A Bayesian approach to risk modeling of autonomous subsea intervention operations

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Abstract

The introduction of autonomy in subsea operations may affect operational risk related to inspection, maintenance, and repair (IMR). This article proposes a Bayesian Belief Network (BBN) to model the risk affecting autonomous subsea IMR operations. The proposed BBN risk model can be used to calculate the probability of aborting an autonomous subsea IMR operation. The nodes of the BBN are structured using three main categories, namely technical, organizational, and operational. The BBN is tested for five unique scenarios using a scenario generation methodology for the operational phase of the autonomous IMR operation. The BBN is quantified by conducting a workshop involving industry experts. The results from the proposed model may provide a useful aid to human supervisors in their decision-making processes. The model is verified for five scenarios, but it is capable of incorporating and calculating risk for other combinations of scenarios.

Keywords: Bayesian Belief Network; decision-support; risk; subsea IMR; autonomy

1. Introduction

Globally, the number of subsea oil and gas installations are increasing leading to the adoption of new subsea intervention technologies. In the subsea oil and gas industry, inspection, maintenance, and repair (IMR) of subsea production systems (SPS) is key to maintaining production uptime. However, maintaining the SPS is challenging due to the risks involved in performing subsea IMR operations. Water depth, weather disruptions, job complexity, job uncertainty, and IMR equipment availability, for example, may affect subsea IMR operational performance [1–3]. Rough weather conditions can disrupt intervention schedules resulting in an increased operational cost. On the other hand, concepts, such as subsea factories, are envisioned by the oil and gas industry to maximize recovery, minimize costs, and accelerate production [4]. Studies to support the claims set forth for the development of subsea factories are currently limited; in that, the scope of autonomous IMR operations for subsea factories are not investigated. New SPS technologies, such as subsea compressors, storage, and garages, increase the need for safe, reliable, and efficient IMR systems in the years to come.

One of the proposed alternatives to achieving safe and cost efficient IMR activities is to introduce autonomous functionality into the SPS and related IMR systems [5,6]. Currently, autonomous IMR systems are still in the conceptual or testing stages of development. A number of research projects have or are currently investigating development and implementation of autonomous functionalities and shared control in underwater vehicles [7–17]. As observed in the literature, the underwater vehicle development trend is to merge abilities of human controlled Remotely Operated Vehicles (ROVs) and Autonomous Underwater Vehicles (AUVs). These future underwater vehicles can be termed *Autonomous Remotely Operated Vehicle (AROV).* Future *AROVs* can be defined as underwater vehicles, which are able to function autonomously, reside in designated subsea docking areas, independently control manipulator functions, permit shared-control between the vehicle and the human supervisor, navigate autonomously, perform self-diagnostics, and are equipped with automatic Remotely Operated Tools (ROT) systems requiring limited operator control [18].

In general, Bayesian approaches are widely used to support decisions in the presence of uncertain input parameters. Related to the offshore oil and gas industry, Sklet et al. [19], for example, propose the barrier and operational risk analysis method (BORA) focused on hydrocarbon releases, using risk influence diagrams. A further development of the BORA method is the operational technical safety (OTS) project [20], followed by the Risk OMT (risk modelling - integration of organizational, human and technical nodes) project, which proposes quantitative modelling of organizational, human, and technical risk influencing factors (RIFs) using a Bayesian approach [21,22]. The resulting Bayesian believe network (BBN) model captures the relationships between different RIFs, emphasizing the prevention of hydrocarbon leaks. Yang et al. [23] develop a Bayesian network to model subsea pipeline failures due to corrosion.to corrosion. Cai et al. [24] propose a Bayesian network to evaluate the reliability of subsea blowout preventer control system.

Currently, limited research has been performed on identifying, analyzing, modeling risk and interrelationships between various hazards affecting autonomous subsea IMR operations. So far, most of the research works focus on mission success for AUVs. Since AROVs shall adopt certain autonomous capabilities, findings from past research on risk related to AUV operations need to be considered. Griffiths and Brito [25] investigate the use of BBN to estimate risk in missions under different sea ice conditions. Brito and Griffiths [26] extend the Bayesian approach to analyze the risk of loss of AUVs during missions. Vehicle type, ice concentration, thickness, environmental constraints, etc. are highlighted to contribute to loss of the AUVs. Expert elicitations are extensively used to quantify BBN models in both oil and gas and AUV applications [21,22,25,26]. The model proposed by Thieme and Utne [27] present a BBN to assess the probability of monitoring success for an AUV mission focusing on human supervisor's actions. Involvement of experts in the development process aids in verifying the BBN structure and quantifying the BBN model. Since BBNs are visualized, they can also aid in risk communication across various engineering disciplines. In addition, the results from operations can be used to update the parameters of the BBN model.

The objective of this article is to present a BBN model, which can provide decision-support to human supervisors during autonomous subsea IMR operations. Consider a decision scenario where an AROV incurs one or more technical failures and the visibility in the subsea environment is low during an IMR operation. What is the probability that the IMR operation needs to be aborted? Finding answers to questions like these are vital for achieving safe autonomous IMR operations, and are addressed in this article through the proposed BBN risk model. Thus, important factors affecting the failure of IMR operation can be identified and necessary risk reduction measures may be implemented. In addition to useful decision input to human operators and managers, such information can also be important for system developers. By developing a novel BBN focusing on autonomous IMR operations, this article aims to add to the body of knowledge in applying BBN modeling to subsea oil and gas applications.

The article is structured as follows: Section 2 describes the method used to develop the BBN model. The BBN development method is applied to an autonomous IMR operation in Section 3. Discussion and significance of the findings from BBN modeling are described in Section 4. Section 5 presents the conclusions of the study and scope for future work.

2. BBN modeling methodology

BBNs are directed acyclic graphs (DAG), which represent the causal dependency between a set of variables using directed links/arcs [28]. Each variable in the BBN consists of finite mutually exclusive states. Conditional probability tables (CPTs) are constructed to determine the probability of the state of "child" variable. The state of child variable is dependent on the occurrence of parent variables. Variables in BBNs can be discrete or continuous in nature. For more general information on BBN, see Jensen and Nielsen [28].

A node in BBN consists of variables with different states. Three basic requirements need to be considered to develop a BBN, 1) Nodes can be identified, 2) State of nodes can be represented by measurable variables, and 3) The target node and any other node in the network have known traceable direct/indirect relationships. A target node is a node for which the joint probability distribution is calculated. In this article, the nodes represent human, technical and organizational RIFs. According to Øien [29], a RIF can be defined *as an aspect of a system or activity that affects the risk level of this system/activity*.

Fig. 1 illustrates the eight steps involved in BBN model development used in this article. The steps highlighted are based on a generic approach for developing BBNs, see Jensen and Nielsen [28], Sigurdsson et al. [30] and Langseth and Luigi [31].

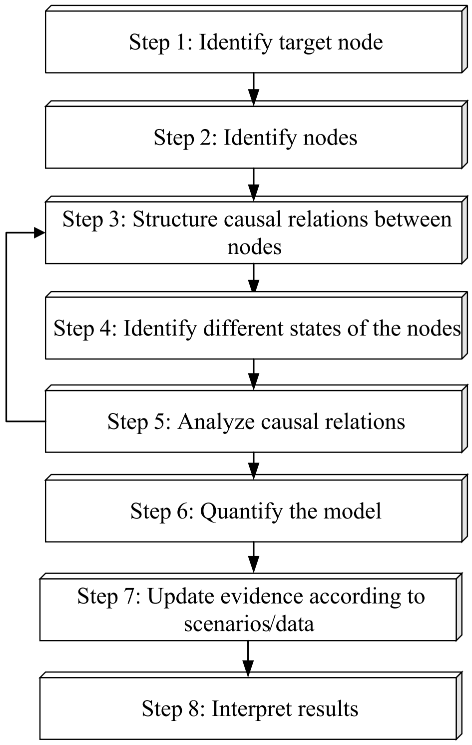

Fig. 1 Generic BBN modeling method used in the article

Step 1 – Identify target node

A target node is a node where the joint probability distribution is calculated in a BBN model. Identification of target node is, therefore, the first step in the BBN development process. This step allows defining the problem, which the BBN model will solve. It also highlights and determines the scope of the BBN.

Step 2 – Identify nodes

The identification of the nodes can be achieved by observing the real world application of the system under study and the potential hazards it is exposed to. This step may resemble the first step in risk analysis; Hazard Identification (HAZID). Empirical data may also be used, for example, extracted from accident investigation reports, see, e.g., Aktar and Utne [32] and Mazaheri et al. [33]. The boundary of the system under study must be established to avoid including nodes, which may not be significant in contributing to the target node. However, the assessor determines this boundary as applicable on a case-by-case basis. Experiences related to the system (literature), the modes of operation, and knowledge about the functions of the system can be used to identify relevant nodes.

Step 3 - Structure causal relations between nodes

The identified nodes from Step 2 are investigated for causal relationships with other nodes. Arcs represent the causal relationships; connecting a parent node to a child node. The outcome of this step is to ensure that the BBN model represents real-world causal relationships between the selected nodes. A complex BBN model can be clustered by use of methods, such as parent divorcing [28]. According to Martin et al. [34], a large-scale BBN can be constructed by a combination of idioms using simple rules or by object oriented BN approaches. Mazaheri et al. [33] and Aktar and Utne [32] also demonstrate that the causal relationships between the nodes can be structured from accident models and past accident investigation reports.

Step 4 - Identify different states of the nodes

The identified nodes can have different states, which have to be determined. One way of determining the states is to identify the best and the worst possible conditions for a given node. Intermediate states can be identified if necessary. The outcome of this step should provide a basis for constructing CPTs for different states at the child node. Nodes can be either deterministic or probabilistic in nature. Statistically, deterministic nodes have states, which have known relationships to an outcome. For example, spare parts available in a warehouse are known deterministic quantity. On the other hand, a probabilistic node consists both a deterministic quantity and a certain uncertainty in the form of random event influencing it. For example, the velocity of falling object has a deterministic parameter in the form of gravity constant and other uncertain random quantities in the form of wind direction, drag, etc. Therefore, a BBN may be constructed using a combination of deterministic and probabilistic nodes.

Step 5 - Analyze causal relations

During the construction of the BBN, causal relationships may be assumed between nodes. However, some of these relationships may not be observable in real-life conditions and are not quantifiable. In such cases, the BBN model needs to be updated by deleting corresponding arcs between the nodes, which render them independent of each other or d-separated. The BBN model should be reviewed to satisfy the d-separation theorem. D-separation occurs when two nodes of a BBN are inter-connected through or blocked by an intermediate node [28]. Identifying de-separated nodes is important because it supplements in structuring the nodes, which are independent of each other and doing so decreases the need to allocate additional CPTs. Once the review is completed, the structure of the BBN model will change, and it might be necessary to iterate from Step 3.

Step 6 - Quantify the model

The outcome of this step is to allocate CPTs for all identified nodes in the model. In large and complex BBNs, allotting CPTs can be a challenge when the node consists of many states and has many incoming causal arcs from its parents. Literature suggests to use techniques, such as parent divorcing [28], or organize the fragments of the BBN into objects [34]. However, if the BBN cannot be fragmented to smaller manageable units, there are proposed methods, such as fuzzy logic to decrease the number of required CPT elicitations [35,36] and expert judgment based CPT elicitations, as reviewed by Mkrtchyan et al. [37,38].

In this article, the method proposed by Røed et al. [39] is utilized to allocate CPTs in the BBN model. This method is preferred for the following reasons:

1) It provides a structured way to derive the CPTs thereby making it relatively less time consuming when compared to other CPT allocation methods involving experts.
2) It ensures that expert knowledge is incorporated during CPT assignments by defining the weights of the arcs and assessing closeness of the relationship between parent and child states.
3) The method can be setup using software tools and can handle a high degree of parent arcs and parent states.

When the assignment of CPTs is completed, the model output based on prior beliefs can be obtained by calculating the joint probability distribution. BBN software tools, such as GeNIe modeling environment developed by the Decision Systems Laboratory of the University of Pittsburgh can be used to develop the BBN model and calculate the joint probability distribution for the target node [40].

Step 7 - Update evidence according to scenarios/data

In this step, either existing data (known updated evidence) or a scenario generation (assumed updated evidence) approach can be used to update evidence of the states. If the new evidence on the state of a node is available, it is updated in the model to obtain the new joint probability distribution. An alternative approach is to generate scenarios in which the updated evidence for a given state of the node is predefined.

Step 8 - Interpret results

In this step, inferences can be made by assessing the resulting probabilities of the target node from Step 7. The effect of different states of the nodes of the target node can be observed. This step can support in examining the result from the model against current decision-making process.

3. BBN development for a case study of autonomous subsea IMR operations

In this section, the method presented in Section 2 is applied to an autonomous subsea IMR operation.

3.1 Identify target node – Step 1

3.1.1 Description of the autonomous IMR operation

Fig. 2 illustrates the AROV operation considered in this article. The autonomous IMR system consists of AROVs, which can perform inspection and maintenance missions. The AROVs (resident AROVs) reside in a subsea-garage, which houses charging pods for charging the AROVs battery. The AROVs do not require running of an umbilical cord or a tether from the subsea garage and rely on acoustic communications. A communication network is established from the subsea garage to either onshore or offshore facility with monitoring from human supervisors.

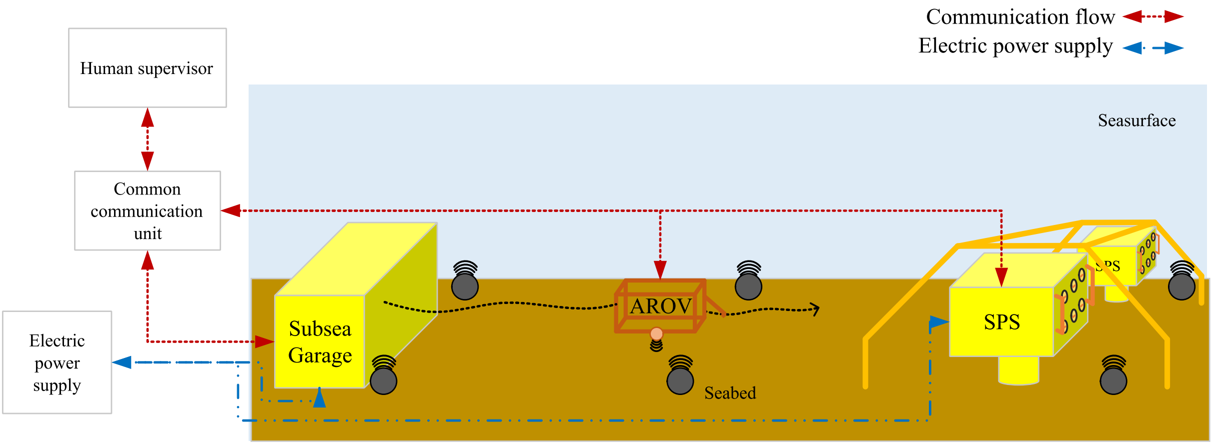

Fig. 2 Illustration of an AROV operation

The unified common communication network can communicate with the AROV, subsea garage, and the subsea control module (SCM) housed in the SPS. The AROVs use an acoustic based positioning system to determine their reference positions in a reliable manner. The AROVs interact with the subsea-garage, subsea environment, and the SPS. A human supervisor monitors the operation but may intervene during contingency situations using a shared control architecture [17]. Either the AROVs can be summoned on a mission by the human supervisor when required, or when a failure alert from the SPS is communicated (on demand).

According to Clough [41], an autonomous system has four levels of autonomy, namely (i) remotely piloted, (ii) remotely operated, (iii) remotely supervised, and (iv) fully autonomous. The current traditional remotely operated vehicles can be categorized into autonomy levels (i) and (ii), while future

AROVs may have functionality in also levels (iii) and (iv). Considering the implementation of subsea compression in the Åsgard field and the adoption of electric actuators, the Åsgard field is the leading the all-subsea-vision of Subsea Factories [4]. Therefore, the Åsgard field is chosen as a case study in this article.

3.1.2 The scope of proposed BBN risk model

The decision process in autonomous IMR operations can be divided into two different phases, as illustrated in Fig. 3. In Fig. 3, the planning phase is the duration when the IMR operation is being planned for an intervention operation. In t_0, both the human supervisor and the AROV evaluate their conditions and compare with requirements of the upcoming intervention operation. In this phase, a simulation using historical data or latest available data can be used to calculate probability of aborting the operation.

However, the scope of this article is limited to the operational phase of IMR operations, as marked with blue shade in Fig. 3. The proposed BBN model shall assist the human supervisor to make decisions based on information about relevant factors influencing the IMR operation in the period t_1 to t_n.

The GeNIe software allows modeling the BBN with a time-step method. Each time-step refers to one static BBN. The advantage of this approach is that the resulting joint probability distribution of the target node can be derived as a continuous curve from t_1 to t_n. This is further explained in Section 3.9. Since the BBN network is developed in the GeNIe software tool, it is possible to customize the network for the chosen case. The AROV will also have its own decision support system during the operational phase, but is not the scope of the proposed BBN.

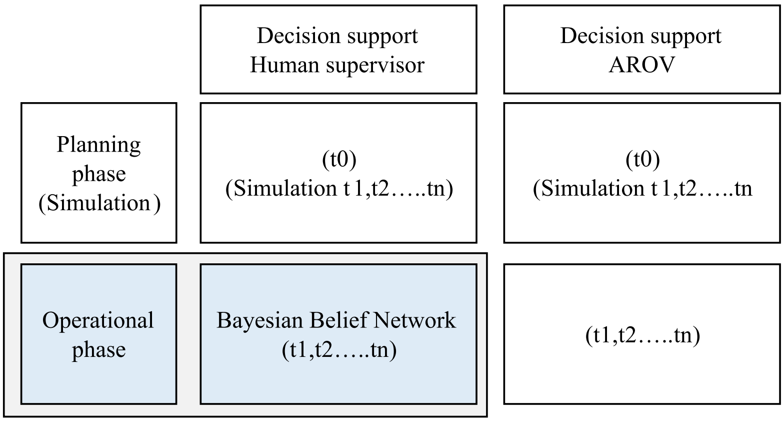

Fig. 3 Scope of the proposed BBN and article

Degradation or failure of the AROV system can lead to either loss of the vehicle or exposure to collision hazards with the SPS and other underwater vehicles [42]. Similarly, unfavorable conditions in the subsea environment and human supervisor's action can also affect the chances of aborting the operation. The decision support system should be capable of providing the human supervisor a probability estimate for aborting the IMR operation. In summary, the operational activities, AROV availability, and the subsea environment influence the overall probability of aborting the IMR operation. The target node for the proposed BBN is named as the *probability of aborting an autonomous IMR operation* and is illustrated in Fig. 5 and Fig. 7.

3.2 Identify nodes – Step 2

Two approaches are utilized to identify nodes affecting autonomous IMR operations. Firstly, identifying hazards and RIFs through studying the different modes of operation of an AROV and grouping nodes into categories. Grouping of nodes into categories of technical, organization and operational nodes promotes the structuring the BBN. Secondly, a review of existing literature on the topic of subsea IMR can highlight the hazards affecting current/traditional IMR operations, which may also apply to future autonomous IMR operations.

3.2.1 Modes of operation of AROVs

Modes of operation can be defined as the change in functionality or behavior of a system during the period of intended operations. For example, an automobile may have two modes of operation: an economic mode and a sports mode. A change in operating mode alters the functionality and behavior of an automobile. Similarly, in each mode of operation of the AROV, different RIFs can affect the target node. Investigating modes of operation of AROVs can highlight the system's interactions with the surroundings systems. The surroundings can either be technical or non-technical systems. For autonomous IMR operations, AROVs are expected to function in five modes of operations, as illustrated in Fig. 4:

1. Launch: The AROV is launched from a subsea garage.
2. Flight to SPS: The AROV maneuvers to the intended SPS location.
3. Intervention mode: The AROV performs the intended intervention operation on the SPS.
4. Flight to the subsea garage: The AROV returns to the subsea garage once the intervention operation is completed.
5. Recovery: Once the intended IMR operation is complete and the AROV returns to the subsea garage.

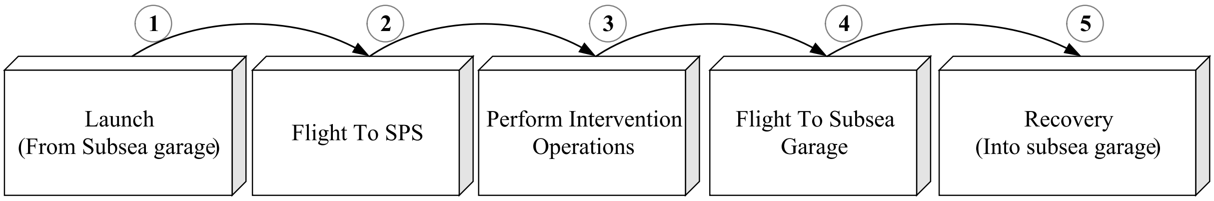

Fig. 4 Modes of operation of AROVs

By studying the modes of operation, it can be inferred that the AROV will interact with the subsea garage during launch and recovery modes, the subsea environment in all modes, the SPS in the intervention mode, operational nodes, which includes the common communication unit, and the human supervisor in all five modes. Each of these subcategories of nodes is required to be included while constructing the BBN model.

3.2.2 Nodes affecting traditional subsea IMR operations

The literature provides input to the identification of numerous nodes affecting the development of subsea fields, service duration of subsea IMR activities and the development of SPS, see, e.g., Uyiomendo and Markeset [1,3]. Markeset et al. [43] present the challenges in maintenance practices for SPSs, including factors leading to SPS failures. The design of the SPS system, maintenance service, and spare parts management are highlighted. Moreno Trejo et al. [44] discuss factors, which influence the installation and maintenance strategy for subsea equipment. Factors related to Health Safety Environment and Quality (HSEQ), costs, experience and competence, technology, legislation, logistics, geographical location, external processes, and surrounding environment were scored by interviewing experts in subsea engineering domain. The findings show that HSEQ costs and experience and competence related factors receive high impact scores.

The review of the literature provides a starting point for identification of nodes affecting autonomous IMR operations. However, they do not highlight any nodes generated due to interactions between AROVs and the subsea infrastructure in an autonomous setting. Technical nodes related to subsystems, such as AROVs, nodes related to the subsea garage, and the level of autonomy are required to develop a holistic decision support BBN.

3.3 Structure causal relations between nodes – Step 3

In this section, the structural description of the proposed BBN model is provided. Fig. 5 illustrates the condensed BBN model with respective casual links between the intermediate nodes and the target node. The three intermediate nodes identified as operational activities, AROV availability and subsea environmental conditions are linked with identified technical, organizational and operational nodes.

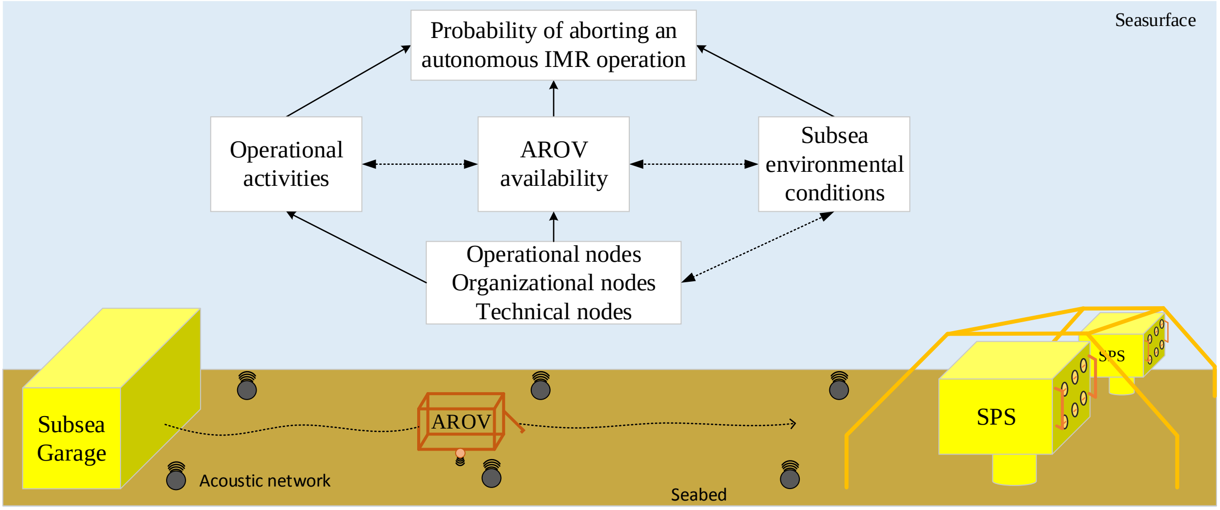

Fig. 5 Overview of nodes influencing the probability of aborting an autonomous IMR operation

3.3.1 Technical nodes

Technical nodes are categorized as nodes, which are directly related to a technical system. The three technical systems are a subsea garage, AROV, and the SPS. Fig. 7 illustrates the developed BBN model and the technical nodes are highlighted in orange ellipses.

Subsea garage

The subsea garage can be powered from an onshore electric supply unit. The electric power is distributed to the SPS and the subsea garage at the subsea field location. The introduction of subsea garages for autonomous IMR operations can result in two identified nodes; namely subsea garage communication system (SGCS) and subsea garage power supply (SGPS). The function of the *SGCS* is to communicate the vitals, such as power capacity, the number of AROVs stationed, etc., to a unified communication unit in a remote location. The function of the *SGPS* is to provide uninterrupted electric power to the battery system of the AROV. The SGCS is dependent on the SGPS for electric power.

AROV system

The BBN model structure for the AROV system is based on a functional hierarchy. The battery system is dependent on the subsea garage power supply node. The battery system and the basic control systems are essential for the functioning of a subsystem of the AROV. Therefore, they are parent nodes to the communication system, manipulator system, safety system, sensor system, lighting system, propulsion system and buoyancy system. The acoustic transducer network communicates with the sensor system. The sensor system consists of various sensors (for example, inertia navigation sensors, echo sounder, cameras, sonars, etc.) and inertia navigation sensors are dependent on the state of the acoustic network. The sensor system provides data required by the navigation system in the form of position, velocity and other nearby vehicle states.

The safety system can override the navigation system because, during collision avoidance maneuvers, the safety system shall dictate the alternative navigational path. During fault scenarios, the safety system can override the state of buoyancy system to surface to the sea surface. The state of buoyancy influences the propulsion required to propel the AROV. AROV availability, an intermediate node aggregates the nodes resulting from the AROV system.

The Subsea production system

The SPS nodes are related to the condition of the subsea equipment. Need for IMR operation is generated only when the subsea equipment requires intervention. This need is dependent on the condition of the subsea equipment. Therefore, the need for IMR operation can arise by three distinct cases. Fig. 6 illustrates the three cases.

- Case 1: a functioning subsea control module (SCM) communicates the condition of the subsea equipment and informs about the required corrective/preventive operations to the human supervisor.
- Case 2: the SPS requires an unscheduled corrective IMR operation (corrective maintenance) when the SCM or other components of the SPS are faulty or failed.
- Case 3: the SPS requires an unscheduled corrective IMR operation when external damage is observed and there is a structural or component fault or failure.

These cases need to be reflected in the proposed BBN model. This is achieved by introducing a need corrective IMR node, which covers the three cases of unscheduled and scheduled corrective IMR operations. The SCM node accounts for the scheduled preventive and corrective IMR operations (i.e., when the SCM is functioning and failed). The node detection of SPS condition aggregates the three cases and propagates it to the type of intervention node.

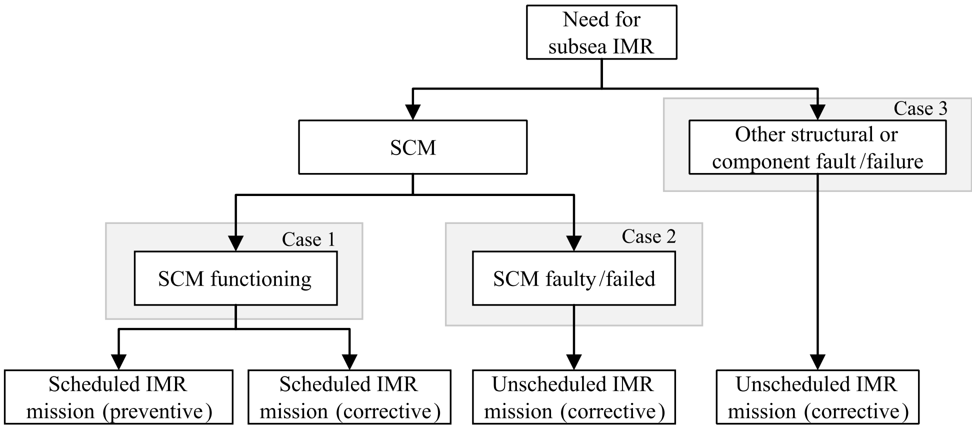

Fig. 6 Cases when subsea intervention is required

The acoustic network in and around the SPS field influences the mission path selection and the sensor system. The acoustic network is dependent on the subsea environmental nodes. For example, if the subsea environment is experiencing turbulent currents, this can degrade the acoustic network.

3.3.2 Operational nodes

Operational activities is an intermediate node that aggregates the operation specific nodes in autonomous IMR operations. Fundamentally, three areas of interests can be identified within this category.

1. Autonomous IMR operations are specialized missions, i.e., they shall comprise strict mission requirements. Aspects that need to be considered are, for example, is the mission an inspection mission?; how far is the subsea structure from the AROV?; is there a need for spare parts and tools?
2. Even though the focus is on autonomous operations, human involvement in the autonomous IMR operation should be evaluated. For example, what level of human supervision is planned for a given IMR operation in the different phases or modes of operation?
3. A common communication system is vital to allow data and information transfer between various technical systems, which is presented to the human supervisors.

The need for intervention has to be translated into detailed requirements. The type of intervention node provides an answer to what type of intervention is needed. Relevant spare parts and tools need to be identified after classifying the type of intervention. As different types of AROV differ in specifications, both, type of intervention and spare parts strategy influence the selection of the AROV required for the IMR operation. Distance to the subsea structure needs to be evaluated because it influences the mission path selection. The type of AROV influences the mission path selection. For example, if the AROV is an inspection vehicle, the mission path selection can highlight suitability of the vehicle for the chosen path by simultaneously considering the available acoustic network and the required travel distance to be covered by the AROV.

3.3.3 Subsea environmental nodes

In contrast to other operational nodes, the modeling of subsea environmental nodes can benefit from referring to existing literature on underwater vehicles. Brito and Griffiths [25,26] provide insight into modeling subsea environmental nodes by focusing on Autonomous Underwater Vehicle (AUV) operations. According to Brito and Griffiths [25,26], subsea nodes, such as objects, seabed slope, underwater hazards, met-ocean conditions, ice concentration, and ice thickness can affect the probability of loss of AUV in open sea, around coastal waters and under ice covers. Consideration has been given to these identified nodes, and this article improves works from Brito and Griffiths [26] on the subsea environmental BBN model by identifying additional nodes for the presented IMR operation.

The thermohaline circulation, which occurs due to the combination of sea depth, water temperature, and salinity, influences the water density. Surface waves together with gravitational tides and water depth can result in underwater currents. The underwater currents also depend on the density of the water layer. The underwater current and seabed characteristics can influence the subsea visibility. For example, if the seabed contains fine grains of sand, a turbulent underwater current can hinder visibility. The terrain obstacles in the seabed can be influenced by the presence of fishing trawls in the region and seabed terrain in the region. Nodes, namely visibility, the terrain obstacles, and the underwater current are aggregated to form a single intermediate node called subsea environment.

3.3.4 Organizational nodes

The level of autonomy influences the human supervisor action. The level of autonomy configured for a given case, i.e., a higher level of autonomy means less intervention from the human supervisors. For example, in the remotely piloted level of autonomy (level i), the operator is responsible for controlling the AROV. However, if the level of autonomy was set to remotely supervised (level iii), the operator has to function as a supervisor and not actively intervene in the operation. The state of the human supervisor can also influence his or her action. The common communication unit provides information to the human supervisor about the state of other systems working simultaneously. The training provided to the human supervisor can influence the actions taken by the human supervisor in both known and unknown operational situations. The physical and mental state of the human supervisor can also influence the actions taken by the human supervisor.

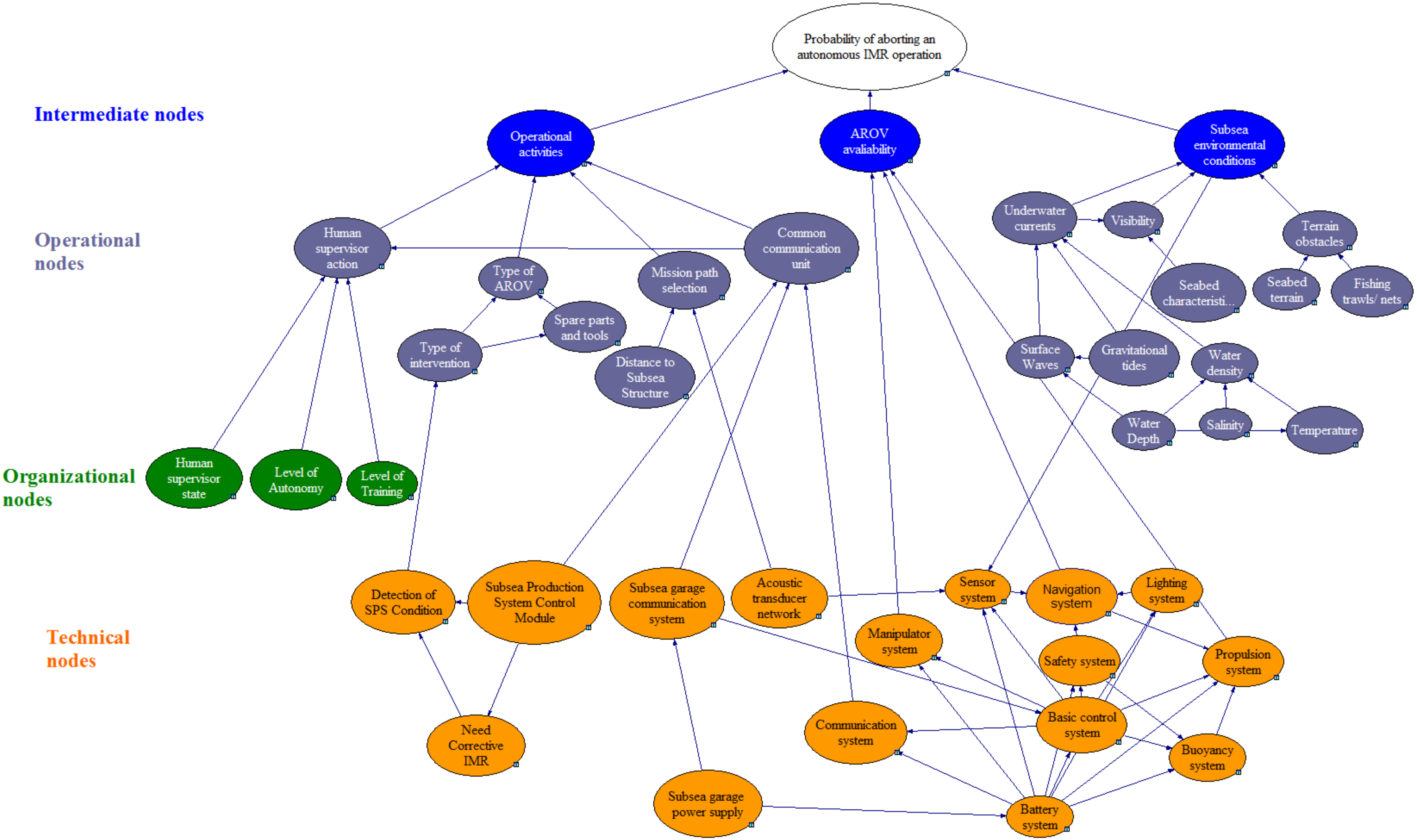

Fig. 7 Proposed BBN model to provide decision-support making process. Node colors: Orange-Technical, Green-Organizational, Light purple-Operational, Dark blue-Intermediate, White-target

3.4 Identify different states of the nodes – Step 4

Each identified node from Step 2 is scrutinized for its possible states. A summary of all the states of the nodes and a brief description of each identified node is described in Table 1.

Table 1 Identified nodes affecting the probability of aborting an autonomous IMR operation

Category	Node	States	Description
Probability of aborting an autonomous IMR operation	Target node	Continue operation, Abort operation	Relates to the outcome node of the network. It provides the human supervisor with a high-level decision support, based on provided evidence in the BBN model.
Intermediate nodes	Operational activities	Acceptable, Unacceptable	Refers to the state of the IMR operation specific requirements (spare parts, type of AROV, etc.,)
	AROV availability	Functioning, degraded, failed	Refers to the availability of the AROV.
	Subsea environmental conditions	Safe, unsafe	Refers to overall assessment of subsea environmental conditions.
Operational nodes	Type of AROV	Inspection AROV, Work-class AROV	Refers to inspection and work class AROVs
	Spare parts and tools	Available, not available, not required	Refers to availability of spare parts in the subsea garage
	Type of intervention	Inspection, maintenance/repair	Refers to what kind of IMR operation is required.
	Distance to SPS	Close, intermediate, long	Refers to distance to the target SPS equipment, i.e., point-of-interest equipment
	Mission path	Predetermined, ad hoc	Refers to the AROV path chosen to carry out the intervention mission
	Common communication unit	Functioning, failed	A communication hub/unit, which connects all subsystems to share data.
	Human supervisor action	Correct action, no action, wrong action	Refers to ability of the human supervisor to take required actions
	Temperature	Warm, cold	Refers to subsea local water temperature
	Water salinity	High, low	Refers to level of salinity in the subsea environment
	Gravitational tides	High, low	Refers to periodic tide changes due to gravitational forces
	Surface waves	Strong, calm	Refers to waves on the surface of the sea
	Water density	High, low	Refers to water density in the subsea environment
	Water depth	Deep, shallow	Refers to depth at which AROV shall operate
	Underwater currents	Turbulent, calm	Refers to water currents along the Subsea garage, AROV path, and SPS systems
	Seabed characteristics	Hard, soft, fine grain, gravel muddy	Refers to the coarseness of the seabed.
	Seabed terrain	Flat, peaks, slope	Refers to the seabed terrain or geographical terrain.
	Fishing trawls/nets	Present, not present	Refers to fishing trawls and nets used by fishing fleets
	Terrain obstacles	Present, not present	Refers to peaks and crests in the seabed
	Visibility	Good, poor	Refers to the visibility of the underwater environment.
Organizational nodes	Human supervisor state	Adequate, Inadequate	Refers to the ability of the human supervisor to focus on the supervision process.
	Level of autonomy	Remotely piloted, Remotely operated, Remotely supervised, Fully autonomous	Refers to the level of autonomy the IMR system is configured. Autonomy level classification is derived from [41]
	Level of training	Adequate, inadequate	Refers to the completion of required training to work as a human supervisor for an autonomous IMR operation.
Technical nodes	Battery	Fully charged, half charged, not charged	Provides electrical power supply to AROV subsystems
	Basic control system	Functioning, degraded, failed	Refers to the control system of the AROV
	Navigation system	Functioning, degraded, failed	Provides navigational ability to the AROV
	Lighting system	Functioning, degraded, failed	Provides required illumination to carry out the IMR operation

Propulsion system	Functioning, degraded, failed	Includes thrusters of the AROV
Manipulator system	Functioning, degraded, failed	Refers to the technical condition of the manipulator system
Communication system	Functioning, degraded, failed	Includes internal communication protocols and connections in the AROV
Buoyancy system	Functioning, degraded, failed	Refers to the ability of the AROV to control buoyancy
Safety system	Functioning, degraded, failed	Refers to the ability of the AROV to execute safety protocols
Detection of SPS condition	Detected, not detected	Relates to the capacity of the diagnostic system onshore to highlight faults and failures to the human supervisors.
Subsea Control Module (SCM)	Functioning, degraded, failed	SCM provides communication, electric supply, and hydraulic power to sensors, logic solvers, and final elements.
Acoustic network	Functioning, degraded, failed	Refers to working condition of acoustic transducers.
Need corrective IMR	Needed, Not needed	Refers to a preventive IMR measure planned.
Subsea garage power supply	Available, not available	Refers to the availability of power supply from onshore power grids, subsea local power generation, etc.
Subsea garage communication system	Functioning, degraded, failed	The communications network established with onshore locations and with AROVs.

3.5 Analyze causal relations – Step 5

In the initial version of the BBN model, certain causal relationships were assumed. Numerous edits to the structure were made for each iteration of the proposed BBN model to streamline and ease the quantification process.

3.6 Quantify the model – Step 6

3.6.1 Constructing conditional probability tables

The complex interactions between the BBN nodes lead to challenges in quantifying and constructing CPTs for the child nodes. Since the autonomous IMR system under study is still in nascent development stages, limited CPT data is available from the literature. Mkrtchyan et al. [37,38] provide a review and application of five existing methods to develop CPTs for BBN applications. In the proposed BBN model, the method proposed by Røed et al. [39] is used to quantify the CPTs of respective child nodes. The CPT allocation method proposed by Røed et al. [39] can be summarized in the following three steps.

Step 1 - Distance calculation: The modular distance between the child state and the parent state is calculated by using Equation 1, where $\left|Z_{ij}\right|$ is modular distance unit and S represents state. For example, for parent state 3 and child state 1, the modular distance is 2.

$$\left|Z_{ij}\right| = Child_S - \ Parent_S \tag{1}$$

Step 2 - Weighted distance: Weights are designated by assessing the influence of the parent node on the child node. Weights are allocated for the arches linking the parent node to the child node in the BBN, which signifies the importance of the parent node linking the child node. Equation 2 calculates the weighted distance. Where $\left|Z_{ij}\right|$ is modular distance unit, W_i is assigned weights, and S represents state.

$$Z_j = \sum \left|Z_{ij}\right| * W_i \qquad where\ Z_j \ \in \ [S_0, S_n] \tag{2}$$

Step 3 – Probability distribution: Equation 3 represents the formula to calculate the probability distribution where the numerator term is the probability mass for j possible states. The denominator term provides a normalization factor, which results in $P_j \ \in \ [0, 1]$. The term R is an index value, which distributes the probability mass among the *j* states. An R-index signifies the strength of the relationship between the parent and the child node. In essence, the R index can either increase or decrease the uncertainties in the quantification of the joint probability distribution.

If experts allot a high value to the term R, it means that the probability of a child state being closer to its parent's state is high. In this article, the term R is bound between values of 0 to 3 to aid the expert judgement process.

$$P_j = \frac{e^{-R*Z_j}}{\sum_{S_0}^{S_n} e^{-R*Z_j}} \quad where\ P_j \in [0,1] \tag{3}$$

3.6.2 Expert elicitation of weights and R index

According to Røed et al. [39], the weights W_i and index R are the two parameters required to be collected from experts in the field. The required data for this article are sourced from experts in industry and research groups working with development of subsea and underwater vehicle technologies.

Design of workshop

Four industry experts working in a subsea supplier company participated in a one-day workshop. The scope of the workshop was communicated to the four experts prior to and during the start of the workshop. The copy of the proposed BBN was also shared as a reference document to the experts one week prior to the workshop. The experts suggested changes to the causal relationships in the BBN, which were implemented before the workshop. The BBN and the relationships between the nodes were explained to the experts at the start of the workshop. The workshop was divided into two parts. Part 1 of the workshop focused on eliciting weights from parent nodes to child nodes and the R index. In Part 2 of the workshop, the experts where provided five different scenarios and where asked to provide their probability estimate to abort the IMR mission.

Table 2 lists the expertise and the years of experience of the four experts involved in this study. Expert 1 (E1) has in total 15 years of subsea engineering experience which includes 9 years of experience in subsea systems engineering and 6 years of experience in assembly and test of ROV tooling. Expert 2 (E2) has 10 years of experience in mechanical engineering which includes 8 years in ROV tooling design. Expert 3 (E3) has in total 31 years of subsea engineering and technology development. Expert 4 (E4) has in total 21 years of experience which includes 8 years of experience in real time ROV simulations.

The values obtained from the experts are averaged and used as input to calculate the CPTs for child nodes. The experts who participated in the study provided inputs to update the causal links between different nodes thereby also verifying the causal structure of the BBN. The calculated CPTs are input to the BBN model using the GeNIe software.

Table 2 Information about the experts involved in the CPT allocation

Expert	Industry application field	Total years of relevant work experience
E1	Subsea systems engineering	15
E2	ROV tooling	8
E3	Subsea engineering	31
E4	Subsea intervention	8

Allocation of expert probability estimation for target node given the scenarios

In the workshop, the experts were given the set of scenarios, as described in Section 3.7.1, and asked to provide their belief about the probability of the target node. The probability estimate from the experts can be used to compare with the probabilities obtained from the proposed BBN model for the same scenarios. A root mean squared error (RMSE) metric was utilized to verify the proposed model as represented by Equation 4, where e_i is estimated probability of target node from experts and m_i is probability of target node obtained for the BBN model, n is the number of scenarios and i is in range (1 to 5).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(e_i - m_i)}{n}} \tag{4}$$

3.6.3 Available historical data

Due to unavailability of open-access AROV failure data sources, CPTs for selected states are traced from existing data of traditional ROVs. Narayanaswamy et al. [45] highlight failure probability of components making the ROSUB 6000 ROV, as shown in *Table 3*. The suggested probabilities of failures for the real-time controller, sea battery, and brushless DC motors of thrusters, tether cable, halogen lamps, and navigational sensors are input to the respective nodes in the BBN model as prior beliefs. These values are input in the CPTs of relevant nodes of the BBN.

Table 3 Probabilities for AROV related nodes from Narayanaswamy et al. [45]

Nodes in proposed BBN	**Components in ROSUB 600 ROV**	**Component failure rate**
Control system	PLC processor with memory	0.003
Battery system	Sea battery	0.088
Propulsion system	Brushless DC motors	0.0037
Communication system	Tether cable	0.0038
Lighting system	Halogen lamps	0.00017
Navigation system	Navigational sensors	0.253
Communication unit	Umbilical	0.0021

The base probabilities for subsea environmental nodes for Åsgard subsea gas compression installation are traced from a variety of sources and are listed in *Table 4*.

Table 5 lists the data obtained from different sources on the SPS-related nodes [46].

Table 4 Probabilities for subsea environmental nodes for the Åsgard field

Subsea environmental nodes	**Data source**	**Data**
Water Depth	Norweigan Petroleum Directorate and Statoil [47,48]	240 – 300 meters
Fishing trawls/nets	Bai et al. [49]	<1 per year – Low frequency
Seabed characteristics	Statoil [48]	Gravel and mud
Terrain obstacles	Buhl-Mortensen et al. and MAREANO [50,51]	Low
Seabed terrain	Buhl-Mortensen et al. and MAREANO [50,51]	Smooth continental slope

Table 5 Probabilities for SPS and subsea garage from SINTEF and NTNU [46]

OREDA data handbook	SPS and subsea garage related nodes	Failure data
Subsea control module	Subsea control module	$1.917 * 10^{-6}$
Control system - multipurpose - static umbilical	Subsea power supply	$1.086 * 10^{-6}$
Control system - multipurpose - fiber optic	Subsea garage communication system	$2.86 * 10^{-6}$

The quantification of the BBN model with CPT inputs results in an initial probability value of 0.42, which relates to the probability of aborting an autonomous IMR operation. Table 6 lists the results from the BBN model with the allocated CPTs.

Table 6 Results from BBN model with base probabilities

State	Probability of aborting an autonomous IMR operation
Continue operation	0.58
Abort operation	0.42

3.7 Update evidence according to scenarios – Step 7

A scenario generation approach is utilized to test the proposed BBN model. The beliefs for the state of nodes are updated in the BBN model, according to the scenarios listed in Table 7. The scenarios follow the modes of operations and the time-steps used. Scenario 1 starts at T1 where all nodes are simulated to be in their best possible states. This allows the model to calculate the probability of loss of AROV when all nodes are in favorable states.

3.7.1 Multiple nodes in unfavorable states

In T2, the AROV is in the flight mode and moving through a muddy terrain with poor visibility; a sudden fault degrades the buoyancy system, the safety system and the acoustic network of the AROV. In T3, the AROV is in intervention mode and incurs faults in the propulsion and lighting system. In T4, during the flight back to the subsea garage, the AROV's basic control system, navigation system, communication system, buoyancy system degrade. Simultaneously, the lighting, navigation and propulsion systems fail. Multiple technical faults during operations confuse the human supervisor resulting in low situation awareness. The state of the human supervisor changes to inadequate and the supervisor is assumed untrained to handle such sudden operational deviation. Due to these failures, the AROV chooses an ad hoc mission path. In T5, the system starts to diagnose the faults and tries to recover to normal working conditions, but the AROV remains in a degraded state.

Table 7 Scenario generation – to simulate multiple nodes in unfavorable states

Node	Scenario 1 T1 Launch	Scenario 2 T2 Flight	Scenario 3 T3 Intervention	Scenario 4 T4 Flight	Scenario 5 T5 Recovery
Type of AROV	Inspection	Inspection	Inspection	Inspection	Inspection
Spare parts and tools	Not required	Not required	Not required	Not required	Not required
Type of intervention	Inspection	Inspection	Inspection	Inspection	Inspection
Distance to SPS	Far	Intermediate	Close	Intermediate	Far
Mission path selection	Predetermined	Predetermined	Predetermined	Ad hoc	Predetermined
Common communication unit	Functioning	Functioning	Functioning	Functioning	Functioning
Human supervisor action	Correct action	Correct action	Correct action	Wrong action	Correct action
Temperature	Warm	Warm	Warm	Warm	Warm
Water salinity	Low	Low	Low	Low	Low
Gravitational tides	Low	Low	Low	Low	Low

Surface waves	Calm	Calm	Calm	Calm	Calm
Water density	Low	Low	Low	Low	Low
Water depth	Shallow	Shallow	Shallow	Shallow	Shallow
Underwater currents	Calm	Turbulent	Calm	Turbulent	Calm
Seabed characteristics	Hard	Gravel muddy	Hard	Gravel muddy	Hard
Seabed terrain	Flat	Slope	Flat	Slope	Flat
Fishing trawls/nets	Low	Low	Low	Low	Low
Terrain obstacles	Low	High	Low	High	Low
Visibility	Good	Poor	Good	Poor	Good
Human supervisor state	Adequate	Adequate	Adequate	Inadequate	Adequate
Level of autonomy	Remotely supervised	Remotely supervised	Remotely operated	Remotely supervised	Remotely supervised
Level of training	Adequate	Adequate	Adequate	Inadequate	Adequate
Battery	Fully charged	Fully charged	Half charged	Half charged	Half charged
Basic control system	Functioning	Functioning	Functioning	Degraded	Degraded
Navigation system	Functioning	Functioning	Functioning	Failed	Functioning
Lighting system	Functioning	Functioning	Degraded	Failed	Degraded
Propulsion system	Functioning	Functioning	Degraded	Failed	Degraded
Manipulator system	Functioning	Functioning	Functioning	Functioning	Functioning
Sensor system	Functioning	Functioning	Functioning	Functioning	Functioning
Communication system	Functioning	Functioning	Functioning	Degraded	Functioning
Buoyancy system	Functioning	Degraded	Degraded	Degraded	Failed
Safety system	Functioning	Degraded	Degraded	Functioning	Functioning
Detection of SPS condition	Detected	Detected	Detected	Detected	Detected
Subsea Control Module (SCM)	Functioning	Functioning	Functioning	Functioning	Functioning
Acoustic network	Functioning	Degraded	Functioning	Degraded	Functioning
Need corrective IMR	Not needed	Not needed	Not needed	Not needed	Not needed
Subsea garage power supply	Available	Available	Available	Available	Available
Subsea garage communication system	Functioning	Functioning	Functioning	Functioning	Functioning

3.8 Interpret results – Step 8

As described in Step 7, the scenario-based evidence is updated in the BBN model using the GeNIe tool. Fig. 8 illustrates the results of the joint probability distribution obtained at the target node for each generated scenario. In Scenario 1, all nodes of the model are in favorable state and this results in a probability of mission abortion of 0.26. On the contrary, in Scenario 4, many faults were induced; the proposed model considered these faults to result in a probability value of aborting an autonomous IMR operation as 0.57. Fig. 8 and Fig. 10 provide an overall change in the probability of target node as the operation goes from favorable to unfavorable states.

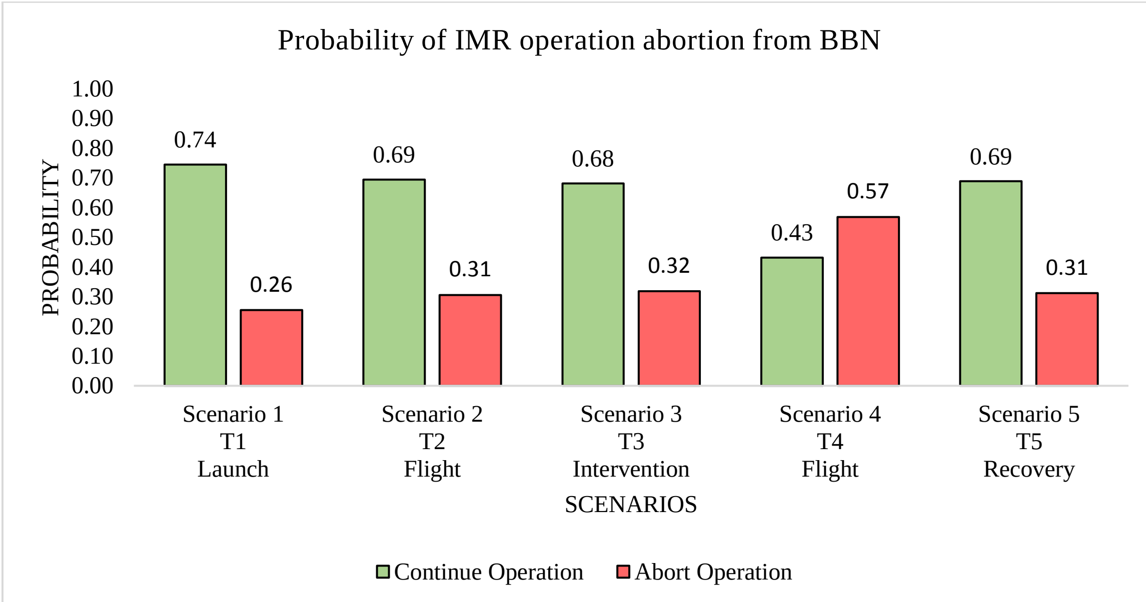

Fig. 8 Results from BBN model with simulated scenario evidence

Fig. 9 illustrates the probability of aborting an autonomous IMR operation for the selected scenarios as allocated by the four experts. The input from the experts is used as expected value. To verify the proposed model a root mean square error is calculated between the expected (from experts) and the estimated (from the model) probability values. Equation 4 is used to calculate the root mean square error, which results in a probability difference of 0.25 between the expected value from experts and the estimated value of the proposed BBN.

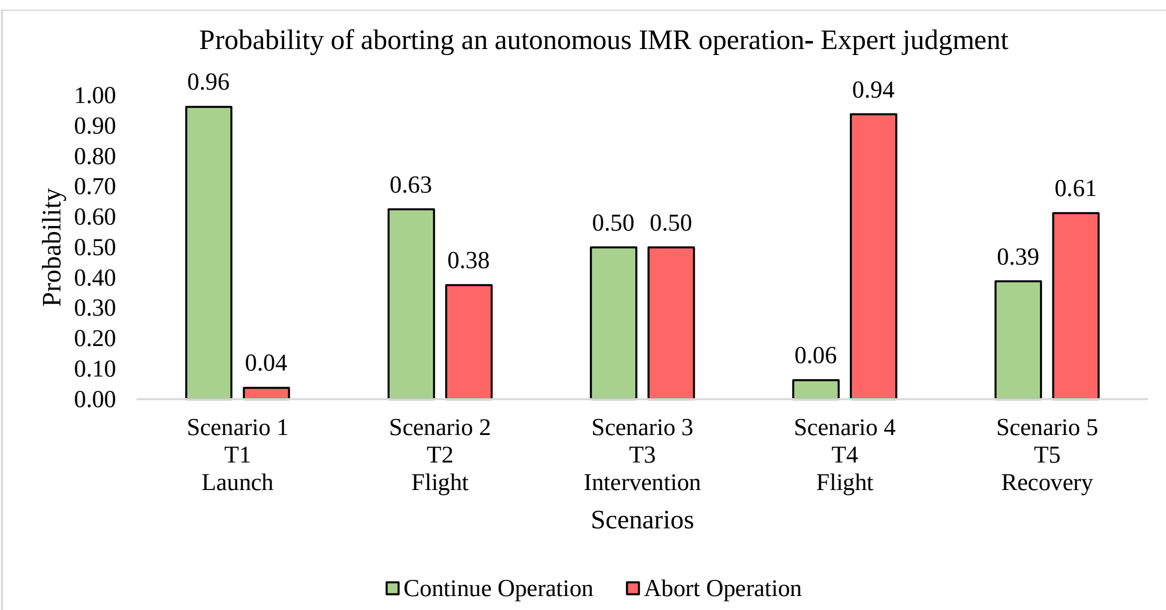

Fig. 9 Allocated probabilities by experts to abort IMR operation

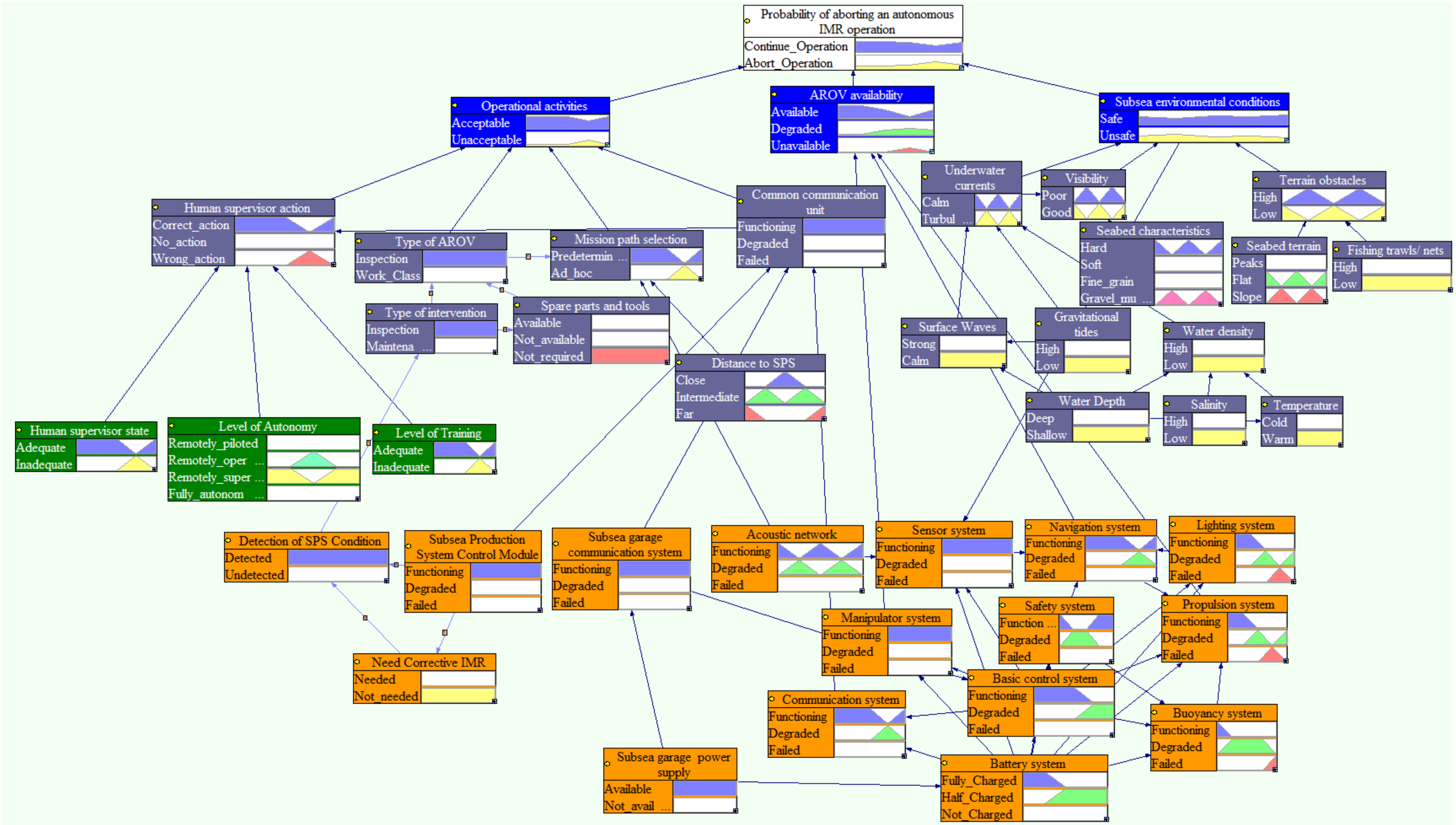

Fig. 10 Resulting joint probability distribution with generated scenarios

3.9 Sensitivity analysis

The GeNIe software incorporates the sensitivity analysis method, as proposed by Boutilier and Goldszmidt [52]. The aim of a sensitivity analysis is to examine the relationship of the posterior distribution of a target node to its parent nodes [53]. In short, the effect of small changes in parent node probabilities is compared with the resulting posterior probability in the target node. If a slight change in the parent node probability results in a substantial change in the posterior probability, the target node is said to be sensitive to the parent node. Therefore, by choosing a target node, the strength of all nodes, which contribute to the posterior probability of the target node, can be observed. Identification of sensitive nodes shall allow end users of the BBN to be mindful of the effect these nodes can have on aborting an IMR operation.

To identify the sensitive nodes in the proposed BBN, the best and worst state for each RIF or node is used as input evidence in the BBN. For example, the best state for the *propulsion system* is *functioning* and the worst state is *failed*. The best and the worst states for all nodes are presented in Table 8. With the base probability in the BBN, the evidence (best and worst state) for each node are updated in the BBN. During the sensitivity test, all other nodes are unchanged (no evidences are updated except the node being tested). The resulting probability of aborting the mission is observed. Fig. 11 illustrates the sensitivity of each node in the proposed BBN. From Fig. 11 it can be observed that technical RIFs contribute significantly to the overall probability of aborting an autonomous IMR operation.

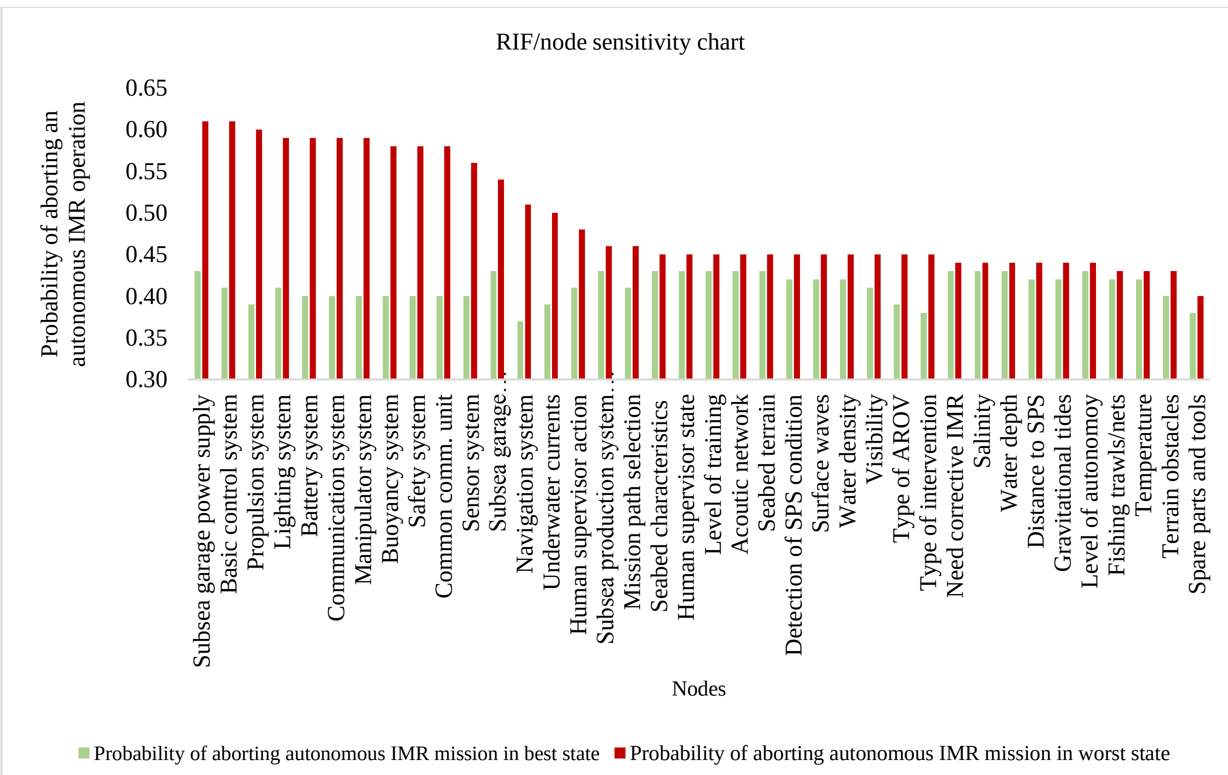

Fig. 11 Sensitivity chart when nodes are in best and worst states

Fig. 12 illustrates the sensitivity of the proposed BBN where *Probability of aborting an autonomous IMR operation* is the chosen target node. When base probabilities from the CPT calculations are utilized, the probability of aborting an autonomous IMR operation ranges from 0.38 to 0.61. Highly sensitive nodes are highlighted in dark red colors, and less sensitive nodes are in a shade of light red. Fig. 12 shows that the influence of subsea power supply, battery system, subsea garage communication system, basic control system, propulsion system and common communication unit nodes on the final node are higher than the other identified nodes. These sensitive nodes need to be considered as a starting point to propose appropriate risk reducing measures. For example, for the battery system, techniques like increasing component redundancy may decrease the probability of aborting a mission. In addition, it can be observed that all nodes in the network contribute to the joint probability distribution. This means that the identified nodes are relevant and are tightly coupled to the target node.

Table 8 Best and worst states for nodes in the proposed BBN

BBN Node	Best node state	Worst node state
Subsea garage power supply	Available	Not available
Basic control system	Functioning	Failed
Propulsion system	Functioning	Failed
Lighting system	Functioning	Failed
Battery system	Full charged	Not charged
Communication system	Functioning	Failed
Manipulator system	Functioning	Failed
Buoyancy system	Functioning	Failed
Safety system	Functioning	Failed
Common communication unit	Functioning	Failed
Sensor system	Functioning	Failed
Subsea garage communication system	Functioning	Failed
Navigation system	Functioning	Failed
Underwater currents	Calm	Turbulent
Human supervisor action	Correct action	Wrong action
Subsea production system control module	Functioning	Failed
Mission path selection	Predetermined	Ad hoc
Seabed characteristics	Hard	Fine grained
Human supervisor state	Adequate	Inadequate
Level of training	Adequate	Inadequate
Acoustic network	Functioning	Failed
Seabed terrain	Flat	Peaks
Detection of SPS condition	Detected	Undetected
Surface waves	Calm	Strong
Water density	Low	High
Visibility	Good	Poor
Type of AROV	Inspection	Work class
Type of intervention	Inspection	Maintenance repair
Need corrective IMR	Needed	Not needed
Salinity	Low	High
Water depth	Shallow	Deep
Distance to SPS	Close	Far
Gravitational tides	Low	High
Level of autonomy	Remotely supervised	Remotely operated
Fishing trawls/nets	Low	High
Temperature	Warm	Cold
Terrain obstacles	Low	High
Spare parts and tools	Not required	Not available

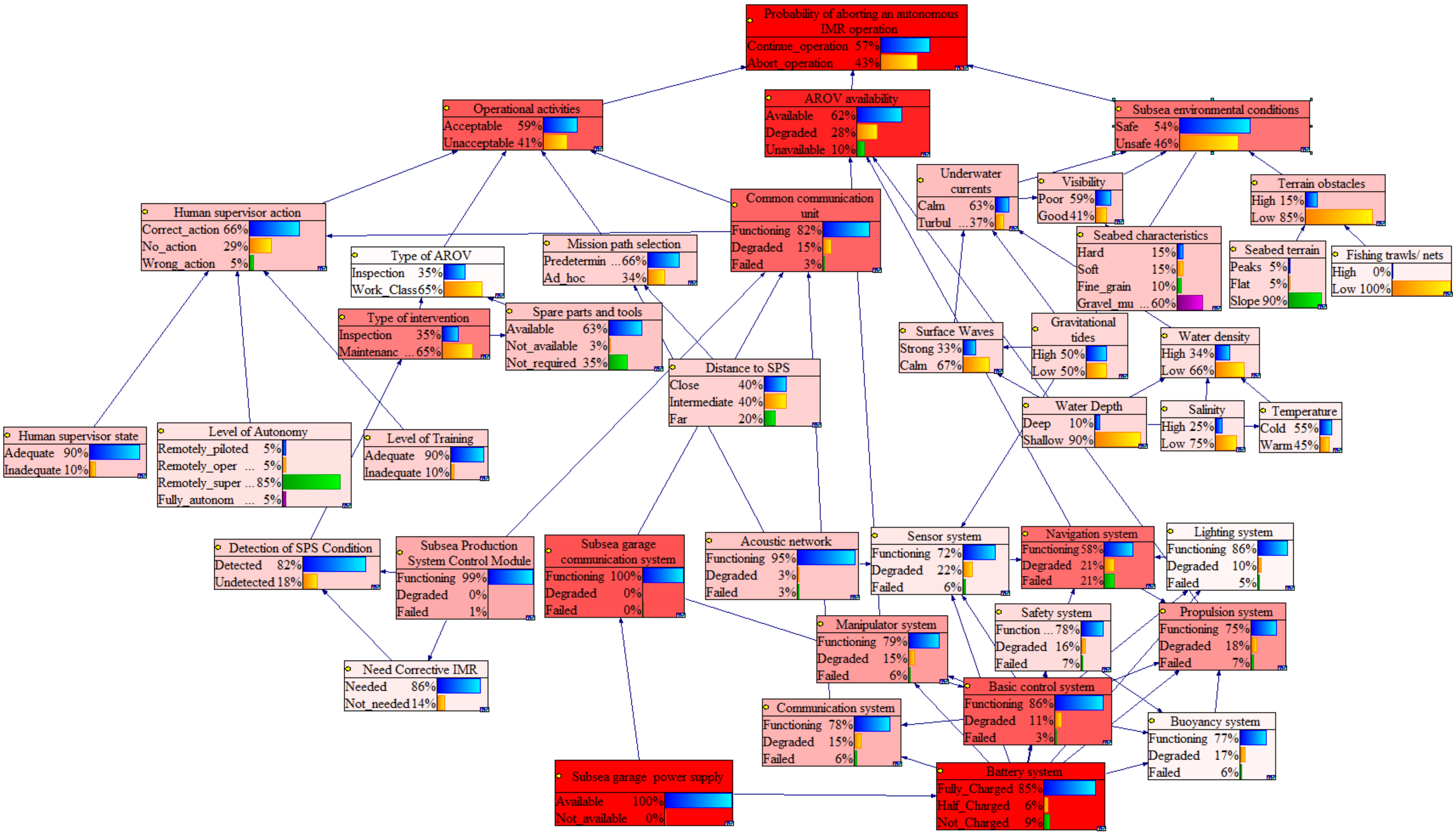

Fig. 12 Sensitivity analysis for BBN with base probabilities in GeNIe software

4 Discussion

From the development of the proposed BBN model, topics for discussions arise, which pertain to the following aspects:

- Inference of results from the proposed BBN
- Usefulness of the proposed BBN
- Challenges with application of BBN to autonomous IMR operations
- Challenges in quantification of CPTs
- Uncertainties in the proposed BBN
- Fully automated evidence updating process

4.1 Inference of results from the proposed BBN

From Table 6, the proposed BBN estimates a probability of 0.42 to the abort an autonomous IMR operation when only base probabilities, i.e., the evidence is not updated in the BBN. The 0.42 probability value can be linked to the CPT allocation method used in the study, which distributes the probabilities using the weights of parent nodes to child nodes and R index, as discussed in Section 3.6.2.

When scenario evidence of nodes are updated in the BBN, the probability of aborting an IMR operation decreases to 0.26. The probability value 0.26 refers to results obtained in Scenario 1 as illustrated in Fig. 8 of Section 3.8. The 0.26 probability value resembles real-life expectations, i.e., when all nodes are in favorable states, the probability of aborting an operation should logically be less. Nevertheless, absolute values from a predictive model is not always a reality due to induced modeling and quantification uncertainties, as discussed in Section 4.5.

When considering Scenario 4, the results from the proposed model vary from the expert judgments. According to experts, Scenario 4 is a high risk scenario because many nodes in the BBN are in their unfavorable state resulting in a mission abortion probability of 0.94. The results from the proposed model, gives a mission abortion probability of 0.57. In Scenario 5, the model provides a probability of mission abortion at 0.31. However, experts allocate the probability of mission abortion for Scenario 5 as 0.61. One of the reasons for the difference in results may be the perception of degraded and failed state by experts. A degraded state could mean that the equipment is not able to function properly and therefore the experts may have allocated a higher probability of mission abortion citing to decreased changes of recovery from a degraded state.

The generated scenarios in this article were used to simulate multiple nodes in their unfavorable states and to check how these changes affected the final probability of aborting the IMR operation. In real-life conditions, the fluctuations in the state of the node, may or may not be similar to the scenarios stated. Nevertheless, generating fault and failure scenarios has benefited the demonstration of how Bayesian decision support model may be used by subsea IMR operators.

The results also highlight that the proposed model has a root mean square error of 0.25 probability when compared with the expert estimation of aborting the IMR mission for the generated scenarios. This deviation between the BBN estimation and expert opinion can be due to three specific reasons: firstly, uncertainties in expert's judgment during the elicitation workshop could have introduced biased allocation of weights and R-index resulting in the model's estimation. Secondly, since the experts have a wide range of expertise within the subsea field, it may have resulted in an availability bias (value based on their recent experiences) while allocating abortion probabilities for the five scenarios. Thirdly, experts may perceive the scope of autonomy in different manner resulting in different operational expectations.

4.2 Usefulness of the proposed BBN

The novelty of this article is the proposed BBN and the quantification of the probability of mission abortion. Literature regarding decision making for autonomous IMR operations are limited and do not focus exclusively on subsea oil and gas industry applications. Therefore, the proposed model contributes to the body of knowledge in the field of subsea IMR. The identification of the nodes present in autonomous subsea IMR operations provides vital information to human supervisors and managers of IMR operations, but also system designers, IMR equipment manufacturers, and contractors can benefit. The proposed BBN model highlights the inherent complex interrelationships between different nodes, which can affect the performance of the autonomous IMR systems. The visual representation of the nodes can help to convey the importance of nodes from one field of discipline to another. Since the proposed BBN provides both a visual and an analytical tool to support decision-making, the industry participants of the NetGenIMR research project have valued the development of the proposed model [54].

By including historical data on the state of the node, decision makers can take risk-informed decisions during future IMR operations. The method presented and the BBN model developed can be adapted and applied to other underwater vehicles, such as snake robots, as well as AUVs. It should be noted that, unlike traditional technical safety assessments (Safety Integrity Level-SIL assessments) where simultaneous/multiple failures are not considered during the estimation of the probability of failures, the proposed BBN model allows updating of multiple failures in the model. Accidents and incidents occur due to both linear and non-linear models of accident propagation [55]. The BBN approach allows capturing both linear and non-linear scenarios leading to accidents.

4.3 Challenges with application of BBN to subsea IMR operations

Developing a BBN for subsea autonomous IMR operations is challenging in that the nodes affecting the IMR operations are plentyful, and they may be sensitive to each other. The nodes also pan across different categories, space and time. The proposed model has tried to provide an overview of this complexity by tracing the relevant nodes affecting autonomous IMR operations. However, it can be observed that the design of future subsea fields and underwater vehicle technology can change the way subsea IMR operations are carried out. For example, in the Åsgard field the IMR operation to open and close electrically actuated subsea valves can be performed from a remote location [48]. This may result in decreased need for work-class AROVs to perform value open/closure operations.

In the future, there might be a need for cooperating AROVs, which depend on the functions of each other. If one of the vehicles is in a degraded or failed state, that may pose a risk in the form of loss of execution time. These aspects are not covered in the proposed BBN model, but the model can be adapted to encompass these future use cases as well. This may also be true for other industries, such as fish farming, deep-sea mining who may rely on AROVs for their routine IMR operations.

4.4 Challenges in quantification of CPTs

One of the main challenges in developing BBNs is the quantification of the model. Data regarding scenarios (conditional probabilities) where two or more nodes are in different states is difficult to source. Nevertheless, quantification of the model is vital to be able to make sensible estimations for a given application.

The first iteration of the quantification phase utilized authors' judgments to generate CPTs to test allocation biases. The resulting joint probability distributions did not correlate to real-life expectations. Therefore, quantifying CPTs using a single assessor method was not practical. The second iteration utilized a scaled CPT allocation as suggested by Renooij and Witteman [56,57]. This method resulted in optimistic joint probability distributions for the target node, which was also not practical. The reason for this can be linked to assessors anchoring to a suggested probability scale, which may lead to biases in CPT allocation. In the third iteration, the method proposed by Røed et al. [39] was adopted. This method provided two unique advantages. Firstly, the method being a way to allocate CPTs was faster to implement in an excel sheet. Secondly, the ability to include expert judgments made it ideal for a conceptual case, such as the one presented in this article.

4.5 Uncertainties in the proposed BBN

BBNs are one of the effective alternatives to reason in the presence of uncertainty. However, the construction of the BBNs can introduce modeling uncertainties: an induced uncertainty. The induced uncertainty can be credited to the subjective nature of BBN development, which applies to the way BBNs are structured, the definition of states, and their allotted conditional probabilities. Contrastingly, the subjective nature of BBN can also promote flexibility in the model, which can be tailored to fit the requirements from one or more application fields.

The presented type of autonomous subsea IMR operations can also induce uncertainties. Bradley and Drechsler [58] classify such induced uncertainties as *Normative uncertainties*. Normative uncertainty is defined as *uncertainty about what is desirable in the case*. For example, if an IMR operation requires two or more AROVs, failure of one AROV can result in a different probability of aborting the IMR operation than that presented in this article. Hence, it may be beneficial to construct BBNs on the basis of a particular IMR case where the requirement of each subsystem is precisely known. This approach can decrease the normative uncertainties. On the contrary, building a generic BBN model, as proposed in this article, can also be advantageous by providing a roadmap to developing application specific BBN models. This approach can also decrease modeling uncertainties.

4.6 Fully automated evidence updating process

In this article, the nodal evidence is updated through generated scenarios, i.e., the state of the node is manually updated in the GeNIe software. This process of manually updating nodal evidence may not be feasible during live IMR operations. A classifier module is required to develop a fully automated BBN. The module shall collect data about the nodes and classify the state of the node during live operation (real-time). For example, the classifier module collects data on remaining AROV battery capacity and classifies it to either fully charged, half charged or not charged states. The output of the classification module can be fed to the proposed BBN to generate a live posterior probability for the target node.

5 Conclusions

Decision making in uncertain environments is challenging. This is particularly the case in dynamic environments, such as a subsea environment. Autonomous system solutions should be designed and operated and not add to the present challenges; rather they should be safe and reliable to realize the goals set for subsea factories. All engineered systems are susceptible to failure, but to know which factors or nodes in the BBN that can affect the process can provide vital information to human supervisors, managers and system developers.

This article presents a BBN that can be used to calculate the probability of aborting an autonomous subsea IMR operation. Thirty-eight nodes have been identified, along with causal relationships. The method used in this article considers a systemic and a holistic approach to BBN modeling, including all relevant technical, organizational, operational nodes. The proposed BBN model is quantified using data from literature and expert judgment. The model is tested by updating the state of the nodes in five different operational scenarios, and the resulting probabilities from the BBN are scrutinized against real-life expectations of experts.

From the results obtained, it can be concluded that a BBN approach for providing decision-support may be advantageous during autonomous subsea IMR operations. In comparison to other risk-modelling techniques, such as event sequence diagrams, fault trees, event trees etc., BBNs can provide a risk model that utilize new evidences in form of empirical data or expert judgements. The probabilities suggested by the proposed model may be used in an operational setting by the human supervisors to determine when to intervene during autonomous IMR operations. The BBN can promote situation awareness among the human supervisors, which is an important means to reduce risk. A further work scope to ease implementation of proposed BBN is to automate the process of updating evidence by developing classifiers, which can classify the state for each identified node in real-time.

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