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Fuzzy bow-tie analysis for mitigating self-heating risks in maritime coal transportation

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ABSTRACT

Coal self-heating presents significant risks to maritime transportation, including spontaneous combustion, environmental damage, and economic losses. This study aims to apply a Fuzzy Bow-Tie analysis to assess and mitigate the risks associated with coal self-heating during transportation. By integrating expert judgments and addressing uncertainties in the data, the Fuzzy Bow-Tie model offers a comprehensive evaluation of risk factors and safety barriers. This leads to more reliable risk assessments compared to traditional deterministic methods, which are less capable of handling imprecise data. In marine pollution, where early identification of potential hazards (e.g., self-heating coal leading to toxic gas emissions) is critical, the Fuzzy Bow-Tie approach allows for more accurate forecasting of incidents that could result in environmental harm. Key findings reveal that improper ventilation, large air gaps between coal particles, and inaccurate declarations of coal properties are major contributors to self-heating incidents. Furthermore, inadequate cargo monitoring and non-compliance with the International Maritime Solid Bulk Cargoes (IMSBC) Code exacerbate these risks. These insights provide practical guidance for maritime stakeholders, such as shipping companies and port authorities, to improve coal handling practices and enhance safety procedures. The Fuzzy Bow-Tie model provided a reliable and flexible tool for handling uncertainties and improving risk assessment in complex maritime environments. Overall, the study offers practical recommendations for shipping companies and port authorities to improve coal handling safety, reducing the potential for accidents and environmental harm.

1. Introduction

Coal is one of the most used and significant energy sources in the world, and it has long been a driving force behind the continued expansion of the global economy (You et al., 2021). Due to the unequal distribution of coal resources throughout the world, enormous quantities of bulk coal must be transported by sea every year, with the number of shipments increasing annually (Popek, 2019). In 2022, global coal consumption continued to increase following a significant rebound in 2021. As a result, worldwide coal supplies reached a new record high of approximately 8582 million metric tons, representing a 7 % increase. In 2023, global coal output is projected to increase by 1.8 %. This growth will be driven by India, China, and Indonesia, while the United States and the European Union are expected to experience decreases. The global coal trade increased to 1376 million metric tons in 2022, representing a 1 % growth compared to the previous year. Coal that was exchanged in trade represented around 16 % of the total demand for coal. The proportion of exports transported by sea increased to around 95 % of the total (IEA, (International Energy Agency), 2023; BIMCO (Baltic and International Maritime Council), 2024).

Safe transportation of coal, which is of special importance for the resource industry, is crucial. There are numerous forms of coal-related hazards in shipping, the most common being flammable atmospheres, liquefaction, asphyxiation, corrosion, and self-heating. Especially, coal self-heating combustion is a common occurrence in coal mining, storage, and transportation processes (Danish and Onder, 2020). Self-heating in shipping is a significant issue in terms of the economy, environment, and safety. Spontaneous combustion leads in the loss of valuable coal cargoes and the emission of harmful gases that endanger the health of seafarers, port workers and residents, including carbon dioxide and methane, which are greenhouse gases (Zhang et al., 2016). Additionally, it has the potential to ignite fires and explode, with catastrophic results like a capsizing, human casualty and the production of greenhouse and toxic gases (Nalbandian, 2010; Domínguez et al., 2021).

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Some types and grades of coal cargo may be more susceptible to self-heating than others. The size of the particles, their surface area, the air gap between the particles, and the volume of air accessible are some of the major variables that may affect self-heating. In the presence of adequate oxygen, coal with a temperature above 55C self-heats rapidly, resulting in igniting without an external source of ignition (Lu et al., 2022). Thus, fires can be challenging to control in the confined spaces of a ship, often leading to severe structural damage, potential loss of the vessel, and fatalities (Kuenzer and Stracher, 2012). From an environmental perspective, coal fires can lead to the release of harmful pollutants into the atmosphere and, if not contained, can result in the contamination of marine ecosystems (Liu et al., 2013). This can have long-term detrimental effects on marine life and water quality, further complicating recovery efforts and regulatory compliance.

Proper ventilation, temperature monitoring, moisture control, and regular inspections are essential practices that help prevent self-heating and spontaneous combustion. To mitigate these risks, the International Maritime Solid Bulk Cargoes (IMSBC) Code sets out specific requirements for the safe loading, carriage, and monitoring of coal cargoes (Djadjev, 2015). The IMSBC Code mandates that coal cargoes must be properly ventilated during transit to dissipate heat and reduce the likelihood of self-heating. It specifies the need for continuous temperature monitoring of the cargo to detect any early signs of self-ignition, allowing for prompt remedial action (Popek, 2019). Even though many carriers have a wealth of industry knowledge, and that detailed guidance is accessible from a wide range of sources, major events involving coal shipments continue to happen (Liu et al., 2013; Popek, 2019). These issues typically result from poor handling practices used by shippers prior to loading and during transportation. In recent years, self-heating accidents involving coal cargoes handled at vessel and ports have become more prevalent. The issue appears to be mostly associated with the composition of the coals, and how they are managed before and during loading may make them worse (UK P&I Club, 2018).

Numerous risk assessment studies pertaining to coal have been conducted by various sectors. The mining industry emerges first, as expected (Mahdevari et al., 2014; Deng et al., 2017; You et al., 2021). Studies in this field have primarily focused on identifying coal mining's risks and developing mitigation strategies. Coal transportation (Kaplan, 2007; Niu and Wang, 2018; Murko et al., 2021; Sivageerthi et al., 2022; and storage (Moghtaderi et al., 2000) are two additional crucial areas where research is conducted. Moroeng et al. (2017) present a case study on the self-heating potential of coal, offering valuable information for assessing risks in coal transportation. Dudzińska et al. (2017) highlight the importance of monitoring coal's self-heating process through gas sorption capacity, which can be crucial for risk assessment. Portola et al. (2019) showed that controlling the temperature of coal is challenging due to its heat retention properties, making gas analysis methods insufficient for detecting early indications of self-heating. Więckowski et al. (2022) introduce an improved method for fire hazard assessment in coal mines, emphasizing the significance of considering various factors, including the primary temperature of a coal seam, which can be applicable to assessing risks in coal transportation at sea. In addition to these studies, many academicians have performed research on the coal self-heating problem and its outcomes by mathematical models and experimental studies (Taraba et al., 2014; Yuan et al., 2019; Li et al., 2021; Wu et al., 2019; Xi et al., 2022). Nonetheless, the shipping sector is barely covered in studies (Chen et al., 2017; Popek, 2019; Chen et al., 2021). In addition to these studies, many academicians have performed research on the coal self-heating problem and its outcomes by mathematical models and experimental studies (Taraba et al., 2014; Yuan et al., 2019; Li et al., 2021; Wu et al., 2019; Xi et al., 2022). Most of these research deal with the liquefaction and stability of coal during ship transport. Insufficient research has been conducted on the factors and possible consequences of self-heating; a significant risk associated with the transportation of coal in the maritime sector. Shen and Wang (2011) highlight the importance of monitoring temperature and promoting air circulation to reduce the dangers of self-ignition and the buildup of methane gas in coal shipments. They emphasize that coal can undergo spontaneous combustion due to oxidation processes, leading to flames and the production of carbon monoxide (CO). The study conducted by Zhang et al. (2016) revealed that transient computational fluid dynamics (CFD) models have been employed to simulate the self-heating behaviors of coal stockpiles at low temperatures. These models take into account factors such as wind velocity and stockpile porosity, and demonstrate that these variables have a substantial impact on the rise in temperature and the patterns of gas transport. Another comprehensive model by Yuan et al. (2019) integrates heat transfer, mass transfer, and chemical reactions to accurately simulate self-heating ignition, validating the model across various experimental configurations and coal origins (Yuan et al., 2019).

Several methodologies for risk assessments have been developed for application in the maritime industry such as Bayesian Belief Network (Li et al., 2014; Zhang et al., 2016 and Chang et al., 2021), Fault Tree Analysis (Uğurlu et al., 2015), Event tree analysis, Formal Safety assessment (Mentes et al. 2015 and Banda et al., 2016), Analytic Hierarchy Process (Wang et al., 2014) and failure mode and effects analysis (Zaman et al., 2017). Each of these approaches has benefits and drawbacks in comparison to the others (Sharafat et al., 2021). On their own, they might be unable to express the complexity of risk occurrences, though; however, bow-tie methodology is crucial in maritime risk analysis as it enhances the precision of risk assessments, effectively handles uncertainty, and improves safety measures (De Ruijter and Guldenmund, 2016). Its application across various industries further demonstrates its versatility and effectiveness in managing complex risk scenarios. Traditional Bow-Tie Analysis combines Fault Tree and Event Tree Analyses to map out causes and consequences with precise probabilities, requiring exact data, which can be a limitation in uncertain scenarios (Shahriar et al., 2012). In contrast, Fuzzy Bow-Tie Analysis incorporates fuzzy logic to address vagueness and imprecision, making it more adaptable to situations with incomplete data by using qualitative expert judgments (Kaptan, 2021). This makes Fuzzy Bow-Tie Analysis more flexible and comprehensive, especially useful in complex environments with high uncertainty to provide a comprehensive framework for assessing risks. This dual representation is particularly beneficial for complex maritime risk assessments like coal self-heating, where understanding both the initiation and progression of risk events is crucial for developing effective mitigation strategies (Arici et al., 2020). Therefore, the purpose of this study is to undertake a quantitative risk analysis utilizing fuzzy logic for a Bow-Tie scheme, aiming to improve the accuracy and reliability of self-heating coal transportation risk evaluations in complex and uncertain environments.

The research is structured into five segments. The “Introduction” section outlines the study's aims, identifies gaps in existing knowledge, and underscores the research's importance. In the “Literature Review” section, previous studies and related works within coal transportation and risk assessment techniques are examined. The “Materials and Methods” section elaborates on the methodologies employed, detailing the areas of investigation and the process of data collection. Lastly, the “Discussion and Conclusion” section delves into the key discoveries, acknowledges study limitations, and offers recommendations for future research.

2. Materials and methods

This study utilized a fuzzy-based bowtie analysis to evaluate the risks associated with self-heating/ignition during coal transportation. The bow-tie approach is a technique that integrates a fault tree on the left and an event tree on the right to visually express causes, threats (hazards), and effects in a unified platform. In our study, detailed accident reports pertaining to coal self-heating were predominantly sourced from P&I Club sites, the IMO GISIS (Global Integrated Shipping Information System), and the EMSA-EMCIP (European Maritime Safety Agency -

European Marine Casualty Information Platform) databases. Due to the constrained availability of full-text reports that elucidate the root causes, we augmented our dataset with safety bulletins. These bulletins offered additional insights into the incidents, thereby ensuring a comprehensive aggregation of data and significantly enhancing the robustness and reliability of our analysis.

2.1. Bow-tie method

The bowtie (BT) method is a probabilistic and graphical way that examines accident situations by establishing a logical relationship between the causes and consequences of an unpleasant event (Beauchamp et al., 2010; Khakzad et al., 2013). Fault tree analysis (FTA) and event tree analysis (ETA) are two well-established risk analysis approaches that are applied and combined in this method, which also contains safety measure aspects. (Ehlers et al., 2017). The FTA's top event, which is termed the center of the bowtie, is linked to the ETA's initiating event (Sharafat et al., 2021). The FT is positioned on the left side of the bow-tie diagram and is composed of intermediate events, beginning with the top event, and concluding with basic events that are likely causes of the accident and on the right side, the possible consequences are represented by ET development (Ferdous et al., 2013). A bow-tie framework has not only established its value in accident prediction, but also in analyzing past incidents and identifying ways to prevent their recurrence (Bellamy et al., 2013). The conceptual framework of the study is shown in Fig. 1.

Fig. 1 illustrates the three fundamental elements of the methodology: The left diagram is a Fault Tree (FT) diagram that is constructed using fundamental events and the likelihood of the top event. The center diagram is a fuzzy sets environment, which is employed to handle the uncertainty associated with expert judgment. The right diagram is an event tree analysis that focuses on the final outcomes.

2.1.1. Fault tree analysis (FTA)

Fault tree analysis (FTA) is a graphical and deductive strategy for identifying the sequence of events that could lead to the occurrence of an undesirable event, known as the top event (TE) and calculate the likelihood that the TE will occur. It begins with a TE and gradually splits presence of causes into branches as intermediate events (IE) and basic events (BE) respectively (Stapelberg, 2009; Ruijters and Stoelinga, 2015). The standard FTA, complete with event symbols, is depicted on the left side of Fig. X. Basic Events are at the bottom of the tree's

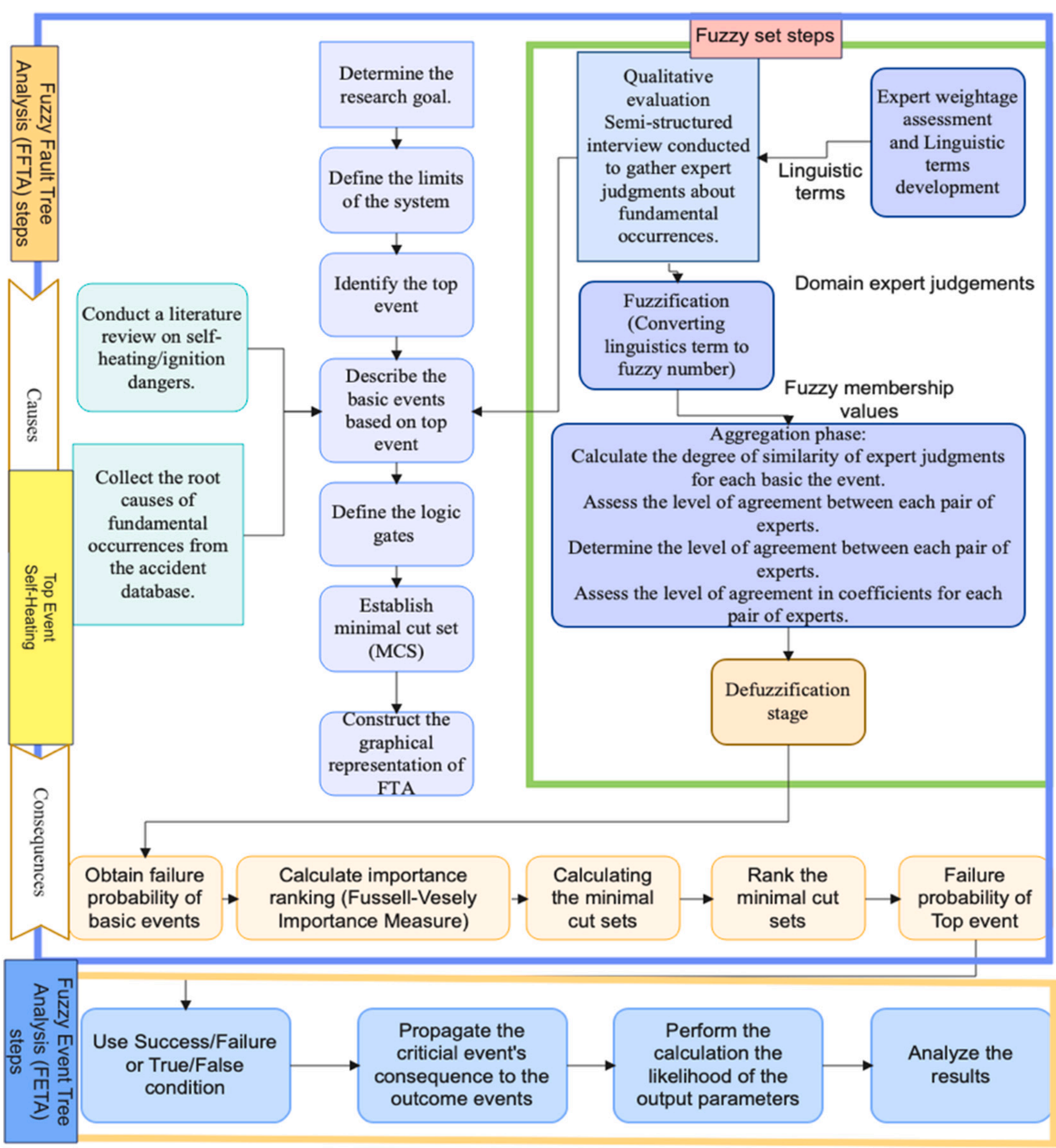

Fig. 1. Conceptual framework of the study.

hierarchy, that cannot be updated further down the tree. The “OR” and “AND” logic gates creating relationship between the occurrence of BEs and TE by using Boolean operations are mainly employed in the standard FTA (Islam et al., 2017). The “OR gate” indicates the failure state output if at least one input is in the failure state, whereas the “AND gate” displays the failure state output if all system inputs are in the failure state (Baig et al., 2013).

After the construction of a fault tree, qualitative analysis can be carried out for the minimal cut set (MCS). A minimal cut set (MCS) is a collection of fundamental events constituting the essential components of the FT. Using an MCS, the structural vulnerability of the system can be identified (Lavasani et al., 2015). The MCS is the smallest set of input events that results in the occurrence of the unwanted event. The numerous ways that component failures or events, either alone or in combination with others, can result in the occurrence of the top event are shown by MC_i (Abdo et al. 2018). The system's risk grows in proportion to the number of MCSs. Boolean algebra rules are used to derive the MCs (Yuanhui, 1999).

$$TE = MCS_1 + MCS_2 + \ldots + MCS_Q = \cup_{i=1}^{Q} MCS \tag{1}$$

With regards to quantitative analysis, the likelihood of every basic event is required in order to determine the probability of the top event P (TE). It represented by Eq. 9, is the sum of the probabilities of all MCSs in the system (Shadiah et al., 2019). The probability of minimal cut set k is P(MCSk), while the total number of MCS in the system is N.

$$P(TE) = \sum_{k=1}^{N} P(MCS_k) \tag{2}$$

In addition to the occurrence probability of the TE, another advantageous is the identifying of the significance of each MC. In this way, the importance can be seen as a representation of the relative risk that each MC poses for the TE occurring (Celik et al. 2010). This study examines the sensitivity of top events likelihood using the Vesely-Fussell Importance Measure (V- FIM) approach. According to Khakzad (2020), the V-FIM metric quantifies the entire input of MCS sets containing an important basic event to the overall MCS sets. This method, which is stated as the following eq. 3, provides the numerical significance grade for basic events presented in the FTA diagram (Arici et al., 2020):

$$I_i^{VF}(t) = \frac{Q_{\cdot}(t)}{Q_s(t)} \tag{3}$$

The preceding equation, $I_i^{VF}(t)$ shows the signifigance degree of MC_i, $Q_{\cdot}(t)$ is the cut set i failure incidence likelihood and $Q_s(t)$ is the likelihood of TE failure incidence over all MCS.

2.1.2. Event tree analysis (ETA)

ETA is a graphical representation and inductive method for assessing the likely outcomes of an initiating event. It concurrently forms two branches, including triumphs and failures, that demonstrate all the potential outcomes of a key risk occurrence (Gheorghe and Mock 1999). The objective of the event tree is to establish the initiating event's repercussions by analyzing safety mechanisms.

The right side of Fig. 2 depicts the fundamental structure of a typical ET, which consists of an initiating event, safety barriers and possible outcomes. To determine the occurrence probability of each consequence, the initiating event, which is identical to the top event (TE) supplied by the FT component of the BT model, propagates branches based on binary conditions, such as success/failure, yes/no, or true/false. Safety barriers are the intermediary events of an ET that lessen the negative impacts of the initial event.

2.2. Fuzzy set theory

Zadeh (1965) created fuzzy set theory to deal with all sorts of uncertainty in human decision-making due to conventional probability theory is insufficient on its own. A significant contribution of Fuzzy Set Theory is its capacity to represent imprecise data and subjective uncertainty by designing linguistic variables to translate qualitative knowledge/judgments into numerical reasoning (Ayyub and Klir 2006, Ferdous et al., 2013). To represent the uncertainty of expert judgments, it uses fuzzy numbers (Lin and Wang, 1997) Fuzzy set theory provides a gradual evaluation of an element's membership in a set. The membership function μ_A of a fuzzy number uses the numerical relationship for a likelihood of input occurrences (uncertain quantity *p)* ranging between 0 and 1 (Ehlers et al., 2017). Triangular and trapezoidal membership functions are the most common, but other shapes are possible (Ferdous et al., 2013). In this study, a trapezoidal membership function is employed to measure subjectivity in expert knowledge utilizing the following equation for trapezoidal fuzzy set numbers: (a, b, c, d)

$$\mu_A(x) = \begin{cases} \dfrac{x-a}{b-a} & , \quad a \le x \le b \\ 1 & , \quad b \le x \le c \\ \dfrac{d-x}{d-c} & , \quad c \le x \le d \\ 0 & , \quad otherwise \end{cases} \quad where\ a < b < c < d \tag{4}$$

2.2.1. Fuzzy fault tree analysis and fuzzy event tree analysis

The failure probabilities of system components are regarded as

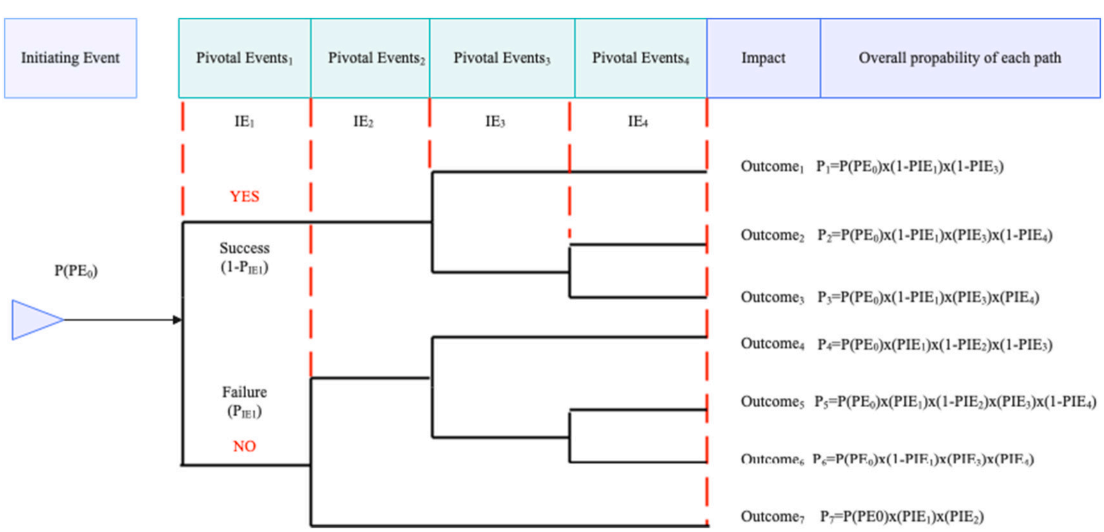

Fig. 2. The framework of ET Diagram.

accurate quantities in traditional FTA (Mokhtari et al. 2011). However, it is frequently challenging to determine the exact failure rates of events in the quantitative analysis of fault trees based on historical data for multiple systems (Celik et al. 2010). The same condition can be said for the examination of event trees. Numerous studies based on fuzzy logic have been conducted in a variety of industries to reduce the amount of uncertainty associated with ETA (Ferdous et al., 2013, Baraldi and Zio, 2008). The application of FST is being studied as a means of overcoming these challenges (Tang et al. 2018). It enables experts to evaluate the likelihood of BEs in a fault tree and Safety barriers in an event tree analysis using language variables rather than numerical values (Abad and Naeni, 2020). In this regard, the failure possibility, which is characterized by a trapezoidal fuzzy value in the range [0,1], is utilized to describe the potential deviation from the basic events.

2.2.2. *Obtain data about failures based on expert opinion*

It can be challenging to acquire historical data on the make-up of maritime works, and a significant amount of this information is undisclosed. The evaluations of the maritime specialists are utilized in the process of dealing with ambiguity data issues (Lavasani et al., 2015, Zarei et al., 2019). The selection of multiple experts with diverse expertise and the consolidation of their various ideas into a single opinion is a common technique (Clemen and Winkler, 1999). Shan et al. (2017) determined the probabilities of the variables using a variety of expert opinions. In this study, a fuzzy-based model is used to estimate the fundamental event failure probabilities of basic event of FTA and safety barriers of ETA. A non-uniform group of specialists was assembled to assess the likelihood of uncertain occurrences. On the other hand, the opinions of specialists might not be identical due to their varying levels of experiences, education, knowledge, etc. The weighted score was expanded by Yuhua and Datao (2005) to highlight the relative quality gaps amongst experts and to provide more accurate judgments.

When dealing with situations that are too complex or ambiguous to be described using traditional quantitative expressions, linguistic phrases are crucial (Kabir, 2018). In this study, seven linguistic variables were used alongside a trapezoidal fuzzy function to calculate probabilities of basic event and safety barriers. It is essential to combine expert viewpoints to arrive at a consensus because each expert may have a different perspective depending on his or her experience and skill in the relevant sector. This study therefore uses the Similarity Aggregation Method (SAM), which is proposed by Hsu and Chen (1996), to turn the linguistic expressions of experts into fuzzy numbers.

The initial stage of SAM is the aggregation of possibilities. To achieve this objective, consider that each expert $E_k (k = 1, 2, \ldots, M)$, uses a specific set of language terms to express their perspective on a given event. After converting them to matching fuzzy numbers, the following improved SAM approach is used to generate the aggregated fuzzy numbers (Ramzali, et al. 2015; Lavasani et al., 2015).

I. Calculate the degree of agreement (degree of similarity): Each pair of experts is indicated by E_u and E_v and $S_{uv}(\widetilde{R}_u, \widetilde{R}_v)$ reflects their beliefs, where $S_{uv}(\widetilde{R}_u,\widetilde{R}_v) \in [0, 1].]$. This method describes $\widetilde{A} = (a_1, a_2, a_3, a_4)$ and $\widetilde{B} = (b_1, b_2, b_3, b_4)$ as trapezoid membership functions for expert opinions. The answer to this equation is between 0 and 1, and the similarity grows as the answer gets closer to 1. This is called the degree of similarity function of S.

$$S(\widetilde{A},\widetilde{B}) = 1 - \frac{1}{4}\sum_{i=1}^{4} |a_i - b_i| \tag{5}$$

II. Calculate the Average Agreement (AA) Degree AA(E_u) of the experts: Eq. 6 is used to figure out how much each expert's opinion agrees with the others on average. The number of experts is shown by the letter "M."

$$AA(E_u) = \frac{1}{M-1}\sum_{\substack{v=1 \\ u \neq v}}^{M} S(\widetilde{R}_u, \widetilde{R}_v) \tag{6}$$

III. Computing the Experts' Relative Agreement (RA) degree, RA(E_u) of the experts. The term "relative agreement" refers to how much one expert's opinion and the opinions of the other experts similar. This is shown in Eq. (7)

$$E_u(u = 1, 2, \ldots, M) \; as \; RA(E_u) = \frac{\mathrm{AA}(E_u)}{\sum_{u=1}^{M} AA(E_u)} \tag{7}$$

IV. Consensus Coefficient (CC) degree predicting, CC(E_u) of expert.

$$CC(E_u) = \beta.w(E_u) + (1-\beta)RA(E_u) \tag{8}$$

The degree of agreement amongst expert opinions is measured by the consensus coefficient. The optimism coefficient, also known as the relaxation factor in the similarity method, shows how important $w(E_u)$ is in comparison to $RA(E_u)$. Its value is between 0 and 1. This equation emphasizes the significance of the expert weight coefficient in assessing relative relevance. "0" means that there is no choice and that a uniform group of experts is selected. "1" means that the degree of expert agreement is equivalent to the weight of the statement.

V. Eq. 9 calculates the expert judgment assembly $\widetilde{R}_{AG}$.

$$\widetilde{R}_{AG} = CC(E_1) \times \widetilde{R}_1 + CC(E_2) \times \widetilde{R}_2 + \ldots + CC(E_M) \times \widetilde{R}_M \tag{9}$$

After the aggregation phase, the next stage is the defuzzification procedure, where the trapezoidal fuzzy numbers $\widetilde{R}_{AG} = (a_1, a_2, a_3, a_4)$ are transformed into the corresponding crisp failure possibility (CFP). This study employs Sugeno's (1999) center of area (COA) defuzzification technique since it is both straightforward and effective. The formula is represented by Eq. (7):

$$defuzz(\acute{A}) : \frac{\int x.\mu(x)dx}{\int \mu(x)dx} \frac{\int_{a_1}^{a_2}\left(\frac{x-a_1}{a_2-a_1}\right).xdx + \int_{a_2}^{a_3}.xdx + \int_{a_3}^{a_4}\left(\frac{a_4-x}{a_4-a_3}\right).xdx}{\int_{a_1}^{a_2}\left(\frac{x-a_1}{a_2-a_1}\right).dx + \int_{a_2}^{a_3}.dx + \int_{a_3}^{a_4}\left(\frac{a_4-x}{a_4-a_3}\right).dx}$$
$$\left. = \frac{-a_1a_2 + -a_3a_{4+}\frac{1}{3}(a_4-a_3)^2 - \frac{1}{3}(a_2-a_1)^2}{-a_1 - a_2 + a_3 + a_4} \right) \tag{10}$$

The final stage is to transform fuzzy possibility (FPs) of root nodes and safety barrier into failure probability (FPr). As demonstrated by Onisawa (1988), CoA output is based on possibility rather than probability. Therefore, it should be modified to probability at this point. The Onisawa equation is utilized to determine the FPr of basic events based on their CFP values (Yazdi and Zarei, 2018). "FPr" stands for fuzzy failure probabilities, "FPs" for fuzzy failure possibilities, and "K" is a constant coefficient in this equation.

$$FPr = \frac{1}{10^K} \; if \; FPs \neq 0$$
$$FPr = 0 \; if \; FPs = 0 \tag{11}$$
$$K = \left(\frac{1-FPs}{FPs}\right)^{\frac{1}{3}} \times 2,301$$

The derived fuzzy probabilities are then assigned as failure probabilities of basic events and safety barriers in the Bow-Tie model shown in Fig. 3.

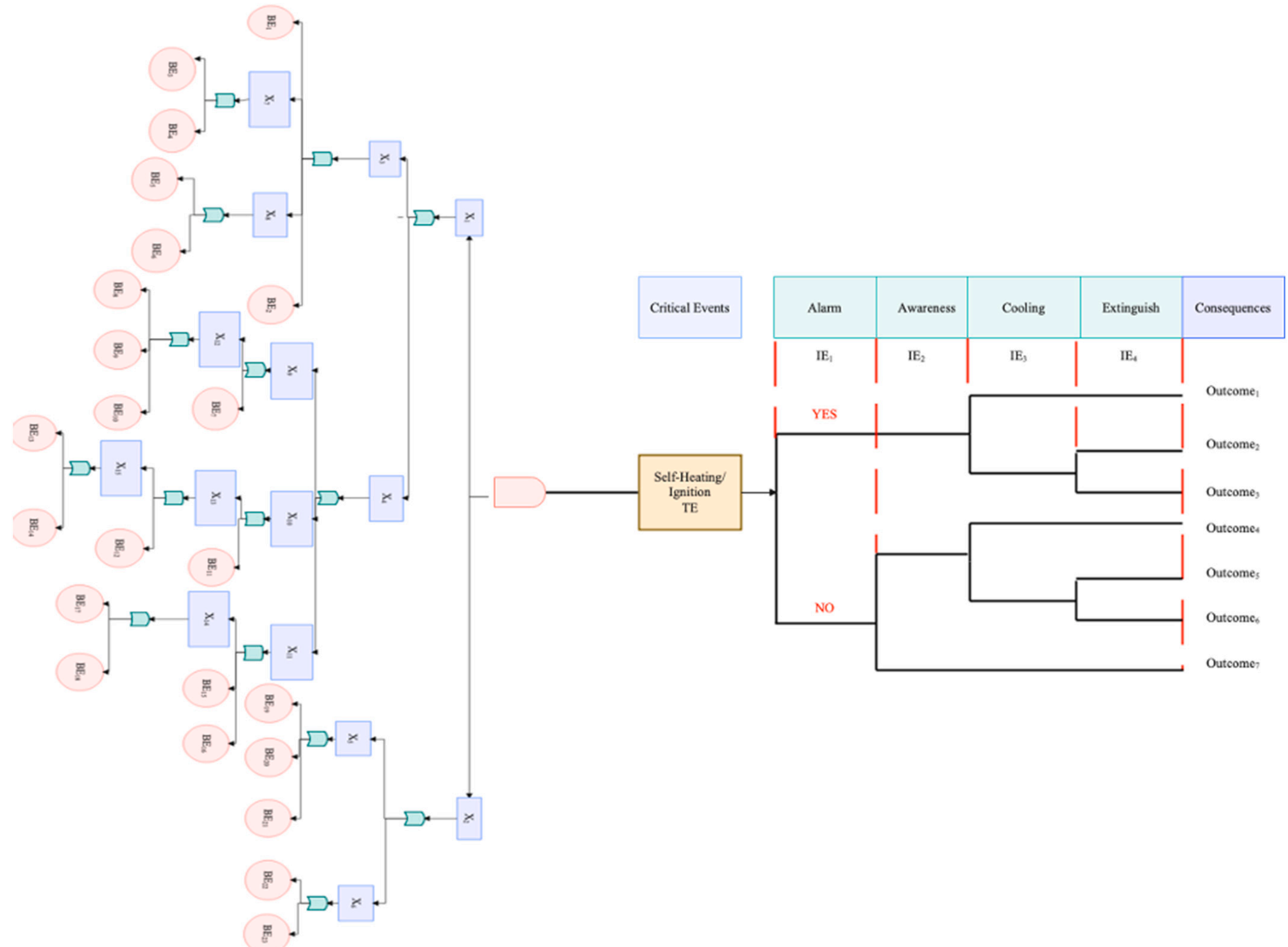

Fig. 3. Bow-tie model.

3. Risk analysis of coal transportation

Coal is a potentially dangerous commodity, and serious incidents continue to arise. In some cases, it appears that those on board were not completely aware of the risks, and on other occasions the coal was not transported in line with the regulations. This chapter focuses on fuzzy bow-tie analysis in the risk assessment of coal cargo in maritime transportation. We used EDRAWMax-Wondershare software to create the visual representations of the methodologies in Figs. 3 and 4.

3.1. Hazards identification of coal transportation

The igniting of coal because of self-heating was defined as the top event (TE) in this study which can endanger a seafarer, the environment, and the ship. This phase comprises an analysis of the relevant literature to determine the variables that contribute to the coal cargo igniting because of self-heating during shipping, as well as an examination of accident reports that can determine potential dangers in the shipping industry. The variables in the reports and literature were then evaluated by using The Det Norske Veritas - Marine Systematic Cause Analysis Technique and updated following the completion of expert interviews. Semi-structured online and face-to-face interviews with six maritime specialists were undertaken to do this, and the resulted in the determination of 23 basic events.

3.2. Construction of FTA

Following the completion of the recognizing for the TE and establishing the basic events, the FT can then be constructed. The FT employs a network of logic gates to depict the sequence of events that produces the TE. Prior to conducting interviews with experts to create FT diagram, the important implementation strategies for the fault tree technique were thoroughly discussed with them. Firstly, an "AND" gate was used to break down the top event, Self-Heating, into two intermediate events, " not comply with IMSBC Code " and " characteristic of coal". After that they were resolved by experts into events that could have triggered them which are presented in Fig. 4. The OR gate was used to establish a link between the remaining intermediate causes and basic events. According to the conducted fault tree, there are four highlighted intermediate events for self-heating, including (1) before loading failure; (2) during loading and transportation failure; (3) geographical location of the type of coal and (4) moisture content. The priority measure is a very helpful tool for ranking risk factors and offering insightful data to increase reliability. The produced FT diagram for coal transportation is depicted in Fig. 4.

The importance measure is a highly beneficial tool for prioritizing risk components and offering significant insights for enhancing reliability. The FT diagram and FV-Importance measure were developed with the assistance of marine specialists listed in Table 1.

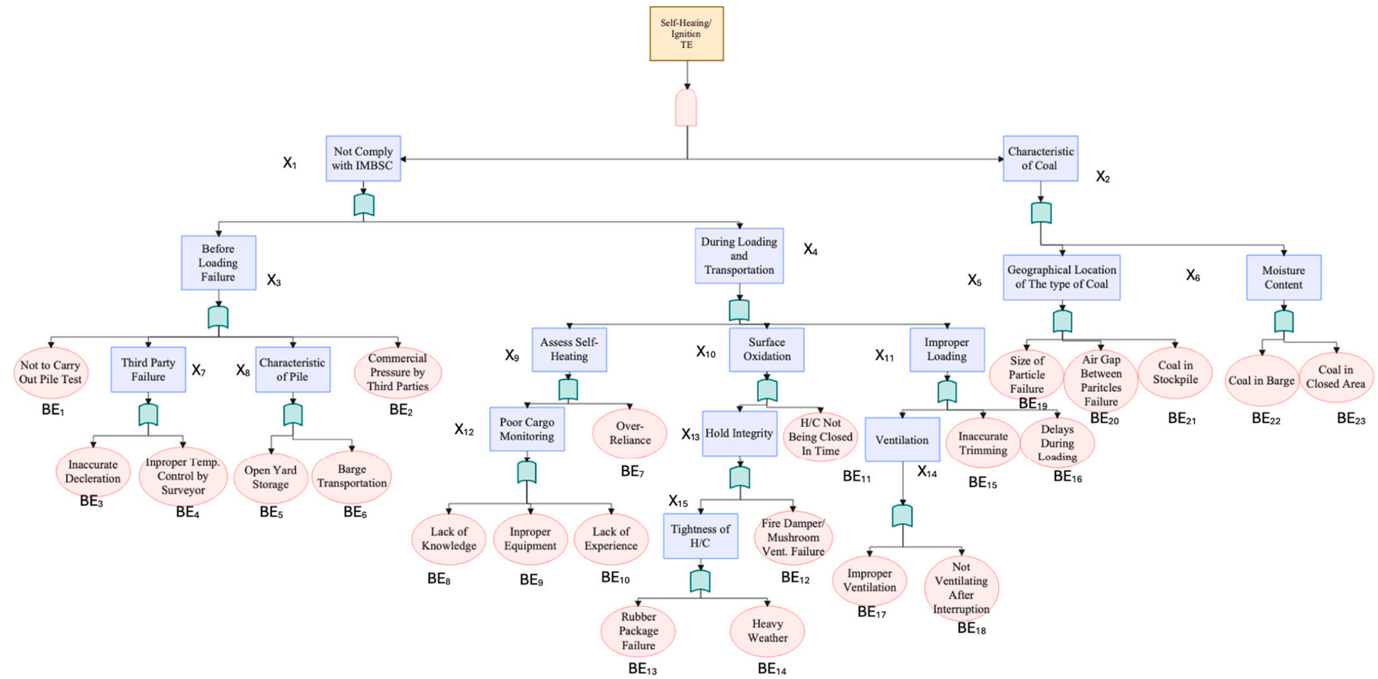

Fig. 4. FT diagram.

3.2.1. *Basic event probabilities estimation*

A significant issue in the risk analysis of marine coal cargo transportation is insufficient data and uncertainty in the risk assessment process. Therefore, this study consulted six experts, who are listed in Table 2, to calculate the likelihood of basic events.

To assess the failure probability of basic events in terms of linguistic terms, six specialists from relevant areas of the marine dry bulk transportation were selected. The expert-selected procedure considers the profession, level of education, and sea/shore service time to describe the situation objectively (Arici et al., 2020), shown in Table 3.

They assessed the failure probability of each root event using language phrases shown in Table 3. The choice of 7 variables is based on the argument that the capacity of the human brain for short-term storage is 7 ± 2 pieces, or because humans can make between 5 and 9 evaluations at once (Huang et al., 2001). Linguistic variables translated to fuzzy numbers using the numerical approximation method of Chen and Hwang (1992). Table 4 provides a thorough explanation of the linguistic words and appropriate membership numbers.

They provided a verbal description of the possibility for each BE in question. Each expert contributed insights, which were incorporated into the research to varying degrees based on the profiles of the experts. By dividing each expert's overall score by the total score of all experts, the relative proportion of each expert is determined. Their ratings are shown in Table 5.

The SAM method, which is explained in more detail in Section 3 by eqs. (5)–(11), is applied to aggregate the opinions of various experts. Analysis of the BEs' significance is a crucial component of the quantitative FTA. Table 6 shows the results in detail regarding FPs, FPr, aggregation and expert's expression for all basic events.

Using “improper equipment failure” as an illustration shown in Table 7, the VL, VL, ML, VL, L, and ML linguistic elicitations of the experts converted the associated fuzzy numbers.

Using an eq. (9), the similarity score per each pair of experts was calculated followed by obtaining average of agreement, relative agreement, and consensus coefficient. β (Relaxation factor) was adjusted to 0.5 because in this computation all experts are treated equally. Regarding the expert weights, the aggregated result in the trapezoidal fuzzy set was (0.0809, 0.1309, 0.2118, 0.3118). Following aggregation, center-of-area (COA) defuzzification method described by eq. (10) was used to get FPs, which is found 0.456. In the end, FPr of E_1 improper equipment failure obtained by eq. (11).

3.2.2. *Calculation of probabilities of Minimal Cut Set (MCS) and Top Event (TE)*

After finding the probabilities of the basic events, the next step is to calculate the likelihood of TE, the initial event of ETA. Eq. 2 was used to calculate a value for TE, and the result was 2.31E-02. After that, the significance of each MCS in the fault tree was evaluated using Eq. 10. This stage tries to prioritize various vulnerabilities by assessing the probability of each MC to assist decision makers in proposing the most appropriate countermeasure, where the MCS with the highest probability should be addressed first (Abdo et al. 2018). Table 8 displays both the results of the sensitivity analysis and the probabilities for each MCS.

3.3. *Construction of ETA and computing the probabilities for the identified outcomes*

The most significant risk during maritime transport of coal is self-heating and its consequences are serious. If it ignites, it will create a massive fire and explosion that will results in loss of life and property. The event tree diagram, once the IE has been defined as self-heating, illustrates all potential outcomes (OE) from the originating event. Additionally, ETA includes existing barriers (PE) to prevent unfavorable outcomes that may result from coal heating. In this stage, the same expert group responsible for the FTA analysis was tasked with identifying all PEs and their probabilities and their outcomes (OE). After reaching consensus, four safety barriers with seven outcomes were established, and an event tree was subsequently created. Table 9 contains a complete description of the outcomes.

The likelihood of intermediate occurrences failing must be established before the probabilities of outcomes can be calculated. The fuzzy probability of the IE was defined using the same methodology that we used to define the fuzzy probability of the Basic events. The discovered IEs and corresponding probability are listed in Table 10. After that, the probability of each possible consequence resulting from self-heating are calculated. Results and ranks for outcomes are shown in Table 10.

Table 1
FTA Gates and Fussell Vessely Importance Factor.

	FTA gates	Event nomenclature	Event name	Fussell Vessely-Importance Factor
1	Top Event	TE	Self – Heating & Ignition	1,00E+00
2	Intermediate $Event_1$	X_1	Not Comply with IMSBC Code	1,00E+00
3	Intermediate $Event_2$	X_2	Characteristic of Coal	1,00E+00
4	Intermediate $Event_3$	X_3	Before Loading Failure	3,16E-01
5	Intermediate $Event_4$	X_4	During Loading and Transportation Failure	6,84E-01
6	Intermediate $Event_5$	X_5	Geographical Location of The Type of Coal	6,06E-01
7	Intermediate $Event_6$	X_6	Moisture Content	3,94E-01
8	Intermediate $Event_7$	X_7	Third Party Failure	2,95E-01
9	Intermediate $Event_8$	X_8	Characteristic of Pile	2,95E-01
10	Intermediate $Event_9$	X_9	Assess Self – Heating	2,72E-01
11	Intermediate $Event_{10}$	X_{10}	Surface Oxidation	3,13E-01
12	Intermediate $Event_{11}$	X_{11}	Improper Loading	4,15E-01
13	Intermediate $Event_{12}$	X_{12}	Poor Cargo Monitoring	5,45E-01
14	Intermediate $Event_{13}$	X_{13}	Hold Integrity	7,09E-01
15	Intermediate $Event_{14}$	X_{14}	Ventilation	8,26E-01
16	Intermediate $Event_{15}$	X_{15}	Tightness of Hatch Cover	9,45E-01
17	Basic $Event_1$	BE_1	Not to Carry Out Can Test	2,60E-03
18	Basic $Event_2$	BE_2	Commercial Pressure by Third Parties	4,08E-01
19	Basic $Event_3$	BE_3	Inaccurate Declaration	8,19E-01
20	Basic $Event_4$	BE_4	Improper Temperature Control by Surveyor	1,81E-01
21	Basic $Event_5$	BE_5	Open Yard Storage	5,02E-01
22	Basic $Event_6$	BE_6	Barge Storage	4,99E-01
23	Basic $Event_7$	BE_7	Overreliance	4,55E-01
24	Basic $Event_8$	BE_8	Lack of Knowledge	2,37E-01
25	Basic $Event_9$	BE_9	Improper Equipment	1,66E-01
26	Basic $Event_{10}$	BE_{10}	Lack of Experience	5,97E-01
27	Basic $Event_{11}$	BE_{11}	Hatch covers not being closed in Time	2,91E-01
28	Basic $Event_{12}$	BE_{12}	Fire Damper/ Mushroom Ventilation Failure	5,47E-02
29	Basic $Event_{13}$	BE_{13}	Rubber Package Failure	5,15E-01
30	Basic $Event_{14}$	BE_{14}	Heavy Weather	4,86E-01
31	Basic $Event_{15}$	BE_{15}	Inaccurate Trimming	1,10E-02
32	Basic $Event_{16}$	BE_{16}	Delays During Loading	1,63E-01
33	Basic $Event_{17}$	BE_{17}	Improper Ventilation	6,79E-01
34	Basic $Event_{18}$	BE_{18}	Not Ventilating After Interruption	3,21E-01
35	Basic $Event_{19}$	BE_{19}	Size of Particle Failure	3,77E-01
36	Basic $Event_{20}$	BE_{20}	Air Gap Between Particles Failure	6,23E-01
37	Basic $Event_{21}$	BE_{21}	Coal in Stockpile	7,00E-01
38	Basic $Event_{22}$	BE_{22}	Coal in Barge	2,33E-01
39	Basic $Event_{23}$	BE_{23}	Coal in Closed Area	6,68E-02

Table 2
Experts description.

Experts	Occupation/current activity	Experience in industry
$Expert_1$	DPA & Operation Manager	Since 2018, he has been the DPA & Operations Manager at a shipping company. Prior to that, he served as master on board for almost seven years and as superintendent for around three.
$Expert_2$	Superintendent	After eight years as a master on board, he was promoted to superintendent in a shipping company in 2018. He is trained and certified in hazard identification and analysis.
$Expert_3$	Superintendent	He has been a master on board for over 10 years and has served as superintendent for 3.
$Expert_4$	DPA & Operation Manager	He has been working as a master on board for >15 years and he worked as DPA & Operation Manager in the past for 16 years.
$Expert_5$	Academician	After a lengthy career aboard dry cargo ships, he is now an associate professor at the institution. He works on risk assessment.
$Expert_6$	P&I Surveyor in the Lawyers & Consultants company	He has been working as a P&I surveyor since 2006 and he was master on board. Specifically, he handles cases involving bulk cargo transit, such as coal.

Table 3
Experts' profiles and decision weights.

Variable	Classification	Score
Title	Academician	5
	Operation Manager / DPA	4
	Superintendent	3
	Oceangoing Master	2
	Oceangoing Chief Officer	1
Sea Service	$\geq$ 16 years	5
	11–15 years	4
	6–10 years	3
	3–5 years	2
	$\leq$ 2 years	1
Education	PHD	5
	Master	4
	Bachelor's degree	3
	Academy	2
	High School	1
	$\geq$ 26 years	5
Shore Service Time	16–25 years	4
	11–15 years	3
	6–10 years	2
	$\leq$ 5 years	1

Table 4
Linguistic variables and fuzzy numbers.

Linguistic terms	Fuzzy numbers
Very Low (VL)	(0, 0, 0.1, 0.2)
Low (L)	(0.1, 0.2, 0.2, 0.3)
Little Low (LL)	(0.2, 0.3, 0.4, 0.5)
Medium (M)	(0.4, 0.5, 0.5, 0.6)
Little High (LH)	(0.5, 0.6, 0.7, 0.8)
High (H)	(0.7, 0.8, 0.8, 0.9)
Very High (VH)	(0.8, 0.9, 1.0, 1.0)

4. Findings and discussion

The research methodology in this study is applied to analyze the risk of coal self-heating during marine transportation. When carrying out the bow-tie analysis, consideration was given to expert opinion. Firstly, a fuzzy fault tree (FFTA) was created to analyze what causes coal to self-

Table 5
Weighting score of non-homogenous expert.

Experts	Weighting factor				Total weight	Weighting score
E_1	4	5	3	2	14	14/80 = 0.175
E_2	3	4	3	1	11	11/80 = 0.138
E_3	3	4	3	1	11	11/80 = 0.138
E_4	4	5	1	4	14	14/80 = 0.175
E_5	5	4	5	3	17	17/80 = 0.213
E_6	4	3	3	3	13	13/80 = 0.163

heating and ignition. According to the FFTA, the probability of self-heating/ignition (TE) is calculated as 2.31E-02. This ratio represents approximately three out of every one hundred coal ship handlings, and there is a possibility of coal spontaneously heating. To limit the risks associated with self-heating of coal, it is crucial to assess each basic event on the fault tree diagram. As for the important basic events, the results showed in Table 1 unequivocally demonstrate that the BE3, BE21, BE17, BE20, and BE10 are the primary contributors to the top event. On the other hand, it was discovered that the greatest priority value for the MCS of "Improper ventilation" and "air gap between particulars" MCS 82 (B17&B20) was estimated as 1,63E-03, which is sufficient for the occurrence of the top event. Since there is a significant air gap between the coal particles, this will raise oxygen levels and result in heating, which is a highly anticipated outcome. MCS7 (BE2-BE20), MCS83 (BE17-BE21), MCS81 (BE17-BE19), MCS8 (BE2-BE21), and MCS32 (BE7-BE21) are further minimal cut sets accountable for the top event. Table 8 shows that the following nine most recent MCSs are obtained. It is noteworthy that BE 20 appears in six of the 10 most important MCSs.

According to the study, BE3 (inaccurate declaration) has a probability of 8,19E-01and has the biggest influence on the top event. This is not unexpected considering some shippers do not classify their goods as susceptible to self-heating or methane production, despite previous incidences with these issues originating from the same source due to commercial issues. To resolve this issue, before loading, the master must visually inspect the cargo and confirm that it fits the description on the shipper's declaration.

Additionally, BE_{21} (coal in open stockpile), which has a probability of 7.00E-01, is the second important element that has an impact on the likelihood of the top event. The risk of self-heating increases for coal stored in open spaces due to moisture build-up, which can assist oxidation process. For this reason, covering the coal with tarpaulin lessens the impact of precipitation and humidity, restricts air movement, and decreases the risk of the coal self-heating.

The B_{17}-B_{21} MCS combination, which had the greatest effect on the peak event, was revealed to be the third and fourth most significant component when assessed separately. Regarding ventilation, only natural surface ventilation is authorized, restricted to the bare minimum period required to eliminate any stored methane. The entrance of air

Table 7
Aggregation calculation for the basic event "BE_9-Improper Equipment Failure".

S (E12)	1	S (E26)	0.725	AA (E1)	0.865	AA (E4)	0.865
S (E13)	0.725	S (E34)	0.725	AA (E2)	0.865	AA (E5)	0.865
S (E14)	1	S (E35)	0.85	AA (E3)	0.805	AA (E6)	0.805
S (E15)	0.875	S (E36)	1				
S (E16)	0.725	S (E45)	0.875	CC (E1)	0.173	CC (E4)	0.173
S (E23)	0.725	S (E46)	0.725	CC (E2)	0.154	CC (E5)	0.192
S (E24)	1	S (E56)	0.85	CC (E3)	0.148	CC (E6)	0.161
S (E25)	0.875						
Weight of expert 1	0.175			RA (E1)	0.171	RA (E4)	0.171
Weight of expert 2	0.138			RA (E2)	0.171	RA (E5)	0.171
Weight of expert 3	0.138			RA (E3)	0.159	RA (E6)	0.159
Weight of expert 4	0.175						
Weight of expert 5	0.213						
Weight of expert 6	0.163						
$\widetilde{R}_{AG}$Aggregation	0.0809			0.1309	0.2118		0.3118
Defuzzification (COA) occurrence likelihood of improper equipment is 0.456.							

Table 8
Top ten Minimal Cut Set (MCS) combination.

	Minimal cut set combination	Basic events	Probability values
1	MCS_{82}	BE_{17}*BE_{20}	1,63E-03
2	MCS_7	BE_2*BE_{20}	1,27E-03
3	MCS_{83}	BE_{17}*BE_{21}	1,19E-03
4	MCS_{81}	BE_{17}*BE_{19}	9,88E-04
5	MCS_8	BE_2*BE_{21}	9,18E-04
6	MCS_{32}	BE_7*BE_{20}	8,59E-04
7	MCS_{87}	BE_{18}*BE_{20}	7,74E-04
8	MCS_6	BE_2*BE_{19}	7,64E-04
9	MCS_{62}	BE_{13}*BE_{20}	7,56E-04
10	MCS_{12}	BE_3*BE_{20}	7,50E-04

Table 6
Expert judgments and their probabilities for basic event.

Events code	Expert judgment						Aggregated fuzzy numbers				K	FPs	FPr
	1	2	3	4	5	6							
BE_1	VL	VL	ML	VL	L	ML	0.081	0.131	0.212	0.312	3.765	0.18586	0.00017
BE_2	MH	H	H	H	VH	M	0.638	0.738	0.774	0.855	1.574	0.75757	0.02668
BE_3	M	H	H	MH	H	M	0.567	0.667	0.685	0.785	1.801	0.67586	0.01581
BE_4	MH	L	MH	L	ML	MH	0.317	0.417	0.485	0.585	2.456	0.45119	0.00350
BE_5	H	M	M	MH	M	MH	0.482	0.582	0.616	0.716	2.012	0.59924	0.00972
BE_6	MH	M	M	MH	M	H	0.481	0.581	0.616	0.716	2.015	0.59830	0.00966
BE_7	MH	MH	H	H	MH	MH	0.563	0.663	0.732	0.832	1.742	0.69735	0.01811
BE_8	ML	M	ML	MH	M	MH	0.369	0.469	0.534	0.634	2.295	0.50188	0.00507
BE_9	M	M	L	ML	M	MH	0.340	0.440	0.473	0.573	2.440	0.45618	0.00363
BE_{10}	MH	MH	H	H	M	M	0.529	0.629	0.662	0.762	1.885	0.64531	0.01304
BE_{11}	MH	M	H	M	MH	H	0.531	0.631	0.667	0.767	1.875	0.64906	0.01335
BE_{12}	ML	M	ML	ML	L	M	0.244	0.344	0.395	0.495	2.749	0.36964	0.00178
BE_{13}	H	MH	MH	M	MH	H	0.550	0.650	0.701	0.801	1.797	0.67719	0.01594
BE_{14}	H	ML	M	H	H	MH	0.553	0.653	0.683	0.783	1.823	0.66798	0.01504
BE_{15}	VL	ML	M	VL	L	M	0.175	0.241	0.291	0.391	3.172	0.27631	0.00067
BE_{16}	M	M	MH	M	H	MH	0.486	0.586	0.618	0.718	2.004	0.60205	0.00990
BE_{17}	H	MH	VH	H	H	H	0.686	0.786	0.815	0.900	1.463	0.79569	0.03447
BE_{18}	MH	M	MH	MH	H	H	0.556	0.656	0.706	0.806	1.787	0.68089	0.01632
BE_{19}	H	MH	H	H	MH	VH	0.648	0.748	0.798	0.882	1.543	0.76838	0.02865
BE_{20}	VH	H	H	VH	H	H	0.734	0.834	0.867	0.934	1.324	0.83997	0.04742
BE_{21}	VH	H	MH	MH	VH	H	0.672	0.772	0.840	0.904	1.464	0.79534	0.03439
BE_{22}	MH	M	MH	H	MH	M	0.501	0.601	0.653	0.753	1.941	0.62474	0.01144
BE_{23}	ML	M	M	ML	ML	MH	0.308	0.408	0.477	0.577	2.485	0.44267	0.00328

Table 9
Expert judgments and their probabilities for pivotal events.

Safety barrier	Expert judgment						Aggregated fuzzy numbers				K	FPs	FPr
	1	2	3	4	5	6							
Alarm work	VL	ML	L	L	VL	L	0,079	0,143	0,193	0,293	3825	0,179	0,00015
Awareness	ML	M	L	ML	M	M	0,288	0,388	0,423	0,523	2614	0,405	0,00243
Cooling	MH	MH	M	ML	M	ML	0,366	0,466	0,531	0,631	2307	0,498	0,00493
Extinguished	VH	H	MH	MH	H	MH	0,618	0,718	0,783	0,867	1608	0,746	0,02469

Table 10
Ranking of possible outcomes.

Outcome	Definition	Occurrences probability scores	Ranking
1	Near miss	2,30E-02	1
2	Minor accident (damaged to cargo)	1,14E-04	2
3	Major accident (Total loss& pollution)	2,82E-06	4
4	Near miss	3,44E-06	3
5	Minor accident (damaged to cargo)	4,21E-10	6
6	Major accident (total loss& pollution)	4,21E-10	6
7	Major accident (total loss & loss of life & pollution)	8,41E-09	5

into the body of the cargo may increase self-heating, hence any vents leading below the level of the cargo should be covered. Using bulldozers or loaders to reduce the air gap between the coal particles is a significant method for preventing self-heating.

The BE_{10} (Occurrence probability: 5.97E-01), lack of experience, was discovered as an additional major factor leading to self-heating. Coal self-heating assessment demands extensive experience in terms of cargo monitoring. Here, it's important to note that experience comes in much ahead of knowledge in terms of importance. This situation demonstrates that practical experience must be added to theoretical information to estimate the heating risks of coal.

On the ETA side of Bow-Tie analysis, Table 9 displays the relative relevance of the outcomes and barriers that will result from spontaneous heating of the coal. The primary barrier with the greatest likelihood of failure is the "failure of extinguishing (PB4) =0.024686" as anticipated. Therefore, the ship's fire suppression systems should always be operational. In addition, the personnel's knowledge, and abilities to extinguish coal fires are crucial for mitigating undesirable consequences. Because of heating the coal, it has been determined that the application of cooling to the heated portion, which is the most significant stage in preventing fire development, is the second most critical barrier. They are followed by "failure of awareness" and "failure of gas detector" respectively.

Regarding outcomes classification, as stated in Table 10, outputs 1 indicating a near miss is the most probable consequence of coal heating. It occurs when all safety barriers are operationally effective. The second event with a high probability because of the fire intervention caused by the coal's temperature exceeding the cooling barrier is cargo damage showing with outcome 2. Third possible consequence is outcome 4, which occurs when the alarm system fails and other barriers come into play, resulting in a near miss. The analysis' results indicate that fire and explosion should be avoided if spontaneous heating happens in the coal and the appropriate safety measures are not followed.

5. Conclusion

Determining the risks that will come from the self-heating of coal during sea transport and the existing safety barriers because of this circumstance is crucial. In this study, a Bow tie strategy for identifying, assessing, and mitigating key risk variables in coal handling is provided. Bow tie analysis has recently been one of the common methods used for risk assessment. It combines two recognized methods for quantitative risk assessment, namely FTA and ETA, and it offers a clear view beginning with the root causes and ending with the final implications of accident scenarios. Integrating expert judgment and a fuzzy based method into bow tie analysis allows for the elimination of uncertainty regarding the input data in the model. FTA part was organized as a fault tree depicting the primary reasons of self-heating at the top, intermediate, and basic levels. With the use of expert judgments and linguistic variables under the fuzzy logic, the probabilities of the basic event occurrences were determined. The fuzzy event tree section of the model simulates the potential outcomes that might emerge from heating the coal and the steps taken to reduce their impact.

The methodology encourages collaboration amongst maritime stakeholders, such as port authorities, shipping companies, and cargo handlers, to collectively assess and manage risks. The following conclusions are reached based on the research's findings:

- Adaptation of Fuzzy Bow-Tie Analysis: We have tailored the fuzzy bow-tie analysis to specifically address the unique risks associated with coal self-heating during maritime transportation. This adaptation allows for a more accurate representation and analysis of the complex interactions and uncertainties inherent in maritime risk environments.
- Integration of Expert Judgment: Recognizing the challenges of limited empirical data in maritime risk scenarios, our study innovatively incorporates expert judgments within the fuzzy logic framework. This approach enhances the robustness and relevance of our risk assessments, providing a nuanced understanding of risk factors that are often not captured by traditional data sources.
- Proposal of Dynamic Simulation Techniques: To further improve the predictive power and adaptability of our risk assessment models, we propose the integration of dynamic simulation techniques, such as Bayesian networks. This advancement will allow for real-time updating and more accurate forecasting of risk scenarios, supporting proactive risk management in maritime operations.

The fuzzy bow-tie methodology, while robust in static analysis, lacks the capability to dynamically simulate the evolving interactions between root causes and their outcomes in real-time. To address this gap, future research could harness dynamic modeling techniques such as Bayesian networks and system dynamics models. These advanced methodologies are well-suited for capturing the continuous changes in risk factors and their interactions within the maritime environment. Incorporating Bayesian networks would allow for more precise quantification of uncertainties and enable real-time updates to risk assessments as new data emerges. System dynamics models could simulate feedback loops and the effects of time-dependent changes, enriching long-term strategic planning and operational decision-making. Furthermore, integrating real-time monitoring data from IoT devices and leveraging big data analytics could transform the fuzzy bow-tie approach into a proactive tool, creating early warning systems that enhance the responsiveness of maritime risk management practices. This holistic approach promises not only to refine existing models but also to significantly advance predictive capabilities, thereby fostering a more adaptive and informed risk management framework in maritime operations.

The applicability of the fuzzy bow-tie methodology can be explored in other maritime risk scenarios beyond ship-to-ship cargo transfers, such as port operations, ship-to-shore interfaces, and vessel traffic management. Adapting and validating the model for these diverse contexts can further demonstrate its versatility and value for the maritime industry. Shipping companies can enhance their safety protocols through better ventilation practices, accurate cargo declarations, and comprehensive crew training on the risks of coal self-heating. Port authorities can strengthen inspection regimes and leverage real-time monitoring technologies to mitigate risks associated with coal combustion. The use of dynamic risk assessment models offers both stakeholders a proactive tool for addressing uncertainties and adapting safety procedures as risks evolve. By integrating these practices, stakeholders can significantly reduce the potential for maritime accidents and environmental pollution, promoting safer and more sustainable coal transportation operations.

This study not only offers valuable insights for maritime stakeholders to mitigate these risks but also lays the groundwork for future research to refine risk analysis techniques in the maritime industry. Future research could focus on integrating dynamic modeling techniques, such as Bayesian networks, with the Fuzzy Bow-Tie methodology to further enhance the precision of risk assessments. Additionally, studies could explore the application of this methodology to other types of cargo that pose similar risks in maritime transportation.

CRediT authorship contribution statement

Barış Temel: Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Cenk Sakar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation. **Muge Buber:** Writing – review & editing, Writing – original draft, Supervision, Software, Resources, Methodology, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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