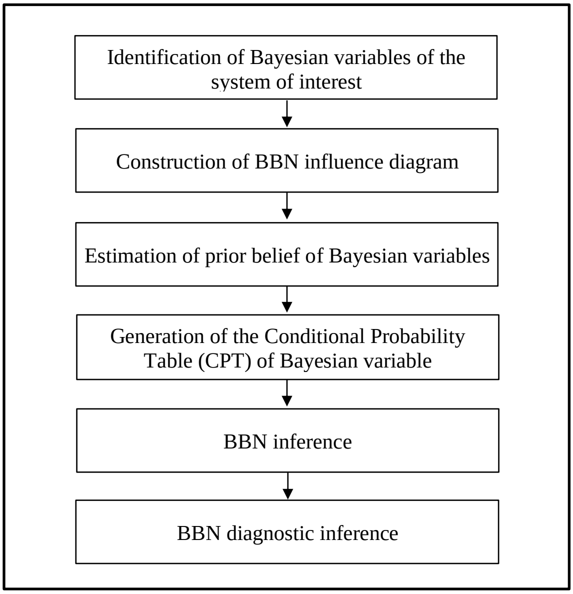


Figure 1. The flowchart of BBN methodology

The estimation of the prior belief by Bayesian variables involved the estimation of prior probability of the parent nodes. At this stage, the selection of the states of the nodes (both child and parent) was carefully carried out. This estimation was achieved through prior knowledge, availability of data and probability distribution function.

Generating the conditional probability table (CPT) for the Bayesian variable involved defining a CPT for the child nodes. In this stage, a CPT was generated for each state of the child node. BBN was made operational by means of a set of CPT that underlay each node. CPT expressed the belief of how the nodes were related to each other while the degree of belief of certainty was represented by a score. The generation of the CPT score using the degree of certainty estimation was the subject matter experts' opinion.

When CPTs were added to the influence diagram, the BBN was formed. Bayesian network inference is the causal inference imposed by the Bayesian variable. It is a probability process of drawing an inference from causes, and it is top-down (Akinyemi and Adebiyi, 2016). In socio-technical system accident modeling, BBN inference involved developing an expression for the probability of accident occurrence when the states of conditions of hazards or causal factors were known. The developed BBN model consequently became a predictive model for accident occurrence. Based on these predictions, accident preventive measures may be taken to mitigate the likelihood of an accident occurring in socio-technical systems.

BBN diagnostic inference is a probabilistic inference process of drawing a cause from the conclusion and it is a bottom-up inference as opposed to BBN inference, which is top-down. Its objective is to obtain the probability of occurrence of parent nodes causing the occurrence of the child node.

### *2.1 Identification of Bayesian Variables of the Lathe Machine System and Construction of the Bayesian Network Influence Diagram*

In this study, Bayesian variables were the causal factors leading to the fly-out accident and these variables were identified by Akinyemi *et al*. (2015). Causal factors leading to fly-out accidents were categorized into seven (Table 1) (Akinyemi *et al*., 2015). It ought to be stated that these causal factors were unique and independent to each other even as their prevalence would have their respective consequences. BBN was engaged to evaluate the probability of occurrence of the fly-out accident and its corresponding consequences. Two Bayesian influence diagrams were developed for the relationship between states of fly-out accident causal factors (parent nodes) and states of fly-out accident (child node); and states of fly-out accident causal factors (parent nodes) and its consequences (child node). These two influence diagrams were developed using Bayesian network software (Netica version 6.09) (Norsys Software Corporation, n.d.).

### *2.2 Estimation of Prior Belief of Bayesian Variables and Generation of the Conditional Probabilities of Child Node Variables*

The prior probability for the occurrence of the seven causal factors, obtained from Akinyemi *et al*. (2015), is given in Table 1 with their corresponding states.

Table 1. States of parent nodes and their corresponding prior probabilities

| S/N | Causal factors/variables | Symbols | States | Prior probabilities (%) |
|---|---|---|---|---|
| 1 | Chuck association fault | CAF | Okay<br>Faulty | 28<br>72 |
| 2 | Workpiece holding failure | WHF | N-Fail<br>FLRE | 95<br>5 |
| 3 | Tool-post fault | TPF | Okay<br>Faulty | 96<br>4 |
| 4 | Coolant fault | CF | Okay<br>Faulty | 99<br>1 |
| 5 | Operating speed | OS | Proper<br>Improper | 98<br>2 |
| 6 | Safety guards fault | SGF | Okay<br>Faulty | 85<br>15 |
| 7 | Wrong feed rate | IFR | Human reliability (HR)<br>Human error (HE) | 90<br>10 |

The CPT was developed for the two child nodes scenarios using the experts' judgments. Most of the experts employed for this study were drawn from a university and manufacturing industry workforce. Two were academic staff that examined workshop practice courses for over 10 years. Two were technologists manning a university engineering workshop for over 12 years. Four have, at least, eight years of experience as factory lathe machinists and two were local lathe machinists who had been doing the job for more than five years. The other three were senior workshop engineers drawn from a manufacturing industry. It should be noted that the two child nodes scenarios were the occurrence of fly-out accident and the occurrence of the consequences of a fly-out accident. Probability expression in a CPT was substituted by probability measures between 0 and 100% (Akinyemi *et al.*, 2019). Table 2 shows the CPT developed with the aid of subject matter experts' opinions for the child node scenario of occurrence of the consequences of a fly-out accident.

Table 2. CPT of the consequences (child node) of fly-out accident

| | Fly-out accident causal factors states (Parent nodes) | | | | | | | Conditional probability (consequences) | | |
|---|---|---|---|---|---|---|---|---|---|---|
| S/N | CAF | WHF | TPF | CF | OS | SGF | IFR | Fatal | Major | Minor |
| 1 | Okay | N-Fail | Okay | Okay | Proper | Okay | HR | 1 | 4 | 95 |
| 2 | Okay | N-Fail | Okay | Okay | Proper | Okay | HE | 5 | 10 | 85 |
| 3 | Okay | N-Fail | Okay | Okay | Proper | Faulty | HR | 5 | 10 | 85 |
| 4 | Okay | N-Fail | Okay | Okay | Proper | Faulty | HE | 15 | 20 | 65 |
| 5 | Okay | N-Fail | Okay | Okay | Improper | Okay | HR | 30 | 45 | 25 |
| 6 | Okay | N-Fail | Okay | Okay | Improper | Okay | HE | 50 | 30 | 20 |
| 7 | Okay | N-Fail | Okay | Okay | Improper | Faulty | HR | 30 | 50 | 20 |
| 8 | Okay | N-Fail | Okay | Okay | Improper | Faulty | HE | 55 | 30 | 15 |
| 9 | Okay | N-Fail | Okay | Faulty | Proper | Okay | HR | 1 | 4 | 95 |
| 10 | Okay | N-Fail | Okay | Faulty | Proper | Okay | HE | 10 | 20 | 70 |
| 11 | Okay | N-Fail | Okay | Faulty | Proper | Faulty | HR | 10 | 20 | 70 |
| 12 | Okay | N-Fail | Okay | Faulty | Proper | Faulty | HE | 15 | 20 | 65 |
| 13 | Okay | N-Fail | Okay | Faulty | Improper | Okay | HR | 30 | 40 | 30 |
| 14 | Okay | N-Fail | Okay | Faulty | Improper | Okay | HE | 50 | 30 | 20 |
| 15 | Okay | N-Fail | Okay | Faulty | Improper | Faulty | HR | 55 | 30 | 15 |
| 16 | Okay | N-Fail | Okay | Faulty | Improper | Faulty | HE | 60 | 30 | 10 |
| 17 | Okay | N-Fail | Faulty | Okay | Proper | Okay | HR | 33.4 | 33.3 | 33.3 |
| 18 | Okay | N-Fail | Faulty | Okay | Proper | Okay | HE | 35 | 35 | 30 |
| 19 | Okay | N-Fail | Faulty | Okay | Proper | Faulty | HR | 35 | 35 | 30 |
| 20 | Okay | N-Fail | Faulty | Okay | Proper | Faulty | HE | 35 | 35 | 30 |
| 21 | Okay | N-Fail | Faulty | Okay | Improper | Okay | HR | 35 | 40 | 25 |
| 22 | Okay | N-Fail | Faulty | Okay | Improper | Okay | HE | 60 | 30 | 10 |
| 23 | Okay | N-Fail | Faulty | Okay | Improper | Faulty | HR | 30 | 50 | 20 |
| 24 | Okay | N-Fail | Faulty | Okay | Improper | Faulty | HE | 60 | 30 | 10 |
| 25 | Okay | N-Fail | Faulty | Faulty | Proper | Okay | HR | 33.4 | 33.3 | 33.3 |
| 26 | Okay | N-Fail | Faulty | Faulty | Proper | Okay | HE | 35 | 35 | 30 |
| 27 | Okay | N-Fail | Faulty | Faulty | Proper | Faulty | HR | 35 | 35 | 30 |
| 28 | Okay | N-Fail | Faulty | Faulty | Proper | Faulty | HE | 35 | 35 | 30 |
| 29 | Okay | N-Fail | Faulty | Faulty | Improper | Okay | HR | 30 | 60 | 10 |
| 30 | Okay | N-Fail | Faulty | Faulty | Improper | Okay | HE | 60 | 30 | 10 |
| 31 | Okay | N-Fail | Faulty | Faulty | Improper | Faulty | HR | 30 | 60 | 10 |
| 32 | Okay | N-Fail | Faulty | Faulty | Improper | Faulty | HE | 60 | 30 | 10 |
| 33 | Okay | FLRE | Okay | Okay | Proper | Okay | HR | 25 | 25 | 20 |
| 34 | Okay | FLRE | Okay | Okay | Proper | Okay | HE | 30 | 30 | 40 |
| 35 | Okay | FLRE | Okay | Okay | Proper | Faulty | HR | 30 | 35 | 35 |
| 36 | Okay | FLRE | Okay | Okay | Proper | Faulty | HE | 45 | 30 | 25 |
| 37 | Okay | FLRE | Okay | Okay | Improper | Okay | HR | 30 | 60 | 10 |
| 38 | Okay | FLRE | Okay | Okay | Improper | Okay | HE | 70 | 20 | 10 |
| 39 | Okay | FLRE | Okay | Okay | Improper | Faulty | HR | 30 | 60 | 10 |
| 40 | Okay | FLRE | Okay | Okay | Improper | Faulty | HE | 70 | 20 | 10 |
| 41 | Okay | FLRE | Okay | Faulty | Proper | Okay | HR | 30 | 35 | 35 |
| 42 | Okay | FLRE | Okay | Faulty | Proper | Okay | HE | 47 | 33 | 20 |
| 43 | Okay | FLRE | Okay | Faulty | Proper | Faulty | HR | 30 | 40 | 30 |
| 44 | Okay | FLRE | Okay | Faulty | Proper | Faulty | HE | 47 | 33 | 20 |
| 45 | Okay | FLRE | Okay | Faulty | Improper | Okay | HR | 30 | 60 | 10 |
| 46 | Okay | FLRE | Okay | Faulty | Improper | Okay | HE | 65 | 25 | 10 |
| 47 | Okay | FLRE | Okay | Faulty | Improper | Faulty | HR | 30 | 60 | 10 |
| 48 | Okay | FLRE | Okay | Faulty | Improper | Faulty | HE | 65 | 25 | 10 |
| 49 | Okay | FLRE | Faulty | Okay | Proper | Okay | HR | 30 | 40 | 30 |
| 50 | Okay | FLRE | Faulty | Okay | Proper | Okay | HE | 45 | 35 | 20 |
| 51 | Okay | FLRE | Faulty | Okay | Proper | Faulty | HR | 30 | 40 | 30 |
| 52 | Okay | FLRE | Faulty | Okay | Proper | Faulty | HE | 45 | 35 | 20 |
| 53 | Okay | FLRE | Faulty | Okay | Improper | Okay | HR | 30 | 60 | 10 |
| 54 | Okay | FLRE | Faulty | Okay | Improper | Okay | HE | 70 | 20 | 10 |
| 55 | Okay | FLRE | Faulty | Okay | Improper | Faulty | HR | 25 | 65 | 10 |
| 56 | Okay | FLRE | Faulty | Okay | Improper | Faulty | HE | 75 | 15 | 10 |
| 57 | Okay | FLRE | Faulty | Faulty | Proper | Okay | HR | 30 | 50 | 20 |
| 58 | Okay | FLRE | Faulty | Faulty | Proper | Okay | HE | 60 | 30 | 10 |
| 59 | Okay | FLRE | Faulty | Faulty | Proper | Faulty | HR | 30 | 50 | 20 |
| 60 | Okay | FLRE | Faulty | Faulty | Proper | Faulty | HE | 75 | 15 | 10 |
| 61 | Okay | FLRE | Faulty | Faulty | Improper | Okay | HR | 30 | 60 | 10 |

Table 2 continued.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 62 | Okay | FLRE | Faulty | Faulty | Improper | Okay | HE | 75 | 15 | 10 |
| 63 | Okay | FLRE | Faulty | Faulty | Improper | Faulty | HR | 30 | 60 | 10 |
| 64 | Okay | FLRE | Faulty | Faulty | Improper | Faulty | HE | 75 | 15 | 10 |
| 65 | Faulty | N-Fail | Okay | Okay | Proper | Okay | HR | 30 | 60 | 10 |
| 66 | Faulty | N-Fail | Okay | Okay | Proper | Okay | HE | 75 | 15 | 10 |
| 67 | Faulty | N-Fail | Okay | Okay | Proper | Faulty | HR | 25 | 65 | 10 |
| 68 | Faulty | N-Fail | Okay | Okay | Proper | Faulty | HE | 75 | 15 | 10 |
| 69 | Faulty | N-Fail | Okay | Okay | Improper | Okay | HR | 20 | 70 | 10 |
| 70 | Faulty | N-Fail | Okay | Okay | Improper | Okay | HE | 75 | 15 | 10 |
| 71 | Faulty | N-Fail | Okay | Okay | Improper | Faulty | HR | 25 | 55 | 20 |
| 72 | Faulty | N-Fail | Okay | Okay | Improper | Faulty | HE | 75 | 15 | 10 |
| 73 | Faulty | N-Fail | Okay | Faulty | Proper | Okay | HR | 30 | 50 | 20 |
| 74 | Faulty | N-Fail | Okay | Faulty | Proper | Okay | HE | 60 | 30 | 10 |
| 75 | Faulty | N-Fail | Okay | Faulty | Proper | Faulty | HR | 40 | 50 | 10 |
| 76 | Faulty | N-Fail | Okay | Faulty | Proper | Faulty | HE | 70 | 20 | 10 |
| 77 | Faulty | N-Fail | Okay | Faulty | Improper | Okay | HR | 30 | 50 | 20 |
| 78 | Faulty | N-Fail | Okay | Faulty | Improper | Okay | HE | 70 | 20 | 10 |
| 79 | Faulty | N-Fail | Okay | Faulty | Improper | Faulty | HR | 30 | 60 | 10 |
| 80 | Faulty | N-Fail | Okay | Faulty | Improper | Faulty | HE | 80 | 15 | 5 |
| 81 | Faulty | N-Fail | Faulty | Okay | Proper | Okay | HR | 40 | 50 | 10 |
| 82 | Faulty | N-Fail | Faulty | Okay | Proper | Okay | HE | 70 | 20 | 10 |
| 83 | Faulty | N-Fail | Faulty | Okay | Proper | Faulty | HR | 30 | 60 | 10 |
| 84 | Faulty | N-Fail | Faulty | Okay | Proper | Faulty | HE | 70 | 20 | 10 |
| 85 | Faulty | N-Fail | Faulty | Okay | Improper | Okay | HR | 40 | 30 | 30 |
| 86 | Faulty | N-Fail | Faulty | Okay | Improper | Okay | HE | 50 | 40 | 10 |
| 87 | Faulty | N-Fail | Faulty | Okay | Improper | Faulty | HR | 50 | 40 | 10 |
| 88 | Faulty | N-Fail | Faulty | Okay | Improper | Faulty | HE | 70 | 20 | 10 |
| 89 | Faulty | N-Fail | Faulty | Faulty | Proper | Okay | HR | 30 | 40 | 30 |
| 90 | Faulty | N-Fail | Faulty | Faulty | Proper | Okay | HE | 60 | 30 | 10 |
| 91 | Faulty | N-Fail | Faulty | Faulty | Proper | Faulty | HR | 60 | 30 | 10 |
| 92 | Faulty | N-Fail | Faulty | Faulty | Proper | Faulty | HE | 70 | 20 | 10 |
| 93 | Faulty | N-Fail | Faulty | Faulty | Improper | Okay | HR | 30 | 60 | 10 |
| 94 | Faulty | N-Fail | Faulty | Faulty | Improper | Okay | HE | 70 | 20 | 10 |
| 95 | Faulty | N-Fail | Faulty | Faulty | Improper | Faulty | HR | 55 | 35 | 10 |
| 96 | Faulty | N-Fail | Faulty | Faulty | Improper | Faulty | HE | 80 | 15 | 5 |
| 97 | Faulty | FLRE | Okay | Okay | Proper | Okay | HR | 40 | 30 | 30 |
| 98 | Faulty | FLRE | Okay | Okay | Proper | Okay | HE | 70 | 20 | 10 |
| 99 | Faulty | FLRE | Okay | Okay | Proper | Faulty | HR | 45 | 45 | 10 |
| 100 | Faulty | FLRE | Okay | Okay | Proper | Faulty | HE | 70 | 20 | 10 |
| 101 | Faulty | FLRE | Okay | Okay | Improper | Okay | HR | 50 | 40 | 10 |
| 102 | Faulty | FLRE | Okay | Okay | Improper | Okay | HE | 75 | 15 | 10 |
| 103 | Faulty | FLRE | Okay | Okay | Improper | Faulty | HR | 70 | 20 | 10 |
| 104 | Faulty | FLRE | Okay | Okay | Improper | Faulty | HE | 80 | 15 | 5 |
| 105 | Faulty | FLRE | Okay | Faulty | Proper | Okay | HR | 70 | 20 | 10 |
| 106 | Faulty | FLRE | Okay | Faulty | Proper | Okay | HE | 80 | 15 | 5 |
| 107 | Faulty | FLRE | Okay | Faulty | Proper | Faulty | HR | 30 | 60 | 10 |
| 108 | Faulty | FLRE | Okay | Faulty | Proper | Faulty | HE | 70 | 20 | 10 |
| 109 | Faulty | FLRE | Okay | Faulty | Improper | Okay | HR | 25 | 65 | 10 |
| 110 | Faulty | FLRE | Okay | Faulty | Improper | Okay | HE | 75 | 15 | 10 |
| 111 | Faulty | FLRE | Okay | Faulty | Improper | Faulty | HR | 25 | 65 | 10 |
| 112 | Faulty | FLRE | Okay | Faulty | Improper | Faulty | HE | 85 | 10 | 5 |
| 113 | Faulty | FLRE | Faulty | Okay | Proper | Okay | HR | 30 | 60 | 10 |
| 114 | Faulty | FLRE | Faulty | Okay | Proper | Okay | HE | 70 | 20 | 10 |
| 115 | Faulty | FLRE | Faulty | Okay | Proper | Faulty | HR | 25 | 65 | 10 |
| 116 | Faulty | FLRE | Faulty | Okay | Proper | Faulty | HE | 75 | 20 | 5 |
| 117 | Faulty | FLRE | Faulty | Okay | Improper | Okay | HR | 20 | 70 | 10 |
| 118 | Faulty | FLRE | Faulty | Okay | Improper | Okay | HE | 80 | 15 | 5 |
| 119 | Faulty | FLRE | Faulty | Okay | Improper | Faulty | HR | 35 | 55 | 10 |
| 120 | Faulty | FLRE | Faulty | Okay | Improper | Faulty | HE | 85 | 10 | 5 |
| 121 | Faulty | FLRE | Faulty | Faulty | Proper | Okay | HR | 30 | 60 | 10 |
| 122 | Faulty | FLRE | Faulty | Faulty | Proper | Okay | HE | 70 | 20 | 10 |
| 123 | Faulty | FLRE | Faulty | Faulty | Proper | Faulty | HR | 40 | 50 | 10 |
| 124 | Faulty | FLRE | Faulty | Faulty | Proper | Faulty | HE | 80 | 15 | 5 |
| 125 | Faulty | FLRE | Faulty | Faulty | Improper | Okay | HR | 30 | 60 | 10 |

Table 2 continued.

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 126 | Faulty | FLRE | Faulty | Faulty | Improper | Okay | HE | 75 | 20 | 5 |
| 127 | Faulty | FLRE | Faulty | Faulty | Improper | Faulty | HR | 30 | 60 | 10 |
| 128 | Faulty | FLRE | Faulty | Faulty | Improper | Faulty | HE | 85 | 10 | 5 |

Failure = FLRE; no failure = N-Fail; HR = human reliability; HE = human error; CAF = chuck association fault; WHF = work piece holding fault; TPF = tool post fault; CF = coolant fault; OS = operating speed; SGF = safety guard fault; and IFR = improper feed rate

## 3. Results and Discussion

### *3.1 Bayesian Network Causal Inferences*

From the Bayesian network causal inference, the probability of occurrence of the fly-out accident was 70.8% while that of the no fly-out accident was 29.2% (Figure 2). The probability of occurrence of the fatal fly-out accident was 26.3%, the serious fly-out accident was 41.8% and the minor fly-out accident was 32.0% as (Figure 3).

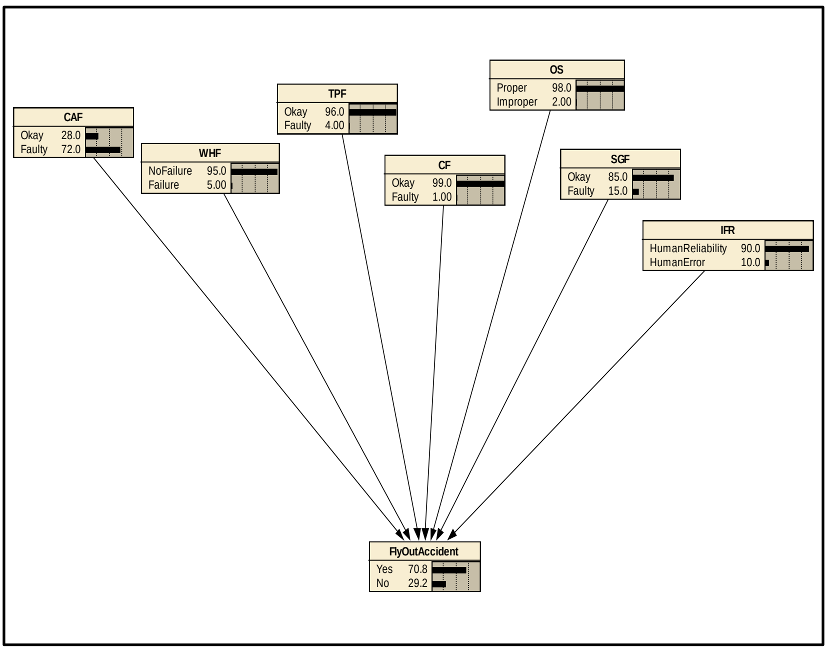


Figure 2. Bayesian causal inference of occurrence of fly-out accident of metal lathe machine operation

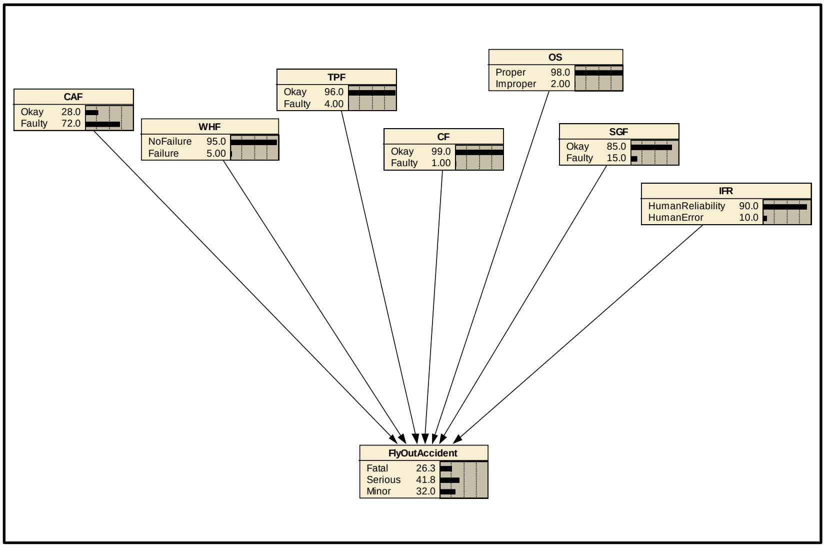


Figure 3. Bayesian causal inference of occurrence of consequence of fly-out accident of metal lathe machine operation

Akinyemi *et al*. (2015) employed FTA to evaluate the probability of occurrence of fly-out accidents which was 74.8%. Unfortunately, FTA was unable to evaluate the consequences of this accident. In this study, BBN was able to overcome this shortcoming by evaluating an appropriate probability of the fly-out accident, which was 70.8%, with the probabilities of its corresponding consequences as shown in Figure 3. This study was also in consonance with Jorgensen's (2016) postulation that accident modeling must consist of three major elements, namely description of causes, activities of causes leading up to the accident and the consequences or damages attributed to the said accident.

### *3.2 Bayesian Network Diagnostic Inferences*

The diagnostic inference determined the posterior probability of the fly-out accident causal factors and consequently, the critical fly-out accident causal factors were evaluated. Figures 4, 5 and 6 show the posterior probability of occurrence of the fly-out accident, fatal fly-out accident and serious fly-out accident, respectively.

When the posterior probability obtained was compared with the prior probability, it was observed that there were changes in the values of the probability of occurrence of the parent nodes for the two child nodes scenarios. Profound changes were observed in the probability of occurrence of the fly-out accident, namely probability of occurrence of CAF = faulty (increased by 244.6%), OS = improper (increased by 25.5%), WHF = failure (increased by 21.8%), TPF = faulty (increased by 17.5%) while marginal changes were noticed in the probability of occurrence of IFR = human error (increased by 2%) and SGF = faulty (increased by 1.3%). Similarly, major changes were also seen in the cases of the occurrence of fatal fly-out and serious fly-out accidents. Notable changes were found in the probability of occurrence of CAF = faulty (increased by 266.4%) and IFR = human error (increased by 115%), WHF = failure (increased by 48.4%), TPF = faulty (increased by 19.2%), OS = improper (increased by 12%) while marginal changes were observed in the probability of occurrence of CF = faulty (increased by 5%) for fatal fly-out accident. In the same vein, notable changes were detected in the probability of occurrence of CAF = faulty (increased by 236.8%), OS = improper (increased by 33%) and SGF = faulty (increased by 10.7%) while marginal changes were observed in the probability of occurrence of TPF = faulty (increased by 6.25%) for the serious fly-out accident.

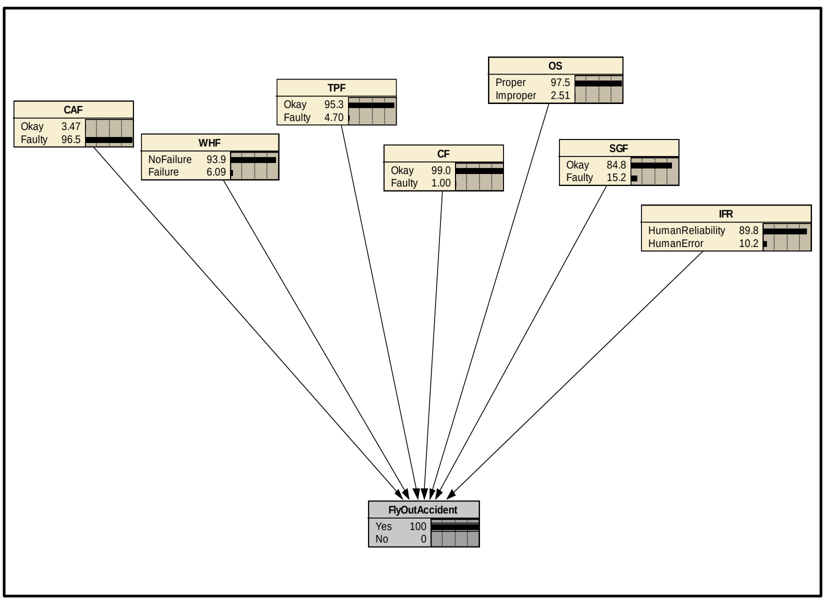


Figure 4. Bayesian diagnostic inference of occurrence of fly-out accident of metal lathe machine operation (Fly-out accident = yes)

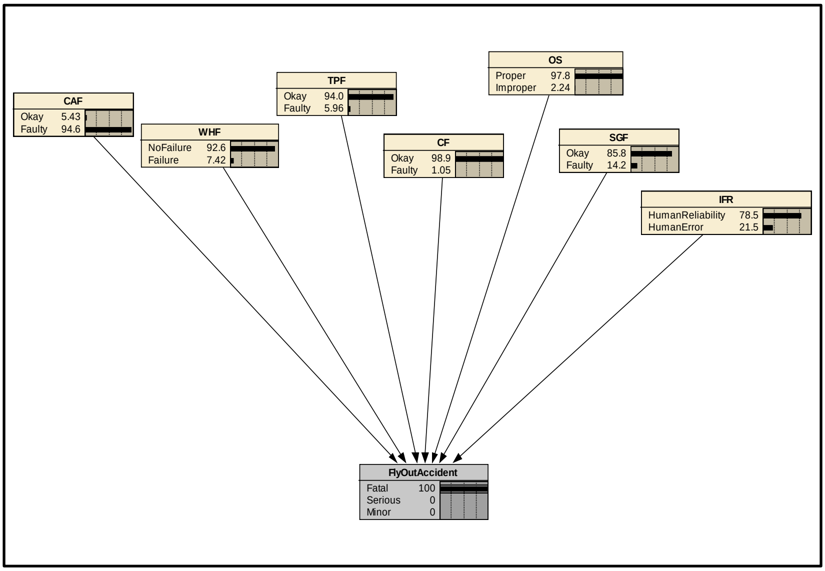


Figure 5. Bayesian diagnostic inference of occurrence of fatal fly-out accident of metal lathe machine operation

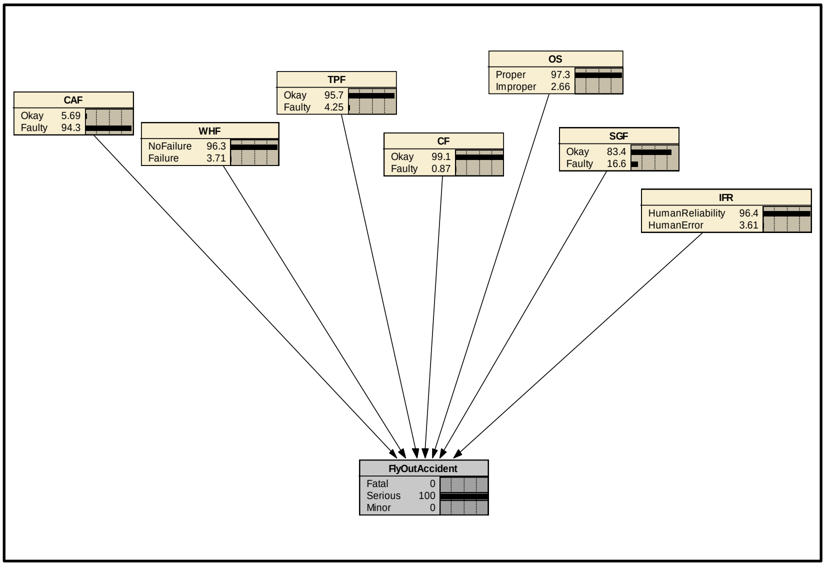


Figure 6. Bayesian diagnostic inference of occurrence of serious fly-out accident of metal lathe machine operation

Figure 7 displays the diagnostic inference for the occurrence of the minor fly-out accident. The inference revealed the change in the posterior probability of occurrence of CF = faulty (increased by 12%). Other causal factors (parent nodes) did not have significant effects on the occurrence of minor fly-out accident.

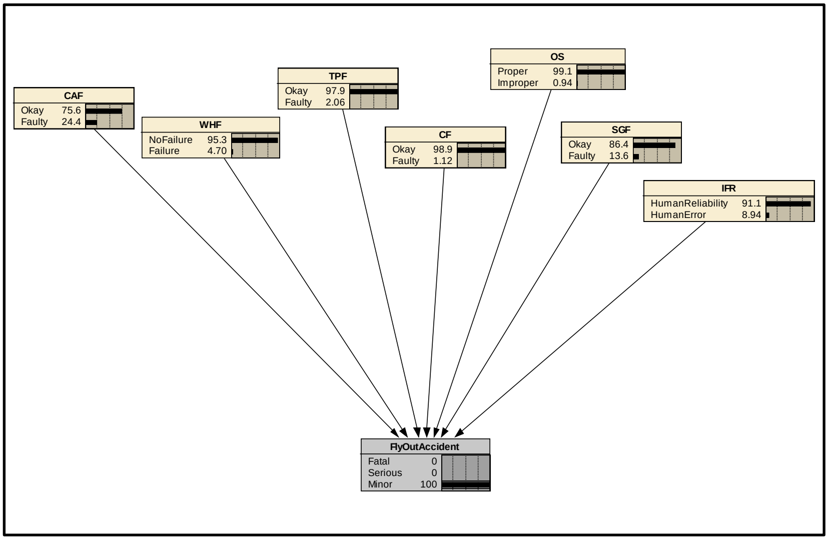


Figure 7. Bayesian diagnostic inference of occurrence of minor fly-out accident of metal lathe machine operation

While FTA showed that the event of the chuck association fault was the only notable causal factor that was sensitive to the occurrence of the fly-out accident (Akinyemi *et al*., 2015), Bayesian diagnostic inference showed that it was not only the chuck association fault that was sensitive to the occurrence of the fly-out accident but also to other causal factors, namely operating speed, workpiece holding failure and tool post fault. This meant that once the fly-out accident occurs, it is most likely that chuck association fault, operating speed, workpiece holding failure and tool post fault are the main significant causal factors. This is interestingly in consonance with the over 40-year-old study of Etherton *et al*. (1981) which identified chips and workholding devices as major causes of injuries among metal cutting lathe operators. Also, diagnostic inference showed that the occurrence of the fatal fly-out accident (consequence) was sensitive to the occurrence of chuck association fault, improper feed rate, tool post fault, operating speed and workpiece holding fault, and these causal factors were the main significant causal factors influencing the occurrence of fatal fly-out accident. No safety concern areas and information are obtainable from the work done by Akinyemi *et al.* (2015). In the same vein, the diagnostic inference showed that the serious fly-out accident was sensitive to the occurrence of chuck association fault, operating speed and safety guard fault. For the occurrence of the minor fly-out accident, the inference revealed that once the minor fly-out accident occurred, it was most likely that coolant fault was the main significant causal factor.

## 4. Conclusion and Recommendation

This study reported the application of BBN methodology for causal and diagnostic inference modeling of occurrence of the fly-out accident during lathe machining operations and its consequences. Causal inference results showed that the probability of occurrence of the fly-out accident was high while that of the no fly-out accident was low. The probability of occurrence of the fatal fly-out accident was low while the serious fly-out accident was moderate but higher than the minor fly-out accident. The diagnostic inference evaluated the causal factors, which are indicators for workshop safety engineers in the areas of concentration for the implementation of effective lathe machine workshop, safety programs and policy. However, as part of the limitations of this study, there was non-availability of data; hence, the use of the BBN methodology, which was based on the subjectivity of the expert's opinions of the subject matter. A similar study in the future can be carried out by including learning capabilities of BBN instead of using the opinions of experts on the subject matter. The practical implications of this study was the identification of safety concerns (an indicator to developing countermeasures/control) during lathe machining operations. It should be noted that accident occurrence is dynamic in nature; hence, lathe machining operations causal factors should be continually identified and updated on the lathe machining operations BBN model to keep tab on the safety of the operations and machinists.

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