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A R T I C L E I N F O

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A B S T R A C T

Since multiple failure events associated with derailments could not be identified and derailment probability could not be reached quantitatively by event tree and fault tree analysis for safety assessment in railway systems, applications of Bayesian network (BN) were introduced over the last few years. The applications were often aimed at understanding safety and reliability of railway systems through various basic principles and unique inference algorithms focusing on particular railway infrastructures. One of the most critical engineering infra-structure, railway turnouts (RTs) have been investigated and analysed critically in order to develop a new BN-based model with unique algorithm. This unprecedented study reveals the causal relations between primary causes and the subsystem failures, resulting in derailment, as a result of extreme weather-related conditions. In addition, the model, which is designed for rare events, has been proposed to identify the probability and un-derlying root cause of derailment. Consequently, it is expected that various weather-related causes of derailment at RTs, one such undesirable event, which can result, albeit rarely, damaging rolling stock, railway infrastructure and disrupting service, and having the potential to cause casualties and even loss of life, are identified to allow for smooth railway operation by rail industry itself. The insight into this weather-derailment will help the in-dustry to better manage railway operation under climate uncertainty.

1. Introduction

Railway transportation seems to be in an upward trend in demand, being not only particularly sustainable, but also considerably cheaper than air operations and faster than shipping. According to the Association of American Railroads (Hamberger, 2015), although the USA has long been known to have the world's longest railway network, its rail network is still being increased and is twice what it was in 80s. Whether developed or not, similar trends for the other countries have often been seen (Kaewunruen et al., 2016). Such an increase gives rise to operational concerns due to a revealing lack of existing management strategies as well as partly understanding of causal relations in various critical railway systems.

A railway turnout system, as one of the most critical systems in railway infrastructure, is manufactured and then installed to enable a rolling stock to divert from one direction to another. A railway has very complex geometry and demands an error-free railway operation since a large number of turnout components interrelate with each other. As a result, turnout railway systems are seen to be a significant railway engineering system quite vulnerable to accidents, e.g. collision, de-railment (Dindar and Kaewunruen, 2018). It is found that derailment accounts for 9% of all accidents types, and the majority of those de-railments occur on turnouts (Dindar et al., 2016a). A derailment is likely to take place on railway turnouts when a rolling stock, such as a train, experiences unauthorised movements, causing it to run off turn-outs for a variety known reasons. The effects the extreme weather conditions, one of these reasons, have on derailment at railway turnout systems are identified to pose serious concern that need to be consider in risk management (Dindar et al., 2017; Sa'adin et al., 2017).

The impact of weather conditions on railway turnout systems in the literature is a new and quite diverse topic followed by quite limited number of scholars within two categories: Conditional-Based Maintenance (CBM), which only suggests a prognostic attitude towards maintenance (Kaewunruen and Remennikov, 2005; Vale and Ribeiro, 2014), and Risk-Based Maintenance (RBM), which suggests an alter-native or complementary strategy to minimise the risk resulting from any kind of failures and accidents or errors in breakdown of manage-ment (Ishak et al., 2016; Sa'adin et al., 2016). The advances in the

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former starts with a simple state-based prognostic method simply aiming at predicting railway turnout failures (Eker et al., 2011). This study is followed by a precipitate statistical investigation showing that a significant number of turnout component failures might be caused by weather conditions (Hassankiadeh, 2011). Also, it is found that sea-sonal changes have a considerable impact on prognostics involving railway turnouts. Mahboob et al. (2012) summarised a number of Component Importance Measures (CIM), deriving the computation of the CIM using Bayesian Networks (BNs) and Fault Tree Analysis (FTA). It has recently been presented that the effect of weather on railway turnouts can be evaluated through a failure prediction model based on Bayesian Networks (Guang et al., 2017). However, all these attempts require the railway industry to understand the link between only components failures with weather conditions on railway turnouts.

As regards Risk-Based studies, it can be stressed that this seems to present a huge gap in the related literature, as these studies often aim to fill the gap associated with derailment events. A probabilistic model was developed to forecast rail breaks and controlling risk of derailment (Zhao et al., 2007). Risk categorisation and prioritisation are achieved for geometry restoration of railway turnout systems in various opera-tional environments (Ishak et al., 2016). Dindar et al. showed how a turnout can be affected by the diversity of risks arising from natural hazards and global warming (Dindar et al., 2016b). This study has been the first investigation to reveal a significant relationship between de-railment and weather/climate conditions. Turnout component failures by several weather patterns are investigated (Wanga et al., 2017). This research is limited to component failures considering only precipitation on a particular location and particular rail lines regardless of con-sequences of such failures, e.g. Derailment. Finally, Dindar and Kaewunruen (2016) developed a risk-based maintenance strategy for geometry problems of turnouts, considering various failures in order to minimise the risk of derailment on them.

In this paper, a risk analysis based on railway turnout systems under uncertainty of all weather and environmental conditions is proposed for a systemic decision support to dealing with derailment. Buckley's confidence interval-based method is used to reach the proposed ap-proach, which is capable of modelling both statistical uncertainty or randomness and linguistic vagueness. The confidence intervals are nested into Fuzzy Bayesian Networks (FBN) to investigate causal re-lationships between weather patterns and derailments on the systems. Sensitivity analysis is implemented into a detailed fuzzy-based in-ference procedure to reduce limitation by scarce data environment and to ensure solid estimate.

To reach more appropriate, realistic and reliable results than con-ventional and fuzzy methods, which are based only on one source of knowledge, this paper uses data information of 50 states, having dif-ferent climate patterns, through real accident reports over the last ten years. The structure of this paper is as follows: in Section 2, a brief introduction of Bayesian networks is given. Then, in Section 3, fuzzy probability using Buckley's approach is explained in detail. In Section 4, possible weather patterns inducing derailment risk on railway turnout systems are discussed. Then, the proposed model and its learning al-gorithm are discussed and shown. In Section 6, the model is applied on a railway turnout and its results are presented. Finally, Section 7 con-cludes this paper.

2. Bayesian Networks

BNs, also known as belief networks, Bayes network or Bayes nets, belong to the family of probabilistic graphical models (PGM), which enable representation and reasoning about an uncertain domain. The nodes in PGM, specifically referred to in BNs as directed acyclic graph (DAG), represent a set of random variables, V = $X_1,\ldots X_i,\ldots,X_n$, from the domain, while the edges between the nodes represent their probabilistic dependencies among the corresponding random variables. Statistical and computational methods allow for estimation of these conditional dependencies in the graph. Thus, BNs utilise from various principles, including graph theory, probability theory, computer science and sta-tistics.

BNs are a set of all parameters in the network. A conditional probability as a parameter in the network is defined through

$\Theta_{X_i|\pi_i} = P_{BN}(X_i|\pi_i)$ for each x_i state of X_i, given the parent set π_i. With a conditional probability and a DAG, a BN defines a joint probability distribution (JPD), also known as "chain rule", for V, which is acquired by the following equation, Eq. (1) (Nielsen and Jensen, 2009):

$$P(V) = P(X_1,\ldots,X_n) = \prod_{i=1}^{n} P(X_i|\pi_i) \tag{1}$$

Any node in BNs is likely not to be any parent in the chain. Thus, the node has only marginal distribution, $P(X_i)$, as being independent of the other variables. Additionally, each node in a BN is associated with a conditional probability, $P(X_i|\pi_i)$, of any variable X_i whose parent set, π_i, is present. This conditional probability is calculated by following equation, Eq. (2) (Nielsen and Jensen, 2009).

$$P(X_i|\pi_i) = \frac{P(X_i \cap \pi_i)}{P(\pi_i)} \tag{2}$$

Considering the BN in Fig. 1, the full joint probability distribution of this BN might be simplified as

$$P(A,B,C,D,E) = P(A)P(B)P(C)P(D|A,B)P(E|C,D) \tag{3}$$

Conditional and marginal probability distributions of these variables are presented in Tables 1–5. A, B and C are classified only in Marginal Probability Tables as they do not have a parent node. On the other hand, conditional probability distributions of D and E are generated in Table 3 and 4.

The joint probability of this BN is calculated with the following Eq.:

$$P(a_i b_j c_k d_l e_n)\, P(A = a_i, B = b_j, C = c_k, D = d_l, E = e_n) = p_{a_i} p_{b_j} p_{c_k} \frac{p_{a_i b_j d_l}}{p_{a_i} p_{b_j}} \frac{p_{c_k d_l e_n}}{p_{c_k} p_{d_l}} \tag{4}$$

This determination of marginal and conditional probability tables en-ables probabilities for these variables, e.g. $P(A|B)$, $P(A|D)$, to be calcu-lated.

3. Fuzzy probability

3.1. Preliminaries

This section sets up the terminology and notation that is not part of the technical contribution, but is needed to delineate material of the

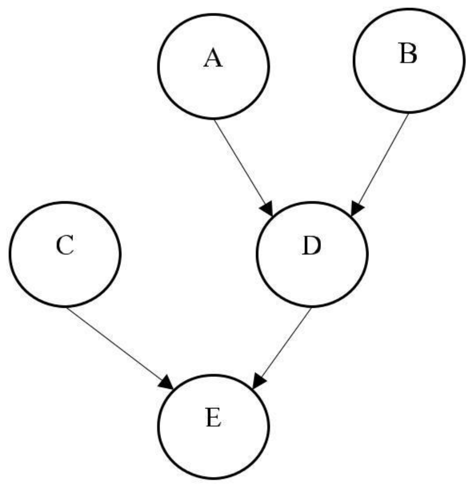


Fig. 1. A BN for variables A, B, C, D, E.

Table 1
Marginal probability table for A.

$P(A = a_1)$	$P(A = a_2)$
pa_1	pa_2

Table 2
Marginal probability table for B.

$P(B = b_1)$	$P(B = b_2)$
pb_1	pb_2

Table 3
Marginal probability table for C.

$P(C = c_1)$	$P(C = c_2)$
pc_1	pc_2

Table 4
Conditional probability table for D.

A	B	$P((D = d_1)\|A,B)$	$P((D = d_2)\|A,B)$
a_1	b_1	$\frac{p_{a_1,b_1,d_1}}{p_{a_1,b_1}}$	$\frac{p_{b_1,b_1,d_2}}{p_{b_1,b_1}}$
a_2	b_1	$\frac{p_{a_2,b_1,d_1}}{p_{a_2,b_1}}$	$\frac{p_{a_2,b_1,d_2}}{p_{a_2,b_1}}$
a_1	b_2	$\frac{p_{a_1,b_2,d_1}}{p_{a_1,b_2}}$	$\frac{p_{a_1,b_2,d_2}}{p_{a_1,b_2}}$
a_2	b_2	$\frac{p_{a_2,b_2,d_1}}{p_{a_2,b_2}}$	$\frac{p_{a_2,b_2,d_2}}{p_{a_2,b_2}}$

Table 5
Conditional probability table for E.

C	D	$P((E = e_1)\|C,D)$	$P((E = e_2)\|C,D)$
c_1	d_1	$\frac{p_{c_1,d_1,e_1}}{p_{c_1,d_1}}$	$\frac{p_{c_1,d_1,e_2}}{p_{c_1,d_1}}$
c_2	d_1	$\frac{p_{c_2,d_1,e_1}}{p_{c_2,d_1}}$	$\frac{p_{c_2,d_1,e_2}}{p_{c_2,d_1}}$
c_1	d_2	$\frac{p_{c_1,d_2,e_1}}{p_{c_1,d_2}}$	$\frac{p_{c_1,d_2,e_2}}{p_{c_1,d_2}}$
c_2	d_2	$\frac{p_{c_2,d_2,e_1}}{p_{c_2,d_2}}$	$\frac{p_{c_2,d_2,e_2}}{p_{c_2,d_2}}$

paper.

Definition 1. the membership function of an element, x, is $\mu_{\tilde{A}}(x)$. The element belongs to a fuzzy set $\tilde{A}$, where each element of x is always mapped to a value between 0 and 1, i.e. $0\ \mu_{\tilde{A}}(x)\ 1$ (Dubois and Prade, 1980).

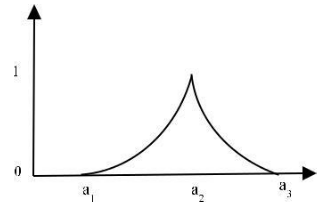
Definition 2. A fuzzy number $\tilde{A}$ is a fuzzy set on . $\mu_{\tilde{A}}(x)$ is its membership function (Dubois and Prade, 1980) such that

i. The α-cut of a fuzzy set $\tilde{A}$ is closed intervals of and denoted as the crisp set $A_\propto$ given by $A_\propto = \{x \in X : \mu_{\tilde{A}}(x) \quad \propto\}$ where $0 \quad \propto < 1$.

ii. A fuzzy set $\tilde{A}$ is said to be convex due to

$$\mu_{\tilde{A}}(\lambda x_1 + (1-\lambda)x_2) \quad \min(\mu_{\tilde{A}}(x_1), \mu_{\tilde{A}}(x_2))\ for\ \lambda \in [0,1]$$

Definition 3. α−*cutFN* is a fuzzy number $\tilde{A}$ by the triplet $\tilde{A} = a_1, a_2, a_3$ with the shape of concave function if its membership function $\mu_{\tilde{A}}(x)$ is given by Buckley (2004):



$$\mu_{\tilde{A}}(x) = \begin{cases} 0 & for\ x < a_1 \\ \frac{x - a_1}{a_2 - a_1} & for\ a_1 < x < a_2 \\ \frac{a_3 - x}{a_3 - a_2} & for\ a_2 < x < a_3 \\ 0 & for\ a_3 < x \end{cases}$$

Definition 4. The mathematical operations of two TFNs, $\tilde{X}(\alpha) = [a_1, b_1]$ and $\tilde{Y}(\alpha) = [a_2, b_2]$ are as follows(Dubois and Prade, 1980; Buckley, 2004):

- $\tilde{X}(\alpha) + \tilde{Y}(\alpha) = [a_1, b_1] + [a_2, b_2] = [a_1 + a_2, b_1 + b_2]$
- $\tilde{X}(\alpha) \cdot \tilde{Y}(\alpha) = [a_1, b_1] \cdot [a_2, b_2] = [\min(a_1 \cdot a_2, a_1 \cdot b_2, b_1 \cdot a_2, b_1 \cdot b_2), \max(a_1 \cdot a_2, a_1 \cdot b_2, b_1 \cdot a_2, b_1 \cdot b_2)]$
- $\tilde{X}(\alpha) - \tilde{Y}(\alpha) = [a_1, b_1] - [a_2, b_2] = [a_1 - b_2, b_1 - a_2]$
- $\tilde{X}(\alpha) / \tilde{Y}(\alpha) = [a_1, b_1] / [a_2, b_2] = [a_1, b_1] \cdot [\frac{1}{b_2}, \frac{1}{a_2}]$

3.2. Probability of fuzzy events

A random variable x is in a sample space X. Then, a crisp event is defined as a subset of A, and its unconditional probability $Pr(A)$ is calculated by the following Eq.:

$$Pr(A) = \int_{x \in A} f(x)\, dx = \int_{-\infty}^{+\infty} X_A(x) f(x)\, dx \quad (5)$$

where $X_A(x)$ is membership of an element in a subset A of X, a binary indicator function with the value 0 for all elements of X not in A and the value 1 for all elements of A.

On the other hand, it has been expressed in previous section that the indicator functions $X_A(x)$ of fuzzy events are their membership func-tions, $\mu_{\tilde{A}}(x)$. Thus, $X_A(x)$ in the Eq. can be replaced with $\mu_{\tilde{A}}(x): X \rightarrow [0,1]$, as such:

$$Pr(A) = \int_{-\infty}^{+\infty} \mu_{\tilde{A}}(x) f(x)\, dx \quad (6)$$

Eq. (6), that is, estimates a fuzzy probability density function through the product $\mu_{\tilde{A}}(x) f(x)$

3.3. Fuzzy estimation based on Buckley's method

The method is quite new application to the BN in risk calculation of engineering systems, but it is proposed that Buckley's approach might be one of the best solution to rare events within a scarce data en-vironment (Ersel and İçen, 2016). To calculate probability on the basis of fuzzy knowledge, Buckley proposes two approaches defining the probability as a triangular-shaped fuzzy number. The differences be-tween the two relates to the source of knowledge from which the sta-tistical model for probability estimate is utilised. In the first approach, a1, a2 and a3 values are defined in accordance with expert opinion, while the other deals with data, considering suitable confidence inter-vals to uncertainness in the clusters.

This approach has long been used by various scholars interested in only two possible outcomes, labelled success and failure. Let *p* be the probability of a success and x be the number of times we had a success in n independent repetitions of this experiment. Therefore, if we want to estimate the value of probability *p* based on this approach, then a random sample, which, here, is running the experiment 'n' independent times, i.e. $X_1, X_2, \ldots, X_n$, should be gathered. The probability density function of this experiment is defined as $f(x, p)$.

Based on this experiment, p, as a single unknown parameter, is calculated with interval cuts. We make $100(1-\propto)\%, 0 \propto 1$, confidence intervals for p. These confidence intervals are donated $[p_1(\propto), p_2(\propto)]$. Moreover, these confidence intervals are nested. The confidence inter-vals are then placed on top of one another in the way of $\propto = 0\ to \propto = 1$

in order to create a fuzzy number p, whose $\propto$ - cuts are the confidence intervals. The mathematical progress of a fuzzy number is explained as follows:

It is known that $(\hat{p} - p)/\sqrt{p(1-p)/n}$, where $\hat{p}$ equals to x/n, donates the point of estimation and also n donates the number of independent repetitions, roughly $N(0,1)$ if n is sufficiently large. Thus,

$$P\left(\hat{p} - z_{\beta/2}\sqrt{\hat{p}(1-\hat{p})/n} \le p \le \hat{p} + z_{\beta/2}\sqrt{\hat{p}(1-\hat{p})/n}\right) \approx (1-\beta)$$

The equation above leads to the (1-β)100% approximate confidence interval for p

$$\left[\hat{p} - z_{\beta/2}\sqrt{\hat{p}(1-\hat{p})/n},\ \hat{p} + z_{\beta/2}\sqrt{\hat{p}(1-\hat{p})/n}\right] \tag{7}$$

Therefore, $(1-\beta)100\%$ confidence intervals for each β might be found. This gives p, and β is suggested to be between 0.01 and 1. In accordance with this range, these intervals can be presented as $[p^L(\beta), p^U(\beta)]$.

To produce a triangular-shaped fuzzy number $\bar{p}$ whose $\propto$ – cuts are the confidence intervals, we can place these confidence intervals in the way of one over another with the following equation for $0.01\ \beta\ 1$.

$$\tilde{P}(\propto) = [p^L(\propto), p^U(\propto)] \tag{8}$$

This allows for gathering more information in p than just a single confidence interval or just a point estimate. Thus, $\bar{p}$, which is a trian-gular-shaped fuzzy number, will be the fuzzy estimator for p.

4. Weather-related derailments

Weather-related derailments continue to account for a significant proportion of general railway accidents. Unlike other kind of derail-ment causes, weather-related derailments are not often given due consideration because, firstly, the occurrence of such derailments is not considerably high and, secondly, there still presents a gap in the lit-erature to understand precisely the fundamental impacts of weather patterns on turnout-related derailments. Therefore, risk management strategies for railway turnout systems in particular might be said to lag behind what the industry currently requires, which leads to a decrease in the asset reliability and efficiency, and, as a result, loss of lives as well as financial burden through the asset failures

4.1. Accident codes

In this study, weather-related derailments are defined as accidents the causes of which primarily refer to any adverse weather patterns or undesirable environment-related condition on the turnout. In other words, extreme environmental conditions, i.e. extremely strong wind might be a reason for derailments. Those happenings cannot be pre-vented, but can generally be predicted based on events in the past. The other causes, e.g. icing track, are assumed to be turnout-related failures, but their primary reasons are weather conditions. This could be re-medied through various engineering methods. Whether it is predictable or remediable, both groups are handled in this study. Accident de-scriptions in the official reports of the U.S. Federal Railroad Administration have been investigated through such a consideration.

Table 6 illustrates a group of codes and its primary causes, ex-plaining why a derailment occurs. The codes are limited as to whether the environmental relation can be matched with derailment cases. As a result, it has been identified that some track alignment irregularities need attention. As seen, some codes, e.g. M101, entail a cluster of primary causes, which are different from one another. Thus, it is not possible to use the raw codes as nodes to establish a Bayes Network, as the nodes should be probabilistically related by some sort of causal dependency. It is also worth noting that, although M199 is used to determine the accidents with any cause out of M101 to M105, low temperature or water flow are seen as primary causes.

Table 6
FRA codes most used in the study.

Code	Situation	Primary cause
M101	Changes in condition of a turnout	Snow, ice and mud on track
M102	Extreme environmental condition	Tornado, high wind
M103	Extreme environmental condition	Flood
M104	Extreme environmental condition	Dense fog
M105	Extreme environmental condition	Extreme wind velocity
M199	Other extreme environmental conditions	Rarely seen, such as low temperature, water flow
T109	Track alignment irregularity	Buckling

4.2. Causes and risk factors

Although the codes allow for capturing every detail associated with the causes and resulting consequences of each accident, it is necessary to find what fundamentally gives rise to derailment. Additionally, it is vital to categorise similar reasons to manage and mitigate well. Considering the primary causes in Table 6, various risk factors driving derailment on railway turnout systems can be stressed as following.

4.2.1. Floods, rains and saturated soil

High waters from persistent heavy rains, flash floods, have been identified to be one of the conspicuous weather-related concerns of the railway industry. Washouts, the consequence of a natural disaster where the track-bed is eroded away by flowing water, have the po-tential to weaken chair and ballast, which might be determined as a serious geometry problem. Although they are mostly seen to occur on plain track, turnouts might be exposed to them in sidings and yards, particularly in the countryside. It was shown that turnouts are quite vulnerable mechanical installations to geometry problems, and those with such problems are highly likely to give rise to derailment accidents (Ishak et al., 2016). Aside from runoff and washout, snowmelt too might result in similar saturation problems on railway turnout bed.

4.2.2. High wind and tornadoes

High winds are frequently seen as a cause of derailment on main lines, blowing rolling stock off tracks. The winds might be more ef-fective in moving rolling stock on railway turnouts as the running safety regarding crosswind stability of the vehicles tends to decrease on curved and moving track systems (Hosoi and Tanifuji, 2012).

4.2.3. Snow and icing

Rail switches, crossing and check rail flangeway are likely to be often exposed to snow and ice accumulations in winter seasons, thereby reducing control of vehicles and increasing the risk of derailments on railway turnouts. In addition to this, the surface of stock and running rail, switch blades might be coated with ice or frost. This gives rise to weakening the friction force between the wheel and rail, and, thus, poses a risk associated with slipping, sliding and loss of control on turnouts. On the other hand, harsh winter conditions, e.g. icing, could make turnout infrastructures, such as signal systems, switch the motor out-of-service.

4.2.4. Temperature

Rail neutral temperature is the operational temperature range at which the rail has no longitudinal stress. Any significant deviation below or above rail neutral temperature might be one of the most disruptive weather events for turnout systems. Extreme high tempera-ture leads to formation of large lateral misalignments in stock and running rails, often resulting in derailments. On the other hand, ex-treme cold also might bring about derailment, not only inducing brittle tracks and separated or broken rail, but freezing moisture often pre-sented on the surface of the rail as well.

Table 7
Derailment-related nodes, their description and relevant situation for railway turnouts.

Node	Description	Relevant situation
R1	Extreme wind	Interaction problems, blockage
R2	Snowfall	Slipping, blockage, vision loss
R3	Fog	Vision loss
R4	Rainfall	Slipping, vision loss, track bed problems, geometry problems
R5	Flood	Track bed problems, blockage, mechanical/electrical based errors
R6	High temperature	Geometry problems
R7	Low temperature	Embrittlement

4.2.5. Slides of mud and rocks

The safety and efficiency of turnout operations can be threatened by slides of weather-caused hazards such as snow, mud and rocks. These hazards induce derailment risk when the ground under or around a turnout moves as a result of freeze-thaw cycles, heavy rains or high wind.

4.2.6. Dense fog

Where the railway signalling systems are used at turnouts, drivers are advised of the status of the section of track ahead. As dense fog is highly likely to reduce visibility, whereby not only might drivers not properly detect such systems, but they also may not even notice turn-outs in time to stop or slow down. This may cause the train to be de-railed, and prevent keeping passengers and goods safe.

4.3. Categorisation

In the light of the many causes and risk factors discussed in the previous section, the situations leading to derailment on turnouts have been categorised in Table 7. The nodes 1–5 have been addressed to extreme conditions. For instance, the node R1 stands for the occurrence of extreme wind, including high wind and tornadoes, while snowfall, resulting in icing on track, or blocking movable parts of turnouts, or vision loss due to high density in the precipitation, is assigned as R2.

On the other hand, nodes 6 and 7 refer to two variations of tem-perature phenomena as, firstly, temperature entails two extreme var-iations, unlike the others in the table, and, secondly, it is noticed, when investigating the data on weather-related turnout failures, that there has been considerable number of derailments occurred at turnouts on high/low temperatures days.

5. Bayesian Network model and probability assessment

5.1. FBN-based probability assessment frame

There is a long record of weather-caused derailments at turnouts, which has enhanced the knowledge of what causes most give rise to derailment. However, we have no idea regarding the interaction of these causes or about what the probability distribution is going to be like in a situation in which one of these causes is impossible to happen, e.g. tornado in areas with mild climate. Hence, there is a need for a generic BN-based weather-caused flow diagram to be developed.

For the implementation of weather-related derailment estimates at turnouts, a systematic Bayesian Network is developed, as seen in Fig. 2. In this proposed approach, the following three steps are adopted:

- Step (1) Problem definition: Carry out a search of available data-bases which refer to all kinds of weather-related derailments; judge data in order to identify all anticipated weather-based causes/fac-tors to potential derailment accidents at turnouts; pay attention to causal relationships among those causes/factors. Step 1 is revealed in detail in Section 4.
- Step (2) BN module construction: Define both variables (nodes) having a finite set of mutually exclusive states as identified root nodes (RNs) or intermediate nodes (INs) to represent the identified hazards; develop failure logic through conditional probability dis-tribution (CPD); establish a network topology to describe condi-tional independence relationships of defined variables. Step 2 is archived in the following sub-headings in this section.
- Step (3) Probability estimates and decision: Specify states and assign input values for probability estimation of RNs; calculate prob-abilities based upon Buckley's alpha cut methods via Eq. (7); update the values of all nodes by calculating posterior probabilities; per-form sensitivity analysis to reveal the performance of each variable's contribution to the occurrence of a derailment accidents at turnouts. Step 3 is discussed in Section 6.

5.2. The Bayesian Network structure of weather-related derailments

The failure-consequence scenarios from the top to bottom nodes using a directed acyclic graph (DAG) are created through the logic diagram in accordance with the accidents reports. Thus, a weather-re-lated derailment Bayesian Network (WRDBN) is established through steps 1 and 2 in Fig. 2. WRDBN, as seen in Fig. 3, is formed of 11 root nodes, which are addressed to intermediate nodes, contributing to the leaf node, derailment. Intermediate nodes have been described as re-levant stations in Table 7. Root nodes, intermediate nodes and the leaf node are encoloured into grey, orange and red in Fig. 3, respectively.

The descriptions of all nodes illustrated in Fig. 3 are given in Table 8. The intermediate nodes are added in accordance with primary causes in the accident records. For instance, high wind (R_1) is shown as a root cause giving rise to inadequacies in railway turnout management system that allow the immediate causes (I_1, I_2) to arise unchecked, leading to the accidents. The intermediate nodes and their relations to root causes are revealed as result of investigation of over 17,000 acci-dent reports between 2006 and 2015. Intermediate nodes firstly aim at identifying what kinds of areas are impacted by weather patterns at turnouts, and, secondly, to investigate to what degree the patterns ef-fect on the intermediate nodes in comparison with the other cases with non-environmental reasons.

As an example, obstructions, I_2, is determined to be one of the most common causes encountered at railway turnouts, and to be formed by not only frozen precipitation (R_2), including snowfall, hail, etc., but also wind (R_1), often blowing debris and trees from the trackside and from neighbouring land onto turnouts. To calculate conditional probabilities, the other cases, such as maintenance errors, vandalism, etc., as well as these two causes-related cases, are considered. In other words, even if either R_1 or R_2 does not present, derailment as the result of any ob-struction is likely to happen. Therefore, each accident report has been examined in detail to find absolute answers regarding the relation be-tween derailment and environmental effects, and to what degree these environmental effects take place in derailments at railway turnout systems.

6. Results

6.1. Marginal and conditional probability assessment

In contrast to utilising the subjective data by means of a review/ interview-based dataset, this research only relies on absolute data of derailment cases collected in the United States for the period between 2005 and 2015. Marginal probabilities of the weather-based events are calculated, considering all accident cases occurring at railway turnout systems. Thus, a marginal probability of an event presents an idea of how likelihood a derailment happens in comparison to the other weather-based events. Table 9 shows lower and upper marginal prob-abilities of three events, including R1, R2 and R5. The table is prepared in accordance with the recommended instructions in Section 2, while

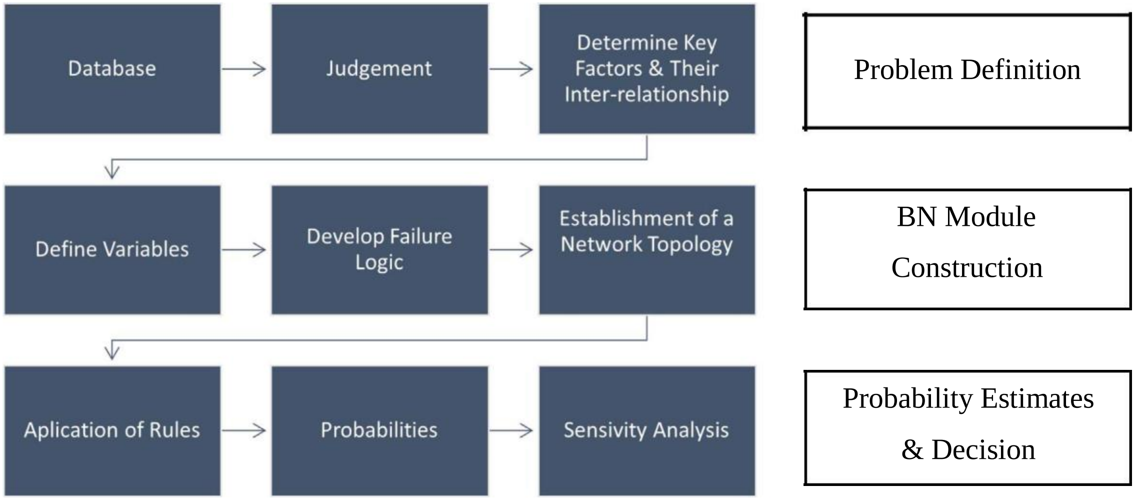


Fig. 2. The frame of Bayes Network-based derailment prediction for railway turnouts.

values against each alpha-cut are calculated by Eq. (7), and then ta-bulated through Eq. (8). These calculations are executed by MATLAB ver.2016b.

As seen in Table 9, marginal probabilities in the network are binary with true and false values e.g. $\tilde{P}(R1 = r1_1)(\alpha)$, $\tilde{P}(R1 = r1_2)(\alpha)$, respectively. In order to make sure and present the behaviours of lower and upper probabilities, α-cuts are aligned with intervals of 0.2.

Aside from marginal probability calculations, seven intermediate nodes and one leaf node are revealed to identify to what degree the notion of degree of belief in their occurrence was conditional on a body of knowledge in WRDBN. The calculation of all conditional prob-abilities is executed through Eq. (2) in compliance with the Bayes rules given in Section 2. Eqs. (7) and (8) are utilised to calculate and tabulate the probabilities.

I1 and I4 out of those nodes are presented in Table 10. According to the nature of conditional probabilities, it is attempted to find all var-iations of the events. For instance, I1 responds to aerodynamic pro-blems and is composed of a root node (R1) (see Section 5.2). Ad-ditionally, a derailment is likely to take place, regardless of this rood node, through tornadoes (see Section 4.2). Therefore, the probability of an event's occurrence given that another event has already happened or not happened is revealed through accident reports.

Table 8
Variables in WRDBN.

Nodes	Node kind	Description
R_1	Root	Extreme wind
R_2	Root	Frozen precipitation
R_3	Root	Fog
R_4	Root	Liquid precipitation
R_5	Root	Flood
R_6	Root	High temperature
R_7	Root	Low temperature
I_1	Intermediate	Aerodynamic problems
I_2	Intermediate	Obstructions
I_3	Intermediate	Slipping
I_4	Intermediate	Vision loss
I_5	Intermediate	Track bed problem
I_6	Intermediate	Geometry problem
I_7	Intermediate	Component failures
D_t	Leaf	Derailment

6.2. Prior and posterior probabilities for WRDBN

Prior probabilities of nodes in WRDBN are the original probabilities of an outcome, which is only related to environmental-based, i.e. weather, derailments at railway turnout systems, and will be updated with new information to create posterior probabilities.

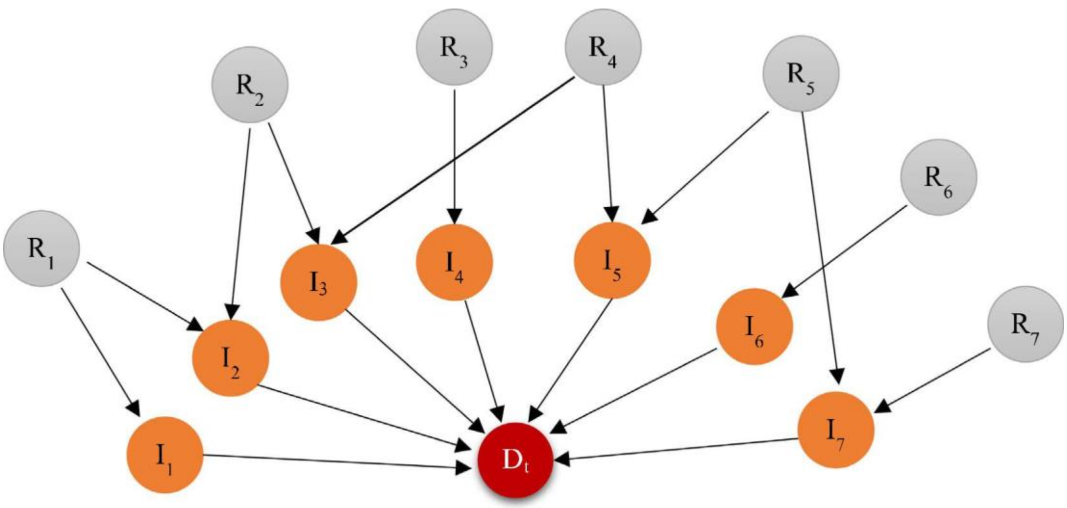


Fig. 3. Established BN model for WRDBN.

Table 9
Marginal probabilities for 'extreme wind', 'frozen precipitation' and 'flood' causing de-railment at turnouts.

Alpha-cuts	$\tilde{P}(\mathbf{R}1 = \mathbf{r}1_1)(\alpha)$		$\tilde{P}(\mathbf{R}1 = \mathbf{r}1_2)(\alpha)$	
	$p^L_{r1_1}(\propto)$	$p^U_{r1_1}(\propto)$	$p^L_{r1_2}(\propto)$	$p^U_{r1_2}(\propto)$
0.00	0.24709	0.27077	0.72923	0.75291
0.20	0.25304	0.26482	0.73518	0.74696
0.40	0.25506	0.26280	0.73720	0.74494
0.60	0.25652	0.26134	0.73866	0.74348
0.80	0.25776	0.26009	0.73991	0.74224
1.00	0.25893	0.25893	0.74107	0.74107
Alpha-Cuts	$\tilde{P}(\mathbf{R}2 = \mathbf{r}2_1)(\alpha)$		$\tilde{P}(\mathbf{R}2 = \mathbf{r}2_2)(\alpha)$	
	$p^L_{r2_1}(\propto)$	$p^U_{r2_1}(\propto)$	$p^L_{r2_2}(\propto)$	$p^U_{r2_2}(\propto)$
0.00	0.46864	0.49565	0.50435	0.53136
0.20	0.47542	0.48886	0.51114	0.52458
0.40	0.47773	0.48655	0.51345	0.52227
0.60	0.47939	0.48489	0.51511	0.52061
0.80	0.48081	0.48347	0.51653	0.51919
1.00	0.48214	0.48214	0.51786	0.51786
Alpha-Cuts	$\tilde{P}(\mathbf{R}5 = \mathbf{r}5_1)(\alpha)$		$\tilde{P}(\mathbf{R}5 = \mathbf{r}5_2)(\alpha)$	
	$p^L_{r5_1}(\propto)$	$p^U_{r5_1}(\propto)$	$p^L_{r5_2}(\propto)$	$p^U_{r5_2}(\propto)$
0.00	0.07301	0.08770	0.91230	0.92699
0.20	0.07670	0.08401	0.91599	0.92330
0.40	0.07796	0.08276	0.91724	0.92204
0.60	0.07886	0.08185	0.91815	0.92114
0.80	0.07963	0.08108	0.91892	0.92037
1.00	0.08036	0.08036	0.91964	0.91964

To identify whether the unequal proportions across nodes present a real difference in the true population or whether the difference is a result of sampling error, prior probabilities that greatly affect the ac-curacy of results in WRDBN are specified and illustrated in Fig. 4. Red bars show the prior-based likelihood of occurrence of a derailment in the nodes, while ∝- cuts equals to '1.00'. I2, obstructions, seems to be an intermediate node, causing mostly a weather-related derailment at railway turnout systems, followed by I3, slipping, and I5, trackbed problems. On the other hand, I4, vision loss, and I7, component fail-ures, are the rarest learned events in WRDBN.

It is seen also from Fig. 4 that most of the weather-based causes have often resulted in derailments at turnouts. However, almost one-sixth of derailments happened as a result of those, since other causes except weather-based ones could give rise to derailments as well. A posterior probability is the probability of assigning observations to groups given the data, and is one of the underlined steps in the Bayes Network frame, as shown in Section 5. It might be significant to understand how the prior probabilities change when a new observation is added into the BN for leaf node. It is supposed that D_t~,derailment at turnouts, is observed to take place, which is notated as $P(D_t = 1)(\alpha_{1.00})$.

Fig. 5 illustrates how the alpha cuts responding to posterior prob-abilities nodes are distributed through all intermediate nodes. $\tilde{P}(I2 = I2_1 | D = 1)(\alpha_{[0,1.00]\,U\,[1.00,0]})$ is calculated to be the most common weather failure types, ranging from 0.48059 to 0.70574, and followed by I3 and I5. It is also found that each probability with different α- cut values entails different intervals. Considering such rare an occurrence of events, this distribution provides probability information with a wide perspective to railway operators. Therefore, the most likely value of probability numbers $P(I2 = \tilde{I}2_1 | D = 1)(\propto)$ is 0.59304, whilst the most likely value of probability number $\tilde{P}(I1 = I1_1 | D = 1)(\propto)$ is 0.01151. This also shows that the posterior probability changes significantly as a result of the existence of non-categorised weather-related accidents (see Sections 4.1 and 4.3). That is, there might be two explanations for this pattern: the impact of a limited number of codes for environmental-related accidents in the FRA database, and the sensitivity of the node I2 and its roots to node D.

Fig. 6 shows four prior probabilities, $\tilde{P}(R1 = r1_1)(\alpha)$, $\tilde{P}(R1 = r2_1)(\alpha)$, $\tilde{P}(I2 = i2_1)(\alpha)$, $\tilde{P}(I5 = i5_1)(\alpha)$, and posterior prob-abilities, $\tilde{P}(R1 = r1_1 | D = 1)(\propto)$, $\tilde{P}(R2 = R2_1 | D = 1)(\propto)$, $\tilde{P}(I2 = I2_1 | D = 1)(\propto)$, $P(I5 = I5_1 | D = 1)(\propto)$ in WRDBN. The prior prob-ability distribution is coloured in magenta, while the posterior prob-abilities are shown as blue lines in the figure. As marginal probabilities are prior probabilities in BNs, the distribution is matched with Table 9, given in Section 6.1. These nodes are found to be the most changing ones, given D equals to 1. The peak of lines occurs when $\alpha{-}cut$ is 1.00, which gives rise to 0 confidence interval. On the other hand, the higher the values of confidence intervals get, the less α-cuts are valued. This provides an opportunity to railway operators, when the uncertainty of any event in WRDBN is high, and the small values of α-cuts are taken. This is because probability intervals get larger and, as result, informa-tion loss is prevented. In contrast, when a database gives concrete in-formation on an event history, it will be better to opt for the high values of α-cuts, which makes probability intervals narrower and, so, results in a more realistic response to investigation.

6.3. Sensitivity analysis

In this study, a preliminary conclusion (i.e. node 'derailment at

Table 10
Conditional probabilities for 'Aerodynamic Problems' and 'Vision loss' causing derailment at turnouts.

Alpha-Cuts	$\tilde{P}(\boldsymbol{I}1 = \boldsymbol{I}1_1 \| \boldsymbol{R}1)(\alpha)$				$\tilde{P}(\boldsymbol{I}1 = \boldsymbol{I}1_2 \| \boldsymbol{R}1)(\alpha)$			
	$p^L_{I1_1,R1_1}(\propto)$	$p^U_{I1_1,R1_1}(\propto)$	$p^L_{I1_1,R1_2}(\propto)$	$p^U_{I1_1,R1_2}(\propto)$	$p^L_{I1_2,R1_1}(\propto)$	$p^U_{I1_2,R1_1}(\propto)$	$p^L_{I1_2,R1_2}(\propto)$	$p^U_{I1_2,R1_2}(\propto)$
0.00	0.40048	0.4271	0.00646	0.01156	0.5729	0.59952	0.98844	0.99354
0.20	0.40717	0.42041	0.00774	0.01028	0.57959	0.59283	0.98972	0.99226
0.40	0.40945	0.41814	0.00817	0.00984	0.58186	0.59055	0.99016	0.99183
0.60	0.41108	0.4165	0.00849	0.00953	0.5835	0.58892	0.99047	0.99151
0.80	0.41248	0.4151	0.00876	0.00926	0.5849	0.58752	0.99074	0.99124
1.00	0.41379	0.41379	0.00901	0.00901	0.58621	0.58621	0.99099	0.99099
Alpha-Cuts	$\tilde{P}(\boldsymbol{I}4 = \boldsymbol{I}4_1 \| \boldsymbol{R}4)(\alpha)$				$\tilde{P}(\boldsymbol{I}4 = \boldsymbol{I}4_2 \| \boldsymbol{R}4)(\alpha)$			
	$p^L_{I4_1,R4_1}(\propto)$	$p^U_{I4_1,R4_1}(\propto)$	$p^L_{I4_1,R4_2}(\propto)$	$p^U_{I4_1,R4_2}(\propto)$	$p^L_{I4_2,R4_1}(\propto)$	$p^U_{I4_2,R4_1}(\propto)$	$p^L_{I4_2,R4_2}(\propto)$	$p^U_{I4_2,R4_2}(\propto)$
0.00	0.48649	0.51351	0.00646	0.01156	0.48649	0.51351	0.98844	0.99354
0.20	0.49328	0.50672	0.00774	0.01028	0.49328	0.50672	0.98972	0.99226
0.40	0.49559	0.50441	0.00818	0.00984	0.49559	0.50441	0.99016	0.99182
0.60	0.49725	0.50275	0.00849	0.00953	0.49725	0.50275	0.99047	0.99151
0.80	0.49867	0.50133	0.00876	0.00926	0.49867	0.50133	0.99074	0.99124
1.00	0.50000	0.50000	0.00901	0.00901	0.50000	0.50000	0.99099	0.99099

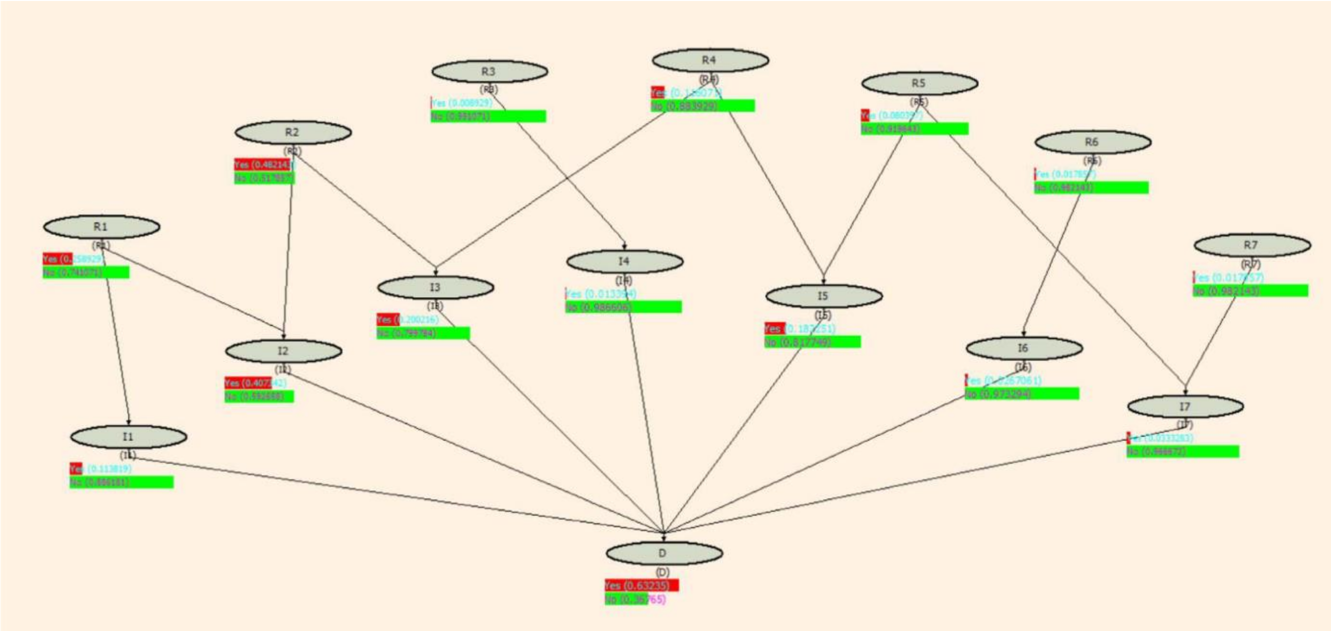


Fig. 4. The distribution of P $_{Prior}$ (∝) of r the root, intermediate and leaf node in WRDBN towards ∝-cuts = 1.

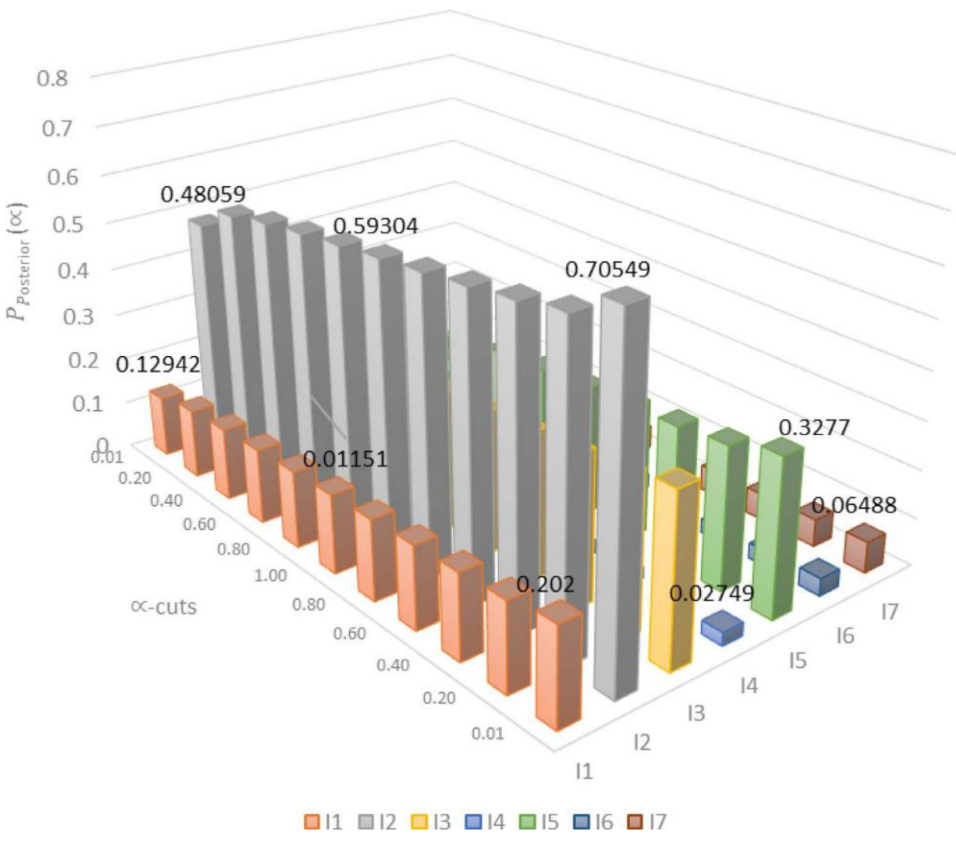


Fig. 5. The distribution of P posterior (∝) of the in-termediate nodes and the leaf node in WRDBN to-wards ∝-cuts.

turnouts due to the reasons in Table 6' is considerably sensitive to node 'frozen precipitation') is drawn based on posterior probabilities, e.g. $\tilde{P}$ $(R\,2 = R\,2_1\,|D = 1)$(∝). Therefore, the sensitivity analysis is performed, inputting the different rational parameters values in order to monitor the impact of these changes on the posterior probabilities through a number of membership functions, $\mu_{\tilde{R}2}(x)$.

In WRDBN, the marginal probability of this node, $\tilde{P}$ $(R2 = r2_1)(\alpha)$, has been found as 0.48214. As a result, the range is kept as large as possible in order to give an idea as to how sensitive the model's performance is to a large range of changes in the input parameters. To reach the results of nine different values, an in-house developed MATLAB program has been implemented into the FBN inference.

Fig. 7 illustrates these results, showing the confidence-based prob-ability distribution of R2 towards the various variations of node R2 from 0.1 to 0.9. As seen in the figure, each peaking curve indicates that $\tilde{P}$ $(R\,2 = r\,2_1\,|D = 1)(\alpha)$ clearly changes with $\tilde{P}$ $(R2 = r2_1)(\alpha)$. It is also shown that there is a positively increasing trend in the posterior probabilities of node R2 when $\tilde{P}$ $(R2 = r2_1)(\alpha)$ steadily increases. Thus,

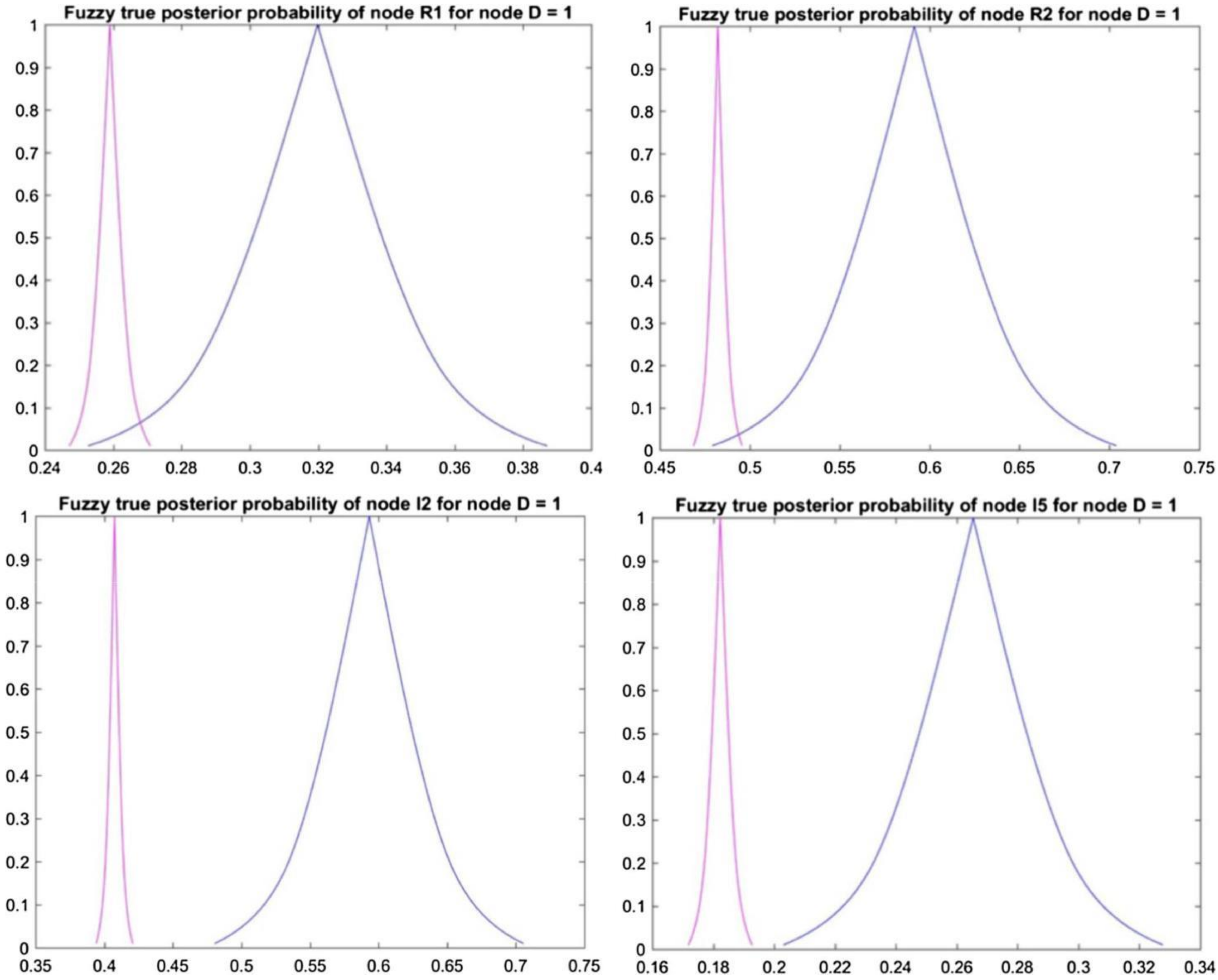


Fig. 6. Prior fuzzy probabilities and posterior fuzzy probability of R1, R2, I2 and I5 in WRDBN.

the figure presents a reason to believe that the above conclusion is reliable.

On the other hand, results match, in a sense, with the previous statement the 'higher the values of confidence intervals get, the less α-cuts are valued'. As node R2 is inputted with higher values, the confidence intervals impact much higher on probability distribution towards alpha-cuts, which stresses how uncertain the node is.

7. Discussion

FBN is a quite prominent technology with huge potential for various applications across many engineering domains. This study discusses FBN and its application in railway turnout systems. The proposed FBN approach, namely WRDBN, uses the probabilities of environmental-re-lated causes of accidents to perform Bayesian inference, which is es-tablished by causal relationship through accident reports. Therefore, the BN provides the model structure of WRDBN, fuzzy prior probability and likelihood calculation, and inference and interpretation. Aside from BN, there have been many other techniques which are suggested to risk, occurrence or consequence analysis of any type of accident across railway systems. Fuzzy fault tree analysis (FFTA) currently seems to be one of the common methods for turnout, along with the other railway engineering systems (Jafarian and Razvani, 2012; Peng et al., 2016; Huang et al., 2000; Ishak et al., 2016). One of the main differences between those FFTAs and this proposed FBN is that FBN might be better able to handle the causal relations in a complex environment, including many engineering works, e.g. trackbed, aerodynamic, adhesion, be-cause FFTAs are mainly comprised of simple Boolean functions such as AND-gate and OR-gate while FBN is based on different causal re-lationships, in particular considering its conditional probability calcu-lation.

Derailments at railway turnouts yield quite serious consequences, including loss of life, operational shutdown and damage to railway assets. Although these derailments account for one-third of all derail-ments on lines, those that are weather-related are quite rare events. As a result, the research only focuses on weather-related accidents to un-derstand what types of causes are dominant in a particular scenario. Frozen precipitation is observed to be considerably responsible for such accidents, which gives rise mainly to preventing proper movement of switch blade. From the perspective of sensitivity analysis, the structure of the proposed WRDBN is observed to produce a reliable measure of performance of this node. The probabilities are extracted and calculated by means of official accident reports over the years between 2006 and 2015 across the US. WRDBN only gives an idea on the risk elements associated with weather and which lead to derailments at various types of railway turnout derailments. Due to the United States' 9.9 million km2 area and mid-continental placement, the country has a widely varying climate, which is unique to understand the impact of different

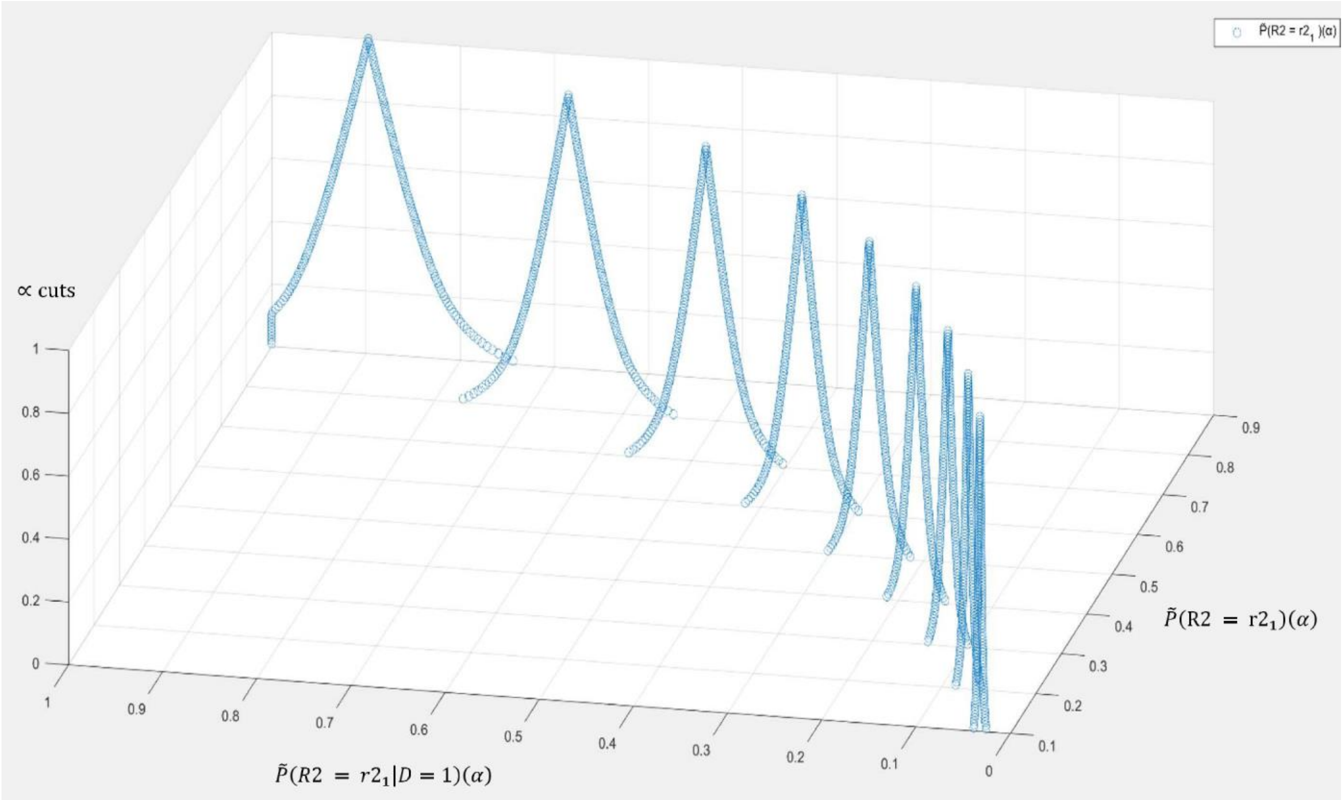


Fig. 7. Sensitivity analysis for $\mu_{\tilde{R}2}(x)$ of $\tilde{P}(R2 = r2_1)(\alpha)$ in WRDBN, corresponding to $\tilde{P}(R2 = r2_1|D = 1)(\alpha)$.

climate patterns on railway turnouts. However, as climate varies on the basis of its prevailing geography, it should be expected that the weather characteristics of different countries lead to different marginal and conditional probabilities of the nodes although the structure of BN is established in the same way, as presented in Fig. 2.

8. Conclusion

In engineering operations, BN is considered to be one of the effec-tive tools of uncertain knowledge representation. This research reveals to what degree a weather pattern impacts on derailments on railway turnout systems, and what kind of causes lead to it. It is proposed to use Buckley's probability calculation on the basis of confidence intervals to obtain marginal and conditional probabilities, and to reach prior and posterior conditional probabilities in the recommended WRDBN. Although data are obtained after the investigation of some 18,000 US-based reports, it is identified that this kind of derailment is a quite rare event. In contrast to conventional BN approaches, this confidence in-terval approach is seen likely to provide the flexibility to make deci-sions on the probabilities of failures resulting in derailments. In other words, it provides how to obtain probabilities in WRDBN as intervals instead of crisp values. Probability intervals using data are found through a theoretical basis of confidence intervals and probability.

It is determined that there are seven root causes, R1 to 7, and seven intermediate nodes, I1 to 7, which are affected by weather patterns and drive derailment at turnouts. A few of those nodes, such as frozen precipitation, liquid precipitation and high wind, seem to draw the attention. The confidence probability intervals of these nodes are ob-served to be larger than the other nodes, as the effect of changing the prior/posterior probability of the leaf node (derailment) is considerably high. In summary, the paper proposes an alpha cut-based FBN model ensuring that its application is conducted in a well-managed, dis-ciplined and consistent manner that promotes the delivery of risk as-sessment results for railway turnouts.

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