A SURVEY ON THE USE OF DIGITAL TWINS FOR MAINTENANCE AND SAFETY IN THE OFFSHORE OIL AND GAS INDUSTRY

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Companies in the oil and gas industry have, since the fall in oil price in 2014, been under pressures to cut costs and improve the effectiveness of their operations. Digitalization is generally considered as an important contributor to achieve this. One barrier to benefit from digitalization that is increasingly being recognized by the industry is data silos. Digital twin is a concept that has been proposed to alleviate this problem, but there is a lack of common understanding of what this concept entails and the potential benefits of this concept. To gain a better understanding of how digital twins are used for maintenance and safety in the offshore oil and gas industry, we have conducted a survey in the form of a web-based questionnaire among practitioners from this industry. 15 responses to the questionnaire was included in the final sample. Nine of these where from respondents that reported to have implemented digital twins in their own organization or in their products or services. Because of the low number of responses, the results cannot be used to draw conclusion on the current state of digital twins for maintenance and safety in the offshore oil and gas industry in general. But the results offer some insights that can be useful for further research.

Keywords: Industry 4.0, digital twin (DT), questionnaire, survey, Industrial Internet of Things (IIoT), offshore oil and gas, predictive maintenance, safety, Norwegian Continental Shelf (NCS), digitalization.

1. Introduction

After the fall in oil price in 2014, companies in the oil and gas (O&G) industry have been under pressure to cut costs and increase the efficiency of their operations (Aalberg et al. 2019; Wanasinghe et al. 2020; DNV-GL 2020b). There seems to be a consensus among the industry actors that digitalization is important to secure the future competitiveness of this industry (Mogos, Eleftheriadis, and Myklebust 2019; DNV-GL 2020b; KonKraft 2018; NTNU 2017).

The potential benefits of digitalization lie mainly in the ability to collect data; turn this data into information and then use this information to make faster and better decisions (Feder 2020; Wanasinghe et al. 2020; Schuh et al. 2020). Collecting and analyzing large streams of data is something that O&G industry have done for decades (Spelman et al. 2017) but the infrastructure has traditionally been built for specific purposes (DNV-GL 2020b). Data silos are increasingly been recognized as an important barrier for effective use of the collected data (KonKraft 2018; Zborowski 2018; Malakuti et al. 2020; Devold, Graven, and Halvorsrød 2017).

Digital twin (DT) is a concept that has been proposed to improve this situation and has been described as a "key enabler for the digital transformation" (Kritzinger et al. 2018, 1016). But "there is currently no common understanding of the term Digital Twin" (van der Valk et al. 2020, 2) and the understanding of DT has changed over time and vary depending on the application context (Boss et al. 2020).

To better understand the current use of this concept in the offshore O&G industry, a survey has been conducted. The survey was organized as a web-based questionnaire. Invitations to the survey was submitted to 69 practitioners from operator companies and service provides invited to a webinar on the current status and challenges related to the use of DT in the Norwegian O&G industry. 15 responses to the questionnaire was included in the final sample. Because the survey is based on a convenience sample (Bryman 2016) and have a low number of responses the results cannot be used to draw conclusions on the current state of DT for maintenance and safety in the offshore O&G industry in general. But the results still offer some insights that can be useful for further research.

The next section of this paper gives a presentation of the current challenges related to digitalization of the O&G industry and presents the DT concept. The method used in the survey is described in Section 3. Section 4 presents the results. The paper ends with a discussion in Section 5 and conclusions in Section 6.

2. Background

2.1. *Digitalization of the Oil and Gas Industry*

One of the barriers to realizing the potential of digitalization in the O&G industry is the use of proprietary software solutions and lack of standardization which have led to data silos (Zborowski 2018; ISO 2019; Devold, Graven, and Halvorsrød 2017; KonKraft 2018). Because of this, manual work is needed to collect, convert, transfer, and validate the available data before it can be analyzed. The problem of data siloes has also been recognized in other industry sectors (Tao, Cheng, et al. 2018; Grieves and Vickers 2017; van der Valk et al. 2020; Hoffmann et al. 2021).

DTs are presented as an approach to reduce the data silo problem (Malakuti et al. 2020; Schulte, Lheureux, and

Proceedings of the 31st European Safety and Reliability Conference
Edited by Bruno Castanier, Marko Cepin, David Bigaud, and Christophe Berenguer
Published by Research Publishing, Singapore.
ISBN: 978-981-18-2016-8; doi:10.3850/978-981-18-2016-8_246-cd

Velosa 2018; van der Valk et al. 2020; Tao, Cheng, et al. 2018). But how to design digital twins to best address this problem is a challenge that remains to be solved (Hoffmann et al. 2021; Tao, Zhang, et al. 2018). One of the challenges with the DT concept is the lack of a generally accepted definition (Uhlenkamp et al. 2019; van der Valk et al. 2020). This is in parts because the understanding of DT has evolved over time and vary between application areas (Boss et al. 2020).

According to Grieves and Vickers (2017) the basic concepts of DT have however been stable over time. The first of these is the idea of the DT as a virtual model of a physical asset that is an entity of its own (Sharma et al. 2018; Zborowski 2018). Another is that these two entities, the physical asset and its digital twin, are linked through the different life cycle phases of the asset (Grieves and Vickers 2017; Tao, Cheng, et al. 2018; Liu et al. 2021).

A key aspect of the DT is to establish a digital model that represents one universally accepted version of the truth that the different stakeholders can use to get the information they need of the physical object (Malakuti et al. 2020). The advantages of this is mainly twofold. Firstly, having the information on the physical object readily available in a digital format makes collecting the information much easier and faster (Schuh et al. 2020). The cost of collecting the information will also be reduced because redundant and overlapping work related to collecting and transferring data from the source is eliminated (Malakuti et al. 2020; Schulte, Lheureux, and Velosa 2018). The other main advantage is that it facilitates sharing of data between the different lifecycle phases of the asset, both backwards (e.g. sensor data from use phase as feedback to improve design), and forwards (e.g. simulation models developed in the design phase as decision support tools in the use-phase) (Wuest, Hribernik, and Thoben 2015; Tao, Cheng, et al. 2018).

One of the areas of controversy related to DT is the need for accuracy in the digital models (Liu et al. 2021; van der Valk et al. 2020). Academics, especially those related to aerospace and aviation (West and Blackburn 2018; Glaessgen and Stargel 2012) but also manufacturing (Tao, Cheng, et al. 2018), have focused on the modelling aspect of DT, and the need for ultra-high fidelity models in order to make accurate simulations of the physical entities. Industry practitioners like the Industrial Internet Consortium (IIC) (Malakuti et al. 2020), and some academics (Grieves and Vickers 2017) are focusing more on aspects related to data handling.

2.2. *Previous Surveys on the Digitalization of the Oil and Gas Industry.*

Previous surveys on the use of DTs in the O&G industry have not been found in the literature. But some surveys related to digitalization of this industry have been found and is presented in this subsection.

In a survey of 13 Norwegian supplies to the O&G industry Mogos, Eleftheriadis, and Myklebust (2019) found that the industry view digitalization as important to cut costs and increase efficiency in order to stay competitive. But they also found that a high proportion of the respondents reported to have little knowledge of concepts such as IoT, Industry 4.0 and CPS. When asked to rate important barrier for the implementation of digital strategies, categories related to knowledge and skills was most frequently chosen by the respondents.

Another source of information on the current use of digital solutions in the O&G industry is the annual survey of the global O&G industry conducted by DNV-GL. These surveys also report that the industry perceives digitalization as important to cut cost and increase production (DNV-GL 2019). In the most recent survey DNV-GL (2020b) reports that there is an increasing attention in the industry to secure that the collected data is available and have the right quality for analysis.

Øien, Hauge, and Grøtan (2020) have conducted a survey of six O&G operators on the Norwegian Continental Shelf (NCS). The focus of this survey was on the use of digital solutions for barrier management and potential vulnerabilities that can be introduced with digitalization.

Øien, Hauge, and Grøtan (2020) found that most of the operators use barrier panels to visualize the status of the safety barriers on the offshore O&G platforms. The barrier status is mainly based on manually collected data such as workorders and reports from the incident management systems. All the companies had examples of safety critical equipment subject to condition monitoring, but none of the operators had automatic updating of the barrier panels based on condition monitoring alarms. Several of the operators reported plans for implementing predictive maintenance (PdM), but few had implemented this maintenance concept. Most operators believe that vulnerabilities will arise from new digital solutions. But the operators do not regard digital security as a major concern when it comes to barrier management because of the limited interconnects between the barrier panels and physical objects (Øien, Hauge, and Grøtan 2020).

2.3. *The Application of Digital Twins*

In this paper we focus on the application of DT related to maintenance and safety.

Maintenance is the application of DT that has received the most attention in the academic literature (Liu et al. 2021). Potential benefits from introducing DT is the ability of combining data from several sources and use this to introduce predictive and prescriptive maintenance policies (Errandonea, Beltrán, and Arrizabalaga 2020). Another application is the use of high fidelity simulations to make synthetic failure data that that can be used to train algorithms for anomality detection and prediction of remaining useful life of equipment (Rao 2020). See Errandonea, Beltrán, and Arrizabalaga (2020) for a literature review on the use of DT for maintenance.

The use of DT for safety is much less prominent in the literature. But Grieves and Vickers (2017) states that the purpose of DT is to mitigate or eliminate unpredicted undesirable behavior from complex systems. They use the Deepwater Horizon disaster (BP 2010) as an example where better situational awareness and predictive capabilities offered by the DT could have helped alerted the operator of the potential consequences of their decisions and by that avoid the accident (Grieves and Vickers 2017).

2.4. *Frameworks for Classification of Digital Twins*

Several authors have proposed different frameworks for classifying DTs. One of these are Kritzinger et al. (2018) which defines three categories of DTs based on the level of integration between the digital and physical entities. Digital models are systems which only have manual data flow between the physical and digital object. Systems with automatic data flow from physical to digital object are labeled digital shadows. Systems with automatic dataflow in both directions are labeled digital twins.

DNV-GL (2020a) divide DTs into six stages based on capability: standalone, descriptive, diagnostic, predictive, prescriptive and autonomy. The first and last of these corresponds to the digital model and twin as defined by Kritzinger et al. (2018). DNV-GL (2020a) also categorizes the confidence levels that is needed of the output from the DTs. The required confidence level is calculated as the product of capability and potential consequences. DTs with high capability and high consequence have the highest requirements for confidence. DNV-GL (2020a) also offers procedures for assuring that the required confidence level of the DTs is met.

2.5. *Research Questions*

DT has become a popular concept but lacks a universally accepted definition. There is also a lack of agreement on how to create and deploy DTs (Liu et al. 2021).

Based on the literature review, we have formulated the following research questions:

- What do the practitioners in the offshore O&G industry perceive as the most important barriers and triggers for implementing DT?
- What are the potential benefits of DT, and is the offshore O&G industry able to realize these benefits?
- What are the capability levels of DTs used by the offshore O&G industry?
- What is the understanding of DT among the practitioners in the offshore O&G industry compared to the academic literature?

3. Research Method

3.1. *Sampling*

Responses to the questionnaire was collected from industry practitioners that was invited to a seminar on the use of DT for maintenance, safety, and control in the offshore O&G industry. The seminar was organized in November 2020 by SUBPRO (2021), a research project focusing on technology innovation for subsea production and processing, and BRU21 (2021), a research project focusing on the digitalization of the O&G industry. Both research projects are collaborations between the Norwegian University of Science and Technology (NTNU) and operators and service providers connected to the NCS. Because a convenience sample was used in the survey the results cannot be assumed to be generalizable to the offshore O&G industry in general (Bryman 2016).

The survey was organized as an anonymous web-based questionnaire using the service Nettskjema (2021). Invitations to the questionnaire was sent out by email to all the 69 participants from the industry, two days before the seminar. During the seminar a short presentation of the survey was given to all participants followed by a short break to complete the survey. No responses were collected after the seminar.

Table 1. Demographics of the final sample (*n* = 15).

	n	**%**
Primary industry		
Supplier / service provider	8	53%
Operator company	7	47%
Primary role		
Engineering	4	27 %
R&D	3	20 %
General management	2	13 %
IT	2	13 %
Operations	2	13 %
Risk management	1	7 %
Sales	1	7 %
Digital maturity compared to peer		
Leading	7	47 %
Average	6	40 %
Lagging	1	7 %
Don't want to disclose / Not relevant	1	7 %
Ability to profit from digitalization		
Leading	4	27 %
Average	5	33 %
Lagging	2	13 %
Don't want to disclose / Not relevant	1	7 %
Don't know	3	20 %

Of the 16 respondents that completed the survey, one respondent reported the education sector as primary industry and was removed from the final sample. This gives a final sample rate of 22%. The demographics of the final sample is presented in Table 1.

When asked to rate the digital maturity of their organization, about half of the respondents (47%) assessed their organization as being leading compared to their peers. In comparison only 21% reported to be "industry leaders in digitalization" in a survey by DNV-GL (2019, 26) of the global O&G industry, indicating that the sample in our survey probably are more digital mature than the average O&G company. This is not surprising given that the selected sample for the survey, participants to a seminar on DT.

3.2. *Survey Design*

Because of the immaturity of the DT concept an exploratory design has been chosen for the survey (Forza 2002). Previous measurement instruments for implementation of DT for maintenance and safety was not identified in the literature, so the questions for the survey was constructed based on previous surveys on use of PdM (Haarman et al. 2018), Industry 4.0 (Staufen 2019; Mogos, Eleftheriadis, and Myklebust 2019) and digital transformations (Kane et al. 2016).

One challenge when designing this survey is the lack of a commonly accepted understanding of the concept DT. In the introduction to the survey the term digital twin was defined as "a digital representation of a real-world entity or system".

4. Results

The results of the survey are presented in a series of frequency tables in this section.

4.1 *General Questions Related to the use of Digital Twins in the Oil and Gas Industry*

All respondents were asked about their perception on the barriers and benefits of DT to the O&G industry in general. The answers in Table 2 through 4 are sorted based on frequency.

Table 2. Answers to the question: "What do you consider to be the most important benefit of using digital twins in the oil and gas industry in general?" (*n* = 15).

The most important benefit	*n*	%
More effective operations	7	47 %
Cost reduction	3	20 %
Reduction of safety, health, environment & quality risks	3	20 %
Improved business decision making	1	7 %
Lifetime extension of aging asset	1	7 %
Improved energy efficiency	0	0 %
Better product design	0	0 %
New revenue streams	0	0 %

The results in Table 2 are in line with the survey by Mogos, Eleftheriadis, and Myklebust (2019) on the motivation for implementing I4.0 in the O&G industry. But in contrast to the same survey few of the respondents reported skills and knowledge as the main barrier (Table 3).

When it comes to the most important trigger for the implementation of DT, 67% of the respondents regarded commercial factors, exemplified by higher demands for effectiveness and efficiency, as being the most important. Only 27% considered the technological development to be the most important trigger. This is in line with observations from the literature survey that the O&G industry regards digitalization as an important contributor to cut costs and increase effectiveness (DNV-GL 2020b).

Table 3. Answers to the question: "What do you consider to be the most important barrier to the use of digital twins in the oil and gas industry in general?" (*n* = 15).

The most important barrier	*n*	%
Lack of data / systems integration	5	33 %
Lack of business case	3	20 %
Lack of organizational agility	2	13 %
Lack of management understanding / commitment	2	13 %
Too many competing priorities	1	7 %
Insufficient technical skills	1	7 %
Don't know	1	7 %
Security concerns	0	0 %
None / no barriers exist	0	0 %

Table 4. Answers to the question: "Which of the following benefits has your organization or customers already achieved by using digital twin(s)?" (N/R = not relevant, *n* = 9).

Benefits achieved	Yes	No	Don't know	N/R
Cost reduction.	100 %	0 %	0 %	0 %
Reduction of safety, health, environment & quality risks.	78 %	0 %	22 %	0 %
More effective operations.	78 %	0 %	22 %	0 %
Improved business decision making.	67 %	11 %	11 %	11 %
Improved energy efficiency.	56 %	0 %	22 %	22 %
Better product design.	44 %	22 %	33 %	0 %
Lifetime extension of aging asset.	44 %	11 %	22 %	22 %
New revenue streams.	33 %	11 %	33 %	22 %

Table 5. Answers to the question: "Which of the following types of models are used in the digital twin(s) in your organization or in your products/services?" (*n* = 9).

Types of models used	Yes	No	Don't know
White box (first principle / physics-based)	78 %	0 %	22 %
Grey box (statistical / stochastic modelling)	33 %	22 %	44 %
Black-box (machine learning, neural networks etc.)	56 %	11 %	33 %

Table 6. Answers to the question: "What of the elements are currently part of the digital twin(s) used in your organization or in your products/services?" (n = 9).

Elements in digital twin	Yes	No	Don't know
3D representation of equipment / installations / plants.	89 %	11 %	0 %
Real-time visualization of process/production status.	89 %	0 %	11 %
Real-time visualization of equipment status.	78 %	0 %	22 %
Real-time visualization of safety barriers.	33 %	0 %	67 %
Simulations used for employee training.	67 %	11 %	22 %
Simulations used for planning or production optimization.	78 %	0 %	22 %
Models that monitor the current health of equipment or processes.	100 %	0 %	0 %
Models that can identify cause-and-effect relationships between different process steps and/or equipment by combining data from different sources.	44 %	22 %	33 %
Models that make predictions on future states of equipment or processes.	78 %	0 %	22 %
Self-learning models (i.e. models that adapt as new data emerges).	44 %	33 %	22 %
Automated decisions making related to process control.	44 %	11 %	44 %
Automated decisions making related to maintenance.	11 %	33 %	56 %
Automated decisions making related to safety.	0 %	33 %	67 %

Table 7. Answers to the question: "To what extent to do you agree with the following statements related to the use of digital twins in your organization" (n = 15).

Statements	Strongly agree	Agree	Neither agree nor disagree	Disagree	Strongly disagree	Don't know / Not Relevant
Digital twins are trusted when it comes to safety critical decisions.	0 %	20 %	33 %	33 %	0 %	13 %
Operators should only use solutions that are provided from one vendor in their digital twin.	0 %	7 %	7 %	33 %	47 %	7 %
Determining the source of inconsistencies between model and measurements is a major challenge in digital twins.	13 %	53 %	27 %	7 %	0 %	0 %
Reasonable estimations are normally sufficient to benefit from the use of digital twins.	0 %	60 %	20 %	13 %	0 %	7 %
A digital model is only a proper digital twin if there is automated dataflow in both direction between the two entities (i.e. the model can control the physical object).	0 %	7 %	20 %	53 %	20 %	0 %
Operators should combine elements from the suppliers that are best in their niche when organizing the digital twin for their assets.	27 %	33 %	27 %	7 %	0 %	7 %
Ultra-high fidelity models are needed in order to give sufficient level of accuracy in digital twins.	0 %	20 %	40 %	13 %	13 %	13 %

4.2. *Company Specific Questions Related to the use of Digital Twins*

Nine of the respondents reported to have implemented DT in their own organization or products/services. Only one respondent considered the implementation of DT not relevant and reported no plans for implementing this in the future. Table 4 shows that the companies that have implemented DT report benefits over a wide range of areas. Table 5 shows that physics-based models are the modelling approach that is most widely used.

As can be seen from Table 6, several of the companies have a level of integration that corresponds to digital shadow as defined by Kritzinger et al. (2018). Only one respondent (11%) confirmed to have automated feedback from the digital model to the physical asset for maintenance and none when it comes to safety.

Another observation from Table 6 is that the capability level, as defined by DNV-GL (2020a) is higher for maintenance compared to safety. 78% reported predictive capabilities related to equipment status. On the other hand, only one third (33%) of the respondents reported that the DT have descriptive capabilities when it comes to safety.

4.3. *Statements Related to Digital Twins*

When it comes to the level of detail that is needed for the DT only 20% agreed that ultra-high fidelity models are needed, while 60% expressed that reasonable estimates normally are sufficient (Table 7). Only one respondent (7%) agreed that there must be automatic dataflow in both directions for a system to be labeled as a digital twin. Regarding implementation of DT more than half the respondents agreed that the operators should combine elements from several providers, while only one respondent disagreed to this statement.

5. Discussion

Several of the results in this survey are in line with previous surveys and literature on digitalization of the O&G industry. Commercial factors was reported to be the most important trigger for the implementation of DT and more effective operations and cost reductions was reported as the most importation benefits.

Among surprising results are the level of maturity when it comes to the use of DT compared to previous surveys on digitalization of the Norwegian O&G industry. Few respondents reported lack of technical skills and management commitment or understanding as the main barrier to DT implementation. This is in contrast to the survey conducted by Mogos, Eleftheriadis, and Myklebust (2019) in 2017 where lack of knowledge and skills was reported as important barriers by a majority of the respondents. Equally surprising is the high capability level of DTs related to maintenance that was found in our survey. While few of the operators was found to have implemented PdM in the survey by Øien, Hauge, and Grøtan (2020) conducted in 2019, about half (47%) of the total population in our survey reported to have implemented DTs with predictive capabilities for maintenance in their organization of products/services.

Both these results indicate that there has been a rapid development in the digital maturity of the O&G companies in the recent years. But this can also be a result of bias in our sample towards more digitally mature companies as indicated in Section 3.

This survey also provides some general insights on how to create and deploy DTs. The respondents report that the implemented DTs have contributed to improvements over a wide range of areas, but their understanding of this concept differs somewhat from the main tendencies in the literature. The first of these differences is related to the level of fidelity needed of the digital models. A majority of the respondents prefer reasonable accurate models over high-fidelity models. In comparison only 22% of papers in a literature review by van der Valk et al. (2020) refers to DTs as partial representations of their physical counterparts. Another area where the respondents in our survey disagree with the majority of publications is regarding the level of integration that is needed between the digital and physical counterparts (van der Valk et al. 2020). Only one respondent agree with the classification by Kritzinger et al. (2018) that require that there is automatic data flow in both directions between digital and physical entities in digital twins.

One possible explanation for this deviation from existing literature is that the need of DTs differs between application areas. Maintenance is one of the most human centric process within manufacturing (Brundage et al. 2019), and human judgement and knowhow is normally applied in addition to input from digital models (Bokrantz et al. 2020) when making maintenance decisions.

The need for fidelity in the digital models and the need for integration in order to profit from the use of DT for maintenance and safety may because of this be lower compared to other areas such as process optimization where existing models are more complex and decision cycles are faster.

This survey also shed some light on how to deploy DTs. A majority of the respondents preferred “best of breed” solutions over solutions from only one provider. This, together with the preference of reasonable accurate models, indicate that a gradual implementation strategy for DT that start with a minimum viable product and then improves from this can be a suitable option for the O&G industry. This is in line with recommendations for how to implement DT from the IIC (Malakuti et al. 2020) and the advisory firm Gartner (Schulte, Lheureux, and Velosa 2018).

5. Conclusion

In this study we have conducted an exploratory survey on the perception and use of DT among industry practitioners related to the Norwegian O&G industry. The contributions from this study can be divided into two parts.

The first is related to the development in the digital maturity of the Norwegian O&G industry. The respondents report that benefits from use of DTs has been achieved across several areas, and few of the respondents consider lack of skills or knowledge as the most important barrier to the implementation of this concept. This indicates that the Norwegian O&G industry has reached a level of digital maturity where it can utilize concepts such as DT to realize real business value.

The other contribution is to shed light on the preferences for design and implementation of DTs for maintenance and safety in the O&G industry. The respondents report that benefit from DTs have been achieved over a wide range of areas even if they prefer simple models over high-fidelity models and lower level of integration between digital and physical entities than normally described in the literature.

There are several limitations to this study in addition to the ones already mentioned. One of them is that several of the questions have a high ratio of respondents that have chosen “don’t know”. A possible explanation for this is lack of clarity in the questionnaire. Closer examination of the data show that the background of the respondents that have chosen “don’t know” changes with the different questions. The number of samples are however too small to conduct quantitative analyses of differences based on the respondents’ backgrounds.

Another limitation is that the size of the benefits from implementing DT have not been estimated, and we do not know if the reported results are achieved through small scale pilots or full-scale implementations. We also do not know if the respondents from the suppliers are referring to benefits achieved in their own organizations or by their customers.

Further research should continue to investigate the use of DT, the potential benefits associated with this concept and different perceptions among suppliers and operators in the O&G industry.

Our survey indicates that the use of DTs offers real business value for the O&G industry. An interesting topic for further research is to investigate more in detail the magnitude of these benefits and how these has been achieved, either through interviews or case studies. Such a study could also investigate if and how the introduction of DTs affects the relationship between operators, suppliers and, third party service providers.

Because of the low number of respondents in our survey, quantitative analysis to identify correlations between the achieved results and the methods and capability level of the implemented DTs was not possible to conduct. A new survey with a sample size large enough to allow for such an analysis might provide valuable information on how to best implement DT.

Acknowledgement

This research is a part of BRU21 – NTNU Research and Innovation Program on Digital and Automation Solutions for the Oil and Gas Industry (www.ntnu.edu/bru21).

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