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Risk Analysis by Monte Carlo Simulation over Large Offshore Projects

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Abstract

Analysis of risks in complex processes involving different stakeholders is a difficult task. In this paper the authors propose a tool which combines data analysis, modeling and simulation and Monte Carlo technique in order to perform assessment of risk in this kind of activities. Case study related to construction of complex offshore solutions for oil & gas sector is presented, while example of estimation of risk to exceed acceptable time is proposed.

Keywords: Monte Carlo Simulation, Project Management, Risk Analysis, Off Shore Projects

1. Introduction

It is a time since, the simulation is widely used to support industrial projects of different scales (Law & McComas, 1987; Banks, 1998). For example, it could be used for virtual prototyping of new autonomous systems (Bruzzone et al., 2019a), experimentations on digital twins (Bruzzone et al., 2019b), optimization of supply chain (Bruzzone et al., 2011) or preparation of personnel (Bruzzone & Longo, 2013). Indeed, in case of availability of data it could be possible to create efficient representations of real-world processes, capable to facilitate development of new solutions or procedures. In fact, once sufficient fidelity of the model is achieved, it is convenient to employ it in order to evaluate possibilities for improvement, forecast results as well as test efficiency of the target system in various initial and boundary conditions.

Apart from utilization of the model to calculate single most probable outcome in given conditions, it is often convenient to employ Monte Carlo techniques in order to perform risk analysis and to find confidence interval of the output value (Reverberi et al., 2005).

In this case, statistical data extracted from existing knowledge bases could be used to feed a stochastic model in order to ensure proper estimation of the parameters of statistical distributions, allowing analysis of outcomes and avoiding development of more complex algorithms for conducting risk analysis on project changes. Indeed, analysis of complex systems and processes is difficult and in case of modeling of such processes, that are characterized by many activities with different probability distributions, it could be quite hard to find a formal solution (Bruzzone & Bocca, 2012; Cheng et al., 2015).

Similarly, utilization of PERT would require identification of critical path, comparison of several near-critical paths with related calculations, while after each modification of the project recalculation would be required (Bruzzone, 1998).

At the same time, introduction of stochastic variables in the model and its repetitive execution is relatively easy and fast to accomplish. Considering this, the Monte Carlo simulation is particularly useful for analysis of complex systems as well as of Systems of Systems (SoS).

Obviously, in order to achieve sufficiently good tolerance, it is essential to feed the model with satisfactory in terms of quality and quantity data; this constraint imposes several limitations on utilization of the methodology. For example, it is necessary to have access to knowledge bases, which could be tricky for a company which has only recently started its activity in a field. Similarly, in case of presence of distinct stakeholders' reliability of stored information could vary; for instance, a stakeholder could compile state of work reports only time to time (e.g. each 2 weeks instead of 1 week), effectively distorting quality and granularity of the data. Despite this potential issue, the amount of high quality data normally outweighs missing values, maintaining overall quality at sufficient level, as it usually happens in case of big amounts of data (Bruzzone et al., 2020a).

2. State of the Art

Various tools are used to support project management and decision making, starting from elaboration of basic KPIs in a spreadsheet and up to utilization of Analytic Hierarchy Process (AHP) and simulation (Petrillo et al., 2017; Lamas-Rodríguez, 2021). In some cases, it could be convenient to employ machine learning algorithms in order to forecast certain values; this approach could be further extended if employed as part of a bigger simulation-based solution (Bruzzone et al., 2020b; Bruzzone et al., 2019c). Nevertheless, there is also an interest in utilization of Monte Carlo techniques, including its application to the risk analysis (Massei et al., 2004).

One of very important factors determining the evolution in data analysis is the Big Data; indeed, this concept includes set of methodologies to acquire, store and elaborate data, often in high quantities, in order to benefit from it in most efficient way (Harrison, 2015). In fact, this set of techniques allows to handle better the information, which in its turn stimulates generation of even bigger quantities of data and so on. From the point of view of risk assessment, Big Data techniques are often used to support decision makers in this regard (Shang et al., 2017).

3. Case Study

The authors decided to apply proposed approach to the field of construction of FPSO (Floating Production, Storage and Offloading) vessels, employed in crude oil extraction in deep waters (Edwin & Sunday 2013; El-Reedy, 2016). FPSO are offshore facilities that correspond to big project with necessity to optimize the process (El-Reedy, 2016;Scully, 2019). The systems of interest are pretty complex and are equipped with various Top Side (TS) modules responsible for extraction, oil treatment and storage, water and gas injection, power generation, etc. As usual in Oil & Gas, the dimension of investments requires do use models to evaluate risks and optimize the decisions (Merrow, 2011; Piantanida, 2006; Guedes & Santos, 2016). In a typical vessel there could be tens of thousands of tons of TS modules, including long and complex piping systems, constructed with utilization of various materials and several types of steel (Duggal & Minnebo, 2020). Typically, FPSOs are built on top of old oil tanker, while in some cases ad hoc vessel is constructed. In any case, preparation of the ship requires significant amount of time and could last several years; indeed, apart from construction of TS modules, it is necessary to prepare the vessel, install and integrate modules, perform testing and corrections in case of leakages or malfunctions. Another important factors are related to location of the production site, which could be subjected to efficiency drops caused by holidays and adverse climatic events. At the same time, in order to reduce delivery time other techniques are applied, such as finalization of operations after departure from the construction site and concurrent engineering.

In the first case it is possible to conclude some of secondary operations out of port, however, moment of departure must be chosen properly - once it is done, there is little to no possibility to deliver additional supplies to the vessel, while overall efficiency of the work is lower. In case of concurrent engineering it is possible to start planning, acquisition and construction activities even before completion of detailed design phase, which saves time to the client but creates risk of incompatibilities and necessity to re-do part of the work with corresponding excessive costs; despite this fact, this approach is widely used due to possibility to reduce drastically construction time, which compensates rise in expenses, if properly applied.

Considering this, it is evident that the case study is related to very complex projects in which proper coordination and timing are fundamental. Hence, the authors propose development of simulation based solution capable to analyze existing data, reproduce construction process and perform risk assessment, especially in terms of time. In particular, it is conducted development of conceptual model of the process, capable to apply productivity information obtained from the past projects to a new one, with logical flow illustrated in the following figure.

Indeed, the simulator allows to the user to upload project reports from which information is extracted and stored in a database. At this point the software analyses KPIs subdivided by phase of construction, type of activity, phase of activity (preparation, steady state & finalization), material, week, yard etc.

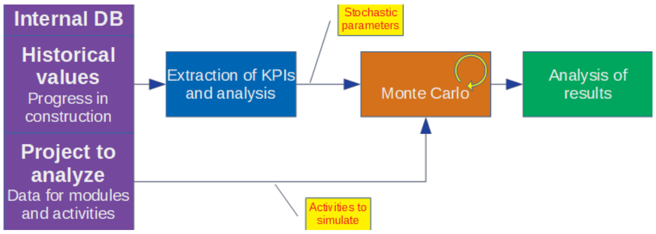

Figure 1. Simulation procedure

Indeed, the stochastic discrete event simulation adopted is very fast in terms of execution time and allow to conduct Monte Carlo Analysis over many iterations quite quickly, providing a good estimation of the confidence band of the different alternative choices respect the target function; the use of Design of Experiments allows to finalize sensitivity analysis and identify most promising mix of parameters and decisions to obtain better results (Kleijnen, 2011). At the same time the user is enabled to upload working plan for a new project, which includes expected production site, quantity of materials to employ etc. From this point, the simulator checks if the reference project is suitable for analysis, e.g. if there are no previously unknown materials and operations added in the newer project. After this step the simulation starts, modeling construction process week by week, activating new activities and calculating expected result by using stochastic variables extracted according to calculated distributions. Once the construction is finished the simulator saves results, resets the environment and starts with the next iteration. Finally, once number of runs is sufficient, the system displays to the user report on expected progress as well as relative confidence intervals. One of main challenges encountered by the authors in this project is uneven data. For instance, different stakeholders provide information in distinct types and formats. Indeed, significant amount of time was dedicated to its conversion in a universal format.

Indeed, we adopted the combined use of:

- Data extracted from pdf files by our Application from reports
- Historical data of past projects of different construction sites evaluated with the KPIs

$$\underset{\text{Persistence}}{EAC'} = \frac{BCWS}{CPI} \qquad \underset{\text{Exhausted Effect}}{EAC'' = BCWS + CV}$$

$$BCWP(t) = \sum_{j=1}^{kt} BC_j \cdot H(eT_j - t) \qquad BCWS = \sum_{j=1}^{kt} BC_j$$

$$ACWP(t) = \sum_{j=1}^{kt} AC_j \cdot H(eT_j - t) \qquad Cv(t) = ACWP(t) - BCWP(t)$$

$$SPI(t) = \frac{BCWP(t)}{BCWS} \qquad CPI(t) = \frac{BCWP(t)}{ACWP(t)}$$

$$Risk(dcr) = \int_{ta`}^{+aoo} \Gamma\left(\frac{dcr - \bar{d}}{ds}\right) dt$$

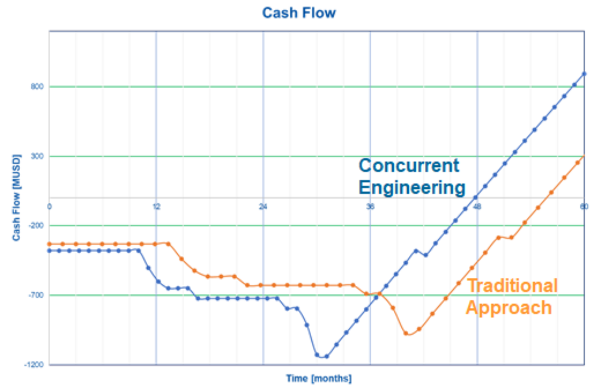

Figure 2. TPBP Benefits by adopting Concurrent Engineering

EAC	**Estimation at Completion**
BCWS	**Budget Cost Work Scheduled**
BCWP	**Budget Cost Work Performed**
ACWP	**Actual Cost Work Performed**
CV	**Cost Variance**
CPI	**Cost Performance Index**
SPI	**Schedule Performance Index**
t	**Time**
d	**Duration**
ta	**Actual Time**
dcr	**Critical Duration for Penalty**
ds	**Duration Standard Deviation**
AC_j	**Actual Cost j-th WP**
BC_j	**Budget Cost j-th WP**
eT_j	**Ending time j-th WP**
H(x)	**Heavyside Function**
WP	**Work Package**

As consequence by simulation it is possible to replicate n runs by changing just the random seeds of on different project management alternatives based on same boundary conditions and to estimate the experimental error defined as Mean Square pure Error (MSpE) depending just on stochastic components (Kleijnen 2008; Montgomery, 2017). In similar way it is possible to obtain for each y target function also the measure of the confidence band as in the following:

$$MSpE(y,n) = \frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n-1}$$

$$CB(y,n) = \pm t_{\alpha,n-1}\sqrt{\frac{\sum_{i=1}^{n}(y_i - \bar{y})^2}{n-1}}$$

4. Results

The Montecarlo Simulation over the project considering risk of changes as well as their consequences is summarized in figure 2 and points out the benefits in terms of cash flow and TPBP (Time Pay Back Period) respect the opportunity to adopt concurrent engineering approach.

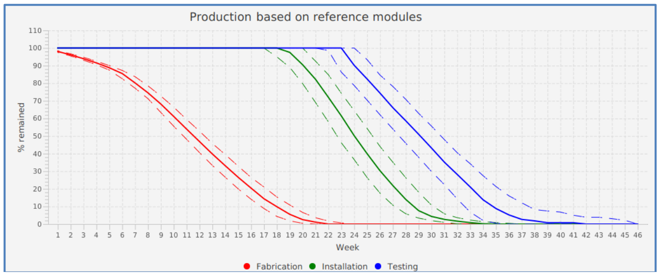

Figure 3. Simulation of construction process with confidence bands.

In the following image it is shown result of simulation of construction of one of TS modules based on productivity data obtained from the reference project. In particular, it is modeled fabrication, installation and testing of relative piping.

On the graph percentage of remaining work is shown in vertical axis, while the horizontal one corresponds to time in weeks, providing so-called inverse shaped S-curve. As it is possible to see, in this case fabrication of piping starts at week 0, while at the moment when it is mostly complete the installation begins; finally, after assembly of first parts of the modules these are tested.

The dashed line on the chart represent quartiles or remaining part of the work which corresponds to 50% of cases around average value. For instance, it is possible to observe that with given reference data the work is expected to finish between weeks 37 and 46, once the testing is done.

Another observation that could be done is that the fabrication and installation are slower during initial and final steps, which corresponds to the behavior observer in real cases.

From this point it is possible for decision maker to ensure that the project will not exceed the deadline, for instance by acquiring additional manpower or materials or by redistributing resources among phases. Furthermore, possibility to check modified course of actions is very useful for identification of the best one among different proposals.

In order to identify sufficient number of replications it was conducted analysis of variance with results presented in the next figure; from the chart it is possible to see that starting approximately at 500th replication the variance stabilizes, which corresponds to minimal number of replications sufficient to produce statistically reliable result (Montgomery, 2017).

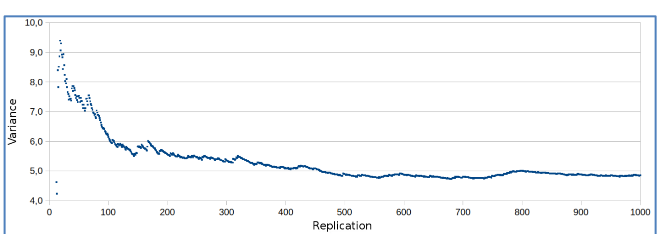

Figure 4. Analysis of variance

The simulator is written in Java 11 with the user interface in JavaFX; execution time for simulation of construction of a single module with 1000 replication on above-average Intel i7 CPU is less than 2 seconds, from which significant time is utilized by the graphic user interface toolkit for the visualization. The software utilizes H2 database engine in embedded mode, which makes it compatible and easily connectable with other industrial and business SQL-supported solutions.

5. Conclusions

Application of Monte Carlo method allows to perform risk assessment of complex industrial processes, as it is shown in case study related to construction of FPSO. Indeed, taking advantage of available datasets it is possible to obtain not only expected durations of activities but to check also the estimation of confidence bands, which would be very difficult to achieve in case of traditional analysis of duration of the project.

Considering this, the proposed solution is proving to be very useful in project management activities as well as in optimization and analysis of related processes, such as definition of material supply and of logistic network's configuration.

The proposed solution is tested in the framework of the FPSO, however, the conceptual model is applicable to various different industrial activities and could be used to support optimization of time and costs and other resources.

Currently the solution is in verification and validation phase, while the first checks show high similarity between forecasts and actual results.

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