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Data Analytics and Machine Learning for very large Oil&Gas Projects

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Abstract

This paper outlines a comprehensive study aiming to develop tailored risk reduction models for large-scale engineering projects, with a focus on FPSO (Floating, Production, Storage and Offloading) design. The study evaluates critical factors related to piping and fitting in FPSO projects, proposing mitigation strategies. Starting with historical project data analysis, preprocessing involves data cleaning and preparation. Employing Business Intelligence and Data Analytics, the study advances to data transformation and interactive visualization. The complexity of crude oil systems requires advanced analytics, and Machine Learning clusters high-velocity data, enhancing project management with data-driven insights. The research deepens understanding of FPSO risk factors, offering practical strategies. The fusion of traditional methods with advanced analytics presents a novel approach to offshore engineering challenges.

Keywords: Risk Analysis; Business Intelligence, Predictive models

1. Introduction

In modern engineering, successful execution of large-scale projects requires profound comprehension of challenges and innovative risk management. This paper presents an investigation at the University of Genoa's DIME, aiming to develop advanced risk reduction models tailored for Project Management in extensive engineering, focusing on Floating Production Storage and Offloading Units (FPSOs) – complex offshore structures for crude oil operations.

The research evaluates pivotal factors in FPSO projects, specifically piping and fitting components, crucial within the domain. Systematic analysis aims to unveil strategies for mitigating risks in these intricate projects. The study begins with historical project data exploration, forming the foundation for subsequent analyses. Rigorous pre-processing involves data cleansing using specialized tools.

Leveraging a robust Business Intelligence and Data Analytics platform, the research transforms data into interactive visualization reports, enabling trend identification in FPSO projects. The complexity of crude oil systems necessitates advanced analytics. Machine Learning algorithms classify and cluster high-velocity data, integrating correlations into the model. The objective is data-driven precision in project management.

Outcomes enrich understanding of FPSO intricacies, yielding insights and pragmatic strategies. The study harmonizes traditional project management with advanced analytics, offering a novel approach to address challenges in offshore engineering.

Subsequent sections delve into the study's fabric, including a review of the state of the art, exposition of the innovative model, analysis and results, and conclusions – synthesizing findings, implications, and future research directions.

2. State of the art

The effective management of large-scale offshore projects presents a unique challenge, especially when it comes to risk mitigation, indeed it should be managed through an holistic and systematic approach (Bruzzone et al., 2021). In recent years a new discipline, called Strategic Engineering, aims to use an innovative approach to solve complex problems based on the integration of Modeling & Simulation, Data Analytics, Artificial Intelligence in closed loop with the data from the field; indeed the challenges of a FPSO requires s strategic engineering approach to be solved (Bruzzone et al., 2018, 2020). A crucial aspect for ensuring the smooth progress of such projects is the management of procurement processes, which can be divided into three key phases necessary for optimizing the supply of materials and components (Araújo, 2017). These phases include bidding, basic engineering, and detailed engineering. In this context, the use of predictive models for defining order anticipation strategies plays a significant role in minimizing risks associated with potential delays, cost overruns, and potential disruptions.

Within the literature, various approaches and key considerations have emerged regarding order anticipation strategies aimed at risk reduction in large-scale offshore projects. One approach is the optimization of the supply chain. Numerous in-depth studies have been conducted on this topic (Liew KC et. al., 2012), which highlights major risks encountered, such as project delays, insufficient storage space, exclusive supply from a single vendor, and fluctuation of raw material prices. To mitigate the latter issue, this article decides to implement a make-to-order policy for the procurement of the most frequent raw material; steel plates will be purchased by the procurement department only when the company obtains a contract for the construction of an oil platform. Subsequently, a new policy of Abundant Purchase is implemented, wherein market prices of steel plates are monitored over time. When the price reaches a sufficiently low and acceptable level for the maritime and offshore company, material will be purchased abundantly up to a point where there is enough for at least two projects.

Another strategy for risk reduction involves the development of models, also derived in this context through analysis of historical data, that can account for the emergence of different variables related, for example, to demand fluctuations (Nagyová, 2021). One example is the model describing the crude oil price forecast based on supply and demand techniques and understanding the reaction of the U.S. economy associated with oil price volatility (Lu Q. et. al., 2021).

Another study describes the forecast of oil prices based on global demand (Ron Alquist et. al., 2011), while another explores the impact of various uncertainties on natural gas price volatility in the US futures market using the GARCH-MIDAS model (Chen J. et. al., 2023). Thanks to the use of advanced forecasting techniques and demand management strategies, it is possible to enhance order anticipation accuracy while simultaneously reducing associated uncertainty.

The advent of a data-driven approach represents another significant contribution. The analysis of big data and predictive modeling allow the development of order anticipation strategies. A study (Edwin Lisowski, 2021) emphasizes how such analysis can reveal underlying trends and assist engineers and project management teams in predicting potential issues. A systematic review published on ResearchGate (Nguyen T. et. al., 2020) further highlights that big data analysis is a critical aspect of the digitalization of the oil and gas industry, focusing on data management and processing. Through the application of machine learning algorithms and tools, the accuracy of order forecasts can be further improved (Natarajan, 2022).

3. Materials and Methods

The model described in this document has been structured through various preliminary analyses on historical datasets related to FPSO projects. By employing dedicated software for creating interactive reports, the major operational issues, as well as information extracted from analyses performed on historical project data, have been defined. These analyses have identified the most critical materials in terms of quantities required for project realization, common to all previously completed projects for which data was available.

Subsequently, correlations among the data were sought in order to establish a predictive model based on customer needs and the process characteristics of systems, such as processed oil flow rate, water pressure for various systems necessary for extraction and cooling of different modules on the vessel, or gas pressure, associated with the characteristics of the well on which the FPSO will operate.

The information obtained from the preceding stages was leveraged to obtain reduced data clusters to be fed into a Multilayer Perceptron-type neural network, appropriately configured to define the predictive model. This approach is necessary to facilitate the network's learning phase, given the significant data variability in terms of magnitudes of the masses involved and the highly diverse operational characteristics of fittings and piping. The aim of this study is to develop a tool that provides valuable information for pricing determination during the bidding phase of a project of the magnitude of an FPSO. In particular, by observing the flowchart in Figure 1, the various phases that a project management team must address during its execution can be briefly identified. The ability to identify and understand the associated criticalities, in our case study, related to piping and fittings components, and thus being able to concentrate efforts and energies on those aspects in order to mitigate the associated risks and costs, allows for advantages to be gained and reduces the margin of error in pricing determination.

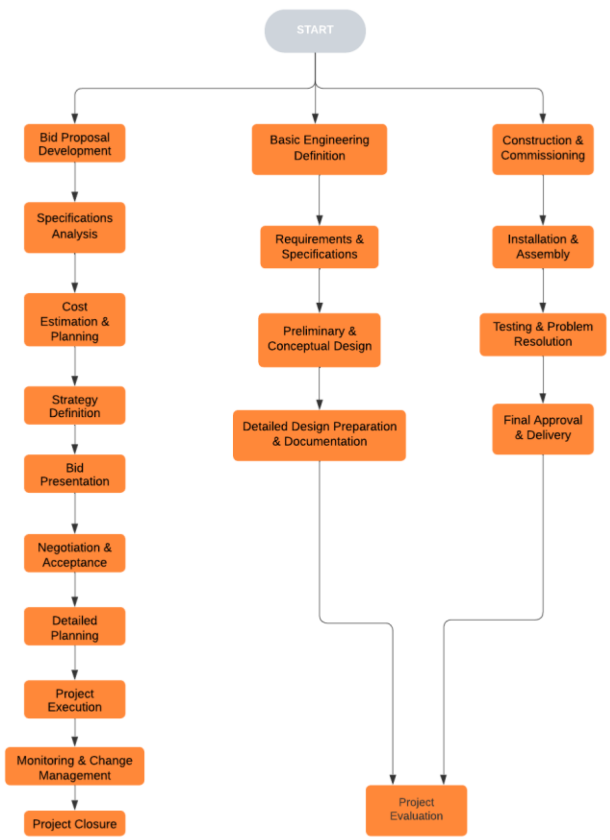

Figure 1. Flow chart for engineering project

Furthermore, it is worth highlighting that if the temporal variable is introduced into the flowchart of Figure 1, an aspect not evaluated to maintain diagram compactness, the phases of basic engineering, conceptual design, and detailed engineering shift significantly lower due to their notably lengthy durations (on the order of 10^6 engineering hours). From this, it becomes evident that the knowledge of quantities required for system realization, by validating the outputs of the predictive model, enables a much more accurate pricing determination, thereby reducing the risks associated with potential market fluctuations that may occur between the bid definition date and the material procurement date, particularly if the latter occurs towards the end of the engineering design phase.Through the utilization of the model, it becomes possible to promptly formulate a procurement plan following the definition of the process characteristics of the FPSO system, and to anticipate potential changes based on client requirements.

Below are listed some strategies that enable the integration of the predictive model into the management of an FPSO project:

- Integration with the project management approach:

1. Incorporation of data-driven insights into the decision-making process to enhance the project management approach.
2. Utilization of predictive information for making more informed decisions and mitigating risks.

- Results and practical strategies:

1. Attaining a deeper understanding of risk factors in FPSO projects.
2. Formulation of practical strategies to reduce potential obstacles.

- Integrated approach: Emphasis on the innovative approach that combines traditional project management methodologies with advanced data analysis and Machine Learning techniques.
- Conclusion: Highlighting the research contributions in addressing challenges in the offshore industry through the proposed integrated approach.
- End of the process: Conclusion of the analysis and utilization of the predictive model for risk analysis in FPSO projects.

4. Results and Discussion

In the context of results analysis, the outcomes of the research undertaken to outline the model are presented. Initial investigations are focused on identifying recurring issues within FPSO projects. The aim is to assess masses and quantities of components in order to identify material families and relevant types of parts. This process leads to the creation of sub-families endowed with significant attributes. The analysis extensively employs visual tools, such as histograms and Pareto diagrams, derived through the utilization of the Power BI software, to illustrate trends and critical aspects. The subdivision into macro-categories simplifies the analysis of piping and fitting components, including the segmentation of flanges – a component belonging to the fitting family that is much more frequent compared to others – into subgroups. This facilitates the understanding of trends and risks. The Pareto principle (80/20 rule) is employed to detect predominant materials within FPS projects, as depicted in Figure 2. The focus is directed towards these main categories by examining the masses and quantities of components. This process of detailed analysis allows for a better understanding of critical categories.

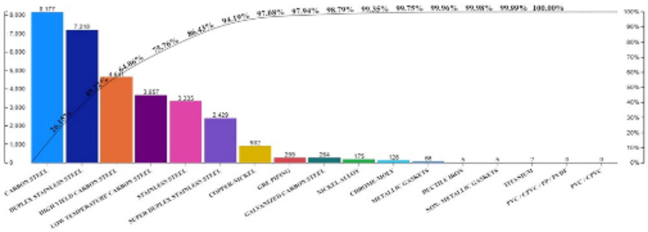

Figure 2. Pareto Diagram

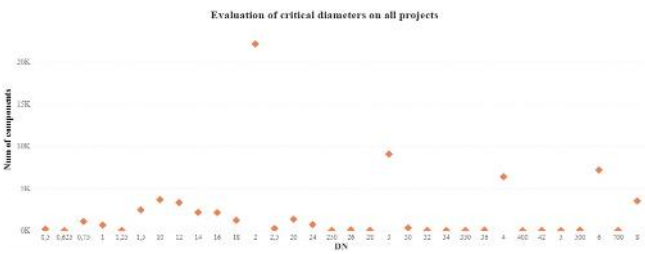

Figure 3. Scatterplot on component diameter

The use of histograms and Pareto diagrams extends to individual projects, involving a comparison of masses among sub-families. Through data tables related to masses and components, the predominance of carbon steel, for instance, is highlighted. The comparison between similar projects reveals the impact of vessel characteristics and client requirements. The analysis provides an extensive view of material families and critical components within FPSO projects. The utilization of visual tools and the Pareto principle contributes to identifying primary sources of issues, enhancing the comprehension of risk factors and trends. Furthermore, specific attention is given to three dimensions of analysis for piping components in FPSO projects. The predominance of nominal diameter 2 (DN 2) emerges, notwithstanding variations across projects. The importance of stainless steel for these components is emphasized, despite the extensive use of carbon steel.

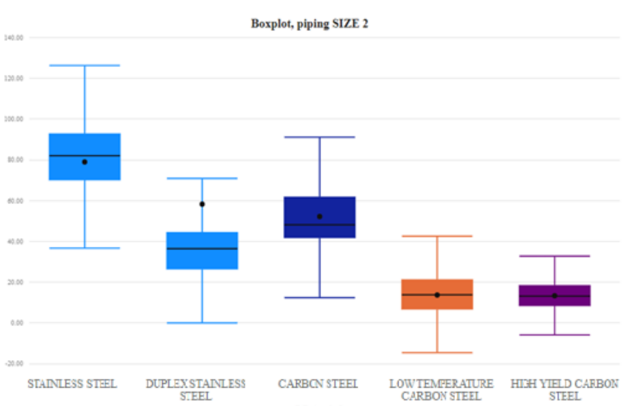

Figure 4. Boxplot for SIZE 2 components

Figure 4 shows the boxplots from which the average, maximum, and minimum values, associated with the previously identified critical materials, are extrapolated for DN 2 components.

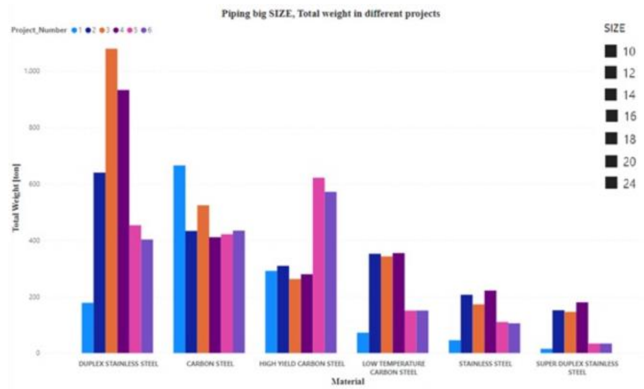

Figure 5. Histogram for large diameter components

Further investigation is dedicated to the evaluation of the normalized modulus and system type, the latter being an identifying number for the type of fluid with which the various components come into contact, serving as dimensions of analysis. The extensive usage of systems encoded as 124 and 342 underscores the predominance of carbon steel in system components.

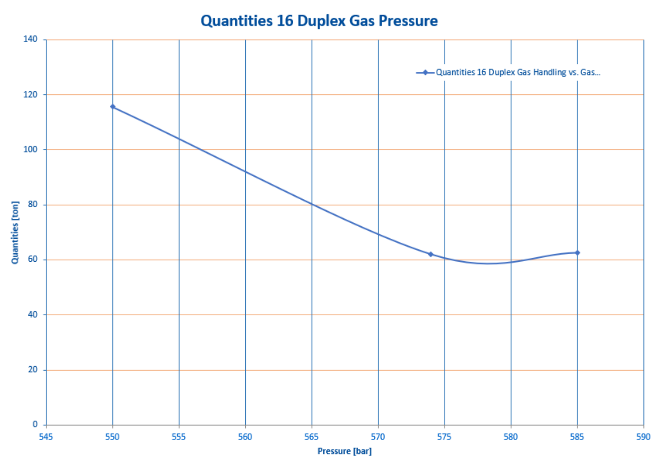

Figure 6. Correlation between gas injection pressure, and components associated with gas treatment systems

The analysis also focuses on pipes with a diameter greater than 8 inches, a particularly critical component due to its limited availability in the market stemming from the specific manufacturing process. This investigation identifies common critical dimensions and the prevalence of carbon steel. Figure 5 compares the mass quantities, broken down by material, in the different projects in the historical dataset

However, the significance of duplex steel emerges. A subsequent step involves evaluating potential correlations among the various columns of data within the dataset, acquired using a tool provided by the Simulation Team to assess correlations and define model outputs based on process and operational characteristics of the system. These characteristics include parameters such as processed oil flow rate, gas injection pressures, or water pressure and flow rate required for system cooling.

In Figure 6 an example correlation between gas injection pressure and the mass of components associated with gas treatment systems can be observed. Extending this approach to all component families, while correlating them to customer-specified characteristics, defines the model.

To automate this process, the utilization of Python and neural networks for data analysis has been explored. However, the complexity of outliers poses a challenge. Data preprocessing aims to enhance prediction, but the diversity of the data limits its accuracy. Within this context, areas for improvement have been identified in terms of error reduction, necessary for the comprehensive validation of the model. This validation will be conducted by introducing clusters of classified and selected data from the total dataset, based on common operational or process trends.

In conclusion, the results analysis provides a detailed overview of dimensions, materials, and systems of piping components in FPSO projects. The significance of both carbon steel and duplex steel is emphasized, and potential future strategies for implementing neural networks to support management and procurement decisions in FPSO projects are outlined.

5. Conclusions

The present paper focuses on the analysis of risk related to piping and fitting components in FPSO (Floating Production, Storage, and Offloading) systems. Through the utilization of Business Intelligence (BI) tools and Machine Learning, a comprehensive data analysis was conducted. Initially, components were grouped into clusters with similar characteristics. These clusters reflect material attributes, naval modules, and associated operational systems.

The results allowed for the estimation of average, maximum, and minimum quantities of critical components for each FPSO project, employing statistical methods. This furnishes critical information to project managers (PMs) for procurement decisions during the bid definition phase. The reduction of risks associated with price evaluation accuracy is attainable through the preventive purchase of components or raw materials, facilitating a more refined determination of final prices.

These outcomes, rooted in the PM's engineering competence and market comprehension, guide decisions regarding quantities to be pre-purchased, falling within the range defined by the analysis. The analysis has demonstrated that piping exerts the greatest influence among various component types. Aspects concerning predominant materials and dimensions have been identified, allowing for their correlation with operational characteristics for future projects.

For components with criticalities tied to production processes and higher prices, targeted analyses have been implemented to mitigate risks. Moreover, future strategies for reducing production costs have been outlined, including the potential for in-house production of laminates for frequently used materials and the utilization of predictive models to steer the pre-purchase of raw materials during periods of lower cost.

An aspect that research can further explore concerns the identification of additional clusters aimed at a more refined enhancement of the model regarding the inevitably present error in a small percentage within the output data. By further reducing the dataset into packages characterized by common trends, it is possible to achieve an even higher level of accuracy, as demonstrated in the course of this study.

Overall, this paper offers a comprehensive approach to assess and mitigate risks associated with FPSO system design. Equipping PMs with tools for informed procurement decisions, it paves the way for further production optimizations.

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