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Fault-Tree-Analysis-Based Health Monitoring for Autonomous Underwater Vehicle

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Abstract: Undersea terrain and resource exploration missions using autonomous underwater vehicles (AUVs) require a great deal of time. Therefore, it is necessary to monitor the state of the AUV in real time during the mission. In this paper, we propose an online health-monitoring method for AUVs using fault-tree analysis. The entire system is divided into four subsystems. Fault trees of each subsystem are designed based on the information of performance and reliability. Using the given subsystem fault trees, the health status of the entire system is evaluated by considering the performance, reliability, fault status, and weight factors of the parts. The effectiveness of the proposed method is demonstrated through simulations with various scenarios.

Keywords: autonomous underwater vehicle; performance analysis; fault-tree analysis; reliability; failure

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1. Introduction

The exploration of undersea resources and terrain using autonomous underwater vehicles (AUVs) is being actively conducted because of the recent advances in AUV technology. Undersea exploration missions are performed over a long period of time during which underwater communication and human accessibility are significantly limited. Consequently, there is a high risk of mission failure or loss of the AUV in the event of failure or degradation in some part of the system. Therefore, continuous monitoring of the operation state of the AUV is essential.

Various studies have been conducted to perform fault diagnosis and health monitoring on key components of the system [1–3]. However, since existing methods only utilize information on whether a component has failed or not, there are restrictions on accurately determining the state of the entire vehicle. In other words, it is not possible to consider the performance degradation condition that occurs during the transitional period right before the failure is judged. The performance of the mission plan/change reflecting the condition of the required parts for each mission is also limited.

The AUV considered in this paper is being developed to perform a long-term submarine topographic exploration mission with an unmanned surface vehicle (USV) (Figure 1). This AUV is being developed for long-term undersea terrain exploration in consideration of cooperation with a unmanned surface vehicle (USV). The AUV is equipped with a variety of equipment for exploration missions, including wireless chargers for charging during missions.

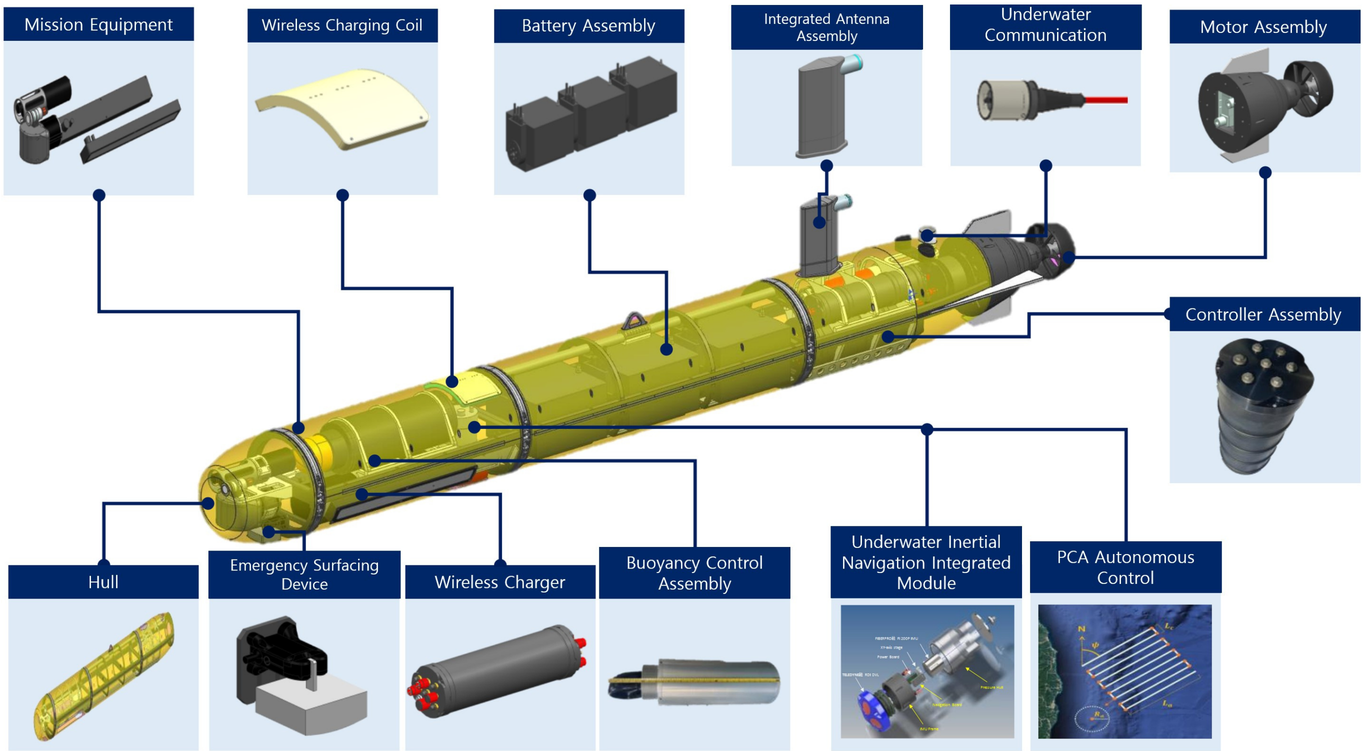

Figure 1. Overview of the autonomous underwater vehicle (AUV) in development.

There are methods, such as fault diagnosis, fault prognosis, and health monitoring, for diagnosing the state of a system. Fault diagnosis is a monitoring method to identify the faults by using hardware or analytical redundancy [4]. Failure diagnosis includes model-based methods, signal-based methods, knowledge-based methods, and hybrid methods. Model-based methods diagnose a fault of the part based on a model of the part [5]. Signal-based methods use sensors measuring the part signal, such as vibration and sound, to diagnose a fault [6].

Knowledge-based methods use historical data for fault diagnosis [7]. Fault prognosis is a method to predict the future status of components and estimate the remaining useful lifetime based on the information [4]. In addition, fault prognosis includes model-based methods [8], data-based methods [9], and knowledge-based methods [10]. Health monitoring is a method that continuously evaluates the health of a part in operation [11]. Earlier health-monitoring methods primarily focused on single parts, such as the battery [12], capacitor [13,14], servo [15], power connector [16], and bearings [17].

In this paper, we propose a method that evaluates the health of the system in real time using fault-tree analysis (FTA). In order to calculate the health of the AUV, we consider the performance, reliability, and fault information of its parts. Performance refers to the ability to perform a task within a specified time frame and is an indicator of the state of the system for the task currently being performed [18]. Reliability refers to the probability that a system containing all hardware, firmware, and software will satisfactorily perform its tasks at a specified time and in a specified environment [19].

The reliability can be used to gauge the current or future operability of the system. The proposed method collects fault diagnosis information and performance information from each part. Based on the pre-designed AUV fault tree, the reliability and performance of the subsystem are computed. We use the reliability and performance to calculate the health of the subsystems. The health of the whole system is computed by considering the health of the subsystems and weights. The novelty with the algorithm proposed in this paper is that we use fault trees to predict the health status of the whole system based on the information about the subsystems, such as the performance degree, weights, and the presence of faults within the components.

2. Literature Review

FTA [20] is widely used as an effective technique to evaluate the reliability and safety of the system based on the fault tree that reflects the system. A fault tree (FT) is a deductive, top-down analysis method used to identify potential causes of undesired system failures. FT uses graphical representations to express the logical relationship between various faults and their causes based on Boolean logic. A top event usually represents a system failure that can result in catastrophic risk or economic loss. From the highest event, the FT is constructed downwards until the basic event is defined. System reliability can be improved by calculating the probability of the occurrence of possible system failure combinations and taking corresponding measures [21].

The study [22] first predicted the theoretical failure rates of sub-assemblies and components of the drive motors and controllers. The reliability of the entire motor system was analyzed based on the results of the failure rate prediction and the FT of the driving motor and motor controller. The study [23] utilized FTA and risk analysis methods for a quantitative analysis of faults to support real-time risk prediction and the safety evaluation of leaks in a storage tank.

The FT requires higher computational costs as the size and complexity of the system increases. Some reliability analysis methods cannot be applied due to the complexity of the problem [24,25]. As the system develops, various parts are used, and the system displays dynamic characteristics due to its complex configuration. However, since the existing static FTA does not consider the dynamic characteristics of the system, it cannot model the statistical dependence between failures [26,27].

To resolve the problems of static FTA, researchers have considered combinations of various reliability analysis techniques, such as the Reliability Block Diagram (RBD), Binary Decision Diagram (BDD), Decision Tree (DT), Bayesian Network (BN), Fuzzy-FTA (FFTA), Petri Net (PN), Monte Carlo simulation, and Neural Network (NN). Some studies showed that RBD [28,29] and BN [30,31] could be effective for analyzing system reliability. The system is analyzed using dynamic FT (DFT) or FFTA or dynamic RBD, and the result is converted into a dynamic BN (DBN) to estimate the reliability of the system [32–35].

Analyzing FT using BDD allows for quantitative analysis of the system and the identification of critical components. In addition, it is possible to identify critical risks that have a significant impact on the system. BDD can be used as a method to deal with the cut set of FT required to calculate the reliability of the system [36,37]. The reliability of the system can be estimated based on the probability of the basic event through the mathematical model designed from the BDD model [38,39]. The study [40] used the BDD and Markov model to deal with the DFT of the solar array drive assembly.

A RBD graphically represents the components of a system and shows how these components are related in terms of the reliability. RBD represents the functional state of the system (normal or faulty) in terms of the functional state of the part. RBD can analyze the reliability and availability of complex systems using a wide variety of methods, such as a series configuration system, parallel configuration system, a mixed configuration system, and k-out-of-n system configuration [29,41]. The study [29] used FTA and RBD based on a functional flow diagram to evaluate the reliability of the LHD (Load-Haul-Dumpers) system. The study [41] developed an integrated FTA-RBD model for complex robotic systems used in advanced manufacturing systems. The study [42] analyzed the reliability of fuzzy system using the RBD and FFTA.

BN is one of the most popular methods in the field of dealing with uncertainty problems. BN can be used to solve the uncertain reasoning problem to deal with an uncertainty between the failure of the system and the cause of the failure. The study [30] combined FT and BN and applied them to system failure diagnosis. The method of combining FT and BN proposed in this study fully utilizes a priori knowledge and has low requirements for data quality as well as data quantity.

The study [43] used FTA and DBN to evaluate the reliability of the flare system. The study [44] proposed a dynamic risk analysis method for a submarine pipeline based on the BN established based on the FTA.

In order to deal with inaccurate information and ambiguities that may occur in FTA and FFTA (which combines fuzzy logic and FT) has been proposed [45]. The reliability of the system was analyzed by applying a decision-making method, such as an analytic hierarchy process. The failure probability of a basic event was converted into a quantitative value [46–48]. The integrated FFTA–BN model was used in the optimization model to determine the optimal maintenance intervals according to the estimated failure probability and total expected cost [49]. The study [50] utilized a FFTA and Noisy OR gate BN model to estimate the occurrence likelihood of navigational accidents.

Research on modeling using PN to evaluate the reliability of a system or mission has also been conducted. By combining FTA and PN, it is possible to analyze the reliability of all failure modes of each subsystem and the mission of the system. It is also easy to modify the PN as the mission changes [51]. The study [52] proposed a hybrid framework with the combination of an algebraic solution, PN, and a Monte Carlo simulation to quantify DFT.

In order to overcome the various limitations of FTA, the FT of the system can be converted into an artificial neural network (ANN), and the reliability of the system can be evaluated. The research [25] proposed a methodology for developing an ANN risk-assessment model based on information from FT. A method of mapping FT to ANN was proposed by analyzing the relationship between the architecture and configuration of ANN and the FT structure.

The existing FTA calculates the reliability of the system by considering only the component failure rate in general. In this paper, we propose a new system-health evaluation method that considers the performance and reliability using FTA. The AUV is divided into several subsystems, and the health of the entire system is evaluated by considering the performance, weight, reliability, and failure of the major parts in each subsystem. To this end, we design a fault tree for the performance and failure of the AUV, structurally analyze the performance and failure of the parts, and use this for health evaluation.

The paper is organized as follows. Following the introduction in Section 1, Section 2 presents a technique for evaluating the system health considering the reliability, performance, fault status, and weighting factors. Section 3 describes the design of FT for AUV. In Section 4, the proposed method is demonstrated with a MATLAB simulation, and our conclusions are discussed in Section 5.

3. Health Evaluation Method

In a system, each component can contribute differently to the system performance. Thus, weights could be applied to each component. Since the role and weight of parts in the overall system are different, the operability of the entire system may vary depending on which parts are faulty.

In this paper, reliability, performance, failure, and weight are considered to evaluate the health of the system. In calculating the performance of the system, the performance weight is used in considering the importance of each component. In addition, since each component failure has a different influence on the performance or operability of the subsystem and the entire system, a weight for failure is set and reflected in the system performance.

The proposed health evaluation method is performed through the process shown in Figure 2. First, fault detection information and performance information of the core elements are collected. The fault detection information includes the results of the fault diagnosis technique applied to each equipment and the results of the fault diagnosis inherent when the equipment is produced. The reliability and performance for the subsystem are calculated using the acquired information and the pre-defined weights for each part based on the FT of the system.

The health of the subsystem is calculated using the reliability and performance of the subsystem. The health of the entire system is calculated based on the health of the subsystems.

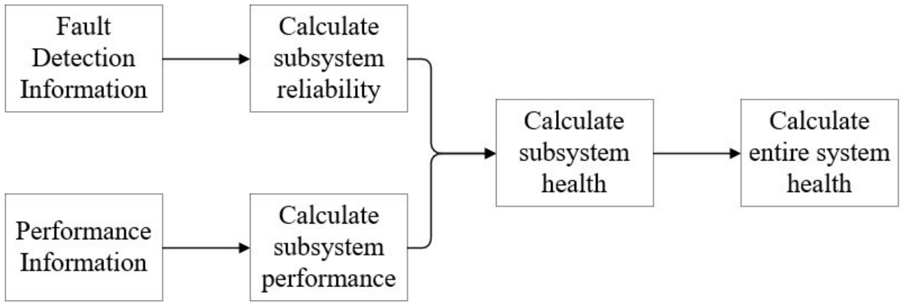

Figure 2. The calculation process of the proposed method.

3.1. Reliability Evaluation Method

When calculating the reliability of a system, the reliability function in exponential form is mainly used. In general, the failure rate is expressed as a constant and serves as a parameter, and the reliability $R(t)$ of the part at time t is used as shown in Equation (2) [53].

$$f(t) = \lambda e^{(-\lambda t)} \tag{1}$$

$$R(t) = 1 - \int_0^t f(t)dt = e^{-\lambda t} \tag{2}$$

where $f(t)$ is the failure probability density function for the part, and λ is the failure rate of the part.

3.2. Health Evaluation Method

To calculate the health of the system, we utilize the performance reliability index proposed in Reference [54] applied to the network. The performance reliability index of application i is as shown in the following Equation (3).

$$RI_i = \sum_{j=1}^{p} \omega_j \times \left(\sum_{l}^{m} \omega_l \times \left[1 - \frac{\sum_{t=1}^{T/\Delta t} F_l(t)}{T/\Delta t} \right] \right) \tag{3}$$

$$\sum_{l=1}^{m} \omega_l = 1, \sum_{j=1}^{p} \omega_j = 1 \tag{4}$$

where T is the system operation time, $F_l(t)$ is the number of failures in time t, Δt is the data collection interval, ω_l is the weight of the failure, and ω_j is the traffic ratio of the application. Based on Equation (3), the performance reliability index of the network is as shown in Equation (5).

$$RI = \sum_{i=1}^{q} \omega_{A_i} \times RI_i \tag{5}$$

$$\sum_{i=1}^{q} \omega_i = 1 \tag{6}$$

where ω_{A_i} is the weight of application i.

In this paper, we propose a method to evaluate the health of the system using Equations (3) and (5). First, the health of the subsystem is calculated, and, based on this, the health of the entire system is calculated.

3.3. Health Evaluation of Subsystem

The health of the subsystem is calculated by applying the weights of the performance, reliability, and component performance based on the performance reliability index proposed in Reference [54]. If the time-dependent failure probability of Equation (3) is converted from discrete time to continuous time, it can be expressed as Equation (7) below.

$$1 - \lim_{T/\Delta t \to \infty} \sum_{t=1}^{T/\Delta t} F(t)\frac{T}{\Delta t} = 1 - \int_0^T F(t)dt = R(T) \quad (7)$$

By applying Equation (7) to Equation (3), the health of the subsystem S_i is calculated using Equation (8).

$$H_{S_i}(t) = \sum_{i=1}^{n} \omega_i \times P_i(t) \times R_i(t) \quad (8)$$

$$\sum_{i=1}^{n} \omega_i = 1 \quad (9)$$

where ω_i is the performance weight of the component, $P_i(t)$ is the performance of the component i in time t, and $R_i(t)$ is the reliability of the component i in time t. For parts without reliability information, this is calculated with $R = 1$.

3.4. Evaluation of System Health

The health of the system is calculated based on the health of the subsystem. The weight of a failure is used to reflect the effects of a failure that can affect the entire system. The health of the system is calculated as follows.

$$H_S(t) = \omega_f(t) \sum_{i=1}^{n} \omega_{S_i} \times H_{S_i}(t) \quad (10)$$

$$\sum_{i=1}^{n} \omega_{S_i} = 1 \quad (11)$$

$$\omega_f(t) = \begin{cases} 0, & \text{a critical failure occurs at } t \\ 1, & \text{a critical failure does not occur at } t \end{cases} \quad (12)$$

where ω_{S_i} is the weight of the subsystem health (H_{S_i}), and $\omega_f(t)$ is the weight of the failure occurring in time t. When a fatal failure occurs and the system cannot operate, $\omega_f = 0$. The system is operable even if a failure occurs, $\omega_f = 1$.

4. FTA for AUV

4.1. System Details

The AUV to be dealt with in this paper is included as part of a complex system consisting of an unmanned surface vehicle and several unmanned submersibles. In this paper, a power-controlled AUV (PCAUV) is considered among various types of AUV. At the beginning of the mission, the AUV is loaded onto the Unmanned Surface Vehicle (USV) and moved to the mission area. When the AUV arrives at the mission area, it sequentially performs various tasks, such as launching, mission execution (exploration), and recovering.

The detailed mission of the AUV are as follows.

AUV Missions

The status information of the AUV system is regularly shared to the mission controller located on the USV through Ethernet before launching. The AUV performs separation control from the USV in accordance with guidance command from the mission controller of the USV. The AUV shares status information with the mission controller. According to the mission controller's command to start the investigation, the AUV is switched to investigation mode. After launching, the AUV dives to a preset location according to the AUV mission scenario, navigates autonomously along the route, and acquires data using the sensors.

The AUV transmits the status information to the mission controller regularly through the underwater ultrasonic communication modem and receives commands from the mission controller. When the mission is completed, it automatically floats and periodically transmits the status of the AUV through the underwater communication modem. After surfacing, the AUV connects to the USV through RF communication, regularly transmits the status of the AUV, and receives the guidance command from the mission controller for recovery.

The mission controller controls the AUV by sending the guidance control command. The mission controller transmits the docking start command and attempts docking by controlling the AUV according to the docking scenario. After recovering, the mission controller in the USV downloads the acquisition data from the AUV and uploads the next mission to the AUV. The AUV reports the findings and the current status. The status of the AUV is regularly shared with the mission controller in the USV through the Ethernet. The AUV battery is charged by receiving power from the USV.

4.2. Fault Tree of AUV

FTA is a top-down system analysis method that defines system failures as top events. It analyzes the causes of failures, and finally identifies failures in component units. By connecting the relationship between each basic event with a logic gate, the influence on the failure of the system, which is the highest event, can be analyzed [20].

For the AUV considered in this paper, internal state monitoring is performed on four main subsystems: a driving unit, a control unit, a mission equipment unit, and a communication unit. The performance and the reliability of the part is monitored in each subsystem. We considered the FT for the above subsystem. The details of the designed FT are as follows:

4.2.1. Fault Tree for Driving Unit (Fault Tree A)

The driving unit includes a deflection propulsion unit, an emergency lift unit, a buoyancy control device, and a driving unit power supply. The deflection propulsion unit is a system, including a deflection controller and a propulsion unit, and performs fault diagnosis on leakage and motor drives. To analyze the health of the driving unit, as shown in Figure 3, the fault tree for the drive unit is designed considering the RPM, current, voltage, controller temperature, and motor direction control performance of the motor. The fault tree is composed of a fault tree for performance and a fault tree for reliability. The details of each item can be found in Tables 1 and 2.

4.2.2. Fault Tree for Controller Unit (Fault Tree B)

The control unit includes an autonomous control computer, a complex navigation computer, a part of communication, a depth sensor, and a power supply. The computer monitors the internal CPU usage, memory usage, HDD capacity, and CPU temperature and checks the interlocking status of communication modems. Based on the above, the control unit fault tree was designed as shown in sub-fault tree B in Figure 3.

4.2.3. Fault Tree for Mission Equipment Unit (Fault Tree C)

The mission equipment unit includes various sensors to perform the mission. A system checks the interlocking status of Sonar or underwater cameras. Cases of Inertial Measurement Unit, Doppler Velocity Log, and CTD (Conductivity, Temperature, and Depth Sensor) can be monitored inside the sensor. Based on the related fault diagnosis and status monitoring, the fault tree was designed as shown in sub-fault tree C in Figure 3.

4.2.4. Fault Tree for Communication Unit (Fault Tree D)

The communication unit consists of an underwater communication device, an underwater position tracker, and an integrated antenna assembly. Each communication device checks the interlocking state. The fault tree for the communication unit is shown in Figure 3 as the sub-fault tree D.

Table 1. Basic performance event description of the fault tree.

Event	Meaning	Event	Meaning	Event	Meaning	Event	Meaning
P1	Motor RPM	P14	Power supply temperature	P27	HDD Capacity	P40	Controller PTM current
P2	Motor voltage	P15	Controller battery voltage	P28	CPU temperature	P41	Controller PCM voltage
P3	Motor current	P16	Controller battery temperature	P29	CPU usage	P42	Controller PCM current
P4	Controller voltage	P17	Controller battery charging state	P30	Memory usage	P43	Charging time
P5	Controller temperature	P18	Charging current	P31	HDD capacity	P44	Pressure sensor
P6	Motor horizontal direction control	P19	Discharging current	P32	CPU temperature	P45	Conductivity
P7	Motor vertical direction control	P20	Motor power transformation module (PTM) voltage	P33	Temperature	P46	Temperature
P8	Hydraulic pump motor ouput current	P21	Motor PTM current	P34	Actuator battery voltage	P47	Pressure sensor
P9	Throttle valve motor output current	P22	Motor power charging module (PCM) voltage	P35	Actuator battery temperature	P48	Underwater sound velocity
P10	Pressure sensor	P23	Motor PCM current	P36	Actuator battery charging state	P49	Position accuracy
P11	LVDT	P24	Charging time	P37	Carging current	P50	Depth accuracy
P12	Battery voltage	P25	CPU usage	P38	Discharging current		
P13	Driver status check current	P26	Memory usage	P39	Controller PTM voltage		

Table 2. Basic reliability event description of the fault tree.

Event	Meaning	Failure Rate ($\lambda \cdot 10^{-6}/h$)	Event	Meaning	Failure Rate ($\lambda \cdot 10^{-6}/h$)	Event	Meaning	Failure Rate ($\lambda \cdot 10^{-6}/h$)
R1	Leak detection	13.59	R13	CAN communication connector	3.624	R25	Pressure sensor failure	1
R2	Motor driver	1.8	R14	Leakage	1	R26	Gyroscope sensor failure	1
R3	SOL	0.1	R15	Actuator battery	0.24	R27	Accelerometer failure	1
R4	Power supply leakage	1	R16	Controller PTM	8.6	R28	Highest temperature warning	1
R5	Controller battery	0.24	R17	Controller PCM	8.6	R29	Lowest temperature warning	1
R6	Motor PTM	8.6	R18	Depth gauge	0.3	R30	Presurre out of range	1
R7	Motor PCM	8.6	R19	SSS transducer	1.5	R31	Gyroscope out of range	1
R8	WIFI/LTE communication modem	3.624	R20	Forward monitoring MBS	1.5	R32	Accelerometer out of range	1
R9	Satellite communication modem	5	R21	Underwater camera	1	R33	Underwater ultrasonic communication transducer	3.624
R10	RF communication modem	3.624	R22	GPS antenna	1	R34	Underwater wireless optical transmitter	0.24
R11	RS232 communication connector	3.624	R23	GPS failure	1	R35	Integrated antenna assembly	0.24
R12	Ethernet communication connector	3.624	R24	DVL failure	0.1	R36	Underwater location tracker	14

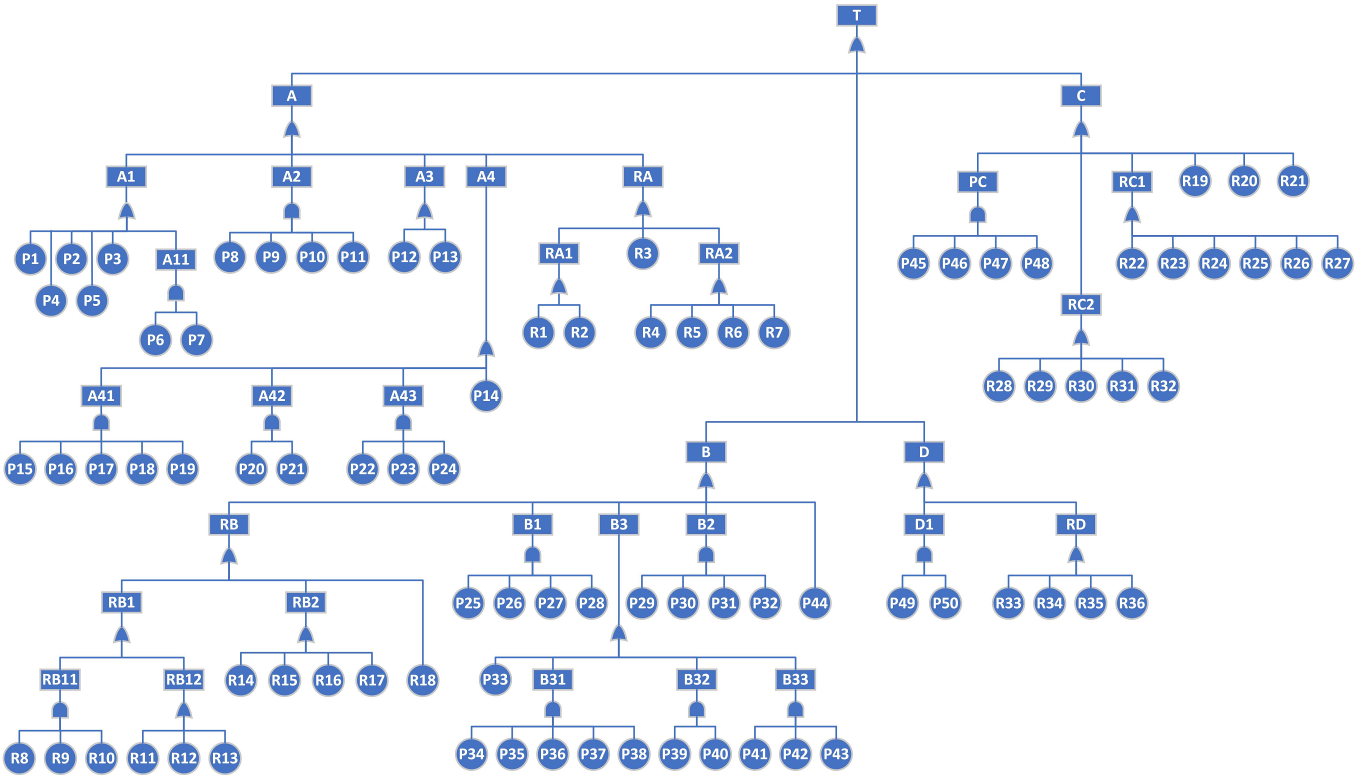

Figure 3. The design of a fault tree for AUV.

5. Simulation

5.1. Simulation Setup

The AUV operation scenario for the simulations consists of two types: exploration/recovery (20 h) and charging (20 h). In order to confirm the effect of component performance degradation and failure influence on the health of the system, simulations are performed for various scenarios, including various failures. We define the priority of a failure in consideration of its influence on the system. A system with a failure corresponding to priority 1 can no longer be operated. If a failure corresponding to priority 2 occurs, the system can be operated with degraded performance. Each scenario is 40 h long and performs a mission that includes exploration/recovery and charging twice.

The scenario for the AUV is set as follows.

- Case 1: Normal operation.
- Case 2: Failure corresponding to priority 1.
- Case 3: Failure corresponding to priority 2.
- Case 4: Transient failure corresponding to priority 2.

The failure rate of the basic event for calculating the reliability of AUV using the fault tree is shown in Table 2 [55–58]. Simulations are performed using MathWorks' MATLAB in a PC environment.

5.2. Simulation Results

5.2.1. Case 1: Normal Operation

The left side of the graph in Figure 4 represents the health of the AUV, and the right side represents the performance of components. In the case of the performance of parts, only four major parts with different performance characteristics are shown on the graph. The performance of parts changes while the AUV performs exploration/recovery and charging. The simulation results of case 1 show the change in the health of the system according to the change of performance of various parts. As the AUV performs its exploration mission, the performance of various parts gradually decreases, and as it charges and transmits data after recovery to USV, the performance gradually improves. It can be seen that the performance change of these parts is well-represented in the AUV health.

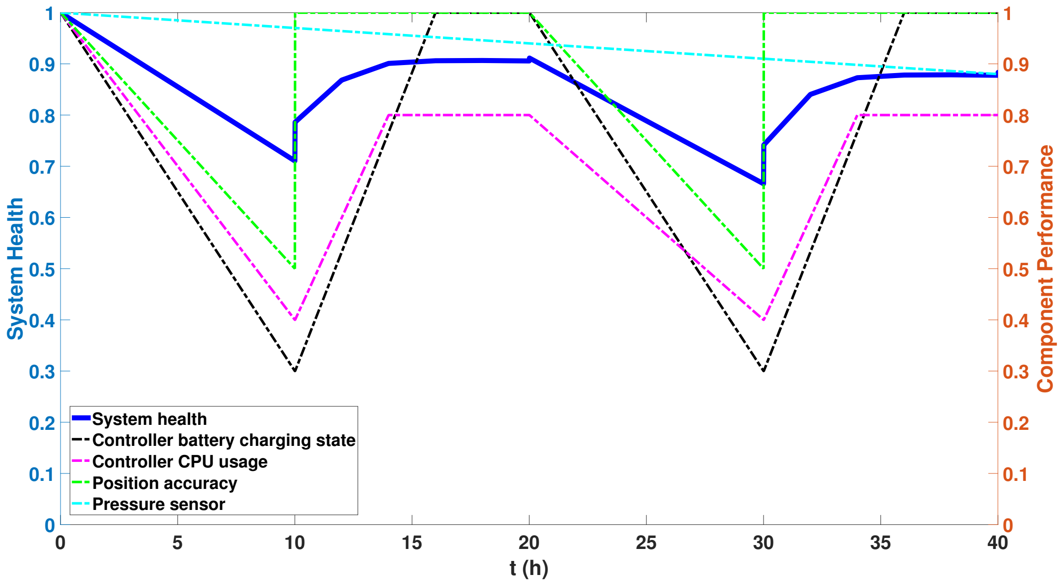

Figure 4. The simulation results of scenario case 1.

5.2.2. Case 2: Failure Corresponding to Priority 1

In the second scenario, it is assumed that a fault corresponding to priority 1 occurs at time 25 h during AUV operation. Figure 5 shows the effect of the performance of parts that change over time and the mission performed by AUV on the health of the system. In addition, it can be seen that the health of the system decreases to zero due to the fault of the motor driver corresponding to priority 1 at time 25 h. It is shown in Figure 5 that a fault corresponding to priority 1, which makes the system impossible to operate, is immediately reflected in the system health.

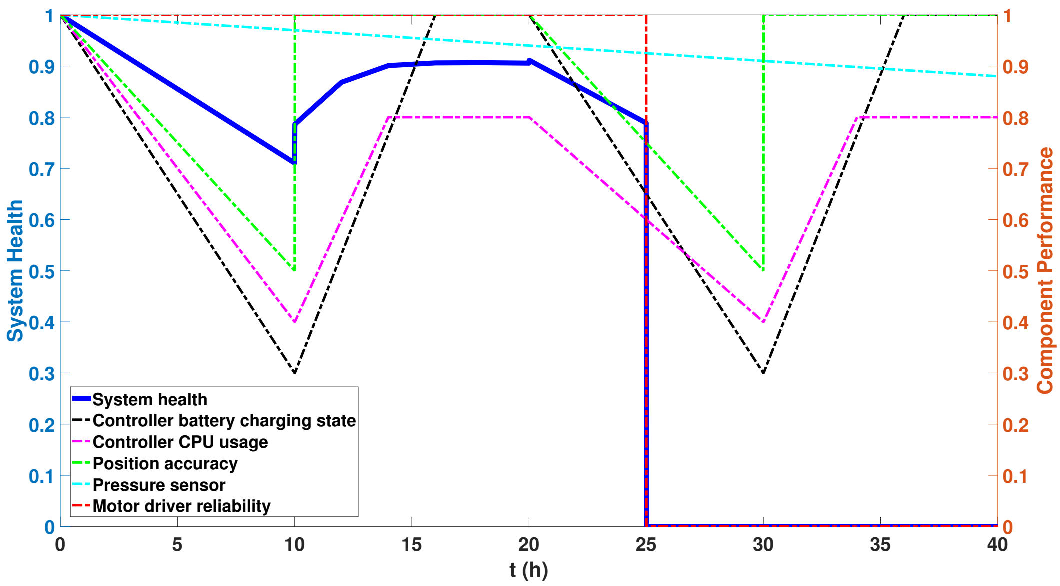

Figure 5. The simulation results of scenario case 2.

5.2.3. Case 3: Failure Corresponding to Priority 2

In the third scenario, it is assumed that a fault corresponding to priority 2 occurs during operation. Figure 6 shows that the health of the AUV decreases when the CAN communication connector failure occurs at time 25 h while performing a mission. Some of performance degradation or multiple faults of multiple components do not cause a complete failure of the system. In that case, it can be confirmed that the health of the system can be estimated by combining the performance and reliability of each component.

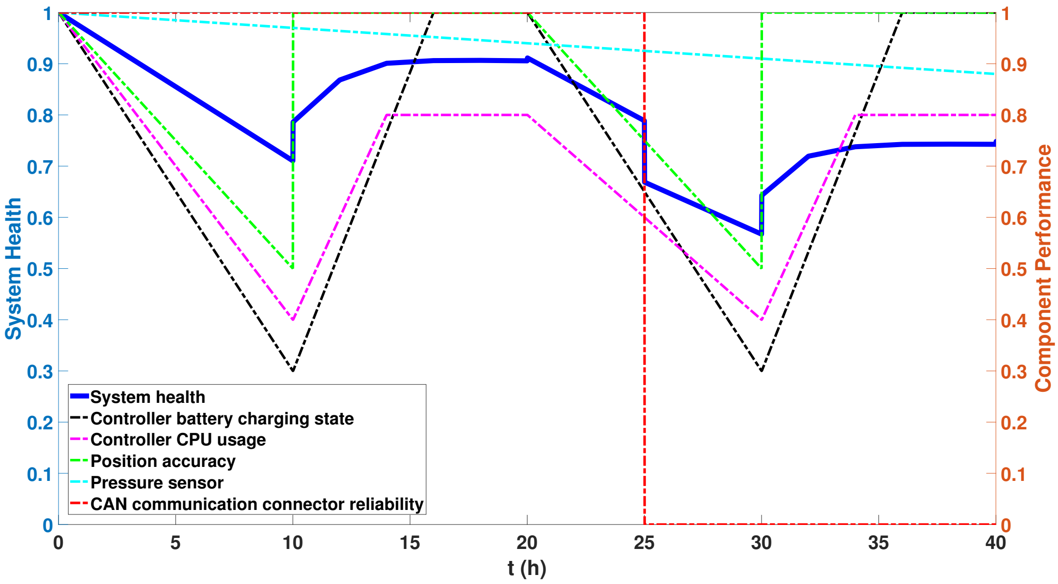

Figure 6. The simulation results of scenario case 3.

5.2.4. Case 4: Transient Failure Corresponding to Priority 2

In the last scenario, it is assumed that a fault corresponding to priority 2 occurs and the fault recovers after a certain time. A CAN communication connector failure occurred at time 25 h while the AUV is operating, and the AUV continues to operate with degraded health. Afterwards, the health of the AUV is restored by recovering from the fault at time 35 h. It can be seen from Figure 7 that the health of the AUV changes as the performance of these various parts degrades and the fault recovers.

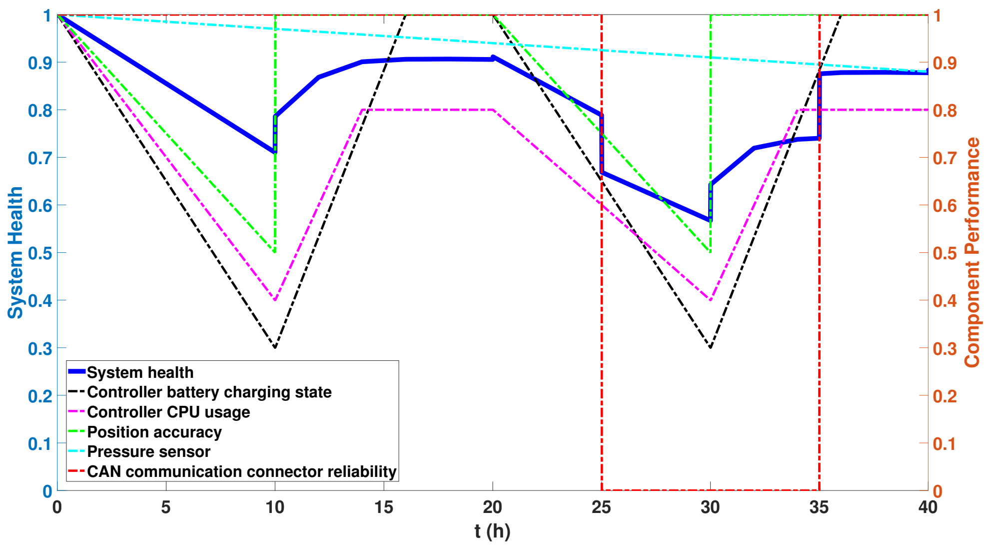

Figure 7. The simulation results of scenario case 4.

6. Discussion

In order to perform a long-duration mission, the AUV requires accurate information on the current system status. In general, information, such as the reliability and performance, is used to determine the system status. In this paper, a method for evaluating the health of a system, which is an index that integrates the reliability and performance, is proposed. By considering the system failure and performance status in real time, it is possible to represent the overall system status more accurately. According to the simulation results, we confirmed that the health of the entire system changes according to the failure and performance changes of various parts of the system.

For operating such a complex system, the information about the health status of each system is critical for efficient system operation. The system-level health status obtained from this algorithm will be used by the higher-level decision-maker, including the mission planner and the path planner, to determine the most desirable system operation mode under the given environment. As a result, it is possible to reduce the social cost by increasing the accuracy of the operation judgment of the system and preventing accidents, such as failure or loss of the system. The advantages and disadvantages between the proposed method and conventional fault diagnosis and prognosis are summarized in Table 3.

Table 3. Comparison of the fault diagnosis, fault prognosis, and proposed method.

Approaches	Advantages	Disadvantages
Fault diagnosis and prognosis [59]	• Effective and powerful to conduct real-time monitoring • Convenient for implementation (signal-base) • Estimate the remaining useful life • Prior warning of a failure	• Need accurate model (model-based) • Sensitive to external disturbances and load changes (data-driven) • Dependent on the quality of the recorded data (data-driven) • Focus on a single part
Proposed method	• Early detection of performance degradation • Effectively reduce failure • Evaluate the health status of the entire system • Reflect the impact of a minor fault	• Time cost at early steps • Needs an experienced system expert

7. Conclusions

In this paper, a health-monitoring method of AUVs considering the reliability, performance, and weight based on a FT is proposed. Fault-tree analysis, including failure and performance, was performed for an AUV. Based on the FT, the reliability and performance of subsystems were calculated by considering the weights of fault and performance. Using the calculated results, the health of the subsystems and, finally, the health of the system were calculated. The effectiveness of the proposed method was verified through simulations, including various failures and performance.

As a result of performing simulations by applying the proposed algorithm to an AUV under development, we confirmed that the current health state of the system could be determined more clearly. The proposed method can be applied to any system with the ability of fault detection and performance evaluation for its components. The system-level health status, which is predicted by the proposed method, may be effectively utilized in determining the optimal system operation mode by a higher-level decision-maker, such as an onboard mission planner and/or a human operator. As future work, the proposed method will be implemented and verified with a fleet of real vehicles consisting of a USV, two AUVs, and two gliders.

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Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Network
AUV	Autonomous Underwater Vehicle
BDD	Binary Decision Diagram
BN	Bayesian Network
DBN	Dynamic Bayesian Network
DFT	Dynamic Fault Tree
DT	Decision Tree
FT	Fault Tree
FTA	Fault Tree Analysis
FFTA	Fuzzy Fault Tree Analysis
NN	Neural Network
PCM	Power Charging Module
PN	Petri Net
PTM	Power Transformation Module
RBD	Reliability Block Diagram
USV	Unmanned Surface Vehicle

References

1. Eng, Y.H.; Teo, K.M.; Chitre, M.; Ng, K.M. Online System Identification of an Autonomous Underwater Vehicle Via In-Field Experiments. *IEEE J. Ocean. Eng.* **2016**, *41*, 5–17. [CrossRef]
2. Castaldi, P.; Menghini, M.; De Marchi, L.; Simani, S. Autonomous Underwater Vehicle Actuators Health Monitoring for Smart Harbour Application. In Proceedings of the 2020 fifth International Conference on Smart and Sustainable Technologies (SpliTech), Split, Croatia, 23–26 September 2020.
3. Kim, E.J.; Kim, S.T.; Kim, Y.H.; Choi, M.J.; Viet, D.H.; Song, J.W. A Dual Fault Detection Algorithm Based on the Federated Kalman Filter to Enhance the Reliability of the Navigation System. *J. Inst. Control Robot. Syst.* **2020**, *26*, 136–143. [CrossRef]
4. Kordestani, M.; Saif, M.; Orchard, M.E.; Razavi-Far, R.; Khorasani, K. Failure Prognosis and Applications—A Survey of Recent Literature. *IEEE Trans. Reliab.* **2021**, *70*, 728–748. [CrossRef]
5. Maliuk, A.S.; Prosvirin, A.E.; Ahmad, Z.; Kim, C.H.; Kim, J.-M. Novel Bearing Fault Diagnosis Using Gaussian Mixture Model-Based Fault Band Selection. *Sensors* **2021**, *21*, 6579. [CrossRef] [PubMed]
6. Glowacz, A.; Tadeusiewicz, R.; Legutko, S.; Caesarendra, W.; Irfan, M.; Liu, H.; Brumercik, F.; Gutten, M.; Sulowicz, M.; Daviu, J.A.A.; et al. Fault diagnosis of angle grinders and electric impact drills using acoustic signals. *Appl. Acoust.* **2021**, *179*, 108070. [CrossRef]
7. Abubakar, S.; Ahmad, I.S.; Gambo, F.L.; Gadanya, M.S. A Rule-Based Expert System for Automobile Fault Diagnosis. *Int. J. Perceptive Cogn. Comput.* **2021**, *7*, 20–25.
8. Xu, G.; Hou, D.; Qi, H.; Bo, L. High-speed train wheel set bearing fault diagnosis and prognostics: A new prognostic model based on extendable useful life. *Mech. Syst. Signal Process.* **2021**, *146*, 107050. [CrossRef]
9. Encalada-Dávila, Á.; Puruncajas, B.; Tutivén, C.; Vidal, Y. Wind Turbine Main Bearing Fault Prognosis Based Solely on SCADA Data. *Sensors* **2021**, *21*, 2228. [CrossRef]
10. Peng, J.; Xia, G.; Li, Y.; Song, Y.; Hao, M. Knowledge-based prognostics and health management of a pumping system under the linguistic decision-making context. *Expert Syst. Appl.* **2022**, *209*, 118379. [CrossRef]

11. Catelani, M.; Ciani, L.; Galar, D.; Patrizi, G. Optimizing Maintenance Policies for a Yaw System Using Reliability-Centered Maintenance and Data-Driven Condition Monitoring. *IEEE Trans. Instrum. Meas.* **2020**, *69*, 6241–6249. [CrossRef]
12. Zhou, D.; Li, Z.; Zhu, J.; Zhang, H.; Hou, L. State of health monitoring and remaining useful life prediction of lithium-ion batteries based on temporal convolutional network. *IEEE Access* **2020**, *8*, 53307–53320. [CrossRef]
13. Wu, C.; Yue, J.; Liu, J.; Wang, L. An online proactive health monitoring method for output capacitors of vehicular auxiliary converter. *IEEE J. Emerg. Sel. Top. Power Electron.* **2021**, *10*, 1219–1231. [CrossRef]
14. Asoodar, M.; Nahalparvari, M.; Danielsson, C.; Söderström, R.; Nee, H.P. Online health monitoring of DC-link capacitors in modular multilevel converters for FACTS and HVDC applications. *IEEE Trans. Power Electron.* **2012**, *36*, 13489–13503. [CrossRef]
15. Zhou, Y.; Zheng, Y.; Tao, J.; Sun, M.; Sun, Q.; Dehmer, M.; Chen, Z. Servo Health Monitoring Based on Feature Learning via Deep Neural Network. *IEEE Access* **2021**, *9*, 160887–160896. [CrossRef]
16. Martínez, J.; Gómez-Pau, A.; Riba, J.R.; Moreno-Eguilaz, M. On-line health condition monitoring of power connectors focused on predictive maintenance. *IEEE Trans. Power Deliv.* **2020**, *36*, 3611–3618. [CrossRef]
17. Wang, D.; Peng, Z.; Xi, L. Theoretical and experimental investigations on spectral Lp/Lq norm ratio and spectral Gini index for rotating machine health monitoring. *IEEE Trans. Autom. Sci. Eng.* **2020**, *18*, 1074–1086. [CrossRef]
18. Tai, A.T.; Meyer, J.F.; Avižienis, A. *Software Performability: From Concepts to Applications*; Springer: New York, NY, USA, 1996; pp. 9–13.
19. Golnas, A. PV system reliability: An operator's perspective. In Proceedings of the 2012 IEEE 38th Photovoltaic Specialists Conference (PVSC), Austin, TX, USA, 3–8 June 2012.
20. Nikoaos, L. *Fault Trees*; ISTE LTD: London, UK, 2007; pp. 49–66.
21. Ruijters, E.; Stoelinga, M. Fault tree analysis: A survey of the state-of-the-art in modeling, analysis and tools. *Comput. Sci. Rev.* **2015**, *15*, 29–62. [CrossRef]
22. Shu, X.; Guo, Y.; Yang, W.; Wei, K.; Zhu, Y.; Zou, H. A Detailed Reliability Study of the Motor System in Pure Electric Vans by the Approach of Fault Tree Analysis. *IEEE Access* **2020**, *8*, 5295–5307. [CrossRef]
23. Ikwan, F.; Sanders, D.; Hassan, M. Safety evaluation of leak in a storage tank using fault tree analysis and risk matrix analysis. *J. Loss Prev. Process Ind.* **2021**, *73*, 104597. [CrossRef]
24. Márquez, F.P.G.; Ramírez, I.S.; Mohammadi-Ivatloo, B.; Marugán, A.P. Reliability Dynamic Analysis by Fault Trees and Binary Decision Diagrams. *Information* **2020**, *11*, 324. [CrossRef]
25. Sarbayev, M.; Yang, M.; Wang, H. Risk assessment of process systems by mapping fault tree into artificial neural network. *J. Loss Prev. Process Ind.* **2019**, *60*, 203–212. [CrossRef]
26. Khakzad, N.; Khan, F.; Amyotte, P. Dynamic safety analysis of process systems by mapping bow-tie into Bayesian network. *Process Saf. Environ. Prot.* **2013**, *91*, 46–53. [CrossRef]
27. Khakzad, N.; Khan, F.; Amyotte, P. Safety analysis in process facilities: Comparison of fault tree and Bayesian network approaches. *Reliab. Eng. Syst. Saf.* **2011**, *96*, 925–932. [CrossRef]
28. Zhifeng, L.; Wang, Z.; Ren, Y.; Yang, D.; Lv, X. A novel reliability estimation method of multi-state system based on structure learning algorithm. *Eksploat. Niezawodn. Maint. Reliab.* **2019**, *22*, 170–178.
29. Jakkula, B.; Mandela, G.R.; Ch S N, M. Reliability block diagram (RBD) and fault tree analysis (FTA) approaches for estimation of system reliability and availability—A case study. *Int. J. Qual. Reliab. Manag.* **2021**, *38*, 682–703. [CrossRef]
30. Zheng, Y.; Zhao, F.; Wang, Z. Fault diagnosis system of bridge crane equipment based on fault tree and Bayesian network. *Int. J. Adv. Manuf. Technol.* **2019**, *105*, 3605–3618. [CrossRef]
31. Sun, B.; Li, Y.; Wang, Z.; Yang, D.; Ren, Y.; Feng, Q. A combined physics of failure and Bayesian network reliability analysis method for complex electronic systems. *Process Saf. Environ. Prot.* **2021**, *148*, 698–710. [CrossRef]
32. Li, K.; Yi, R.; Ma, Z. Reliability analysis of dynamic reliability blocks through conversion into dynamic bayesian networks. In Proceedings of the 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bali, Indonesia, 4–7 December 2016.
33. Mi, J.; Li, Y.; Huang, H.Z.; Liu, Y.; Zhang, X. Reliability analysis of multi-state systems with common cause failure based on bayesian networks. In Proceedings of the 2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering, Chengdu, China, 15–18 June 2012.
34. Montani, S.; Portinale, L.; Bobbio, A.; Codetta-Raiteri, D. Radyban: A tool for reliability analysis of dynamic fault trees through conversion into dynamic Bayesian networks. *Reliab. Eng. Syst. Saf.* **2008**, *93*, 922–932. [CrossRef]
35. Jafari, M.J.; Pouyakian, M.; Khanteymoori, A.; Hanifi, S.M. Reliability evaluation of fire alarm systems using dynamic Bayesian networks and fuzzy fault tree analysis. *J. Loss Prev. Process Ind.* **2020**, *67*, 104229. [CrossRef]
36. Márquez, F.P.G.; Pérez, J.M.P.; Marugán, A.P.; Papaelias, M. Identification of critical components of wind turbines using FTA over the time. *Renew. Energy* **2016**, *87*, 869–883. [CrossRef]
37. Jiang, G.-J.; Li, Z.-Y.; Qiao, G.; Chen, H.-X.; Li, H.-B.; Sun, H.-H. Reliability Analysis of Dynamic Fault Tree Based on Binary Decision Diagrams for Explosive Vehicle. *Math. Probl. Eng.* **2021**, *2021*, 5559475. [CrossRef]
38. Jiménez, A.A.; Muñoz, C.Q.G.; Márquez, F.P.G. Dirt and mud detection and diagnosis on a wind turbine blade employing guided waves and supervised learning classifiers. *Reliab. Eng. Syst. Saf.* **2019**, *184*, 2–12. [CrossRef]
39. Muñoz, C.Q.G.; Márquez, F.P.G.; Lev, B.; Jimenez, A. New Pipe Notch Detection and Location Method for Short Distances employing Ultrasonic Guided Waves. *Acta Acust. United Acust.* **2017**, *103*, 772–781. [CrossRef]

40. Huang, T.; Huang, H.-Z.; Li, Y.-F.; Shi, L.; Qian, H.-M. 3-Reliability analysis of solar array drive assembly by dynamic fault tree. In *Advances in Reliability Science, Safety and Reliability Modeling and its Applications*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 31–42.
41. Fazlollahtabar, H.; Niaki, S.T.A. Integration of fault tree analysis, reliability block diagram and hazard decision tree for industrial robot reliability evaluation. *Ind. Robot.* **2017**, *44*, 754–764. [CrossRef]
42. Abbasi, F.; Allahviranloo, T. Estimation of Failure Using Fault Tree Analysis Based on New Operations on LR-Type Flat Fuzzy Numbers. *New Math. Nat. Comput.* **2021**, *17*, 153–174. [CrossRef]
43. Kabir, S.; Taleb-Berrouane, M.; Papadopoulos, Y. Dynamic reliability assessment of flare systems by combining fault tree analysis and Bayesian networks. *Energy Sources Part Recover. Util. Environ. Eff.* **2019**, 1–18. [CrossRef]
44. Wang, W.; He, X.; Li, Y.; Shuai, J. Risk analysis on corrosion of submarine oil and gas pipelines based on hybrid Bayesian network. *Ocean. Eng.* **2022**, *260*, 111957. [CrossRef]
45. Ferdous, R.; Khan, F.; Sadiq, R.; Amyotte, P.; Veitch, B. Fault and Event Tree Analyses for Process Systems Risk Analysis: Uncertainty Handling Formulations. *Risk Anal.* **2011**, *31*, 86–107. [CrossRef]
46. Abdelgawad, M.; Fayek, A.R. Comprehensive Hybrid Framework for Risk Analysis in the Construction Industry Using Combined Failure Mode and Effect Analysis, Fault Trees, Event Trees, and Fuzzy Logic. *J. Constr. Eng. Manag.* **2012**, *138*, 642–651. [CrossRef]
47. Hyun, K.C.; Min, S.Y.; Choi, H.S.; Park, J.J.; Lee, I.M. Risk analysis using fault-tree analysis (FTA) and analytic hierarchy process (AHP) applicable to shield TBM tunnels. *Tunn. Undergr. Space Technol.* **2015**, *49*, 121–129. [CrossRef]
48. Purba, J.H.; Lu, J.; Ruan, D.; Zhang, G. A Hybrid Approach for Fault Tree Analysis Combining Probabilistic Method with Fuzzy Numbers. *Artificial Intell. Soft Comput.* **2010**, *6113*, 194–201.
49. Soltanali, H.; Khojastehpour, M.; Farinha, J.T.; Pais, J.E.d.A.e. An Integrated Fuzzy Fault Tree Model with Bayesian Network-Based Maintenance Optimization of Complex Equipment in Automotive Manufacturing. *Energies* **2021**, *14*, 7758. [CrossRef]
50. Zhao, C.; Yip, T.L.; Wu, B.; Lyu, J. Use of fuzzy fault tree analysis and Bayesian network for occurrence likelihood estimation of navigational accidents in the Qinzhou Port. *Ocean. Eng.* **2022**, *263*, 112381. [CrossRef]
51. Yan, R.; Jackson, L.; Dunnett, S. Automated guided vehicle mission reliability modelling using a combined fault tree and Petri net approach. *Int. J. Adv. Manuf. Technol.* **2017**, *92*, 1825–1837. [CrossRef]
52. Kabir, S.; Aslansefat, K.; Sorokos, I.; Papadopoulos, Y.; Konur, S. A Hybrid Modular Approach for Dynamic Fault Tree Analysis. *IEEE Access* **2020**, *8*, 97175–97188. [CrossRef]
53. Chang, Y.; Brito, M. On the Reliability of Experts' Assessments for Autonomous Underwater Vehicle Risk of Loss Prediction: Are Optimists better than Pessimists? In Proceedings of the Probabilistic Safety Assessment and Management (PSAM), Los Angeles, CA, USA, 16–21 September 2018.
54. Wang, X.; Huang, N.; Chen, W.; Li, R. A new method for evaluating the performance reliability of communications network. In Proceedings of the 2010 International Conference on Information, Networking and Automation (ICINA), Kunming, China, 18–19 October 2010.
55. Department of Defense. *MIL-HDBK-217F, Military Handbook: Reliability Prediction of Electronic Equipment*; Department of Defense: Arlington, VI, USA, 1991.
56. Bian, X.; Mou, C.; Yan, Z.; Xu, J. Reliability analysis of AUV based on fuzzy fault tree. In Proceedings of the International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering (QR2MSE), Chengdu, China, 9–12 August 2009.
57. Hu, Z.; Yang, Y.; Lin, Y. Failure analysis for the mechanical system of autonomous underwater vehicles. In Proceedings of the International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering (QR2MSE), Chengdu, China, 15–18 July 2013.
58. Aslansefat, K.; Latif-Shabgahi, G.; Kamarlouei, M. A strategy for reliability evaluation and fault diagnosis of Autonomous Underwater Gliding Robot based on its Fault Tree. *Int. J. Adv. Sci. Eng. Technol.* **2014**, *2*, 83–89.
59. Gao, Z.; Liu, X. An Overview on Fault Diagnosis, Prognosis and Resilient Control for Wind Turbine Systems. *Processes* **2021**, *9*, 300. [CrossRef]