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# Operational Aspects and Risk Management of an Autonomous Well Service Pump for Offshore Installations

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**Abstract:** The paper discusses operational aspects and establishes the basics of risk management for autonomous technology applied to the topside well service pump for offshore installations. In the analysis, a specific machine is investigated, an electrically driven pump with a power of 725 horsepower equipped with a computer-controlled system. The system enables performing basic tests, control checks, and maintenance, for example, from the operator's office onshore. The research is divided into two parts. The first describes machine learning applications and determines autonomy levels for offshore well service pumps. The computer-controlled system in this paper is considered the first stage of autonomy. The level of autonomy (LoA) was gradually increased by applying machine learning, implementing predictive maintenance techniques, and creating the digital twin. The highest autonomy stage enables the machine to make critical decisions. That feature brings many profits, for instance, reducing the number of people in dangerous places or prevents from making bad decisions. The risk assessment analysis was performed in the second part of the paper. The risk description for every LoA was provided, and the hazard events were specified and described providing the causes and solutions. Lastly, the experienced team assessed the risk, presenting the results in the risk matrix. The analysis shows that the most hazardous events are related to the connection and environmental conditions with the unit. The research shows that there is a potential for the application of machine learning in machinery systems for the offshore industry. Therefore, there is a need for more research in that field.

**Keywords:** offshore technology, machine learning, autonomous technology, risk assessment

## 1. Introduction

Offshore work is one of the most dangerous jobs in the world [1]. All people working on offshore structures are exposed to threats every day. However, safety has become the most critical factor for many offshore companies. Therefore, many are trying to limit the dangerous influence on their employees. Due to safety reasons, trips to offshore facilities are enabled only for those whose presence is required. Nevertheless, the number of people working on the oil platforms can still be reduced.

This problem can be solved by implementing autonomous technology in machines in offshore facilities. Additionally, this idea is very innovative and follows the trend of Industry 4.0. Lately, it has been observed that automation and digitalization have become more popular, and for that reason, engineers are trying to make machines more intelligent and resistant to human errors. Also, researchers started building digital versions of the physical units. And as a result, most of the tests are performed virtually in real time, and there is no need to stop physical machines from working to check whether the upgrade is beneficial. This resolution is called a digital twin. The creation of a digital twin can reduce the number of people on oil rigs, and the application of machine learning can allow making units brighter. Companies that provide their services offshore also follow this trend [2]. For instance, some oil production companies started to collaborate with data scientists. As a result, they created a database where they share industrial data. For example, one of the operating companies has been transmitting data from the compressor installed on the oil platform in the Val hall field in the North Sea. Now, this database is fully open, and everyone can use it for their own needs [3].

This example indicates that the digitalization of machines used in the industry is becoming more common. The analysis presented in Chatzimparmpas et al. [4] shows that the number of publications related to machine learning, digital twins, or predictive maintenance increases yearly. Moreover, big oil and gas companies take this topic very seriously, so they have started developing and testing autonomous technology in their products.

On the other hand, most of the available publications related to intelligent systems in the offshore industry refer to autonomous ships and subsea operations [5–7]. The study shows that there is a

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lack of publications associated with the application of artificial intelligence and digitization of offshore machinery equipment. For that reason, research in this field is needed. This paper provides the risk analysis of a specific well-service pump and introduces the operational aspects of autonomous technology applied to the pump system.

An analysis is carried out on a topside well service pump with a power of 725 horsepower and is powered by electricity (WSP 725 CCE) (Figure 1). The device is equipped with a computer-controlled system to operate the pump remotely. The pump is intended to inject the seawater into the offshore well.

**Figure 1**
**Well-service pump WSP 725 CCE equipped with HMI module**

The pump is driven by electricity, bringing several pros compared to the conventional diesel engine unit. The electric engine is quieter and more efficient. What is more, it does not produce pollution in the atmosphere. The downside of it is that it is more expensive [8].

Before the pump is delivered to a customer, Interactive Customer Acceptance Test (ICAT) is performed. The client does not have to travel to the supplier's store to test the unit. All acceptance checks can be carried out remotely via an HTML-based link that will grant access to operate the unit. It means the client can fully control the machine in real time from his office in a different county, thousand kilometers away. This solution can also be used oppositely. When the unit is delivered to the client or installed on the offshore rig, the supplier can perform essential maintenance such as troubleshooting and software updates or guide a technician. Additionally, the test can be observed by multiple people. It allows brainstorming and cooperation with other engineers and technicians to fix a failure more efficiently. This solution of performing tests reduces the number of people in hazardous places and improves safety.

## 2. Autonomous systems

Around 37% of oil and 28% of gas world production come from reservoirs located under the seabed. The sea environment makes production very difficult and extremely dangerous. Oil and gas production often requires building complex subsea installations such as Christmas trees or manifolds. With the development of autonomous technologies, engineers have started using unmanned underwater vehicles to make work safer. These robots allowed building and installing structures underwater without human presence. This example shows that the term "autonomy" or "autonomous systems" in the offshore industry was primarily focused on underwater vehicles. Today, scientists are looking for new autonomy applications in the offshore sector to make it safer. The offshore industry requires using many topside machines, such as pumps, generators, and vacuum units. To operate them safely and efficiently, the person who operates them must have a lot of knowledge and experience. Machines can become independent and resistant to human mistakes by applying autonomous technology.

Huang [9] defines the autonomous system as a system that is able to perform the planned tasks without human intervention while adapting to working and environmental conditions. According to Rødseth and Nordahl [10], a system can be called autonomous if it has the ability to operate independently of an operator. It can be possible by installing a whole range of intelligent components, from automated sensors to a decision-making system created based on machine learning.

Due to the complexity and various application advancements of autonomous systems, it seems obvious to create different autonomy groups. In the available literature, it is possible to find many divisions of autonomous levels. Rødseth [11] and Fukuto [12] propose four different levels of autonomy (LoA). However, National Research Council of the National Acedemies [13] divides autonomous systems into four and ten different stages. On the other hand, Vagia et al. [14] states that one correct division system does not exist, and classification depends on a designer.

Table 1 provides a definition of four different levels of autonomy for the well-service pump system. Level zero (no autonomy) means the machine lacks an intelligent system. The autonomy level increases with the gradual addition of smart components like programmable logic controllers (PLC) and a human–machine interface (HMI). The application of those parts allows the system to control it remotely and develop the unit to the second level of autonomy (LoA). The following two stages (third and fourth) permit the system to make recommendations and decisions. The last stage of autonomy (fourth) makes the system completely independent and eliminates human presence and intervention.

### 2.1. Human–machine interface

The pump system can be controlled in a more human-friendly way by installing the HMI in the unit. HMI is a simple screen that is usually resistant to aggressive environments such as dust or water, making it ideal for industrial conditions. The interface shows the status and settings of the unit graphically, so it is easier to understand and operate the machine for less experienced operators [15]. Moreover, the HMI can display the unit's real-time data and enable operational modifications.

The pump unit described in the introduction is equipped with a HMI device. Figure 2 presents an example of the interface on the module's screen. The view is updated in real time, so the operator sees the actual and the most updated process state. The panel is fully interactive so that every parameter can be quickly changed. For example, if the operator decides to close or open one of the valves in the system, it is enough to tap the component on the screen and press the option "close" or "open." The system is also equipped with a warning system. If the software detects any error or potential danger, it immediately informs the operator about the threats. And in undeniably dangerous situations, the machine will shut down.

The HMI in industrial conditions can have different formats depending on the application and customer requirements. The most popular variant is the screen mounted on a metal pedestal next to the unit. Due to the risk of lousy reception in offshore conditions, the HMI is connected to the main electrical panel by the cable to keep the connection stable. On the other hand, it is possible to use the HMI panel small or portable device. It is

**Table 1**
**Levels of autonomy in offshore machines for well service**

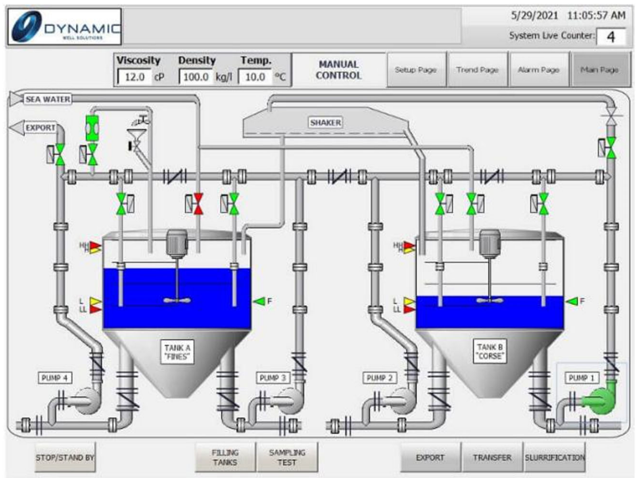
| Level of autonomy | Description |
|---|---|
| 0. No autonomy | The system is fully controlled by humans and cannot give any advice or make any decisions related to the operation. The system can only notify about basic required actions, such as low fuel or a battery needing to be charged. |
| 1. Human control system | The system can perform the mission by following the algorithm created by the operator; however, it cannot give recommendations or make any independent decisions. This stage of autonomy enables control of the system remotely by application of programmable logic controllers (PLC) and human–machine interface (HMI). |
| 2. Computer control system | The system performs the mission by following an uploaded algorithm and also gives recommendations related to the operation. The system's advice may only be implemented if the operator approves it. Some basic tests and measurements may be automatically carried out if the system has specific sensors. |
| 3. Semi-autonomous system | The system can make decisions if the time is too short for the operator to react. The operator can change the mission parameters in case of errors. Data and reports are continuously sent to the operator to inform him about the task's progress. Machine learning is applied to the system and, based on collected data, can predict when maintenance is needed. |
| 4. Fully autonomous | The system is fully autonomous and can perform the mission automatically and without help from the operator. Human presence or assistance is not necessary any longer. The machine can recognize and solve threats or problems by changing the mission's parameters. The operator is informed about the progress of the task. |

becoming popular to use small and handy industrial tablets. That solution allows operating the pump unit remotely, for instance, from the operator's office or even a hundred kilometers from the workplace. In that way, the customer or engineers can remotely follow the production, collect data, or apply changes in an operation. Nevertheless, it requires keeping a stable connection that can be difficult due to the natural offshore environment.

## 2.2. Machine learning

With the development of artificial intelligence technology, machines that are used in different kinds of the industry have become more intelligent. All devices are becoming more independent and can work with limited or without supervision. It is because people started to "teach" machines how to work and

**Figure 2**
**Visualization of the system displayed by the human–machine interface (HMI)**




make the right decisions. This development is called machine learning [16].

The machine is able to learn how to make a correct decision by analyzing collected data. The data are collected by sensors installed in the system. All data are analyzed following a specific algorithm and statistical models. Then, the machine can decide whether the decision is correct based on the results. Machine learning can be applied to the device using two basic approaches, (*i*) supervised learning and (*ii*) unsupervised learning.

The first approach uses datasets to train the system to classify data or accurately predict outcomes. With the time system can learn them and measure their accuracy. The second approach is to analyze unlabeled datasets. The unsupervised learning algorithm discovers hidden patterns in data and, what is more, works without human intervention. It is also possible to use a third approach called semi-supervised learning, which offers medium possibilities for supervised and unsupervised learning [17].

The Well Service Pump is equipped with sensors that collect data related to the working process. Next, these data are sent to the database and analyzed. The statistical models are created based on all collected data. And then, the pump system is trained to make decisions and work without human supervision.

The application of artificial intelligence and machine learning to the pump unit creates an opportunity to go some steps further, create a digital twin of the pump, and apply safe predictive maintenance.

## 2.3. Digital twin

A digital twin is a virtual version of the physical component, device, machine, or system. The virtual version of the system is built based on collected historical data from the actual unit. The studied system is equipped with various sensors that monitor the components and collect different parameters influencing the system, such as temperature, pressure, and degradation. Based on these data, the system performs a simulation on the virtual version of the model. The results of various simulations show whether the system is able to increase efficiency. Based on the results, the operators can decide if the process is efficient enough if the efficiency should be increased, or if maintenance is needed [18, 19].

**Figure 3**
**Principle of digital twin applied to the pump system**

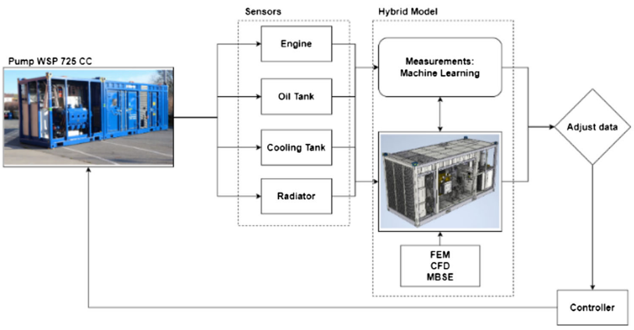



Figure 3 presents the working principle of a digital twin applied to the WSP 725-horsepower electric pump. The sensors are installed in the unit to monitor the critical components and parameters, such as bearings, filters, pump pressure, temperature, or flow. Then the real-time data are transferred and applied to the digital twin of the unit. Based on the data, the system carries out FEA and CFD simulations. Next, the improvement is accepted or rejected. If the unit is fully autonomous (4th level), the system decides whether the improvement is beneficial. This decision depends on the operator if the system is on the 0-3 level.

## 2.4. Predictive maintenance concept

All machines in the world will finally break down. However, it is possible to extend their life by performing conservations, updating software, or changing parts. These actions are called maintenance. There are many scenarios of how to carry out maintenance of machines. The most popular are reactive and preventive maintenance [20]. In reactive maintenance, a component, a device, or a system is used until it breaks down, and then, it is replaced. The most significant advantage of this solution is that a part is used until the end of its lifetime. On the other hand, it is impossible to predict when a component will break down. In preventive maintenance, a component, a device, or a system is changed after a fixed period, e.g., after one year. By applying this solution, the maintenance is planned, so there is no unexpected failure, but the potential of a component is not fully used.

With the development of machine learning, the new maintenance scenario started to become popular in the machinery industry. In this scenario, the system can predict when maintenance is needed. This solution is called predictive maintenance. Predictive maintenance is a technique to predict behavior patterns, trends, and correlation by statistical or machine learning models based on historical data, domain knowledge, and available models. Applying predictive maintenance to the physical model makes it possible to predict the failure before it happens [21, 22]. Very often, if the system is extensive and complex, it is difficult or sometimes impossible to predict which part will fail. However, this technique will indicate the exact component that will break, no matter how big the system is.

## 3. Risk management

It is challenging to define risk in one general way. The standard ISO 3100 (International Standard ISO 31000:2018(E) [23] defines risk as "the effect of uncertainty on objectives." The standard NORSOK Z-013 [24] provides another definition of risk, which is a "combination of the probability of occurrence of harm and the severity of that harm." However, the most common definition of risk is the formula:

$$Risk = Probability \cdot Consequences \tag{1}$$

In this formula, the probability is related to the likelihood that the event can happen, and the consequences impact the situation when an event occurs.

The more precise definition of the risk is described by equation (2). The probability for two events might be the same, but the assessor's knowledge about these two events can be different. That means that the likelihood that an event can happen will be completely different. This formula includes the strength of knowledge of a risk assessor.

$$Risk = (A, C, Q, K) \tag{2}$$

In equation (2), A is a hazardous event, C is consequences related to event A, Q is a probability measure, and K is the assessor's knowledge to estimate the risk. This equation provides a good definition of risk because it consists of knowledge, probability, and black swans.

Clearly defining what event can be called a black swan is very difficult. Risk scientists still discuss this term. According to Taleb [25], a black swan is an unexpected event with large magnitude and extreme consequences. According to Aven [26], the black swan is "a surprising, extreme event relative to the present knowledge/beliefs." Also, Aven [27] categorizes black swans' events as (*i*) events unknown to experts and unknown to others (e.g., new discovery); (*ii*) unknown circumstances for experts but generally known phenomena, and (*iii*) events known but not believed to occur.

Risk management is dealing with the conflicts inherent in exploring occasions and avoiding accidents, losses, and failures [24]. Risk management is fundamental in the process of making decisions, essential to achieve the safe and cost-efficient design and operation of a complex system. Risk management is established by risk assessment, monitoring, and decision-making.

Table 2 presents a description of risk for every LoA defined in Table 1. It is impossible to eliminate the threats. However, with increased system independence, the risk of hazards is lower. Furthermore, Table 2 indicates the most significant probability of a hazardous event to level zero (no autonomy). With the increase of system independence, human error is considered less likely to occur. If the system is fully autonomous (fourth level), there is no risk of human error since their intervention is uninvolved. The only risk considered in that stage is an occurrence of an unknown situation or black swans.

This paper provides the risk assessment of an autonomous well service pump using the formal aafety assessment (FSA) method. This method was presented in Hamann & Cichowicz [28] by International Maritime Organization. This method was created to evaluate new regulations for marine safety and the protection of the marine environment. In this study, the FSA methods have been chosen due to its wide application in the marine and offshore industry. The FSA methods consist of five steps: (*i*) identification of hazards, (*ii*) risk analysis, (*iii*) risk-control options, (*iv*) cost–benefit assessment, and (*v*) recommendation for decision-making.

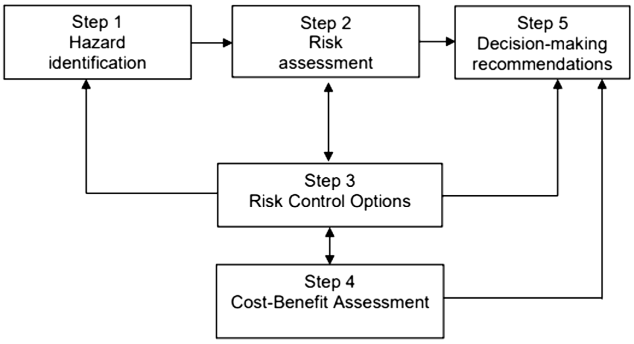
## 3.1. Identification of hazards

Establishing the list of hazards is the first step of the FSA method (Figure 4). This step aims to identify hazardous events that might occur during the operation. Chang et al. [29] proposed category list of hazards for offshore autonomous vehicles. This list is adjusted for offshore pump installation and placed in Table 3. Each category contains a short description.

**Table 2**
**Brief risk description for each autonomous level**

| Level of autonomy | Brief risk description |
|---|---|
| 0. No Autonomy | Special training and certification of the operator are strictly required. Creating procedures is essential. Also, the operator should be experienced and know how to work with the unit. |
| 1. Human control system | The risk is dependent on the operator. The operator must complete the training and be certified to use the unit. Creating procedures is essential. |
| 2. Computer control system | The risk is still dependent on the operator's decision. However, the system's recommendation can help reduce the risk of danger. The safety since the system follows the given algorithm. |
| 3. Semi-autonomous system | The risk is dependent on the situation. The autonomy of the unit highly decreases human error. However, the system still requires remote supervision. Notification about maintenance increases the robustness of the unit. |
| 4. Fully autonomous | The risk is entirely dependent on the efficiency and resistance of the system. Risk will be increased if an unknown situation for the system occurs. |

**Figure 4**
**Formal Safety Assessment (FSA) methodology [28]**




### *3.1.1. Equipment failure*

The equipment failure contains all failures related to hardware or tools. For instance, engine failure or worn-out bearings belong to this category. Equipment failure is serious damage because it can lead to many catastrophes, such as human death, fire in offshore facilities, loss of machine control, and long-term cessation of oil and gas production.

### *3.1.2. System failure*

The system failure contains all failures related to software and algorithm design. This system is responsible for the correct execution of hydrocarbon production. For example, software failure and loss of control belong to this category. This kind of damage may lead to enormous consequences, such as loss of control of the machine, loss of communication with the unit, lack of internet connection, and an incorrect decision made by the autonomous system.

**Table 3**
**Hazard categories**

| Category | Description |
|---|---|
| Equipment failure | Strongly this failure might bring severe consequences and harm people. This malfunction can cause loss of control, fire, or sensor failure. The failure of a single component of the system can also decrease production efficiency. |
| System failure | This failure causes a lack of communication with the machine. The system is equipped with an HMI, and the unit cannot operate in case of failure. It can create severe consequences if the device is used remotely, and it is impossible to turn it off from the operator's office onshore. |
| Interaction with the environment | This failure is dependent on weather conditions. The unit is powered by electricity, and water in undesirable places can create a current short circuit and cause severe damage. Bad weather might also lead to a loss of connection with the machine. |
| Human error | Even though the system is autonomous, there is still a probability that human error might occur. The system is programmed and designed by a human. So, mistakes, for example, can be present in a code. |
| Cyberattacks | This failure is dependent on connection security. The unit is connected to the computer in an operator's office wireless. That means cyberattacks are a serious threat. A cyberattack can lead to system and equipment failure. |

### *3.1.3. Environmental interaction*

The interaction between the pump unit and the environment may be dangerous. The probability that this type of threat will occur is low, but it still has to be considered a hazardous event. The presence of this kind of failure is entirely dependent on weather conditions and the resistance of the equipment. To this kind of failure belong a current short circuit, equipment flooding, and thunder strikes.

### *3.1.4. Human error*

Although the unit is fully autonomous, there is still room for human error. Ahvenjärvi [30] claims that this factor can never be entirely eliminated because human is always involved in design and remote-control operation. Human error can occur, e.g., during structural or software designing, coding, planning the mission, and maintenance operations.

Planning a mission is a very critical point of the production operation. Mistakes at this stage will affect the rest parts of the process. The only way to decrease the risk of this hazard is to use an experienced team and check multiple times if all conditions and factors were chosen correctly.

**Table 4**
**Risk assessment for different hazard scenarios**

| Hazard | Hazardous event | Probable causes | Consequences | Prob. | Cons. | Risk |
|---|---|---|---|---|---|---|
| Equipment failure | Sensor failure | Vibration; dust; wear out | Loss of control; stop data collection | 3 | 3 | 9 |
| | Bearing failure | Wear out; neglect in maintenance | The operation stoppage | 2 | 5 | 10 |
| | Shaft failure | Corrosion, abrasion, cracks | The operation stoppage | 1 | 5 | 5 |
| System failure | Loss of communication during an operation | Jamming or spoofing | Operation failure | 4 | 5 | 20 |
| | Wrong interpretation of data by the system | Not enough storage data | Poor decisions made by an autonomous system | 1 | 4 | 4 |
| | Temporary loss of electricity | Blackout | Temporary stoppage; use of a spare generator | 2 | 2 | 4 |
| Environment interaction | PLC component failure | Too low temperature | Temporary operation stoppage | 2 | 5 | 10 |
| | Poor internet connection | Bad weather conditions | Temporary operation stoppage | 4 | 4 | 16 |
| Human error | Errors in a code | The vast complexity of the programming | Poorly/wrongly working operating software | 3 | 5 | 15 |
| | Error in a physical contact maintenance | Poor experience | More frequent maintenance is needed; temporary stoppage | 2 | 4 | 8 |
| | Error in remote control | Weak knowledge of the operation | An operation performed incorrectly; unit failure | 2 | 5 | 10 |
| Cyberattack | Communication breakdown | Poor cybersecurity | Production/operation failure | 2 | 5 | 10 |
| | Operation system failure | Poor cybersecurity | Production/operation failure | 2 | 5 | 10 |
| | Loss of data | Poor cybersecurity | Lack of historical data used for machine learning | 2 | 4 | 6 |

The system uses a predictive maintenance technique. That means that the role of the human is limited to physical installation work. However, this operation must be done without mistakes and according to the standards and procedures. If the replacement of parts is not performed correctly, it will lead to severe damages or catastrophes.

*3.1.5. Cyberattacks*

Due to the pump system is autonomous and controlled remotely, the probability of occurrence of a cyberattack is considered very high. It has been observed that cyberattacks have been reported more frequently lately [31]. This type of failure can lead to serious damage to the equipment or system. A way to avoid this event is to improve cybersecurity systems.

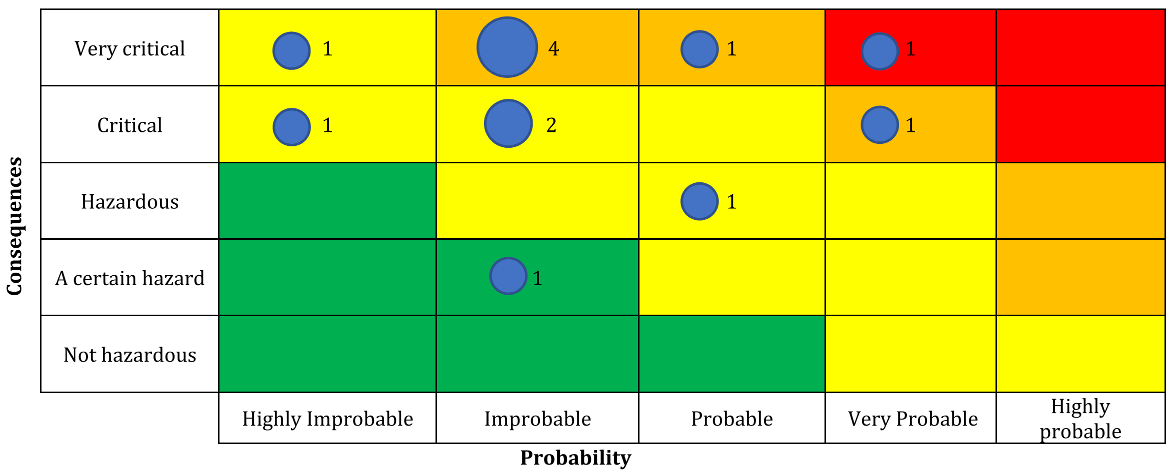
## 3.2. Preliminary hazards analysis

Risk assessment is a process to establish sources of risk, hazards, and opportunities. Risk assessment also deals with understanding how risk sources can occur or cause events and what consequences they can bring. In order to assess the risk in the most professional way, the best available knowledge data or information should be used [32].

There are many ways of assessing the risk. The most used methods are failure mode event analysis, hazard operability analysis, fault tree analysis, risk matrix, and Bayesian networks. The risk assessment provided in this study was performed using preliminary hazard analysis, risk matrix, and ALARP techniques.

The preliminary hazard analysis (PHA) was performed by a team with rich working experience in the machinery and automation

**Figure 5**
**Risk assessment for different hazard scenarios**



industry. The hazards that are chosen for this analysis are the most common threats in well-service units and autonomous systems.

The analysis started with hazard identification. For each hazard category, three hazardous events were chosen. For every event, the probable causes and consequences were obtained. Next, the probability and consequences were assessed. And the risk was calculated according to Equation (1). The results are presented in Table 4.

Once the risk was assessed using the PHA technique, the results were presented in the risk matrix. The risk matrix is displayed in Figure 5. Each point in the matrix displays the risk ratings, and the number corresponds to the amount of cases. Risk assessment is qualitative and represents a general understanding of presented hazards.

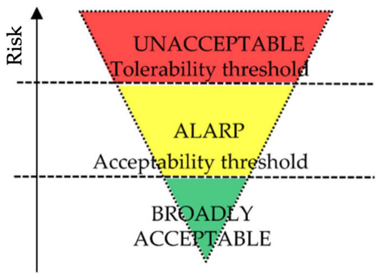
The performed studies consist of 14 hazard scenarios belonging to five categories. Carried out risk analysis shows that most of the results (eight cases) lie in the medium-high-risk area. These events are considered as ones that can bring critical or very critical consequences. However, they also belong to events with a lower likelihood of occurring.

### 3.3. ALAR principle

The ALARP (As Low As Reasonably) principle says that risk-reducing measures should be applied unless the burdens are grossly disproportionate to gains [33].

Figure 6 presents the scheme of the ALARP principle. The top red part of the triangle is where the risk measure is unacceptable and should be reduced (except for extraordinary situations). The middle yellow part of the figure consists of tolerable risk measures that cannot be reduced due to the cost of risk reduction that excites the benefit gained. The last green part of the triangle consists of acceptable events. It is essential to maintain the events' risk on that level.

**Figure 6**
**Scheme of ALARP Principle [34]**




## 4. Conclusion

The paper presents the operational aspects of the autonomous topside well service pump with 725 horsepower (WSP 725 CCE) for offshore installation. Moreover, the study provides the foundation for risk management of the pump system. The first part of the analysis describes how the autonomous system applied to the unit works and its possibilities and limitations. Furthermore, the research introduces the cooperation between machines and humans via HMI module. Next, a detailed description of possibilities that give the application of machine learning to the pump is presented. Finally, the authors of the paper divide the autonomous system into four levels of autonomy (LoA) and provide a description as well as advantages and disadvantages for each stage.

The risk assessment analysis was performed in the second part of the paper. The FSA method was used in the risk study. First, the foundation of risk was introduced. Second, the risk description for every LoA was provided. Next, the hazard events were specified and described providing the causes and solutions. Finally, the experienced team assessed the risk, and the results were presented in the risk matrix.

The risk assessment in this paper was performed using the FSA method. In the beginning, the list of hazards has been identified. The primary and most significant hazard categories for autonomous systems are equipment failure, system failure, environment interaction, human error and cyberattacks. A hazardous event and probable causes and consequences have been identified for each category. The risk of event occurrence has been assessed based on the available sources and experts' knowledge. All results we placed in the risk matrix. Performed analysis shows that the most probable and critical event is operation failure due to loss of communication during an operation caused by jamming or spoofing. The second highest risk rate has been assigned to temporary operation stoppage caused by bad weather conditions and poor internet connection. Moreover the results show that the most hazardous events belong to the group of probable events.

Overall the most probable events with critical risk are related not to the mechanical components but to the connection and environmental conditions with the unit. For that reason, the connection technology must be improved to decrease the risk of operation failure. Moreover, if this technology is improved, it will be possible to apply a higher LoA to the units and decrease the number of people working offshore. This will ensure safety in the dangerous workplace. The paper shows that there is significant potential for the application of machine learning in machinery systems for the offshore industry. Therefore, there is a need for more research in that field.

## Acknowledgement

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## Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

## Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

## Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

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