Tool Compatibility Index: Indicator Enables Improved Tool Selection for Well Construction

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Abstract

In the area of well construction, the tool reliability and the field environment are two contributing factors that influence drilling job efficiency and success. Either using high specification tools in low-risk environmental or applying tools of low reliability in harsh environments is inadvisable. Thus, how to select a suitable tool fitting the environment of an approaching drilling job is of great significance for tool planning. However, today, the tool selection decision is not optimized because it is often based on partial data availability and understanding.

This paper presents an indicator called tool compatibility index, which can support improved tool selection decision making. This index takes part reliability, part criticality, and field environment into consideration, and gives a score indicating the compatibility of the tool to a specific environment. Moreover, the tool compatibility index is computed based on a weighted average method, which is computation simple and can be easily deployed. This work is part of a long-term project aiming to construct a risk based decision advisor for drilling and measurement tools.

1. Introduction

The drilling system (shown in Fig. 1) in the oil and gas industry is usually consisting of a drilling rig, drillpipe, a bottom hole assembly (BHA) and a drill bit. The BHA is an important part of the drilling system because it must provide power for the bit to rotate and break through the rock, survive a harsh operating environment, and provide accurate directional control of the well (Schlumberger, 2022). The BHA is configured based on drilling operation requirements; thus, different drilling jobs could have different BHA configurations. Nevertheless, the BHA frequently includes measurement-while-drilling (MWD) tool(s), logging-while-drilling (LWD) tool(s), and rotary steering system(s) as shown in Fig. 2. The MWD tool on the top of the BHA is responsible for delivering real-time data to the surface, powering and transmitting data from multiple LWD tools, and determining the position and orientation of the drillstring (Schlumberger, 2022). The LWD combines a complete set of functions, including formation evaluation, well placement, and drilling optimization measurements into a single collar (Mosallam, Laval, Youssef, Fulton, & Viassolo, 2018). The rotary steering system at the bottom of the BHA is designed to rotate the drill bit in the desired direction; thereby, control the well path (Kirschbaum et al., 2020). MWD, LWD, and rotary steering system are collectively termed drilling and measurement (D&M) tools or technologies.

Each D&M tool is an electronics-rich system and through decades of development, the built-in electronic boards have had various design revisions, which cause the reliabilities of the boards to be different. This in turn affects the overall tool reliability. Meanwhile, the reliability of D&M tools plays an important role in drilling operation (Kale, Carter-Journet, Falgout, Heuermann-Kuehn, & Zurcher, 2014). Another main

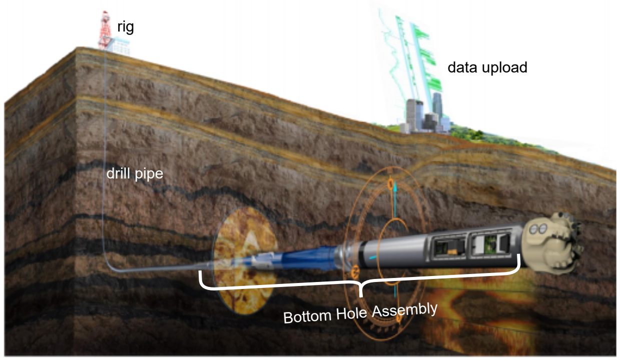

Figure 1. Drilling system schematic.

Figure 2. Bottom hold assembly schematic.

factor affecting the success of a drilling job is the field environment because operating conditions could have a great impact on tool reliability. For example, elevated vibration can cause mechanical structure damage, and high temperature and humidity can cause electronic malfunctions (Bhargava et al., 2020). For an upcoming drilling job, if the D&M tools that make up the BHA are not compatible with the field environment, this would cause the job to fail and/or tool failures, resulting in a huge economic loss. From the perspective of field team, they definitely would prefer to use the most reliable D&M tools to configure the BHA. In this way, the BHA reliability can be maximized, but this is unrealistic and nonoptimal. On the one hand, the availability of tools of high reliability is limited. If these tools were used for low-environmental-risk drilling jobs, then there might not be suitable tools for high-risk drilling jobs. On the other hand, tools of low reliability might be not compatible with harsh environments but could be suitable for drilling operations in moderate environments. In addition, tools of higher reliability or configuration generally means added manufacturing cost. Therefore, selecting the correct D&M tool for the correct field environment is of great significance for tool planning and cost savings.

Unfortunately, today's the tool selection decision is not fully centralized because it often relies on partial well parameters (e.g., hole size) and the technician's understanding of the tool. In addition, the tool selection is usually requires the technician to manually check many datasheets, a labor intensive and inefficient prcocess. We will go into more details about the current tool selection in next section. Considering these mentioned challenges, we propose a new indicator to characterize the compatibility or fitness of tools vs. different field environments. To the best of our knowledge, this paper is the first to study the D&M tool selection in oil and gas industry.

The remainder of this paper is organized into four sections. The first section presents extra information about the research problem, current tool selection processes, and limitations. The second section presents the proposed solution in detail. The following section presents application scenarios using actual data to confirm the solution. The final section summarizes and proposes some research directions for the future.

2. Problem Formulation

In this section a brief introduction of the digital fleet management system (DFMS) used in current tool selection decision-making is presented. Then, a detailed description about current tool selection processes and limitations are presented. At the conclusion of this section, we clarify the research problem presented in this paper.

2.1. What is DFMS?

The DFMS is a commercialized business information dashboard to help field teams choose the most reliable D&M tool for a given job. As mentioned, the revision design of D&M tool electronic boards develops with time. Even with the same design, the electronic components can slightly differ from batch to batch. Indeed, no two tools today have the same hardware configuration or reliability. The DFMS is designed to extract equipment quality and tracking system data for all boards, and compute a reliability score based on the following:

- Manufacturing process changes
- Supplier traceability
- Design changes

The reliability score has three levels; i.e., Level 1 meaning the least reliable and Level 3 indicating the most reliable.

The DFMS output is a dashboard containing the configurations, e.g., equipment hierarchy, parts status (e.g., active, junked, and lost in hole), and parts identity information (i.e., part number, serial number), parts revision and parts reliability scores of all active D&M tools for each location. The two words, part and board are used interchangeably in this paper unless otherwise specified.

2.2. Current Tool Selection Process and Limitations

Currently, the tool selection decision making involves the following three steps as shown in Fig .3:

1. The field engineer obtains some general parameters (e.g., geographical coordinate, temperature, flow rate, and hole

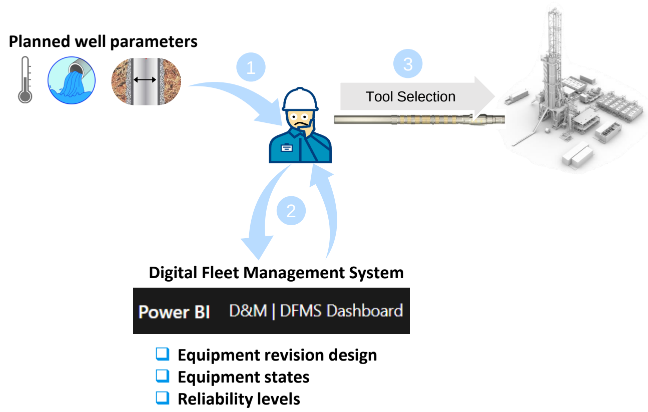

Figure 3. Current tool selection process.

size) of the planned well where the upcoming drilling job will take place.

2. The field engineer refers to the DFMS where information is available about equipment revision design, equipment states and parts reliability levels of tools in the location.
3. According to the DFMS output and experience, the field engineer decides which tool to deploy.

Although the DFMS provides the parts reliability levels profile, the parts reliability levels do not contain environmental definitions or hold systematic criticality information. That is, field environment and parts importance are not considered when computing the reliability scores. Thus, the DFMS output only reveals which tool or part is more reliable, it does not quantify the compatibility of the tool with respect to the field environment. This makes current tool selection decision making rely greatly on empirical knowledge. As mentioned in Section 1, the current tool selection is also labor intensive. In order to achieve objective, effective, and efficient tool selection decision making, it was decided to develop a tool compatibility computation method, which can provide the field user scores range from 0% to 100% indicating the comparability of tools under a specific field environment (e.g., high temperature, medium vibration, and shocks) where the upcoming job will demonstrate.

3. Proposed Solution

This section will first describe the criticality rules. Then, we will formulize the proposed tool compatibility computation method and demonstrate it with an example. Finally, an overview of the the proposed solution framework will be presented.

3.1. Criticality Rules

The criticality rules are defined by subject matter experts (SMEs). Different tools have different rules. The rules contain parts criticality information and environment definitions, which overcome the disadvantages of the DFMS reliability levels.

Table 1. An excerpt from the criticality rules of a specific LWD tool

Part Name	DFMS Reliability Level	Temperature	Lateral Vibration	Lateral Shock	Criticality
X215	1	NA	NA	NA	4
X215	2	1,2	1,2	1,2	4
X215	3	1,2,3	1,2,3	1,2,3	4
X105	1	NA	NA	NA	3
X105	2	1,2	1,2	1,2	3
X105	3	1,2,3	1,2,3	1,2,3	3
SX207	1	1	1	1	2
X207	2	1,2	1,2	1,2	2
X207	3	1,2,3	1,2,3	1,2,3	2
X117	1	1	1	1	1
X117	2	1,2	1,2	1,2	1
X117	3	1,2,3	1,2,3	1,2,3	1

Not all parts share the same failure impact. Moreover, different parts have different failure rates. As a result, SMEs define the importance of the parts based on historical service quality statistics. More specifically, the service quality statistics SMEs used here is failure event occurrence. Since the failure events of each part are recorded, SMEs can easily obtain the number of failure events for each part. The criticality of each part can be then determined based on simple binning approaches. For example, one can assign criticality of 1 to those parts whose failure event occurrences are less than or equal to 5, and assign criticality of 2 to those parts whose failure event occurrences are between 6 and 10. SMEs also help to define rules of mapping between parts' reliability levels and critical environments. Here the critical environments mean the contributing environmental factors (e.g., temperature, vibration) that can cause tool failure. Different D&M tools may have different critical environments.

Table 1 shows an excerpt from the criticality rules of a specific LWD tool which are defined by the corresponding SME. In the table, the 'NA' means this part is not fit for any environment, in other words, this part is obsolete. The number '1', '2', and '3' in Temperature column indicating low, medium, and high temperature, respectively. The same applies for the Lateral Vibration and Lateral Shock columns. The Criticality column shows the importance of parts. The larger the value, the more important or critical is the part. For example, the first row of the table indicates X215 parts with reliability level 1 should not used, X215 parts have criticality value of 4. The fifth row suggests that X105 part with reliability level 2 can be used in a field environment of low and medium temperature, low and medium lateral vibration, low and medium lateral shock. X215 parts have criticality values of 3.

DFMS output		Criticality Rules				x_i
Part name	Reliability levels	Temperature	Lateral Vibration	Lateral Shock	Criticality w_i	
X215	3	1,2,3	1,2,3	1,2,3	4	1
X103	2	NA	NA	NA	4	0
X106	3	1,2,3	1,2,3	1,2,3	4	1
X106	3	1,2,3	1,2,3	1,2,3	4	1
X105	2	1,2	1,2	1,2	3	0
X102	2	NA	NA	NA	3	0
X010	3	1,2,3	1,2,3	1,2,3	3	1
PNG	3	1,2,3	1,2,3	1,2,3	2	1
X316	2	1,2	1,2	1,2	2	0
X207	2	1,2	1,2	1,2	2	0
X001	2	1,2	1,2	1,2	2	0
X211	3	1,2,3	1,2,3	1,2,3	2	1
X113	3	1,2,3	1,2,3	1,2,3	1	1
X012	2	1,2	1,2	1,2	1	0
X214	3	1,2,3	1,2,3	1,2,3	1	1
X022	3	1,2,3	1,2,3	1,2,3	1	1
X123	3	1,2,3	1,2,3	1,2,3	1	1
X004	3	1,2,3	1,2,3	1,2,3	1	1
X117	1	1	1	1	1	0
BU201	3	1,2,3	1,2,3	1,2,3	1	1
BD001	3	1,2,3	1,2,3	1,2,3	1	1
X009	3	1,2,3	1,2,3	1,2,3	1	1

Non-compatible parts

$I = 60\%$

Figure 4. Tool compatibility computation example.

3.2. Weighted Average Based Tool Compatibility Index

The proposed tool compatibility index I is mathematically expressed as

$$I = \frac{\sum_{i=1}^{N} w_i x_i}{\sum_{i=1}^{N} w_i} \times 100\% \tag{1}$$

where N is the number of parts in the tool, w_i is the criticality value of part i in the tool, x_i is 1 if part i can be used for the specific environment; otherwise, x_i is 0. We can infer the w_i and x_i according to the criticality rules defined by SMEs.

Next an example of an LWD tool shows how this compatibility index is calculated. The example is shown in Fig 4. Suppose the upcoming job is going to be run in an oil field of medium temperature, high lateral vibration, and high lateral shock environment. Then according to the DFMS output and criticality rules, we can infer the x_i of the tool that is shown in the right-hand side of the figure. For example, the X105 part in the fifth row can be used in a medium temperature environment but cannot be used in high lateral vibration or high lateral shock environment according to the criticality rules; thus, the corresponding x_i is 0. After obtaining the x_i of all parts in this tool, plugging both the criticality value w_i and x_i into Eq. (1), we determine the tool compatibility index of this tool under the specified environment is 60%. In addition, The zeros of x_i indicate the noncompatible parts of this tool, which suggest these parts need to be upgraded if the field engineer wants to use this tool for the specified environment.

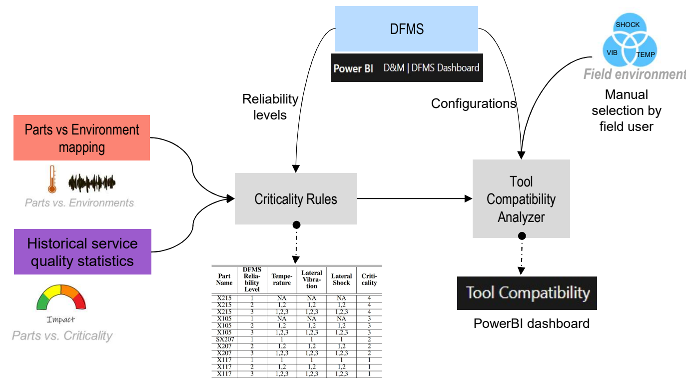

Figure 5. Framework of the proposed solution.

3.3. Framework of The Proposed Solution

Based on previously mentioned criticality rules and compatibility index calculation method, the framework of the new solution for tool selection is shown in Fig. 5. The steps in the framework are described as follows.

1. The SMEs define the criticality rules for D&M tools derived from the mapping of parts vs. environment, historical service quality statistics, as well as DFMS reliability levels.
2. As specified by DFMS, the tool configurations can then be derived. The configurations are combined with the field environment chosen by the field user, and then fed into the tool compatibility analyzer (i.e., weighted average based tool compatibility index).
3. The compatibility index of the tool is outputted. In addition, if needed, noncompatible parts and their upgrade cost information can be acquired.
4. By use of step 2 and 3 for the tool fleet and all field environment combinations (e.g., there are $3^3 = 27$ combinations for three environment categories (e.g., temperature, lateral vibration, lateral shock) of three levels (i.e., low, medium, high)), the compatibility indices of the tool fleet for each environment combination can be achieved. A dashboard can be established using these outputs.

4. Use Cases

The output of the proposed solution is a dashboard that contains compatibility indices of tool fleet vs. different environments. This section presents the use case diagram and two application scenarios to demonstrate the effectiveness of our solution. It should be noted that some information is not included due to confidentiality.

4.1. Use Case Diagram

Figure 6 shows the use case diagram. The dashboard users are field engineers who are responsible for tool operation. The field user selects the field environment of the upcoming job

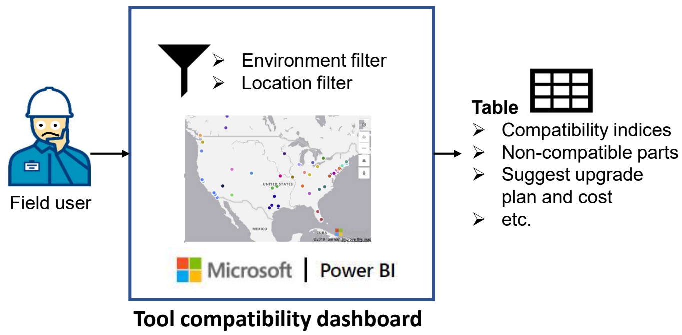

Figure 6. Use case diagram.

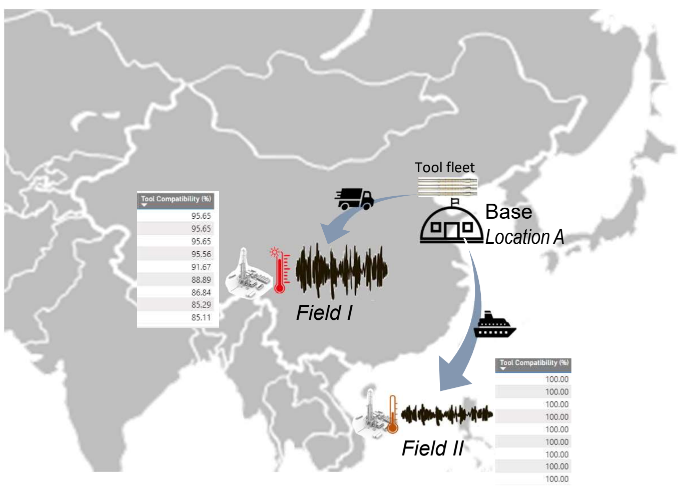

Figure 7. Two application scenarios.

and the user base location using the environment filter and location filter. The dashboard will then output a table containing compatibility indices information of the tool fleet in that location, suggest upgrade plans and costs for noncompatible parts of each tool, and etc.

4.2. Application Scenarios

This subsection presents two scenarios (see Fig. 7) to demonstrate the solution.

Scenario I: A new drilling job was to be operated in *Field I*, a *high temperature, high lateral vibration and shock* environment. The job was assigned to the *Location A* base. The compatibility indices of the tool fleet for this environment are also shown adjacent to 'Field I' in Fig. 7.

Scenario II: A new drilling job was planned for *Field II*, a *medium temperature, low lateral vibration and shock* environment. The job was also assigned to the *Location A* base. The compatibility indices of the tool fleet under this environment are shown adjacent to 'Field II' in in Fig. 7.

Based on the compatibility indices for the two scenarios, it is shown that under different environments, the same tool fleet has different tool compatibility indices. The tool compatibility indices of the harsh environment (i.e., Scenario I) are less than the mild environment (i.e., Scenario II). If setting a compatibility index threshold of 90% as tool selection criteria, then only the first five tools are compatible with the harsh environment; i.e., only those tools can be used for the Scenario I drilling job. On the other hand, all of the tools can be selected for the Scenario II drilling job because all of the compatibility indices are greater than 90%.

5. Conclusions and Future Work

A new solution for D&M tool selection in oil and gas industry has been presented in this paper. The proposed solution has two main advantages, that is, it integrates potential environmental risks and part criticality into a tool selection decision making process. The new solution is successfully implemented into a business information platform (i.e., Microsoft Power BI) and verified through field tests. By applying this solution, the tool selection becomes more objective and efficient because some of the manual checking processes are optimized.

Several challenges exist for our solution that will be examined in the future. For example, one major challenge is that the proposed solution needs a user to select the potential field environment of the approaching job based on the user's domain knowledge. Considering this challenge, the authors developed a dashboard for field environment characterization based on historical tool environmental exposure data, and will study how to link this dashboard to tool compatibility. In this way, user selection of field environment will become needless. Furthermore, the tool compatibility is regardless of part reliability affected by cumulative environmental exposure. Then, considering part cumulative environmental exposure into compatibility index computation is also worthwhile study.

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BIOGRAPHIES

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