Highlights

- Human errors causing derailments at switches and crossings were identified and classified.
- A novel methodology dealing with the errors was proposed.
- A novel DAG (Directed Acyclic Graph) built through Bayesian network was proposed.
- The risks of errors were identified and analysed using new mathematical expressions.
- Risk is prioritised by a most-to-least-critical importance ranking of human errors.

Bayesian Network-based Human Error Reliability Assessment of Derailments

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Abstract

The knowledge acquired in relation to failures associated with components has made significant contributions to the development of components with increased reliability, as well as a reduction in the number of rail incidents caused by certain system defects. These new systems have led to innovative developments in both the operations and technology of rail networks. Hence, rail employees must now function in conditions that have high complexity that are hard to comprehend. The risk of failure caused by human error (such as by dispatchers, train crews and track engineers) has developed into a significant safety problem. This study provides insight into better understanding human errors, which result in derailments at rail turnouts. A most- to-least-critical importance ranking of these errors is established throughout a novel risk management technique. Moreover, the findings and recommendations of the research study have a strong potential for industry to improve the reliability of rail operation, and avoid safety concerns regarding derailments at rail turnouts.

Keywords: Human-errors, Railway operation, Derailment, Bayesian network, Fuzzy logic

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1. Introduction

Railways are technical systems whereby people feature to the same degree as any of the mechanics. Technical systems are now broader in scope and increasingly complicated, therefore it is crucial to take into consideration their impacts upon [1, 2] :

- *The abilities, skills, and knowledge of individuals*
- *The demands of the job put upon those individuals performing the work*
- *The organisation and its employment of insdividuals as valuable assets requiring investment and the systems needed for supporting safe and effective company operations.*

Human factors[1] support railway system designs which increase performance. The integration of human factors activities at the beginning of the project can decrease the requirement for re-design when the systems become operational, lowering the possibility of staff turnover and improving productivity across the entire company. On the other hand, human error[2] is usually seen as causal in incidents and accidents, yet people rarely intentionally make errors. Handling human errors and factors in the application reduces the chances of accidents or incidents and any consequent losses to property or human life. A proper risk analysis can reduce the potential for error and increase safety [3].

Railway operational safety is significantly dependent on various aspects, such as the standard of rail organisation, rail traffic regulations, the dependability of rail vehicles and systems, and human factors[4]. *Considering human factors*

[1] In systems where there are a number of people and devices, like a railroad system, human characteristics can variously affect whole system functions. The study makes reference to such characteristics of humans in the system as "human factors." Such factors are denoted as root nodes.

[2] The study defines "human errors" as "system work requirements and a work environment inconsistent with human characteristics (human factors) and work differing from system expectations (deviant behaviour)". Such errors are expressed as intermediate nodes.

lacks a long tradition in Europe. Even though a high percentage of accidents are due to human error, integrating human contributions into system safety is frequently analysed in a rudimental manner in railway engineering [5]. Recently conducted research has shown that within Europe, at least one quarter of all rail accidents that involve fatalities in the past 20 years have been caused by a variety of different human errors, like passing signals indicating danger, excessive velocity, communication issues, and signal or dispatch errors [6, 7]. Moreover, the outcomes of these human errors within the rail sector have been demonstrated to cause serious or disastrous accidents, which frequently lead to operational downtime, destruction of rail equipment, casualties or even the loss of life [8, 9].

Much research has identified railway turnout linked to accidents and incidents in other domains than human error, for instance component failures [10, 11] and environmental conditions [12, 9, 13]. Yet, up to now there has not been any scientific research examining the contribution of human error to rail accidents and incidents at railway turnout systems. Previous research in a railway engineering context have primarily focussed on summarising the research into relevant accident causation and outlining error frameworks which are incapable of modification through new knowledge, and which are not associated with railway turnouts. A recent study [10] indicated the unfavourable nature of the working environment and the repetitive nature of driving a train, these are discussed because of attentional deficit reductions. Additionally, a Railway Safety Checklist was constructed to identify the safety perceptions of train drivers. Vanderheagen [14] analysed human reliability, which defined human reliability as a degradation function linked to deviations of both human behavioural and system states as a result of such behaviour. Therefore, this study concentrates only on three factors, and cannot cope with any derailment case. Conversely, the roles/tasks of train drivers [15], maintenance personnel [16], and signallers [17] are reviewed and frequent error types for such roles are then identified. It should be noted that such research is unable to be implemented into railway turnout-related accidents since unique errors linked to turnouts may go unnoticed.

It could be argued that the distinctions observed between risk analysis of human research and different types are more significant on collecting linguistic information by industrial specialists than in addressed statistical reviews based on accident reports[18]. Resultantly, a large percentage of the data analysis conducted in the present study is focused on mathematically analysing linguistic context.

In order to find answers to *to what extent can a novel methodology investigate, monitor and manage human-errors within the turnout operational context of process excellence*, this study endeavours to adopt a phased strategy: (1) outline the effect of distinct kinds of switches and crossings on human errors; design a specific methodology to manage the complex nature of risk analysis; emphasise the generic theory to readers and demonstrate how fuzzy Bayesian networks and fuzzy set theory can be applied to the human error likelihood of derailment; (2) disclose through processing data specific human errors that cause train derailments at crossings and switches; ascertain risk nodes and allocate them in a particular causal Bayesian network; illustrate the findings arising from the stochastic procedure; and lastly (3) elucidate and explain the importance of the results offering a variety of recommendations that can permit the rail sector to resolve human errors, and emphasise new understandings in regard to the overall research problem.

2. Switches and Crossings

Railway switches and crossings (S&C) are a must-have infrastructure of any complex railway network. The movement of a train to another rail line is performed by S&Cs. They typically account for about 30% of the total budget spent on maintenance and construction, which is equivalent to that for almost 0.3km of plain line track [19]. The EU countries are estimated to operate S&C at the density of just over one turnout every rail km [11].

The operation of a railway switch is commonly performed by two approaches, namely, a human operator (hand-operated switch), and a radio-controlled elec-

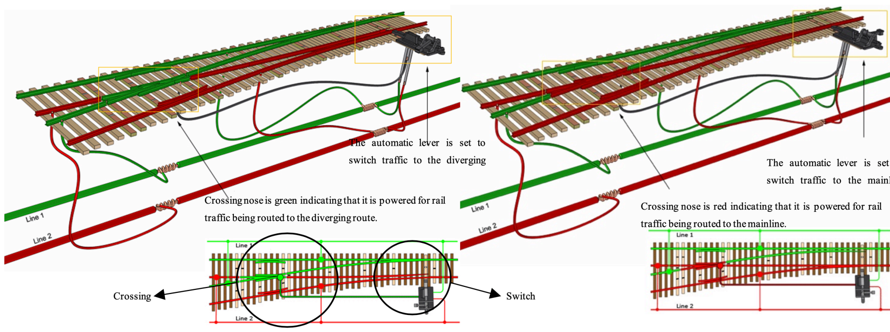


Figure 1: The mechanism of a simple radio-controlled switch and crossing

tric motor through pneumatic or hydraulic actuation. Prior to the widespread availability of radio-controlled electric motors to move the switch mechanism from one position to the other, as seen in Figure 1, switches were quite often operated by hand by a train crew member or a dispatcher. This type of rail operation is still in use even in rail networks of developed countries. Use of a switch motor that aligns the points with one of the possible routes by either an electric, hydraulic or pneumatic mechanism is now a common practice and controlled only by dispatchers in headquarters. The motor has generally contact detection abilities that enable dispatchers to identify whether the switch is completely locked or set. In the event that the switch fails, the governing signal indicates red, which means that further movement of a train is now allowed in this particular section of rail line. In some rare cases, it is observed that one of crew member can intervene using a manual handle to change switch position of a remote-controlled switch to continue on the rail line, although this is not strictly permitted.

On the other hand, the weight of the train and the flange of the wheels are used by a special type of switch, i.e. spring switch and weighted switches[3], to enforce naturally the switch out of the way while passing through. A spring switch ensures to enable a train to pass throughout the reverse leg of the switch

[3] All these kinds of passive switch mechanisms are referred as spring switches.

in the trailing[4] point direction except for the normal route when passing through facing[5] points direction.

3. Methodology

The study methodology is founded on four key stages, illustrated in Figure 2, where each is designed to address a discussion of the fundamental logic why specific techniques were utilised to formulate the optimal comprehension of human errors caused by derailments with any outcomes at switches and crossings. Further explanations of each of these stages are briefly summarised below:

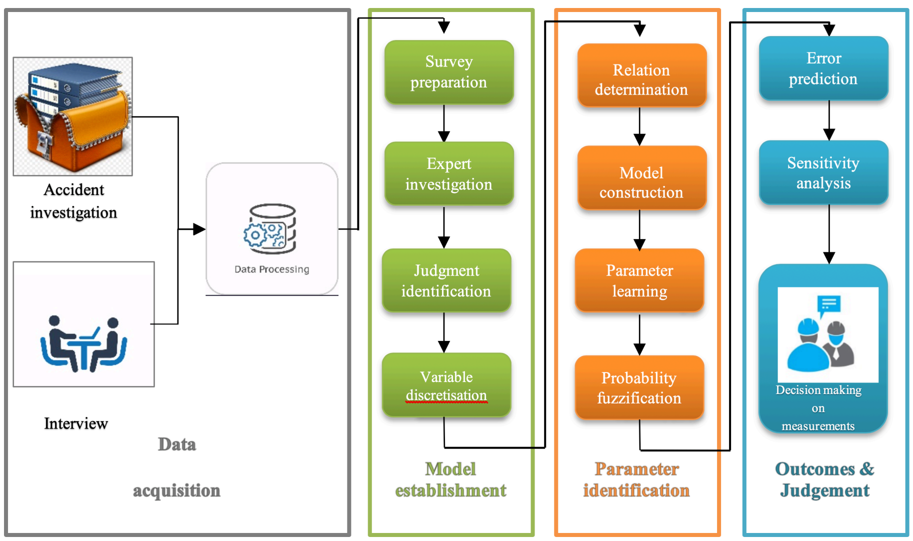


Figure 2: Presentation of techniques used in methodology

As there is a general deficiency in terms of the understanding of fundamental errors associated with crossings and switches in the literature, the present study aims to conduct a data investigation based on two phases: data collection and processing.

[4]A set of points at which two routes converge in the direction of travel.
[5]A set of points at which two routes diverge in the direction of travel.

The data are collected from formal accidents reports and interviews. While the Turkish Railway Agency (TCCD) has not made its accident reports publicly accessible, the researchers were afforded access to information about different types of rail incidents like collisions and other types of rail infrastructure, such as plain track.

Interviews were conducted with rail professionals who had more than 20 years of experience to determine whether the data was sufficient or certain values were absent. The format of the interviews was semi-structured, whereby the main problems were prompted to emerge from those being interviewed, instead of being forced by the interview structure. Interviewees were sourced from a variety of different professions as it was necessary to conduct a more comprehensive qualitative investigation of the viewpoints of persons from diverse origins. A summary of the distribution of professions is shown in the bar chart on the left side of Figure 3.

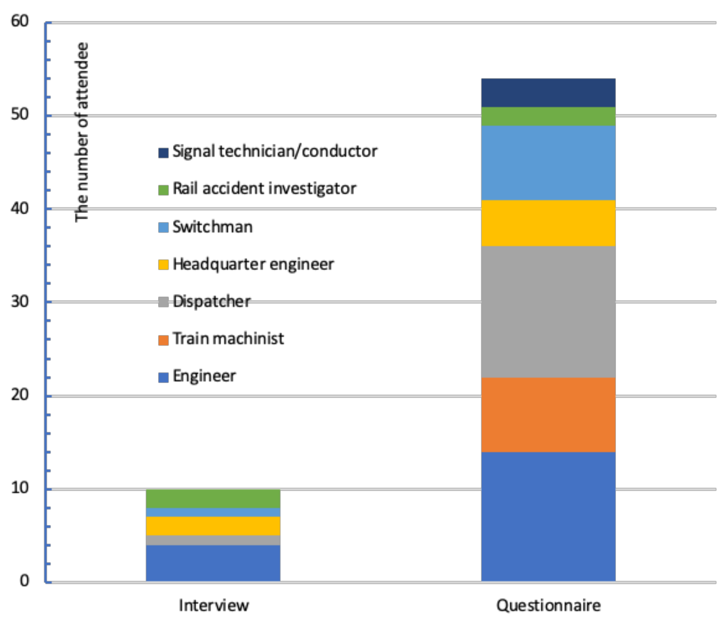


Figure 3: The number of attendees by occupation

A total of 10 specialists in the rail sector were questioned to acquire a general understanding, which not only formed the basis of a suitable questionnaire designed by the researchers, but additionally to perceive the establishment of their rail fields to acquire a more comprehensive or 'in-depth' appreciation of the relationships among risk groups, like errors caused by communication or signalling problems. Based on the calibre and abundance of the data sources from the interviews conducted to prepare the questionnaire, the interview transcripts were employed to formulate more than 70 multiple-choice questions. Subsequently, the same 10 specialists were invited to provide feedback on the suitability of the questions, and where it was indicated that changes were necessary, appropriate alterations have been applied.

The railway professionals who comprised the sample group that responded to the questionnaire were different to those previously contacted. However, both sets of experts were sourced from a variety of demographic groups, such as rail engineers (predominantly mechanical and civil engineers), switchmen, dispatchers, rail accident investigators (largely statistical experts, train mechanics, central engineers (largely experienced engineers with diverse backgrounds, signal specialists and train conductors. States 2, 3 and 4 are outlined and discussed in the below parts.

4. Understanding Human Error in Switches and Crossings

4.1. Types of human error

Distinct kinds of human errors have been determined on the basis of the underlying reasons for these errors in numerous studies in the literature [20, 21, 22]. The categorisations that are addressed in this research are based on the groups defined below:

Design-related errors occur in relation to rail incidents due to human incongruities with the S&C or operational design. A variety of different challenges for railway workers, such as train machinists or dispatchers, could emerge as a result of the properties of equipment design or design flaws in relation to S&C and signal functionality.

Human-related errors are attributes of rail operators that enhance the likelihood of errors. Frequently observed factors could include tiredness, lack of concentration, confusion, extreme stress, reduced motivation, lack of attention, forgetfulness, skill and knowledge deficiencies, indecision, complacent attitude, false expectancy, drug usage, and insufficient or reduced perceptual or cognitive capability.

System-related errors are caused by human inadequacies resulting from the manner in which systems of railway management are installed. This category of human errors is considered to incorporate certain errors arising from the designation of groups or amounts of rail workers, in the coordination of training, in the maintenance specifications for S&C and in communication.

4.2. Identification of Human Factors

Although the overall volume of dangerous incidents in the wider global rail sector is generally decreasing, the underlying causes that impact such hazardous events have thus far been seen to be rising [23]. The proportion of report worthy accidents and events attributed to human errors is approximately 13 percent in the United States [24]. Moreover, it is underlined that human errors are responsible as contributory factor for the great majority of derailments [19]. [6].

While the outcome of a series of incidents and various different situations or states are often deemed to be responsible for derailed trains, it appears that human aspects are sufficient to cause such incidents on their own. The physical characteristics, neglectful attitudes, actions and various other behaviours of rail workers have been blamed as the main causal factors behind rail incidents/accidents. Hence, it is important to categorise the human-induced causes into the

[6] As the Turkish rail authorities requested that statistics from official reports should not be included in this study, figures from the United States are given as examples. Nevertheless, it should be noted that similar patterns can be seen in Turkey as well as numerous other countries in Europe.

groups detailed below:

4.2.1. Use of Brakes

Where a type of train protection system[7], PTC, is neither available nor in use for some reason, failures in brake of use have often been observed to take place as primary cause. The total human errors are illustrated in Table 1. Locomotives equipped with loco driver[8] brakes to control the speed often fall into the responsibility of loco drivers as being. Some rare events particularly in rural areas, non-railway employees (A7) are observed to be involved in derailments. While a train siding[9] takes place on the rail line, hand brakes of locomotive (A5) or, where possible, wagons (A6), are required to prevent undesired movement. Otherwise, a locked pair of switch blades on exit or entrance of a siding lead a sliding train to run off its rails. A sufficient number of hand brakes, on the other hand, should be applied by a loco driver to ensure safe passage on a particular long rail turnout (A2). As a result of failure to apply hand brakes on wagon(s) (A1) or failure to release hand brakes on wagon(s) (A3) by any railway employee, insufficient braking forces allowed the speed of the train to increase, where a slope exists in trailing direction, or to remain out of speed allowance.

4.2.2. Train handling

Loco drivers have an obligation to apply common sense and preparation in order to ensure that their vehicle operates in a safe and efficient manner. The engineer is responsible for managing the slack in the train. Optimal train handling requires the appropriate mixture of behaviours illustrated in Table 2.

[7] An advanced rail safety system designed to automatically lessen the speed of train or stop before certain accidents occur, and thereby to prevent derailments caused by excessive train speed, train movements through misaligned track switches, unauthorized train entry into work zones and train.

[8] It is referred to a railway employee who can drive and stop a train in cab, and let the brakeman or conductor dismount, and throw switch blades to the correct position.

[9] A short stretch of railway track used to enable trains on the same line to pass or store rolling stock

Table 1: Human errors associated with brake of use.

Node	Description	Type of human error
A1	Failure to apply hand brakes on wagon(s) (railway employee)	Human-induced errors
A2	Failure to apply sufficient number of hand brakes on wagon(s) (railway employee)	Human-induced errors
A3	Failure to release hand brakes on wagon(s) (railway employee)	Human-induced errors
A4	Failure to control speed of wagon using hand brake (railway employee)	Human-induced errors
A5	Failure to properly secure loco(s) (railway employee)	Human-induced errors
A6	Failure to properly secure wagon(s) (railway employee)	Human-induced errors
A7	Failure to properly secure engine(s) or wagon(s) (non-railway employee)	Human-induced errors

4.2.3. Physical state of rail workers

Rail workers are frequently confronted by occupational health and safety (OSH) risks as a result of the reasons detailed in Table 3. Most of the rail employees who participated in the interviews emphasised that it is not always possible to address the OSH risks appropriately, despite the increasing recognition and cognisance of the broader and more varied group of OSH risk factors that workers must face. Besides Turkey, countries within the European Union find it challenging to devise an appropriate solution to the problem of the significant worsening of rail workers' psychological and physical wellbeing. Approximately 20% of those employed in the rail sector within the EU member countries expressed that they encountered problems related to stress, anxiety and depression, and this has been observed to be a continuing trend for some time [25]. Particular attention should be given to rail turnout systems as a result of their operational susceptibility. Resultantly, human error(s) could arise due

Table 2: Human errors associated with Train Handling.

Node	Description	Type of human error
B1	Automatic brake, excessive	Human-induced errors
B2	Automatic brake, failure to use split reduction	Human-induced errors
B3	Automatic brake, insufficient	Human-induced errors
B4	Slack action excessive, train handling	Human-induced errors
B5	Dynamic brake, excessive	Human-induced errors
B6	Dynamic brake, excessive axles	Human-induced errors
B7	Dynamic brake, insufficient	Human-induced errors
B8	Dynamic brake, other improper use	Human-induced errors
B9	Dynamic brake, too rapid adjustment	Human-induced errors
B10	Failure to allow air brakes to fully release before proceeding	Human-induced errors
B11	Failure to properly cut-in brake valves on locomotives	Human-induced errors
B12	Failure to properly cut-out brake valves on locomotives	Human-induced errors
B13	Failure to properly cut-out brake valves on locomotives	Human-induced errors
B14	Improper placement of wagons on train between the terminal	Human-induced errors
B15	Lateral drawbar force on curve excessive, wagon geometry (short wagon/long wagon combination)	Human-induced errors
B16	Lateral drawbar force on curve excessive, train handling	Human-induced errors

to a mixture of C1, C2, C3 and C4, which cause depression, anxiety or stress. Most are recognised as system-related errors as they (C1, C2, C3) could occur due to flaws in human management systems that are managed in central offices. Frequently occurring errors are: (1) feedback is not obtained from rail workers regarding shift schedules and working hours; (2) adjustments to working hours are not evaluated; (3) no appropriately established policy that particularly focuses on and controls working hours, shift-trading and overtime so as to prevent excessive tiredness among workers.

Table 3: Human errors associated with employee physical condition.

Node	Description	Type of human error
C1	Employee asleep	System-induced errors
C2	Employee restricted in work or motion	System-induced errors
C3	Impairment of efficiency or judgment because of drugs or alcohol	System-induced errors
C4	Incapacitation due to injury or illness	System-induced errors

4.2.4. Control systems

The most frequently utilised train control systems include Automatic Train Protection (ATP) and Cab signal systems. Cab signal functions via a visual indication in the train's crew compartment that continuously indicates the condition of the forward track or continuously reminds the train driver of the previous wayside signal. Automatic cab signal systems have been installed on most locomotives on the Turkish rail network. Additionally, Automatic Train Control, which provides completely automated train control by predicting accelerating and braking as well as an indication of the position of the switch, is also functioning within Turkey. The potential causes of human errors linked to control systems that could involve a train derailment are shown in Table 4. It is possible that both reasons could not only cause incidents of derailment, but could also act as influencing factors. For example, safety control systems that are intended to automatically constrain a train's speed could be deactivated by the train's driver. In that circumstance, the train control system contributes to the problem of over-speeding (main cause), thus resulting in the train accelerating from the turnout.

Table 4: Human errors associated with control systems

Node	Description	Type of human error
D1	Control system signal cut out	Human-induced errors
D2	Control system, failure to comply	Human-induced errors

4.2.5. Speed

When a train passes via the diverging path of a turnout, this generally creates increased speed and strong lateral forces, predominantly at the location of the switch and the crossing nose (frog). Resultantly, turnout designs allow diverging speeds to be allocated based on their specific peak lateral accelerations and the interaction between wheel and rail. In the event that a control system is not installed or inoperable, it is likely that excess speed (E1, illustrated in Table 5) will occur in switch functionality. Conversely, the signalling that governs the movement of a train from a turnout to another, or siding to the main line, would not satisfy the engineering requirements for a turnout.

Table 5: Human errors associated with speed

Node	Description	Type of human error
E1	Switching movement, excessive speed	Human-induced errors
E2	Failure to engineer design of restricted speed	Design-induced errors

4.2.6. Flagging, Fixed, Hand and Radio Signals

Rail workers who show or provide signals are necessitated to have the suitable equipment. Moreover, users are responsible for ensuring that the equipment is functioning correctly and is operable (F8 and F11, see Table 6). To ensure that all signals are acknowledged and followed in the correct manner, rail workers must adhere to the purpose of the signal (F1, F5 and F9), and must not follow any signal that could be directed towards a different train or that they cannot comprehend (F3). The delivery of clearly visible signals in light and dark conditions is achieved by rail workers utilising the appropriately coloured reflective lights or flags (F7 and F8). Additionally, train drivers should be able to clearly observe the signals and they must be given in a manner that enables easy comprehension. In order for rolling stock to move correctly, all rail operations require effective radio communications. Rail workers are expected to satisfy particular instructions assigned to every movement (F10). Moreover, both train drivers and dispatchers must ensure that they are aware of the specific moves that will be conducted via radio communications (F11 and F12).

Table 6: Human errors associated with Flagging, Fixed, Hand and Radio Signals

Node	Description	Type of human error
F1	Automatic block or interlocking signal displaying a stop indication – failure to comply	Human-induced errors
F2	Blue Signal, absence of	Design-induced errors
F3	Improper signal location	Design-induced errors
F4	Any signs covered by obstacles or damaged signs	System-induced errors
F5	Failure to comply with failed equipment detector warning or with applicable train inspection rules	Human-induced errors
F6	Failure to observe hand signals given during a wayside inspection of moving train	Human-induced errors
F7	Fixed signal (other than automatic block or interlocking signal), failure to comply	Human-induced errors
F8	Flagging signal, failure to comply	Human-induced errors
F9	Flagging, improper or failure to flag	Human-induced errors
F10	Hand signal improperg	Human-induced errors
F11	Radio communication, failure to comply	Human-induced errors
F12	Automatic brake, failure to use split reduction	Human-induced errors
F13	Radio communication, failure to give/receive	Human-induced errors
F14	Radio communication, improper	Human-induced errors

4.2.7. Use of switch

The majority of switches, even those that are defined as Automatic Switches, could be hand-operated. As shown in Table 7, there are three distinct types of switch functionality: hand-operated, spring switch and radio-controlled. Those that can be operated manually are defined as hand-operated switches. A member of the train's crew must ensure the train is stopped and then verify that (1) the alignments of the hand-operated switches are suitable for the chosen route (G1); (2) the turnout points should fit correctly and if a target is installed, it should correspond with the position of the switch (G1); (3) subsequent to the switch or derail being locked, the member of the train's crew should verify whether it is in fact locked securely (G1); and (4) in cases where the operating level has a latch, it is important that the crew member does not step on the latch to operate the lever apart from when the switch is thrown (G5), which is the responsibility of maintenance crews. When operating spring switches, it is important that rail employees adhere to these human-related rules: (1) Trains must come to a complete stop when performing a facing point movement over a spring switch, and the switch must be tested by a member of the train's crew (G2); the train must be stopped and the slack should be controlled when trailing through and stopping on a spring switch (G2); (3) when a train approaches a spring switch in an area that has no signals, it must transition through the facing points of a spring switch ready to stop until a far signal indicates clear or where the switch is shown to have correct alignment (G2). When operating a radio-controlled switch (also known as automatic switch), train crew must adhere to the following guidelines: (1) it is not possible to perform siding operations when the train is moving prior to traversing the overlap sign, even where it shows proceed (G3 and G4); (2) a train moving onto the main track must travel past the overlap sign, and when the signal covering movement indicates proceed, it can move further (G3 and G4). Train drivers are obligated not to run through switches, apart from spring switches (G6). In the event that such run-through does occur, the train must continue its motion across the switch

(G6).

Table 7: Human errors associated with use of switch

Node	Description	Type of human error
G1	Moveable point switch frog improperly lined, hand-operated	Human-induced errors
G2	Spring switch not cleared before reversing	Human-induced errors
G3	Radio-controlled switch not locked effectively	Human-induced errors
G4	Switch improperly aligned, radio controlled	Human-induced errors
G5	Switch not latched	System-induced errors
G6	Switch previously run through	Human-induced errors

4.3. Fuzzy Bayesian Networks and Fuzzy set theory

To deal with uncertainty stemming from the imprecision and vagueness, fuzzy set theory (FST) is used for this study. FST provides a basis to generate powerful problem-solving techniques with wide applicability, especially in the field of decision making. Fuzzy numbers, which are an extension of real numbers, have their own properties associated with the theory of numbers.

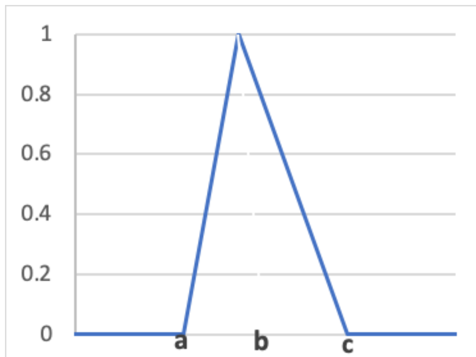
Definition 1: Let E and A be a Fuzzy Subset and a set contained in E, respectively. Then, $(x, \mu_A(x))$ refers to the fuzzy subset A of E, where $\mu_A(x)$) is the degree of membership of x in E, and x is a single element E.

Definition 2: A membership function for a fuzzy set A is expressed as $\mu_A : X \rightarrow [0, 1]$, where each element of X is mapped to a value between 0 and 1.

Definition 3: A Fuzzy Number ($\tilde{A} = (a, b, c)$) is called a triangular fuzzy number if its membership function is given by

$$\mu_A(x) = \left\{ \begin{array}{ll} 0, & x < a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & x = b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c < x \end{array} \right\}$$

Where a, b and c are plotted on a two-dimension graph as follows:



Definition 4: The operators between two fuzzy sets are defined as follows:

$$\begin{cases} \widetilde{A_1} \oplus \widetilde{A_2} = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \\ \widehat{A_1} \ominus \widetilde{A_2} = (a_1 - a_2, b_1 - b_2, c_1 - c_2) \\ \widetilde{A_1} \otimes \widetilde{A_2} = (a_1 a_2, b_1 b_2, c_1 c_2) \\ \widetilde{A_1} \oslash \widetilde{A_2} = \left(\frac{a_1}{a_2}, \frac{b_1}{b_2}, \frac{c_1}{c_2}\right) \end{cases}$$

4.4. Integration of expert review into fuzzy sets

Reliability levelling

Since experts are often invoked when quantities of interest are uncertain, a defensible quantification of uncertainty, thereby, is required to be established. This study proposes an expert confidence indicator (ECI) to judge the reliability of the data obtained from surveys with experts. With regard to ECI, the reliability of expert opinions is conducted through the following equation:

$$\omega = \gamma.\zeta \tag{1}$$

where γ and ζ denote the position and experience, respectively, of the rail employee. Those are proposed to be measured by Table 8 and Table 9.

Linguistic variables

Table 8: Subjectivity reliability levels

Levels	Definition	γ
1	Rail accident investigator	1.0
2	Field supervisor	0.9
3	Engineer (at headquarter)	0.9
4	Train dispatcher chief	0.8
5	Train dispatcher	0.7
6	Train machinist / Switchman	0.7
7	Signal technician/Conductor	0.5

Table 9: Expert experience levels

Levels	Definition	ζ
1	Rail accident investigator	1.0
2	Field supervisor	0.9
3	Engineer (at headquarter)	0.8
4	Train dispatcher chief	0.6
5	Train dispatcher	0.4

The ineffectiveness of probability calculation in carrying out humanistic systems might be argued to be a manifestation of what is called the principle of incompatibility [10] [26]. Therefore, it might be suggested that, in order to analyse an appropriate risk in research-based human behaviour systems, the high level of preciseness of any mechanical system might be abandoned. In coping with the overpowering complexity of an intended system, it is a scientifically natural approach to use linguistic variables.

Linguistic variables provide concrete insight to analysis properly human knowledge representation. The variables are generated from an artificial lan-

[10]It asserts that high precession is incompatible with high complexity.

Table 10: Divisions of occurrence probability intervals

Linguistic labels	Probability intervals (i), $((a_i), (c_i)]$		
	Lower boundary (a_i)	Upper boundary (c_i)	Mean of interval (μ_i)
Impossible	0.00	0.00	0.00
Almost impossible	0.00	0.05	0.25
Quite unlikely	0.05	0.15	0.075
Unlikely	0.15	0.25	0.15
Improbable	0.25	0.35	0.25
Possible	0.35	0.45	0.35
Even chance	0.45	0.55	0.45
Better than even	0.55	0.65	0.55
Likely	0.65	0.75	0.65
Quite likely	0.75	0.85	0.75
Highly probable	0.85	0.95	0.85
Almost certain	0.95	1.00	0.925
Certain	1.00	1.00	0.975

guage or words or sentences, and as a natural consequence, are less specific than numbers. On the other hand, the variables can be represented through membership functions that fit into what has been achieved mathematically in the Fuzzy theory section of this paper.

Table 10 is prepared to divide likelihoods of nodes, which are asked to railway employees, by twelve equals intervals. Then each responds to a fuzzy domain with a unique lower boundary (a_i) and a unique upper boundary (c_i) . The first column of the table illustrates linguistic labels of events, while the other columns express fuzzy definition of given linguistic labels. Considering the subjective nature of the language used to describe probability, the probability intervals are given to railway employees before the questionnaire and interview so that comprehension of the chances of events is provided properly.

Thus, reliability level and experience level are modelled and nested into the lower and upper boundaries throughout the following equation;

$$\mu_{node}(x) = \begin{cases} 0 & , \quad x \leq \frac{\sum_{i=1}^{N} w_i(a_i)}{\sum_{i=1}^{N} w_i} \\ \frac{x - \frac{\sum_{i=1}^{N} w_i(a_i)}{\sum_{i=1}^{N} w_i}}{\frac{\sum_{i=1}^{N} w_i(b_i)}{\sum_{i=1}^{N} w_i} - \frac{\sum_{i=1}^{N} w_i(a_i)}{\sum_{i=1}^{N} w_i}}, & \frac{\sum_{i=1}^{N} w_i(a_i)}{\sum_{i=1}^{N} w_i} \leq x \leq \frac{\sum_{i=1}^{N} w_i(b_i)}{\sum_{i=1}^{N} w_i} \\ 1 & , \quad x = \frac{\sum_{i=1}^{N} w_i(b_i)}{\sum_{i=1}^{N} w_i} \\ \frac{\frac{\sum_{i=1}^{N} w_i(c_i)}{\sum_{i=1}^{N} w_i} - x}{\frac{\sum_{i=1}^{N} w_i(c_i)}{\sum_{i=1}^{N} w_i} - \frac{\sum_{i=1}^{N} w_i(b_i)}{\sum_{i=1}^{N} w_i}}, & \frac{\sum_{i=1}^{N} w_i(b_i)}{\sum_{i=1}^{N} w_i} \leq x \leq \frac{\sum_{i=1}^{N} w_i(c_i)}{\sum_{i=1}^{N} w_i} \\ 0 & , \quad x \geq \frac{\sum_{i=1}^{N} w_i(c_i)}{\sum_{i=1}^{N} w_i} \end{cases}$$

where w denotes the reliability of expert opinion, which is shown Eq.1. i denotes i-th rail employee which gives an opinion to the sample pool. N is the number of railway employee (54). $\mu_{node}(x)$ denotes the membership function of a node in the bayesian network.

4.5. Establishment of noisy-Or Bayesian network

4.5.1. Causal Independence

A standard BN is used to compute the probabilities of the presence of several variables mostly in the presence of a causal independence. The network represents a set of variables and their conditional dependencies throughout a directed acyclic graph (DAG) (probabilistic graphical model). As seen in Figure 5, considering hierarchical levels of the network, nodes higher than a given node in the same lineage are parents, and the given node, in turn, is the child's parent. Bayesian networks do not often place any restrictions on how a child node is assigned to its parent(s). Thus, nodes are labelled with random variable(s) in the following way.

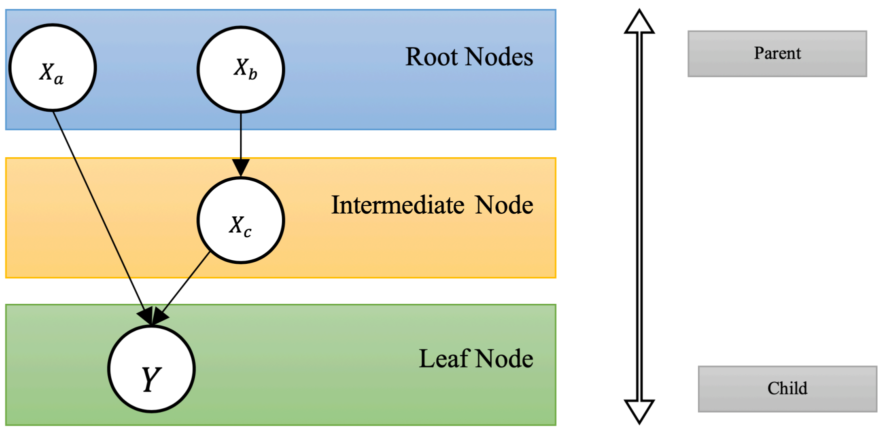


Figure 4: Directed acyclic graph (DAG) representing two independent roots and an intermediate node causing an evidence (leaf node)

Let's say, X_a and X_b are two independent potential causes (root nodes) of Y, as shown in the Figure 4. X_c is determined as an intermediate node of the network. The overall goal is to compute the posterior conditional probability distribution (PCPD) of each of these independent causes given a new evidence (leaf node) takes place, i.e. $P\left(X_a|Y\right)$. To do this, the conditional independence assertions and the conditional probabilities together of these two independent potential causes and the intermediate node entail a joint probability over Y. By the chain rule,

$$P\left(Y, X_a, X_b, X_c\right) = P(Y)P\left(X_a\right)P\left(Y|X_a, X_b\right)P\left(X_b\right)P\left(X_c|X_b, \right) \qquad (2)$$

where $P\left(X_a\right)$ and $P\left(X_b\right)$ notate marginal probabilities of the given network. Conditional probabilities of causal relationships are expressed through $P\left(Y|X_a, X_b\right)$ and $P\left(X_c|X_b,\right)$, both of whose derivations are illustrated in Table 11 and Table 12 respectively.

Table 11: Conditional Probability of $\mathrm{P}\left(\mathrm{X_c}|\mathrm{X_b},\right)$

X_b	$P\left(\left(X_c = x_{c_1}\right)\|X_a\right)$	$P\left(\left(X_c = x_{c_2}\right)\|X_a, X_b\right)$
x_{b_1}	$\frac{p_{x_{b_1}, x_{c_1}}}{p_{x_{b_1}}}$	$\frac{p_{x_{b_1}, x_{c_2}}}{p_{x_{b_1}}}$
x_{b_2}	$\frac{p_{x_{b_2}, x_{c_1}}}{p_{x_{b_2}}}$	$\frac{p_{x_{b_2}, x_{c_2}}}{p_{x_{b_2}}}$

Table 12: Conditional Probability of $\mathrm{P}\left(\mathrm{Y}|\mathrm{X_a}, \mathrm{X_b}\right)$.

X_b	X_b	$P\left(\left(X_c = x_{c_1}\right)\|X_a\right)$	$P\left(\left(X_c = x_{c_2}\right)\|X_a, X_b\right)$
x_{a_1}	x_{b_1}	$\frac{p_{x_{a_1}, x_{b_1}, y_1}}{p_{x_{a_1}, x_{b_1}}}$	$\frac{p_{x_1, x_{b_2}, y_2}}{p_{x_{a_1}, x_{b_2}}}$
x_{a_1}	x_{b_2}	$\frac{p_{x_{a_1}, x_{b_1}, y_1}}{p_{x_{a_1}, x_{b_1}}}$	$\frac{p_{x_{a_1}, x_{b_2}, y_2}}{p_{x_1, x_{b_2}}}$
x_{a_2}	x_{b_1}	$\frac{p_{x_{a_2}, x_{b_1}, y_1}}{p_{x_{a_2}, x_{b_1}}}$	$\frac{p_{x_{a_2}, x_{b_2}, y_2}}{p_{x_{a_2}, x_{b_2}}}$
x_{a_2}	x_{b_2}	$\frac{p_{x_{a_2}, x_{b_1}, y_1}}{p_{x_{a_2}, x_{b_1}}}$	$\frac{p_{, x_{a_2}, x_{b_2}, y_2}}{p_{x_{a_2}, x_{b_2}}}$

True, i.e. $P\left(\left(x_c = x_{c_1}\right)|x_a\right)$, and false, i.e. $P\left(\left(X_c = x_{c_2}\right)|X_a, X_b\right)$, conditional probabilities along with their statistical expressions are presented. As seen, a node in the network is assigned a particular set of values as input for its parent variables and given the probability (as output) of the variable represented by the node. In other words, a node with n parent(s) constitutes n Boolean variables, which means that a table of 2^n entries should exist to perform the joint probability of the node. Thus, excessive burden of calculation is required in a network with a large number of causal relationships. As the research has been modelled by dealing with over 60 nodes, a standard BN model would need over 100,000 inputs, which makes the research ineligible to be conducted. As a result, a canonical-based distribution, namely Noisy-Or method, is applied to the study.

4.5.2. Noisy-Or gate

The Noisy-OR model is a generalized version of the logical OR gate, and it is established by assuming that there is a disjunctive causal interaction among child, parent, and/or leaf node(s), rather than a conjunctive causal interaction. This interpretation is often associated with a cause and effect model where the child node is assigned as an event sufficient to impact each parent node. In contrast to standard BN considering every parent-state combination, the Noisy-OR based BN model, therefore, entails only that a node be parameterized for the cases where a single parent event takes place. To be more specific, two assumptions are made by the Noisy-OR model. (1) Each of the causes (X_i), (whether it is root or intermediate node) a probability of p_i, which is quite enough to absence of other causes. (2) The ability of each cause, which is quite enough, is independent of the presence of other causes in the network. These two assumptions enable identifying the entire conditional probability distribution with only n parameters $(p_a, \ldots, p_n)$, representing the probability effecting child nodes. Providing that only one of the causes (parents) exists in the network, the child takes place by the following equation.

$$p_i = P\left(y|x_a, x_b, \ldots, x_n\right) \tag{3}$$

Thus, the probability of y given a subset X_p of X_i s is calculated by the equation below.

$$P\left(y|X_p\right) = 1 - \prod_{i:X_i \in X_p} \left(1 - p_i\right) \tag{4}$$

The conditional probabilities (p_i) of nodes are given in the specification of the Bayesian network. Eventually, arbitrary probabilistic reasoning in a network is achieved. For instance, the given probabilities by Table 12 are rearranged through Eq.3 in Table 13.

Table 13: Rearrangement of a conditional probability.

X_b	X_b	$P\left((Y=y_1)\,\vert X_a, X_b\right)$	$P\left((Y=y_2)\,\vert X_a, X_b\right)$
x_{a_1}	x_{b_1}	$1-\frac{p_{x_{a_1},x_{b_1},y_1}}{p_{x_{a_1},x_{b_1}}}\times\frac{p_{x_{a_2},x_{b_2},y_2}}{p_{x_{a_2},x_{b_2}}}$	$\frac{p_{x_{a_1},x_{b_2},y_2}}{p_{x_{a_1},x_{b_2}}}\times\frac{p_{x_{a_2},x_{b_2},y_2}}{p_{x_{a_2},x_{b_2}}}$
x_{a_1}	x_{b_2}	$1-\frac{p_{x_{a_1},x_{b_1},y_1}}{p_{x_{a_1},x_{b_1}}}$	$\frac{p_{x_{a_1},x_{b_2},y_2}}{p_{x_{a_1},x_{b_2}}}$
x_{a_2}	x_{b_1}	$1-\frac{p_{x_{a_2},x_{b_1},y_1}}{p_{x_{a_2},x_{b_1}}}$	$\frac{p_{x_{a_2},x_{b_2},y_2}}{p_{x_{a_2},x_{b_2}}}$
x_{a_2}	x_{b_2}	0	1

As seen, the noisy-OR parameterization allows the original 4 parameters of CPT to be condensed down to 2 parameters. In other words, in contrast to the standard BN model which requires 2^n entries, the number of CPT entries is 2n in the Noisy-OR model. Therefore, it is said that this technique will enable dealing with a large number of nodes as the number of CPT parameters associate with a linear function with Noisy-OR rather than an exponential increase.

4.5.3. Integration of the nodes in a Bayesian network

A BN is technically a graphical model that displays nodes (also referred to as variables), their conditions and independencies. Therefore, causal relationships between nodes, which generally illustrates cause and effect, are established through the links in the network (also known as arcs). As revealed in section 4.2, the BN that handles risk distribution and causal relationships between various human errors leading to a derailment at S&C is revealed to form of 51 intermediate nodes and 1 leaf node. So, the probabilistic independencies between the nodes as displayed on the graph first required to be identified. As a result of interviews, Table 14 exhibits the one-way-relations of the nodes. Relationships between nodes are made through Boolean data as this is the most straightforward way to represent the two truth values of logic. Two possible values; virtually 1, 0, are assigned as shown in Table 14. It is brought out that employee physical conditions (employee asleep (C1), employee restricted in work or motion (C2), impairment of efficiency or judgment because of drugs or alcohol (C3), incapacitation due to injury or illness (C4)), aside from its primary impact, often lead to a contributory impact on the other human-error nodes. On the other hand, some nodes are observed to be linked only to a group, such as control system failures. It is also worth noting that Table 13 disregards nodes without any link to intermediate nodes to facilitate the visualisation and understanding of the significant fundamental relations throughout the BN.

Considering Table 13 and the relationship between some intermediate nodes (A, B, C, D, E, F, G) and a leaf node (Y; namely, derailment), Figure 6 is prepared to provide a visual representation of the concealed structure of joint probability distributions. In other words, the structure reveals human error-based derailment causes at S&C by encoding raw information about the conditional independence relationships among all random variables. As shown in Figure 4, a set of intermediate nodes (A, B, C, D, E, F, G) is added to the DAG structure. Each is associated with a subset of failure nodes and named through a unique prefix of these failure codes. For instance, Node A, coloured as yellow hollow hoop in the structure, refers to human errors in the brake of use (see 4.2.1), which encapsulates node names A1 to A7 (see Table 1).

5. Results

5.1. Execution of marginal and conditional probability distributions

The proposed DAG is composed of 59 unique nodes, each of which responds to various human behaviour errors which might result in derailments at rail turnouts. As discussed in section 4.2.5., the main reason for the choice of such a comprehensive methodology built-in a Noisy-OR approach is that data is provided by rail employees with different background and occupations. For instance, Node B (human errors associated with Train Handling) is of 16 parent-nodes (B1 to 16). Therefore, they would be asked $65,536\left(2^{16}\right)$ times to reach the conditional table of the node.

Instead of such an impossible reviewing event, a unique Noisy-OR data gathering process (see Sec.6 has been developed and integrated into modified equa-

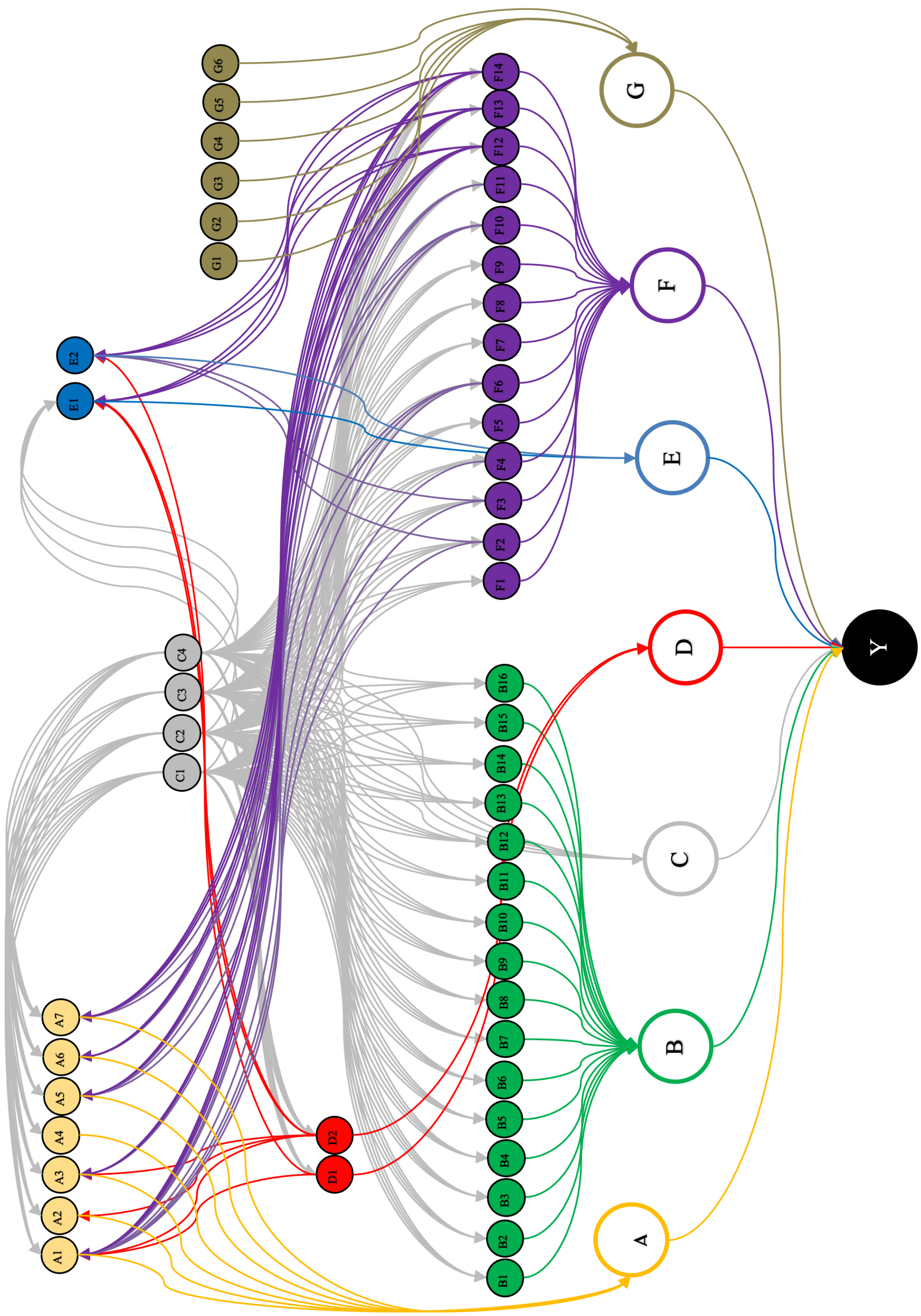


Figure 5: DAG establishment of human error-based derailment causes at S&C (HEDC)

Table 14: Causal relationships between nodes

	Parent Nodes															
Child Nodes	C1	C2	C3	C4	D1	D2	F1	F2	F3	F4	F6	F10	F11	F12	F13	F14
A1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
A2	1	1	1	1	0	1	1	1	0	0	0	0	0	0	0	0
A3	1	1	1	1	0	1	1	1	0	0	1	1	1	1	1	0
A4	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0
A5	1	1	1	1	0	0	0	0	0	0	1	1	0	1	1	1
A6	1	1	1	1	0	0	0	0	0	0	0	0	0	1	1	1
A7	1	1	1	1	0	0	0	0	0	0	1	1	0	1	1	1
B1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B3	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B5	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B6	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B7	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B8	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B9	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B10	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B11	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B12	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B13	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B14	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B15	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
B16	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0

Table 14 *(Continued)*.

Child Nodes	Parent Nodes															
	C1	C2	C3	C4	D1	D2	F1	F2	F3	F4	F6	F10	F11	F12	F13	F14
D1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
D2	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
E1	1	1	1	1	1	1	0	0	0	0	0	0	0	1	1	1
E2	0	0	0	0	1	1	0	1	1	0	0	0	0	1	1	1
F1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F2	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F3	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
F4	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F5	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F6	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F7	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F8	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F9	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F10	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F11	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F12	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F13	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0
F14	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0

tions in Table 13. This process enables the preparation of CPD tables. In this study, over 200,000 CPD executions were performed through a comprehensive MATLAB-based programme developed specifically for this research.

Figure 6 illustrates measures of all probabilities of the event ‘D1’ given that either one of the parents (or more) in the DAG or another event that is not presented in the DAG has occurred. As seen in Table 13, C1, C2, C3 and

C4 are assigned as parents of the D1. In other words, the sample space of 2^4 combinations are distributed in a way that each probability computation between D1 and the others ($\mu_A(x)$) is represented. As the methodology of exaction includes leaky Noisy-Or Structure, $P\left(D1_T|C1_F, C2_F, C3_F, C4_F\right)$ is quite higher that the other combinations. Therefore, reviewers consider the occurrence of any human associated failure of control systems (Dl) is highly unlikely to be by any employee physical condition (C1).

Aside from conditional probability, marginal probabilities are found out using equations in section 4.5.1. Figure 7 illustrates fuzzy calculations of both occurrence and non-occurrence of a marginal node 'D1'. The ranges of $\mu_{D1T}(x)$ and $\mu_{C1_F}(x)$ are different from each other as the probabilities are composed of a ratio of one percent.

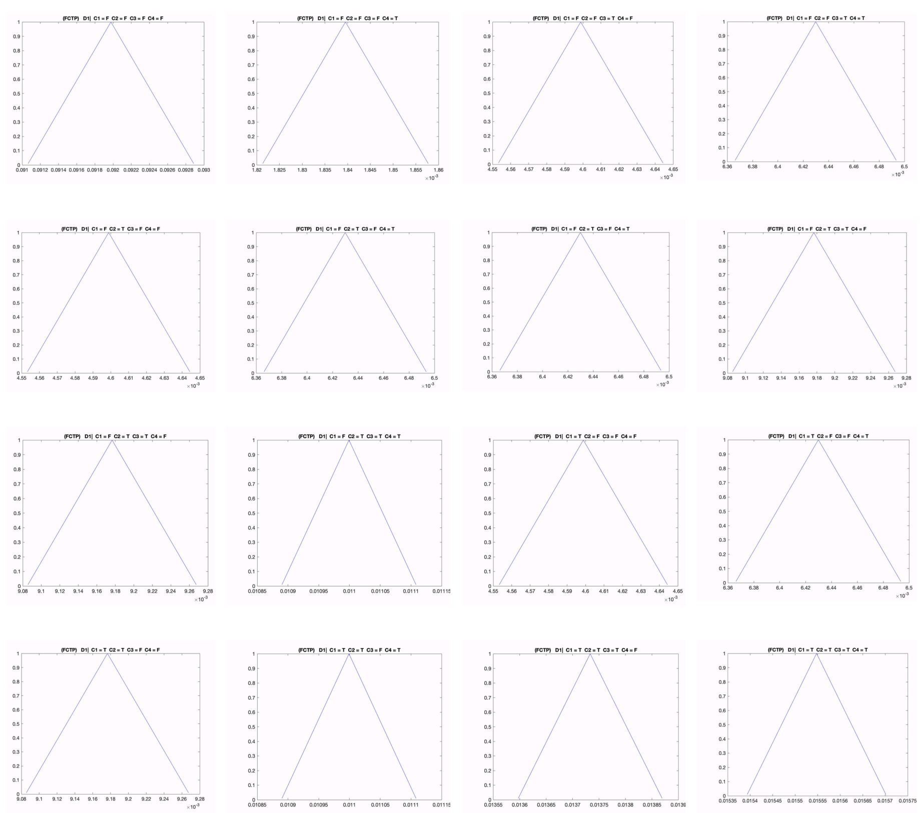


Figure 6: Fuzzy CPDs of D1

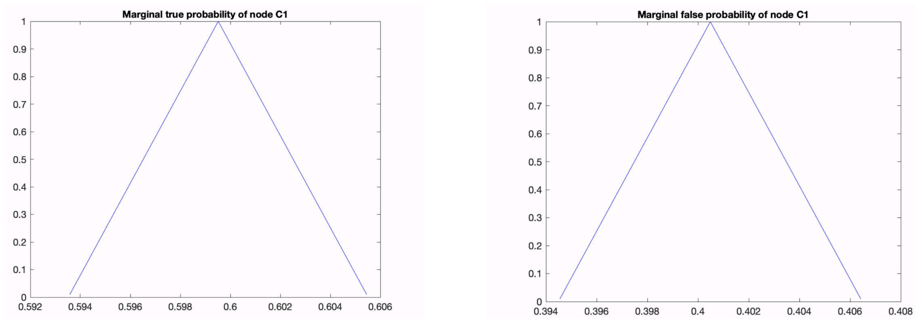


Figure 7: Fuzzy MPD of C1

5.2. Prior and posterior calculations

Having obtained Marginal and Conditional Probability Distributions of all nodes in the HEDC, the unique proposed BN is set to perform an analytic understanding of human-error risks. In order to this, joint probabilities of all conditions have been revealed, which has enabled prior probabilities of the nodes in the proposed Bayesian network to be conducted. A prior probability of a specific human error in the HEDC might be expressed to deliver definite information about how it is evaluated and prioritised.

On the other hand, the significant feature of a BN is in reversing probabilities of events on account of observations of others. As a result, not only can the posterior probabilities of any human errors be determined, but also the probabilities in the network are able to be updated. The inference of posterior probability calculation has begun with the assignment of the node 'Y', which is leaf node; that is, derailment. The node has been calculated assuming that the observation takes place.

Table 15 illustrates the mathematical expression of priori ($\mu_i(x)_{\text{ Prior }}$) and posteriori ($\mu_i(x)_{\text{ Posterior }}$) occurrence of many significant nodes. The impact of choosing lower and higher bound of fuzzy membership function is clearly seen as a_{prior} and c_{prior} as well as $a_{posterior}$ and $c_{posterior}$ are found out to not be diverted considerably from b_{prior} and $b_{posterior}$, respectively. This means that the proposed unique methodology gives rise to much precise results compared to previous studies at its kind. As the proposed Bayesian network has

59 nodes, majority of which possess conditional dependencies to one (or more) other node(s), posterior probabilities seem to not be diverted from prior posterior. Another reason for this desired behaviour is of the sample of a large number of professions, which enables the study to have solid comprehensive data.

Whether $\mu_i(x)_{\text{Prior}}$ or $\mu_i(x)_{\text{Posterior}}$ is considered, human errors associated with train handling (B) and control systems (D) are found out to influence derailments at an ignorable level. Brake of use (A), speed (E), flagging, fixed, hand and radio signals (F) along with use of switches (G) are ascertained to be the primary reasons for human error-related derailments at S&Cs. Moreover, employee physical condition (C) is identified to be the most derailment-driving cause in the HEDC.

5.3. Sensitivity analysis

The proposed Bayesian network might be identified to be exposed by the changes in marginal probabilities of employee physical conditions (C1, C2, C3, C4), as the majority of nodes are in relation to them, and thereby the output of the network (Y) is affected by these dependent nodes as well as the marginals. Therefore, a study of how the uncertainty in the output of this Bayesian-based mathematical model could be apportioned is necessary to be examined under different inputs of employee physical conditions.

Figure 9, obtained throughout AgenaRisk, illustrates the posterior probabilities of intermediate nodes A, B, D, E, F and G in response to changes in the inputs of C1, C2, C3 and C4. The bar lengths of tornado diagrams represent the extent to which the probability of the intermediate nodes varies. As seen on tornado diagrams, the probability of intermediate nodes is found out to be most influenced or sensitive to C1. The bars of C1 point out the range of changes in various target states for intermediate nodes. Around 1.5% of their current posterior value down and up is identified. Therefore, it can be said that the network is not affected much by a given specific set of variables defined by numerous scenarios.

Table 15: Lowest, middle and highest values of fuzzy prior and posterior distributions

			$\mu_i(x)$ Prior			$\mu_i(x)$ Prior		
Node Names (i)	Marginal Probability	$x = x_1$	$x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
A1	No	True	0.599	0.594	0.587	0.607	0.613	0.617
A2	No	True	0.464	0.459	0.455	0.468	0.472	0.476
A3	No	True	0.321	0.318	0.315	0.322	0.325	0.328
A4	No	True	0.006	0.006	0.006	0.006	0.006	0.006
A5	No	True	0.039	0.039	0.038	0.038	0.039	0.039
A6	No	True	0.007	0.007	0.007	0.007	0.007	0.007
A7	No	True	0.002	0.002	0.002	0.002	0.002	0.002
C1	Yes	True	0.606	0.600	0.594	0.596	0.602	0.608
C2	Yes	True	0.661	0.654	0.647	0.649	0.656	0.663
C3	Yes	True	0.158	0.156	0.155	0.156	0.157	0.159
C4	Yes	True	0.179	0.177	0.175	0.175	0.177	0.179
E1	No	True	0.744	0.737	0.730	0.750	0.756	0.763
E2	No	True	0.522	0.517	0.512	0.530	0.534	0.538
F1	No	True	0.082	0.081	0.079	0.080	0.081	0.082
F2	No	True	0.081	0.080	0.079	0.080	0.081	0.082

Table 15 *(Continued)*.

Node Names (i)	Marginal Probability	$x = x_1$	$\mu_i(x)$ Prior			$\mu_i(x)$ Prior		
			$x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
F3	No	True	0.234	0.231	0.229	0.234	0.235	0.238
F4	No	True	0.122	0.121	0.120	0.121	0.122	0.123
F5	No	True	0.246	0.242	0.239	0.245	0.247	0.251
F6	No	True	0.040	0.040	0.040	0.040	0.040	0.040
F7	No	True	0.281	0.278	0.276	0.283	0.285	0.287
F8	No	True	0.171	0.169	0.168	0.171	0.172	0.174
F9	No	True	0.043	0.042	0.042	0.042	0.042	0.043
F10	No	True	0.029	0.029	0.029	0.029	0.029	0.029
F11	No	True	0.033	0.032	0.031	0.031	0.032	0.033
F12	No	True	0.327	0.323	0.320	0.329	0.332	0.336
F13	No	True	0.188	0.186	0.185	0.188	0.189	0.191
F14	No	True	0.100	0.099	0.098	0.099	0.100	0.101
D1	No	True	0.100	0.099	0.098	0.099	0.100	0.101
D2	No	True	0.075	0.073	0.072	0.073	0.074	0.075
B1	No	True	0.027	0.027	0.026	0.026	0.027	0.027

Table 15 *(Continued)*.

Node Names (i)	Marginal Probability	$x = x_1$	$\mu_i(x)$ Prior			$\mu_i(x)$ Prior		
			$x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
B2	No	True	0.023	0.022	0.022	0.022	0.022	0.023
B3	No	True	0.018	0.018	0.018	0.018	0.018	0.018
B4	No	True	0.007	0.007	0.007	0.007	0.007	0.007
B5	No	True	0.008	0.008	0.008	0.008	0.008	0.008
B6	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B7	No	True	0.008	0.008	0.008	0.008	0.008	0.008
B8	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B9	No	True	0.015	0.015	0.015	0.015	0.015	0.015
B10	No	True	0.005	0.005	0.005	0.005	0.005	0.005
B11	No	True	0.006	0.006	0.006	0.006	0.006	0.006
B12	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B13	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B14	No	True	0.001	0.001	0.001	0.001	0.001	0.001
B15	No	True	0.003	0.003	0.003	0.003	0.003	0.003
B16	No	True	0.002	0.002	0.002	0.002	0.002	0.002

Table 15 *(Continued)*.

Node Names (i)	Marginal Probability	$x = x_1$	$\mu_i(x)$ Prior $x = a_{prior}$	$x = b_{\text{prior}}$	$x = c_{prior}$	$\mu_i(x)$ Prior $x = a_{posterior}$	$x = b_{\text{posterior}}$	$x = c_{posterior}$
G1	Yes	True	0.712	0.705	0.698	0.744	0.749	0.755
G2	Yes	True	0.265	0.262	0.259	0.268	0.270	0.273
G3	Yes	True	0.209	0.207	0.204	0.210	0.212	0.214
G4	Yes	True	0.199	0.197	0.195	0.200	0.202	0.204
G5	Yes	True	0.138	0.137	0.135	0.138	0.139	0.140
G6	Yes	True	0.242	0.239	0.237	0.244	0.246	0.249
A	No	True	0.537	0.529	0.521	0.572	0.577	0.583
B	No	True	0.012	0.012	0.012	0.012	0.012	0.012
C	No	True	0.659	0.649	0.639	0.643	0.653	0.662
D	No	True	0.024	0.024	0.024	0.027	0.027	0.027
E	No	True	0.568	0.558	0.549	0.611	0.617	0.624
F	No	True	0.337	0.331	0.326	0.365	0.368	0.374
G	No	True	0.615	0.609	0.595	0.691	0.701	0.704
Y	No	True	0.781	0.771	0.758	1.000	1.000	1.000

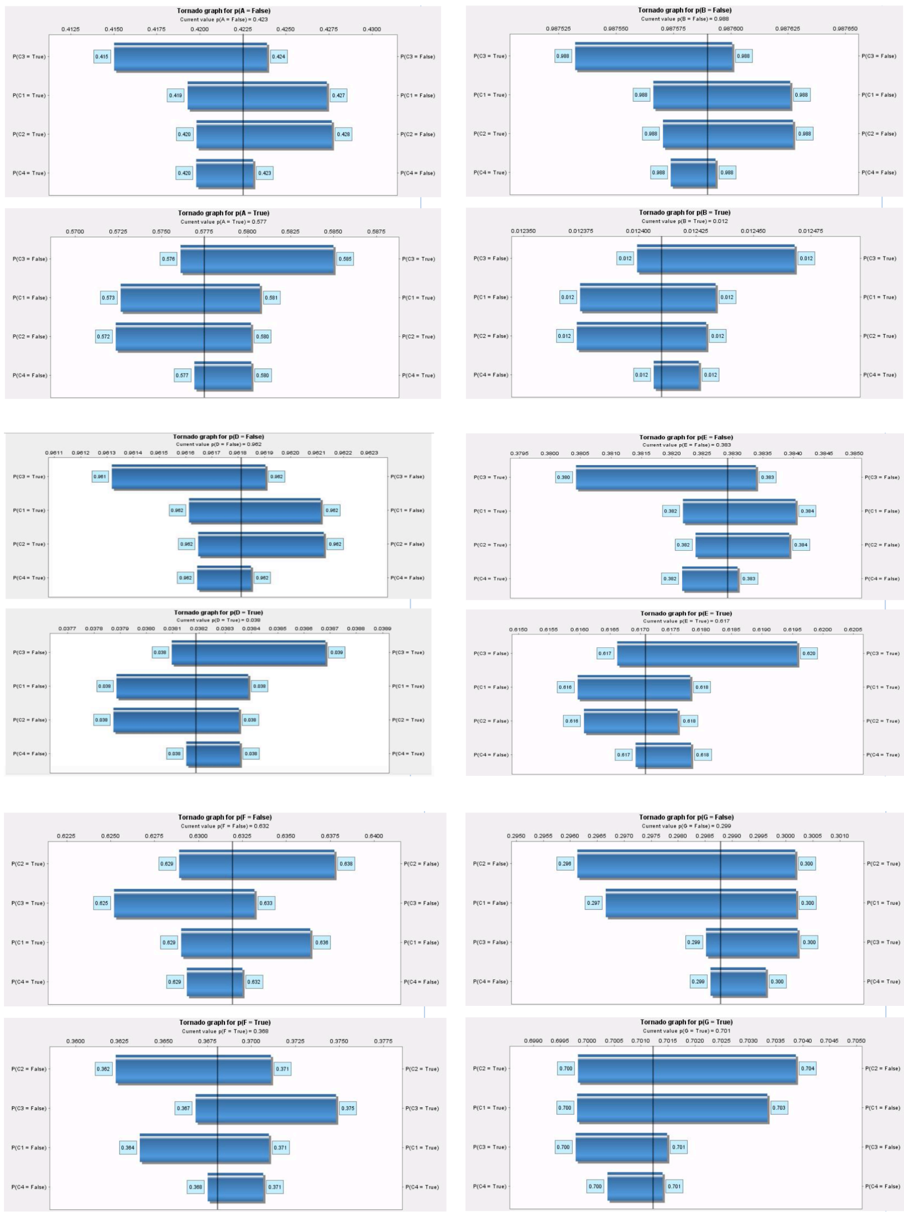


Figure 8: Sensitivity analysis of HEDC for the probability of all intermediate nodes being ‘true’ against probability changes of employee physical conditions.

5.4. Scenario generation

In many cases, scenarios based on Bayesian networks are developed to analyse probable future events by considering the possibility of some events that will not likely be available. Developments in railway risk management, and more importantly adaptation of them progress at a slow pace. Thus, the strategy of possible scenario is taken on the suspicious nodes making them ineffective in probability chain of HEDC. As a result, the authors take an action of elimination of Human errors associated with employee physical condition (i.e. employee asleep due to overworking) in the network as all attendees, whatever the occupation is, could exaggerate the results to benefit from high expression of this, or transferring problems on this kind of errors.

To eliminate such concerns, a new Bayesian inference with Boolean variables are assigned the marginal nodes C1 to 4 (0) and the Leaf node Y (1).

Figure 11 shows the highest value (b) of membership functions ($\mu_{i_b}(x)$) of all nodes in the network. Due to the nature of the posterior, C1 to 4 is ineffective, and result in ample drop in the probabilities of various intermediate nodes such as A1, A2. Although C1 to 4 are inferred as false, it is seen that D has a posterior probability of 2.64%. This is mainly from expert opinions on the probability that the observer having spotted any employee physical condition given that this observed condition is not impacted by C1 to 4. B, C and D are identified as negligible errors, whereas A, E, F and G are revealed to require an action to minimise the derailments that result from human error.

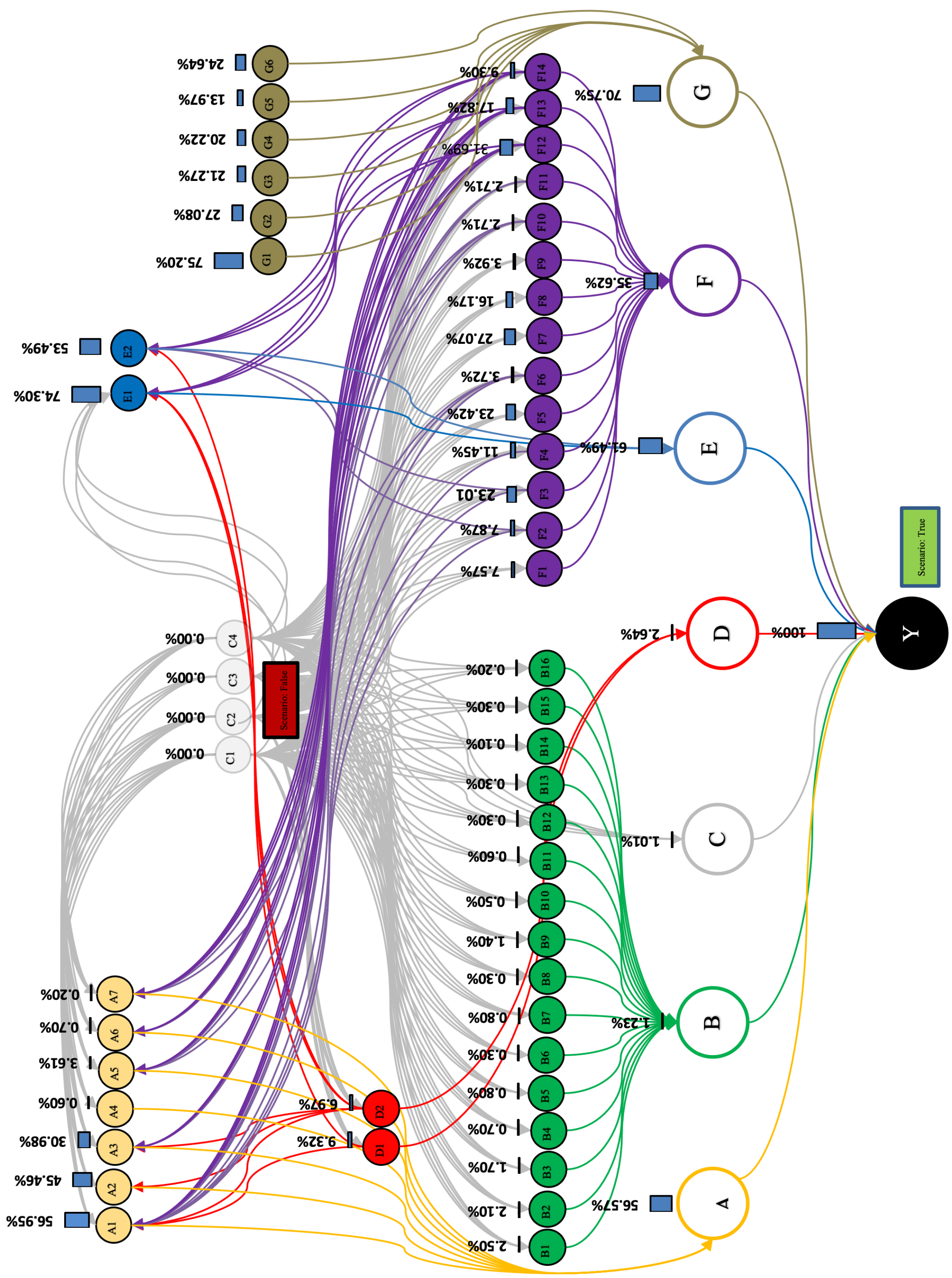


Figure 9: Results of the potential scenario for HEDC

In this study, human error-based derailment (HEDC) causes at S&C was combined with a Bayesian network (BN) in order to reveal and analyse the degree of contributing factors. The proposed novel methodology uses fuzzy membership functions to achieve a proper risk analysis and generate possible scenarios under uncertainty, so that the investigation of the system reliability and the identification of activities that could carry risk are performed. The discussion of the results is presented as follows:

From a perspective of posterior-based (P (Y) =1) risk analysing, it is identified, as seen in Table 16, that use of switches is the most violated type. Although the hand operation of switches is not common practice on urban rail network, they are occasionally still in operation at sidings on interprovincial main tracks in Turkey. It is also determined that failures at facing or trailing are expressed as a fundamental contribution to derailment at S&Cs. The term refers to converging (trailing) and diverging (facing) in the direction of rail travel. Where interlockings and signalling are absent on Turkish rural areas, particularly facing S&Cs is expressed to be remarkably hazardous, even though the Turkish code of practice follows FRA rules. This is fundamentally because the Turkish rail network is operated on single lines, which leads to the necessity of using a tremendous amount of sidings. Considering the high volume of rail traffic that the Turkish rail network has, and the exhausted train drivers from overwork, the high-risk proportion of errors at using switches is seen to be rational.

On the other hand, brake of use (A), employee physical conditions (C) and speed (E) are identified to be other significant derailment drivers at S&Cs. In Turkish rail operation, three types of brakes are used, namely: (aside from emergency brake that all rolling stock have) independent brakes [11], automatic

[11] This is air brakes (only in use when the brake pipe air pressure is reduced) that machinists can apply on the locos only.

Table 16: Distribution of risk proportions through the major nodes

		Brake of Switches	Train Handling	Employee Physical Conditions	Control Systems	Speed	Flagging, Fixed, Hand and Radio Signals	Use of Switches
P(Y)=1	$\mu_i(x)$ Posterior	0.577	0.012	0.653	0.027	0.617	0.356	0.701
	Risk proportion	0.220	0.010	0.210	0.010	0.210	0.120	0.240
$P(Y) = 1$	$\mu_i(x)$ Posterior	0.566	0.012	0.010	0.026	0.615	0.331	0.707
$P(\text{Cl to } 4) = 0$	Risk proportion	0.250	0.010	0.000	0.010	0.270	0.150	0.310

brakes[12] and dynamic brakes[13]. These brakes can be controlled by machinists, and are seldom used as automatic train protection[14] (ATP) have been applied to a great deal of rolling stock in Turkey. It is identified that the remaining trains, albeit limited in number, are seen to be a potential source of adverse effect on the derailments. Shutting down the ATP system (mostly by machinists) is also identified to seldom take place in Turkish rail operations, which leads to an outrageous risk of derailment at S&Cs. In other respects, the majority of interviewees underlined that the heavy workload of rail employees presents due to two fundamental reasons: 1) limited number of the employees against increasing over time; 2) increased demand for rail transportation. This drives stress and job dissatisfaction, both of which are likely to result in human errors in a direct or indirect way. As a direct way, employee physical conditions are determined to be one of the major risk groups with a proportion of 21%. Where ATP or signal do not exist, the critical speed range that is identified for particular rail turnouts might be exceeded, which has often been stressed as the most costly type of human error, due to the high amounts of damage not only to the switch, but also, depending on the point of derailment, wagons and locomotives.

From the perspective of scenario-based (P (Y) = 1&P(Cl to 4) = 0) risk analysing, an indirect way of risk analysing, an indirect way of employee physical conditions is pinpointed by means of fluctuation in proportional changes of results between $P(Y) = 1$ and $P(Y) = 1\&P(C1 \text{ to } 4) = 0$. The impact of Employee physical conditions on derailments plunged to almost 0% due to

[12]The brake system takes action automatically applying not only a loco but the rest of the train as well. The amount of braking by this system is dependent on the amount that the system is charged.

[13]The traction motors of a rolling stock are turned to electric generators which produce current either dissipated as heat by the braking grid or fed back into the power supply system. This system allows only to decrease the speed.

[14]The speed of the train is continuously monitored, and the driver with speed limit information on particular tracks is provided to machinists, and ATP indicates a warning if any failure at decreasing the speed takes place. Moreover, if ignored the brakes are automatically applied to stop safely the train.

the nature of a Bayesian network. It can be highlighted that brake of use is affected more than the others by employee physical condition since risk proportion increases relatively less. In contrast to risk proportion of brake of use, that of speed and use of switch rise by 6% and 7%, respectively. The reason behind this pattern is that the probability of brake of use is also contributed to by employee physical conditions, whereas speed is partly affected (due to E1, see Figure 6). Where the absence of the contribution in conditional probability calculation, as expected, the probability of brake of use becomes lower. However, as a posterior probability (P(Y) = 1) takes place, it has taken roughly the proportion of 3% from employee physical conditions.

6. Conclusion

A smooth railway operation requires complex engineering systems, in which all employees are as much an integral part as any rail mechanical component. The more the systems become wide-reaching and comprehensive, the more human factors impact the design of railway systems in ways that optimise performance. Therefore, an extensive risk analysis of human errors as being causal in rail derailments is required to enhance the margin of safety and reduce the number of derailments. To identify potential errors, interviews have been conducted individually. Informative and descriptive data has been collected from ten professionals , only focussing on a particular phenomenon (derailments at switches and crossings). The collected data has enabled a probabilistic graphical model that represents conditional dependence, and therefore causation. The data also provides insight into the preparation of the questionnaire, which was asked of over 50 rail employees. The linguistic values of them are converted to mathematical expressions throughout a novel approach using fuzzy memberships.

As a result, the errors associated with the use of switch are found out to account for a quarter of all which lead to a derailment at S&Cs. The major drivers for this particular problem are the application of outdated S&Cs, which have not any kind of turnout motors to electrically and remotely operate the position of the rail switch. We identified that the Turkish rail network still has hand operated S&Cs. In particular, the entry and exit of rural sidings entail considerable risk. On the other hand, employee physical conditions, including employee asleep, employee restricted in work or motion, incapacitation due to injury or illness and impairment of efficiency or judgment because of drugs or alcohol are identified to have strong conditional dependencies on the associated nodes; namely use of switch, control systems, train handling and speed. However, as control systems and train handling have too low values to be considered, it might be suggested not to take any serious action to manage the derailment risk.

The model can be adapted to other national rail networks through the same process of proposed mathematical-linguistic conversion. However, the condition and existence of nodes in the proposed BN are required to be validated with domain experts as well as reliable data arisen from event reports and experiments.

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