MULTIDIMENSIONAL DATA ANALYSIS, INFORMATION VISUALIZATION AND COMPUTATIONAL INTELLIGENCE IN COMPLEX INDUSTRIAL PROJECTS,

Emiris Dimitrios, Pavlos Eirinakis
University of Piraeus, Greece

Abstract

Shutdown, Turnaround, and Outage (STO) projects dealing with preventive, proactive or reactive maintenance are among the most complex and challenging ones in process industries. Their management is improved by incorporating advances in digital technologies and, particularly, in data analytics, computational and artificial intelligence (AI), leading to "Data-Driven Project Management (DDPM)". A key issue arising is the type/nature of data that are used to support DDPM. We herein identify the key attributes of such data and show that they form a multidimensional set.

Further, we explain how this multidimensional nature shapes the approaches to capture and analyze data and highlight the interplay between data analytics and the digital transformation that companies undergo, to increase their PM maturity. We demonstrate how multidimensional data analysis (MDDA) and information visualization (IV) leverage PM efficiency, and inversely, how the increased need for holistic PM triggers the development of sophisticated data analysis algorithms and tools. We critically evaluate how and to what extent, the advent of machine learning (ML) can supplement/replace existing approaches and highlight experiences from recent, pragmatic turnaround projects. A set of implemented "digital best practices" corroborates the importance of MDDA and IV in this family of projects and favors their use.

Keywords: Data-driven project management, data analytics, information visualization, digital transformation, computational intelligence.

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1. Introduction

Shutdown, Turnaround, and Outage (STO) projects that deal with preventive, proactive or reactive maintenance are considered among the most complex and challenging ones in process industries. They take place periodically depending on the needs of safe operation and quality production and their main objective is to allow for inspections, repairs, replacements and overhauls that can be carried out only when the plant facilities are taken out of service.

Turnarounds (T/A) typically refer to a periodic planned period of maintenance in a plant. They take place every 3 to 5 years, with this period depending on the equipment condition, the type of industrial units, the necessity of expansion to enrich the variety of products, etc. During their execution, the plant is not operational in its entirety, which also gives the opportunity to inspect, revamp and perform overhauls. Turnarounds are characterized by intense labor activity resource needs (exceeding 1,200 people/day on average), dense and high expenditures (typically ranging between \$80M to \$150M), strict time constraints (4-6 weeks), and increased uncertainty. Moreover, during turnarounds, production completely pauses, leading to a reduction of revenue which may affect financial outcomes (Sahoo, 2014; Tsang; 1998). On the other hand, this maintenance window allows not only for corrective repairs but also for planned inspections, revamping, process redesign, replacements, overhauls, etc., thus safeguarding the plant operation for the foreseeable future.

Shutdowns resemble to turnarounds, but they may affect a smaller part of the plant, usually a unit or a cluster of units, and they do not necessarily require the full pause of operations. They may also be unplanned, or maybe scheduled to take place when some type of shortage in the incoming raw material is anticipated, or even may stem from an unexpected accident or a disaster. Finally, outages happen when failures of equipment occur, when product deliveries fail to arrive, or even the power supply is interrupted; thus, outages are mostly unplanned.

The management of STO projects presents different challenges depending on the project type. The key challenge is to execute the correct scope with minimum operational disruption, while fully respecting the safety requirements, at the same time. In this regard, T/A projects are characterized by the complexity and the plurality of the scope to be performed (typically exceeding 20,000 tasks), a situation often aggravated because of the inherent uncertainty in the condition of the equipment to be maintained which in turn increases risks. Thus, these projects require highly detailed, meticulous planning for an extended period, well before their scheduled start (Bevilacqua, M., Ciarapica, FE., et. al., 2012; Shaligram, P., and Jiao, J., 2008). It is common for a devoted and aware planning team to spend at least 2 years for that purpose.

Shutdown projects face similar challenges, differing however in the complexity and plurality of tasks, and quite often, in the financial impact to the industrial organization, as operation suspension is not always necessary. As they are also mostly preventive in nature, they avail time for planning and procurement preparation. They may profit from good practices for T/A projects, and they may generate valuable knowledge and insights for the future. Finally, outage projects are mainly reactive in nature, thus they require established plans and processes to exist, and they are susceptible to issues related to a lack of spare parts, at least for critical equipment.

Evidently, T/A projects are the most intriguing of all; they require long-term preparation, solid and holistic PM, well-organized personnel, systematic knowledge and expertise, as well as the ability to profit from technological advancements. They are tightly linked to the enterprise asset management strategy of a company, may have an impact on the supply of critical products or increase the strain on other suppliers to meet demands, and are directly related to the financial viability of an enterprise. Therefore, *in this work we focus on turnaround projects since they encompass the most complex and ambitious goals for a process industry*.

This work is structured as follows. In Section 2, we review the evolution of T/A Project Management approaches driven by technological evolutions. Then, in Section 3, we explain the multi-dimensional nature of data, we introduce the term of data-driven project management (DDPM), and we highlight the areas most affected and profited from data analysis. Section 4 establishes the contextual frame of our case study, which capitalizes on experiences over the past fifteen years in pragmatic T/A project. A set of implemented "*digital best practices*", elaborated in Section 5, strengthens the importance of MDDA, information visualization and computational intelligence in this family of industrial projects. Finally, in Section 6, we critically evaluate how and to what extent, the advent of computational and artificial intelligence can supplement/replace existing approaches,. we summarize our key findings and highlight areas of future research.

2. The Evolution of Turnaround Project Management

The management of T/A projects has followed an evolution path during recent decades. Although the core characteristics and objectives have solidly held their place, a multitude of augmented characteristics have appeared, activated primarily because of the capabilities that accompany the growth in data science and information management. In particular:

- During the ‘90s, industrial companies strove to secure a complete scope of activities, to be performed at a planned duration, subject to safety requirements. The delegation of maintenance activities was largely a matter of expertise, while planning was tedious and often limited to only a few thousand tasks. The scope of equipment to be maintained was rather broad and often included unnecessary items, only to profit from the operational downtime. Communication was vertical and progress feedback was elementary. PM was primarily targeted to internal stakeholders.
- During the ‘00s, PM information systems permitted the planning of a larger number of tasks, while risk evaluation tools enabled the more precise identification of equipment to be maintained. The communication grid became denser and the progress feedback was improved. PM now included in-house personnel as well as contractors and suppliers and addressed financial aspects.

- During the ‘10s, knowledge management systems enabled rapid development of plans and offered accurate identification and prioritization of equipment needing maintenance; information systems and reporting permitted the generation of targeted, customized, multi-level reports; progress-feedback became richer, timely, more accurate and more complete. Data analytics methods were adopted to profit of the vast amount of available data and to support the corresponding DT efforts (Lee, J., Kao, H.-A., and Yang, S., 2014; O’ Donovan, P., et al., 2015; Karim, R., et al. 2016; Uhlmann, E., et. al., 2017).
- During the ‘20s, PM has been largely affected by the growth of data analysis, Machine Learning (ML) and AI tools, and is becoming far more sophisticated addressing areas well beyond the planning, execution, monitoring, and control of the T/A activities; these areas now include procurement management, enterprise asset management, information and knowledge management, supply and demand management, etc.

The above evolution scheme is representative of the approach that most oil & gas industries have approached T/A projects and was propelled by the parallel burst of technological (mostly digital) advancements. This evolution, however, necessitated the adaptation and gradual change of companies, to encompass the benefits of the digital era, not only in the form of digital transformation but mostly in terms of culture and governance.

The importance of data collection, analysis and utilization for the improvement of processes in T/A projects is well documented. Shou et al. (2020) analyze and classify value-adding and non-value-adding activities in maintenance processes, outlining the pitfalls of ineffective data management, i.e., collecting data with no value or failing to collect vital data. The importance of data reliability is also stressed in (Rantala, Kortelainen and Ahonen, 2021), with respect to the preparation (e.g., asset condition and maintenance history), the execution (e.g., information sharing and quality monitoring) and closing of T/A projects (e.g., properly updating Enterprise Resource Planning (ERP) systems with data gathered during the process). Karim et al. (2016) use the term “maintenance analytics” to refer to the process of data acquisition, transition, fusion, mining and information extraction and visualization in order to support effective maintenance decision-making. The increasing volume of related data and hence of big data analytics in T/A projects is discussed in (Al-Turki, Duffuaa and Bendaya, 2019) and references therein, also in view of the application of “Industry 4.0” tools and techniques in maintenance (Jasiulewicz-Kaczmarek and Gola, 2017; Silvestri et al., 2020; Tortorella et al., 2024). Accordingly, frameworks utilizing data to establish decision support tools for T/A projects have also been proposed (Bumblauskas et al., 2017; Mitrofani, Emiris and Koulouriotis, 2020).

In this work, we attempt to highlight the interplay between data analytics and the various dimensions of transformation that industrial companies undergo, as they increase their project management maturity. We demonstrate how MDDA and information visualization leverage the project management efficiency for turnaround projects, and inversely, how the increased needs for more efficient and holistic project management trigger the development of ever more sophisticated data analysis algorithms, techniques and tools.

3. The Multiple Dimensions of Data and their Role in PM Evolution

The management of complex and challenging projects (including industrial ones, such as turnarounds), can be vastly improved by profiting from the advances in digital technologies and particularly, in data analytics. A plethora of data from diverse sources can be obtained and processed for various purposes and different objectives to support the management of challenging projects and to lead eventually to a “*data-driven PM*” (or *DDPM*), a term we coin herein to describe the goal of continuous improvement and transformation of PM approaches.

The question that arises therefore, is what type of data can be used to support DDPM and what is their nature. The key attributes of these data constitute a multi-dimensional set, *each dimension of which corresponds to one attribute*. We have identified these *independent* dimensions to be:

- The appropriate *data acquisition frequency* (implicitly affecting the size of the data set) – this is also related to the change pace of data and to the ability of data sources to produce/provide updated datasets
- The *change pace* of data (fast to static; affects the span of information validity) – fast changing data are those that have a very brief validity lifecycle, as in the case of work updates; semi-static data may be sensory readings for a slowly-evolving malfunction
- The *data types* (technical, financial, etc.) – these data can be obtained from field operations (for instance, to report progress), from other software applications (for instance, when financial or inventory data are needed), from planning teams (for instance, when updates and re-planning are performed), etc.
- The *data sources* (e.g., sensors, people) – data regarding project progress are mostly provided by humans using appropriate digital tools, while data that are used for predictive maintenance purposes are mainly obtained by on-board equipment sensors (e.g., vibration, temperature, acceleration, etc.)
- The *diversity of information dissemination objectives* (e.g., field guidance, management overview) – this characteristic has an impact on the tools and strategies that may be employed to serve the purpose
- The expected *frequency of updates* of derived information – this is mostly important when primary data is varying, thus prompting the need to frequently update information
- The *criticality of information-based decisions* (proactive, tactical, strategic)
- The *lifecycle of the data analysis results* and of the generated information (e.g., eventual or knowledge generation)
- The information *computational and visualization requirements* and types

Evidently, there may also exist other parameters/ dimensions that may characterize data, such as cybersecurity, content sensitivity, etc., yet these are often context-specific and are thus omitted in the present analysis.

Project teams that plan to employ data to develop tools and practices that may boost project management in an industrial environment, inevitably should consider these multiple dimensions. This, however, is not sufficient, as any digital tools or practices need to consider the internal and external context of operation, the involved parties, the technological infrastructure and limitations, the culture, etc. We thus identify four additional data-related dimensions, as follows:

- *Stakeholders*: Which stakeholders are involved? What is their type (internal, external, etc.), their population and their attitude towards providing data and using derived information? Are they perceiving the change as an opportunity or as a threat? Who should be involved first and in what role? How can we ensure their efficient engagement? What is the existing culture and how does it change over time?
- *Technology*: What types of software and systemic tools are in place and/or available? What technological or technical limitations exist? Are there enough data sources to support a data-driven transformation of PM? How can the technical integrity be assured through the seamless operation of the Information Technology (IT) ecosystem?
- *Knowledge*: Are there any historical data, templates or knowledge sources and repositories that could support the transformation? Are there any processes in place? Does a coherent training plan exist? Are mistakes and lessons learned recorded?

- *Difficulty of implementation*: What are the technical elements that facilitate (or obstruct the implementation) of data collection and processing? What are the human-related factors (e.g., attitude) that may inhibit the implementation and use of data practices?

Moreover, the scope of implementation of digital tools and the timing of application may decisively affect their adoption or rejection. These two additional dimensions can thus be considered to complete the set of data-related dimensions. These are briefly elaborated below.

- *Scope of Implementation*: How extensive can / should a DDPM implementation be? Are there any constraints, industrial standards or legal obligations that dictate the need to transform? Should the transformation concern a small internal community, or should it affect the entire organization or even external partners?
- *Timing*: What is the starting point? What actions should be performed, and in what sequence so that people trust the process? Which transformation activities are implemented over time? How does stakeholder feedback affect the timeline? How often is the time plan revisited? When are quick wins scheduled and what is their content?

We have therefore identified a set of fifteen different data-related "dimensions", all of which need to be considered when coupling data analytics methods with project management practices. Evidently, the mining, processing, usage and transformation of data related to all phases of an industrial project also affects the efficiency of project planning and replanning, the project governance through the conformance to standards and regulations, the safety through the assurance and communication of regulations and recording of incidents, and the control of project execution through timely, accurate and targeted information. In our study, however, we confine our analysis to the aforementioned data-related dimensions.

4. Context of the Case Study

We hereby illustrate the implementation of DDPM, the distinct aspects of multi-dimensional data analysis to support it and the resulting DT outcomes. Our findings are the result of fifteen years of working on turnaround (and shutdown) projects in a leading oil & gas company, in two out of three main industrial sites (refineries).

The key characteristics of our case study are:

- The timespan of our study starts in 2007 and ends in 2022; during this period, ten (10) major turnarounds (and several shutdowns) were implemented while the functionalities of the software centrally used (MS Project Server) were vastly improved (Fig.1).

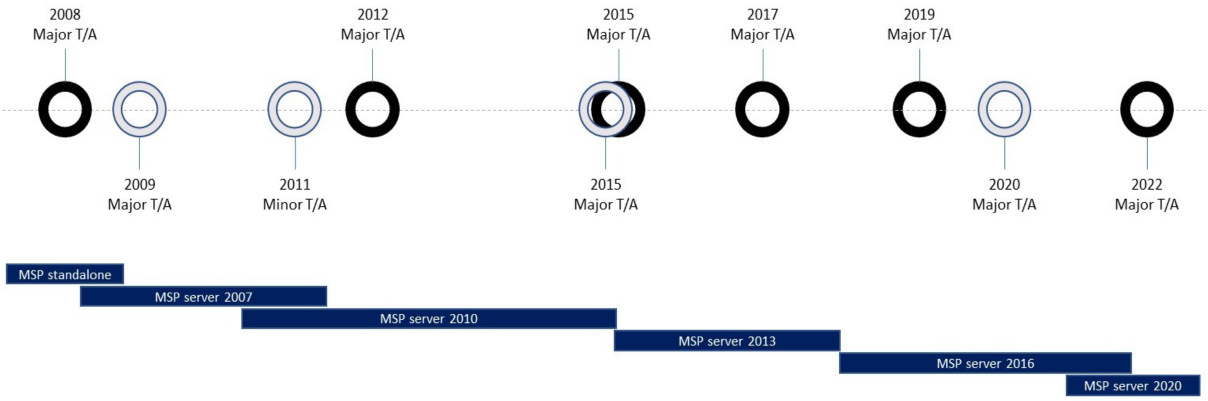


Fig. 1 Timeline of Major Events and Platform Evolution (different colors for distinct sites).

- The average duration of execution was 38 days (on a 24/7 schedule) with an average of 750.000 person-hours in total, from almost 2.000 people per day.

- The human resources were internal and external, multi-national, individuals or contractors, with appropriate training; special (and support) teams were also involved.
- All types of equipment that can be encountered in such an industrial environment were subject to maintenance; these were heaters, columns, heat exchangers, reactors, vessels, compressors, valves, instruments, etc. The scope of maintenance progressively increased through the years as a result of implemented DDPM practices (Fig. 2).

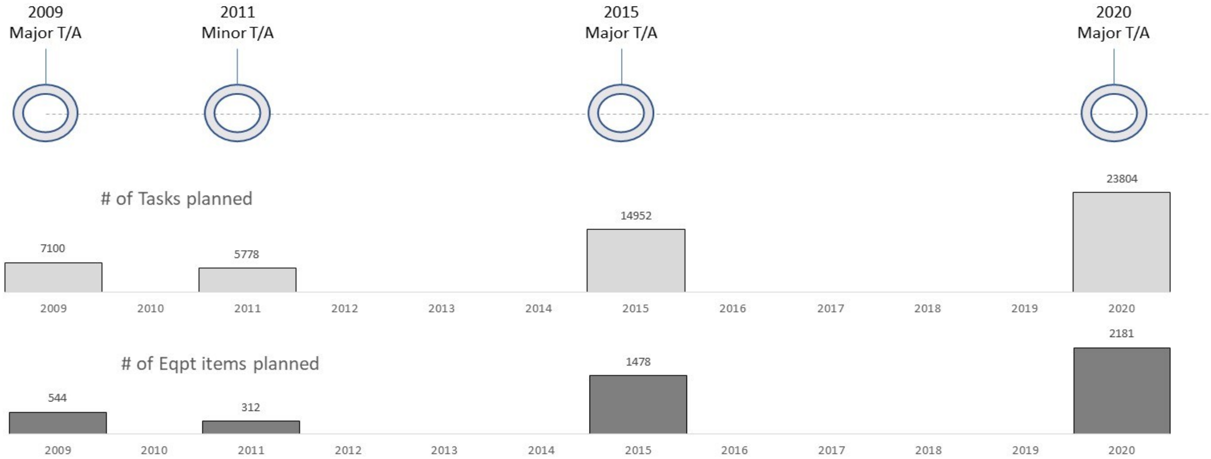


Fig. 2 Temporal Evolution of Scope (for one site).

- Apart from the typical maintenance works, inspections, repairs, and overhauls were also performed; planning also integrated general stoppage/startup and decontamination/commissioning tasks.
- The average planning duration to provide the pre-execution baseline was about 2.5 years and involved multiple divisions and departments of the company.

Our efforts culminated with the time-phased development of a number of "digital practices" (DPs) that addressed the ever-growing needs and requirements and ended up forming a robust infrastructure for DDPM. These DPs were then standardized and adopted.

In Table 1 below, we summarize the timeline of requirements, tools, a delegation of the implemented digital practices, and other useful indices that explain our methodology.

Table 1 Timeline of Requirements, Tools and Implemented Digital Practices

	REQUIREMENTS*	T/A	Key Digital Practices (DPs)	Areas affected
2008-09	• To have a good depiction of schedules for static equipment only → *Establishment of SPMO*	2	DP1: Standardization of PM processes and development of Shutdown Project Management Office (SPMO)	Integration Scope
2010-12	• **To obtain good estimates** • To include plant and unit works in the scope • **To model and monitor major contractors** • *To establish key planning and controlling processes and issue KPIs* • *To report the progress of critical tasks* • *To integrate in the MSP server and organize portfolio*	2	DP1: Improved version DP2: Development of tool for risk-based scope freeze DP3: Templates for equipment (as flow charts, WBS and schedules) DP4: Projects and portfolio repository	Scope Scheduling Procurement
2013-15	• To include all works for all equipment types • *To create templates for work families* • *To enable collaboration* • ***To create visual reports*** • *To develop knowledge repositories*	2	DP3, DP4: Improved versions DP5: Knowledge repository DP6: Visual tools for collaboration and communication	Scope Scheduling Communication Knowledge
2016-18	• ***To pluralize communication tools & channels*** • ***To integrate data from different sources*** • *To employ newer tools and functionalities* • *To utilize lessons learned*	1	DP2: Development of tool for risk-based scope freeze using fuzzy logic DP4, DP5, DP6: Improved versions	Scope Scheduling Communication Knowledge
2018-20	• *To create fully dynamic, real-time, visual reports* • *To develop robust forecasting algorithms* • *To be risk-proactive* • *To address procurement needs* • *To employ more advanced data analysis methods*	2	DP6: Improved version DP7: Graphical tools DP8: Business Intelligence (BI), reporting & forecasting tools	Integration Strategy Communication Knowledge Asset Management
2021-	• *To integrate into one platform as a single point of communication* • *To test the feasibility of predictive maintenance in pilot equipment*	1	DP7: Improved version with geographic info DP9: Automated data acquisition and analysis for fault diagnosis using ML	Communication Knowledge Asset Management

*** Items in bold indicate requirements that created conflicts among stakeholders**
** Items in italics indicate Digital Transformation relevant requirements and/or technological challenges*

The above table sheds light into the modular, time-phased, and enriched implementation that took place and progressively created a DDPM mentality and methodology, which contributed to the overall digital transformation of project management in this company, largely by profiting of the advent on digital technologies. It should, however, be stressed that success cannot be accomplished by merely applying data analysis tools and methods; rather, it requires that one has a broader perspective and understanding on the multiple dimensions of data, which are not only technical but also (and probably, mostly) human oriented.

Notice that Digital Practice 1 (Standardization of PM processes of SPMO) is considered fundamental for the efficient PM of T/A projects. It turned out that the use of PM tools and techniques is very useful for T/A projects due to the complexity of the process, the high cost, high risk, the large amount of resources involved and the short duration. Additionally, the standardization of processes triggers the examination of necessary aspects to be managed in these projects, such as the collection of requirements, the analysis and freezing of the scope, the scheduling structure and techniques, the communications mentality, the procurement monitoring, etc. A formal organizational structure, an SPMO, is thus absolutely essential for the proper management of such projects. The results of this effort have been presented in (Emiris, 2013).

5. Implementation Cases

We now highlight the role of data multidimensionality through four distinct cases of data usage and the corresponding DPs, obtained from our experience on T/A projects:

(i) Data were obtained from focus groups and key stakeholders and were used to develop DP2 that resulted to a tool for risk-based scope freeze using fuzzy logic;
(ii) Field data obtained from execution teams (workers) to report the progress of works and generate instructions; these were employed to develop DP6
(iii) Secondary data generated from the PM information system to extract forecast completion times and costs; these were employed to develop DP8
(iv) Sensor data were obtained from equipment to evaluate maintenance needs and to produce DP9 dealing with the automated data acquisition and analysis for fault diagnosis using ML

In view of the above, we can characterize these data as follows (Table 2).

Table 2 Characterization of Data Types and Data Dimensions

	Data Types			
Data Dimensions	***Focus groups***	***Field data***	***Project data***	***Sensor data***
Data acquisition frequency	2-3 times during planning	1-2 times per day	1-2 times per day	A few seconds every day for a week
Data change pace	Almost invariant	Varying	Slowly varying	Semi-static
Data types	Technical, cost	Technical, safety	Time, cost, KPI	Technical
Data sources data	People, historical	People	Information system	Sensors
Diversity of dissemination objectives	Planning Safety	Field guidance Reports and updates	Management overview	Maintenance planning
Frequency of information updates	Twice/year	Once/day	Once/day	Once every 3-6 months
Decisions criticality	Proactive Strategics	Proactive Tactical	Tactical Strategic	Proactive
Data analysis and information lifecycle	Permanent Knowledge dev't	Eventual	Eventual	Knowledge dev't

Computational and visualization requirements and types	BI and Fuzzy Logic (FL) tools	BI tools	BI tools	ML and BI tools
Stakeholders	Motivated engineers, contractors, need training	Field workers, internal, express concerns, need training, motivated	Middle and senior management, positive, main source of requirements	Engineers, internal & external, specialized, enthusiastic, need encouragement
Technology		Simple digital tools, spreadsheets, tablets	Existence of project or portfolio IS	Advanced and specialized software tools, high-computing power
Knowledge	Past reports	Templates for progress reporting, required training for accurate reporting	Customized and standardized forms, graphs, reports	Benchmarks, historical data, failure analysis
Implementation difficulty	Low	Moderate to low	Moderate	Moderate to high
Scope of implementation	Starting from focus groups, approval from top management	Starting from internal teams and focus groups and expanding to all sorts of people and works	Starting from internal management team and expanding to all departments and levels	Long-term efforts for specific family of equipment, expanding gradually
Timing	Fundamental planning activity	Among the very first data-related activities	Once systems are in place and enterprise PM is established	Appropriate only for mature stages

We now elaborate on these digital practices.

5.1 DP2: Development of Tool for Risk-Based Scope Freeze using Fuzzy Logic

In this DP, data obtained from focus groups and key stakeholders to evaluate, mitigate and freeze the project scope, using fuzzy logic (FL). Towards this, we developed a Decision Support System (DSS) that employs fuzzy logic to help define the scope of maintenance works in T/A projects. The developed system encompasses and combines crisp technical and functional parameters with experts' judgment to generate a "verdict" on whether or not to include the equipment in the project scope; moreover, constraints were applied to ensure the fulfillment of legal obligations or operational necessity and to exclude compromise in Health, Safety and Environment issues.

Proper scope definition is fundamental for project planning and execution, and of paramount importance in T/A projects. The necessary data were collected only a few times during planning, as they remain rather invariant. Stakeholders were positive in providing the data and in maintaining a historical information database. We first invited stakeholders, organized in focus groups, to provide data for certain parameters that were combined to calculate the so-called *Justification Factor* (or *J-factor*) introduced by Shell company

(Shell, 2000), which is based on the evaluation of risk factors (before and after maintenance); this factor is then compared with the relevant maintenance cost, resulting to a mostly cost-centric decision. In our implementation, we modified this decision mechanism by introducing new parameters for which data were obtained. These parameters were: the *Mean-Time-to-Repair* (MTTR), the *Mean-Time-Between-Failures* (MTBF), the *Reliability* (REL), and the *Value of the Equipment* (VAE), for each piece of equipment, along with the *Criticality* (CRT) of the equipment to the overall operation (as evaluated by experts) and the *Total Operational Cost* (TOC) resulting from equipment failure.

A fuzzy-logic tool developed specifically for this purpose, generated a ranking and categorization of equipment in terms of need and urgency to maintain, and provided a much more reliable scope of works. Figure 3 displays the structure of the developed system, while Figure 4 illustrates the membership functions for the variable CRITICALITY and decision surfaces for combined criteria. These explanatory visualizations of the decision surfaces and the resulting numerical results helped mitigate risks and optimize scope freeze. More results were presented in (Mitrofani and Emiris, 2019; Mitrofani, Emiris and Koulouriotis, 2020).

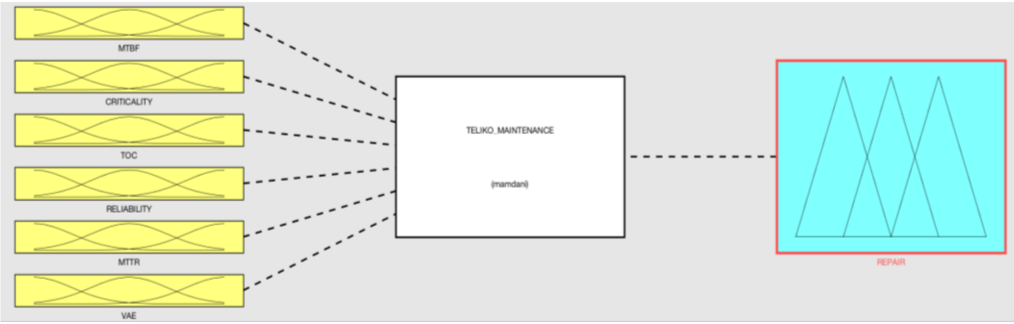


Fig. 3 Structure of the Fuzzy Logic System to Evaluate Maintenance Needs

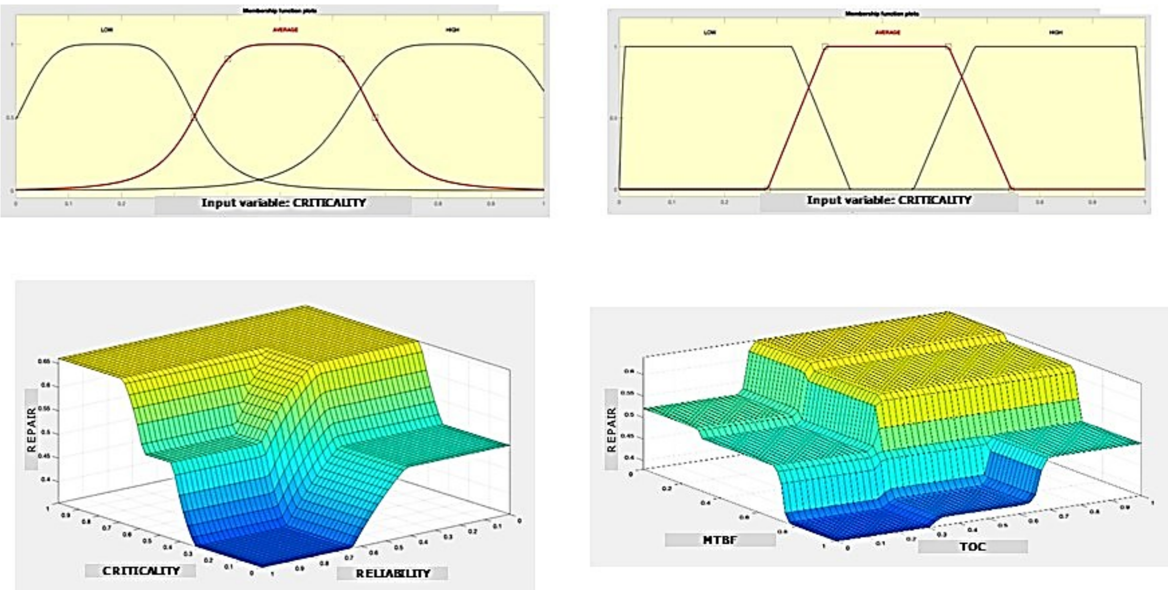


Fig. 4 Membership Functions for the CRITICALITY Attribute and Decision Surfaces for Combined Criteria

5.2 DP6: Visual Tools for Collaboration and Communication

In this DP, we faced from key stakeholders the requirement to create clear, well-understood, friendly, dense and meaningful reports, preferably visual, to enhance communication and to encourage collaboration. This requirement aimed to bridge a bi-directional gap: firstly, the gap between the need to obtain accurate and timely information from the field and the often scarce, erroneous, and unreliable information realistically obtained; secondly, the gap between the need to produce clear, timely and focused instructions to the workforce and the reality of spontaneous, generic, redundant set of instructions generated.

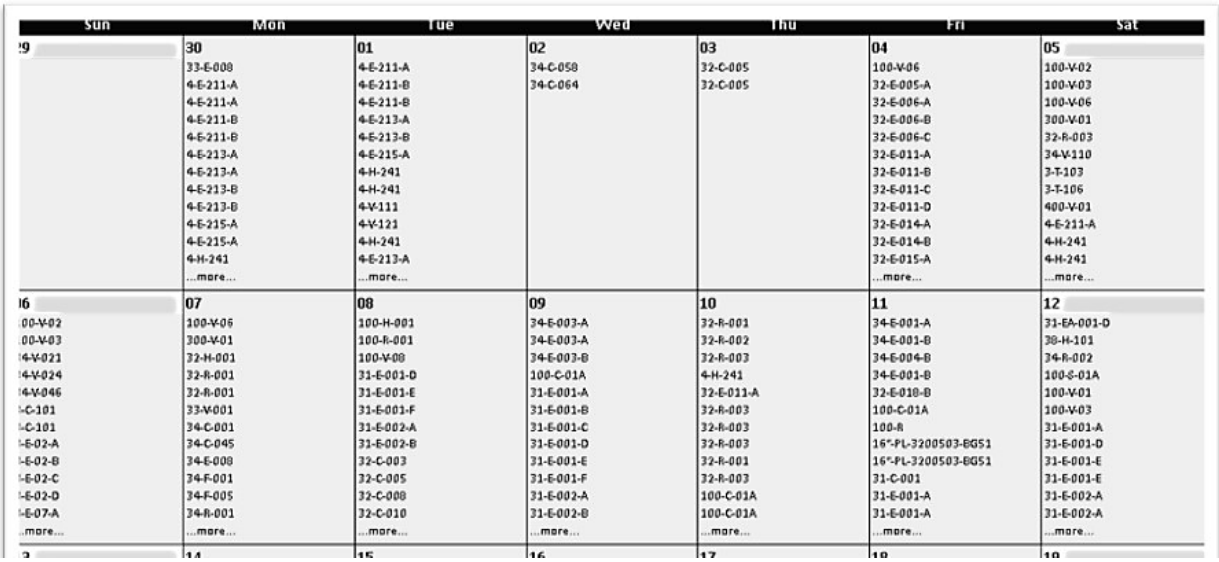
In a pragmatic T/A setting, this is indeed a very crucial requirement: simplicity and friendliness of reports enhances participation and improves accuracy; accuracy supports prompt decision-making with clarity; clarity helps saving time and increases safety, etc. We thus organized the frequent collection (twice a day) of massive field data from a large number of people for a large number of tasks (>1.200 per day). These were all eventual data in the sense that their lifecycle was limited only for the time between two reports.

Technology played a crucial role in the implementation of solution, as it enabled the development of visual tools and the use of reports in mobile devices. Although stakeholders were skeptical (if not negative, at times) with frequently reporting their work progress, their attitude swiftly changed to positive as they overcame the technological barrier and realized that the reports simplified their work.

Figure 5 illustrates such a visual report specifically designed to collect data from the field for the progress of works from the directly involved stakeholders; this easy to use report fetched data and fed them automatically to the information system. The implementation of this (and other similar reports) required the use of SharePoint and MS Project Server BI functionalities. Figure 6 displays another visual report that dynamically updates a short-to-long-term calendar of upcoming works for a particular job center, based on the input data.

Un	START DATE	EQUIPMEN	Task	RITICA	FINISH DATE	TASK DURATION	%	ACTUAL START	ACTUAL FINISH	SAP	GO	PREDECESSORS
U-4100	19/9/2020 08:00	K-4102	K-4102: Refractories inspection on the vessel wall (ID:108)		21/10/2020 19:00	48	75 %					(K-4102: Catalyst cleaning around cyclones, bracings, dipleg and
	25/9/2020 17:00	Z-4118N	Z-4118N: Check accumulator pre-charge		21/10/2020 08:00	255	%					(Z-4118N: Clean reservoir)
	25/9/2020 17:00	Z-4119N	Z-4119N: Check accumulator pre-charge		21/10/2020 08:00	2	50 %					(Z-4119N: Clean reservoir)
	27/9/2020 07:00	O-4106	O-4106: Inspection (ID:13)		21/10/2020 10:00	6	50 %					(O-4106: Cleaning vessel)
	1/10/2020 15:00	V-4101 (BLOWER)	V-4101 (BLOWER): Placing fixed and adjustable guide vanes (ID:20)		21/10/2020 15:00	16	50 %					(V-4101 (BLOWER): Placing blower-gear box
	2/10/2020 07:00	V-4101 (BLOWER)	V-4101 (BLOWER):Placing blower-gear box (ID:19)		22/10/2020 11:00	32	50 %					(V-4101 (BLOWER): Cleaning)
	4/10/2020 07:00	K-4102	K-4102: Shell gunning (ID:123)		21/10/2020 00:00	401	99 %					((K-4102: Installation of lining, Handpack Actchem 85))
	7/10/2020 07:00	Z-4105	Z-4105: Rafractories inspection (ID:300)		21/10/2020 08:00	25	96 %					(Z-4105: Portable lighting) - (Z-4105: Catalyst cleaning)
	7/10/2020 07:00	K-4101	K-4101: Refractories maintenance stripper section (ID:66)		21/10/2020 15:00	141	95 %					(K-4101: Refractories inspection)

Fig. 5 Visual Report to Collect Work Progress Data from the Field in Near-Real Time.



Sun	Mon	Tue	Wed	Thu	Fri	Sat
9	30 33-E-008 4-E-211-A 4-E-211-A 4-E-211-B 4-E-211-B 4-E-213-A 4-E-213-A 4-E-213-B 4-E-213-B 4-E-215-A 4-E-215-A 4-H-241 ...more...	01 4-E-211-A 4-E-211-B 4-E-211-B 4-E-213-A 4-E-213-B 4-E-215-A 4-H-241 4-H-241 4-V-111 4-V-121 4-H-241 4-E-213-A ...more...	02 34-C-058 34-C-064	03 32-C-005 32-C-005	04 100-V-06 32-E-005-A 32-E-006-A 32-E-006-B 32-E-006-C 32-E-011-A 32-E-011-B 32-E-011-C 32-E-011-D 32-E-014-A 32-E-014-B 32-E-015-A ...more...	05 100-V-02 100-V-03 100-V-06 300-V-01 32-R-003 34-V-110 3-T-103 3-T-106 400-V-01 4-E-211-A 4-H-241 4-H-241 ...more...
6 00-V-02 00-V-03 4-V-021 4-V-024 4-V-046 -C-101 -C-101 -E-02-A -E-02-B -E-02-C -E-02-D -E-07-A ...more...	07 100-V-06 300-V-01 32-H-001 32-R-001 32-R-001 33-V-001 34-C-001 34-C-045 34-E-008 34-F-001 34-F-005 34-R-001 ...more...	08 100-H-001 100-R-001 100-V-08 31-E-001-D 31-E-001-E 31-E-001-F 31-E-002-A 31-E-002-B 32-C-003 32-C-005 32-C-008 32-C-010 ...more...	09 34-E-003-A 34-E-003-A 34-E-003-B 100-C-01A 31-E-001-A 31-E-001-B 31-E-001-C 31-E-001-D 31-E-001-E 31-E-001-F 31-E-002-A 31-E-002-B ...more...	10 32-R-001 32-R-002 32-R-003 4-H-241 32-E-011-A 32-R-003 32-R-003 32-R-003 32-R-001 32-R-003 100-C-01A 100-C-01A ...more...	11 34-E-001-A 34-E-001-B 34-E-004-B 34-E-001-B 32-E-010-B 100-C-01A 100-R 16"-PL-3200503-BG51 16"-PL-3200503-BG51 31-C-001 31-E-001-A 31-E-001-A ...more...	12 31-EA-001-D 38-H-101 34-R-002 100-S-01A 100-V-01 100-V-03 31-E-001-A 31-E-001-D 31-E-001-E 31-E-001-E 31-E-002-A 31-E-002-A ...more...

Fig. 6 Dynamic, Long-Term Calendar of Upcoming Works.

5.3 DP8: BI, Reporting and Forecasting Tools

This DP resulted as a response to the requirements of developing robust forecasting algorithms and to be risk-proactive, by using even more advanced data analysis tools. Forecasts that can be easily updated, and which can be easily drilled-down per operational unit, were needed in order to plan when works would be completed, thus permitting production and sales planning. This in turn, minimizes risks of running out of inventory, permits determining the time that on-field logistics support will be needed (decreasing again the costs) and helps identify problematic areas that need special attention, acceleration of works, etc.

To develop these tools, we used secondary data, that is, data generated once or twice a day from the PM information system through data analysis. We produced either ready-made indices or customized ones and we implemented forecasting algorithms that were fine-tuned to minimize forecasting error. These tools helped produce meaningful reports, welcomed by the top management, and permitted strategic decision-making. An additional benefit was that these data were all integrated in a knowledge base with historical information that may be used in the future.

Figure 7 displays a summary progress report for one family of equipment, where works are grouped in phases. Here, the primary data were input in the project plans and secondary data were generated to create this report.

SECTOR	EQPT/UNIT	MAT	LateFinish	1. MECHANICAL ISOLATION	2. OPENING EQUIPMENT	3. CLEANING - INSPECTION	4. CLOSING EQUIPMENT	5. HYDRAULIC TEST	6. BLINDS RESTORATION
DISTILLATION	M-2403-C	●	18/10/2020	✔	✔	✔	✔	✔	✔
DISTILLATION	M-2403-D	●	18/10/2020	✔	✔	✔	✔	✔	✔
DISTILLATION	M-2405	●	18/10/2020	✔	✔	✔	✔	✔	✔
DISTILLATION	M-2407-A	●	18/10/2020	✔	✔	✔	✔	✔	✔
DISTILLATION	M-2407-B	●	18/10/2020	✔	✔	✔	✔	✔	✔
DISTILLATION	M-2403-A	●	18/10/2020	✔	✔	✔	✔	✔	✘
DISTILLATION	M-9213-C	●	20/10/2020	✔	✔	✔	✔	✔	✘
DISTILLATION	M-9213-D	●	20/10/2020	✔	✔	✔	✔	✔	✘
DISTILLATION	M-2022	●	16/10/2020	✔	✔	✔	✔	✘	✘
DISTILLATION	M-2024	●	16/10/2020	✔	✔	✔	✔	✘	✘
DISTILLATION	M-2023	●	16/10/2020	✔	✔	✔	✘	✘	✘
DISTILLATION	M-2057	●	26/9/2020	✔	✔	✔	N/A	✘	✘
DISTILLATION	M-2105-A	●	17/10/2020	✔	✔	✔	✘	✘	✘
DISTILLATION	M-2105-B	●	17/10/2020	✔	✔	✔	✘	✘	✘
DISTILLATION	M-2107	●	17/10/2020	✔	✔	✔	✘	✘	✘

Fig. 7 Summary Progress Report Using BI Tools.

Figure 8 illustrates a forecasting report for one unit, updated twice a day, that integrates most widely used Earned Value Management (EVM) indices along with several custom ones. Again, the cumulative indices are a result of processing of the primary data to generate secondary ones.

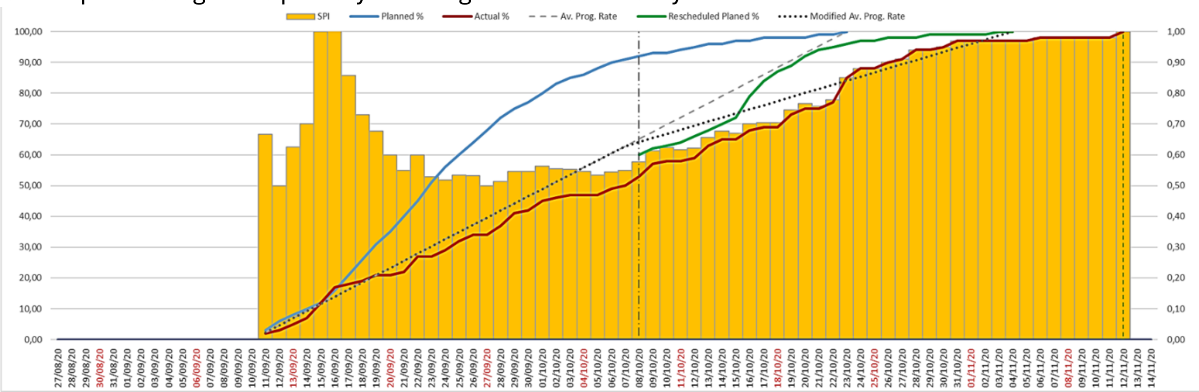


Fig. 8 Forecasting Report Generated from Secondary Data.

5.4 DP9: Automated Data Acquisition and Analysis for Fault Diagnosis using ML

In this DP, we dealt with the problem of Predictive Maintenance (PdM) for rotational equipment and, particularly, compressors, and we applied ML techniques on large data sets obtained from on-board sensors. Equipment with rotational components exhibit vibrational behaviors, thus we attempted to evaluate the fault levels of certain components by analyzing vibration frequencies data (El-Thalji, I., 2019; Mukherjee, S., Kumar, V., Sarangi, S., Bera, T.K., 2020).

We first collected high-sampling frequency data for short time periods and identified the most useful features in the frequency and time domains from these on-board sensory datasets, that enable efficient classification and pre-processed (filtered and denoised) the data to extract these crucial features using computationally efficient techniques; we thus created a palette of features to be considered, and ranked these features based on the importance and redundancy using the one-way ANOVA technique. Figure 9 displays a snapshot of the time-series of these high-frequency data obtained from experimental and real-world settings. We, then, experimented with two different clustering and classification algorithms, namely, k-Nearest Neighbor (KNN), Support Vector Machines (SVM) with different kernel options, to train and test fault classification. The obtained results, illustrated in Figure 10 along with the flowchart of the ML tool, demonstrated high classification accuracy (to the order of 93,5%) of faults and justified the feasibility of implementation in industrial setups.

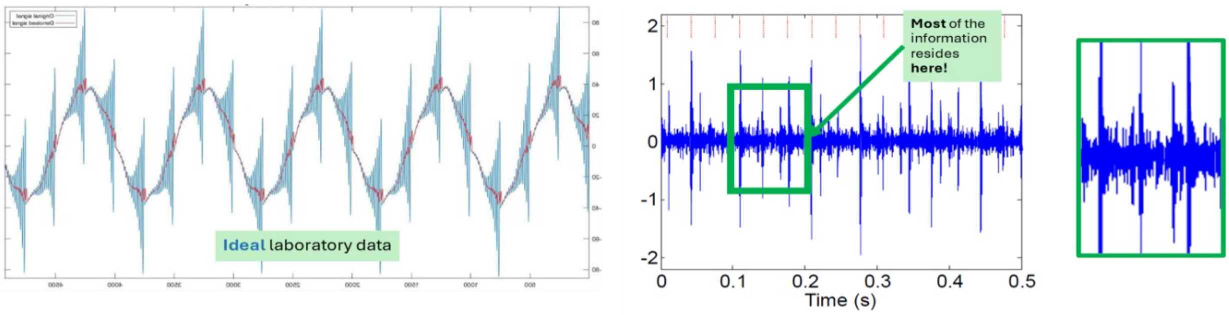


Fig. 9 Time Series of Data Used for Machine Learning and Fault Diagnosis

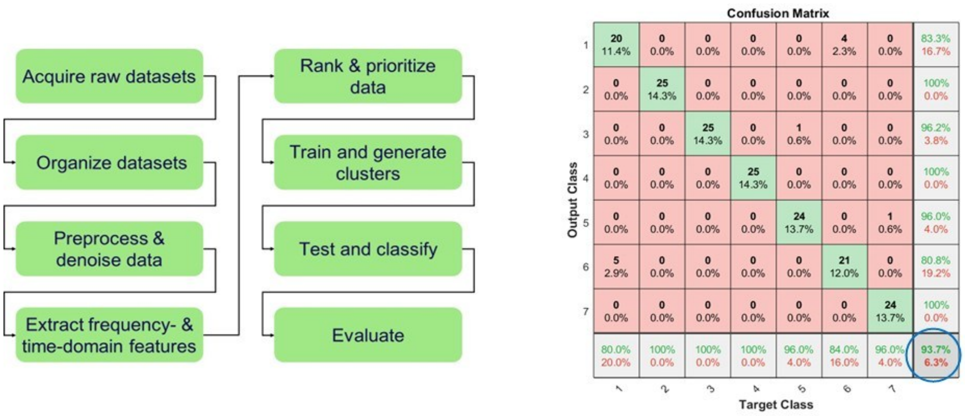


Fig. 10 Flowchart of ML Algorithm and Classification Accuracy of Faults

A key benefit of this DP was proving the feasibility of detecting where exactly the failure occurs remotely using only sensory data; moreover, it was shown that it is possible to identify the level of severity of the failure to plan maintenance works. Additionally, these actions may be implemented remotely, without disassembling the equipment, thus leading to decrease of maintenance cost and time, increase of uptime, and implementation of predictive maintenance strategies which help eliminate unnecessary replacement of spare parts, reduce work effort, and minimize the risk of accidents. A detailed presentation of these results can be found in (Emiris, 2023).

6. Critical Evaluation, Conclusions and Guidelines for the Future

In this work, we have highlighted the interplay between computational intelligence and data analytics approaches, and the digital transformation that industrial companies undergo, as they increase their PM maturity and culminate to DDPM. We demonstrated how multidimensional data analysis and information visualization leverage the project management efficiency for turnaround projects, and inversely, how the increased needs for more efficient and holistic project management trigger the development of ever more sophisticated computational algorithms, techniques and tools.

Our findings were based on experiences and practices in pragmatic T/A projects over a 15-year time span in two main industrial settings. The main limitations encountered were related to existence and use of technology and S/W tools, as well as to the adoption of digital practices from certain stakeholders. We have observed that the advent of technology and the adoption of similar practices from other companies, especially in most recent years, is acting as an enabler of DDPM; we expect this to improve further in the coming years. We have further highlighted the use and applicability of MDDA to create visual information tools and reports; we have also illustrated set of implemented "digital best practices" which corroborate the importance of MDDA and information visualization in this family of industrial projects. These can be used to support DDPM and to facilitate digital transformation efforts in companies dealing with industrial projects.

Several of the digital practices we implemented have involved elements, methods and techniques in the domain of machine learning and computational intelligence; other digital practices have not. DP1 (Standardization of PM processes and development of a Shutdown Project Management Office) has little to benefit from the advent of computational and artificial intelligence. In the first category, we have witnessed a beneficial contribution in practices such as, the "development of a tool for risk-based scope-freeze using fuzzy-logic" (DP2), "Automated data acquisition and analysis for fault diagnosis using ML" (DP9), "Business Intelligence (BI), reporting & forecasting tools" (DP8), "Visual tools for collaboration and communication" (DP6), to name a few. The development of these practices is expected to be further facilitated and become more efficient, even using common AI tools (such as Copilot for designing reports). Data acquisition, filtering, denoising, clustering, etc., is also expected to become far easier. Moreover, WBS development, task planning and scheduling, is already feasible in short times with the use of AI tools (although we noticed that human intervention is still necessary).

On the other hand, there exist digital practices we developed which are not discernably benefited by computational intelligence tools, such as, the "Standardization of PM processes and development of Shutdown Project Management Office (SPMO)" (DP1) or the "Development of projects repository" (DP4), although substantial use of information technology platforms is made. The soft skills of the PM and the PM team are critical in such endeavors and will continue to be necessary for the foreseeable future.

We have also examined the information visualization virtues as an outcome of systematic data analysis and demonstrated that it is pivotal in decision-making and communication, when supported by structured data. It is far more efficient in quickly perceiving the status and the forecasts, such as when progress monitoring is performed. Even in fault diagnosis, visualization tools may assist in capturing the temporal evolution of a problem and lead to decisions regarding the repair or replacement of a part or equipment.

Finally, we identified fifteen different data-related attributes/dimensions, which form a multi-dimensional set; these dimensions are not only technical but also correspond to managerial, behavioral, and strategic aspects of project management. A crucial conclusion of this discussion is, that the implementation feasibility and success heavily depend on the acceptance of the data analysis outcomes by the users. To that end, proper interpretation of requirements along with appropriate timing and stakeholder management must be performed. An equally important conclusion is that data analysis knowledge, tools, methods and S/W are widely available, thus offering multiple opportunities for the development of creative solutions at all levels and aspects of industrial projects. We have demonstrated in this work, some of these solutions, in the planning, execution or controlling phase, ranging from strictly technical to strategic, differing in criticality and purpose, and encompassing data that are sensor generated or provided by people, either slowly or rapidly varying, and maybe accepted with enthusiasm or criticism.

The effort of cultivating DDPM is an ongoing one. The range of applications is broad and may grow to include portfolio decision making, long-term enterprise asset management and investment decisions as well as the implementation of digital twins for a small part of the equipment. In all these tasks, MDDA, information visualization and computational intelligence are the common denominator and guide.

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