Vol.67: e24231238, 2024
https://doi.org/10.1590/1678-4324-2024231238
ISSN 1678-4324 Online Edition

BABT
Brazilian Archives of Biology and Technology

Article - Engineering, Technology and Techniques

Converting the Data Culture in a Power Company: a Case Based on Improving its Construction Management Processes

Rafael Martins[1]
https://orcid.org/0000-0002-0776-2978

Luciane Chaves de Sousa[1]
https://orcid.org/0009-0008-7082-9750

Allan Said Fadel[1]
https://orcid.org/0009-0008-9771-6596

Clailton Leopoldo da Silva[1]
https://orcid.org/0000-0001-7840-0352

Mauro José Bubniak[1]
https://orcid.org/0009-0003-4657-9767

Isabel Canalli Travagin[1]
https://orcid.org/0009-0000-0407-9842

Vitor Augusto Fiates Silva[1]
https://orcid.org/0009-0006-0509-7931

Gilmara Gonçalves da Cruz Maiola[1]
https://orcid.org/0009-0006-0831-9739

Bruna Machado Mulinari[2]
https://orcid.org/0000-0001-5838-6178

Clayton Hilgemberg da Costa[2]
https://orcid.org/0000-0002-7117-1785

Dierli Maiara da Rosa Maschio[2]
https://orcid.org/0000-0002-1268-0790

Flavio Lori Grando[2]
https://orcid.org/0000-0002-2563-4953

Germano Lambert Torres[2]
https://orcid.org/0000-0003-3789-4696

Joceleide Dalla Costa Mumbelli[2]
https://orcid.org/0000-0003-0511-5811

Fabio Alessandro Guerra[2]
https://orcid.org/0000-0001-8429-2263

Milton Pires Ramos[2*]
https://orcid.org/0000-0002-9244-2417

[1]Copel - Companhia Paranaense de Energia, Curitiba, Paraná, Brasil; [2]Gnarus Institute, R&D Department, Itajubá, Minas Gerais, Brasil.

Editor-in-Chief: Alexandre Rasi Aoki
Associate Editor: Alexandre Rasi Aoki

Received: 29-Dec-2023; Accepted: 19-Feb-2024

*Correspondence: miltonpiresramos@gmail.com, Tel.: +55-41-98402 3423 (M.P.R.).

HIGHLIGHTS

- Optimize construction management with Artificial Intelligence techniques.
- Converting the data culture in a power company in a practical context.
- Intelligent computing tools deployed on the application of Proofs of Concepts.
- Complex methodologies integration between systems and teams in collaboration.

Abstract: This paper presents the strategies and initial implementations of a data culture conversion process at a company in the electricity sector. Solutions are being developed within the scope of the construction management macro-process, which involves multiple sectors of the company, as well as external agents. The strategy is based on implementing Proofs of Concept as tools for converting the data culture within the company and, at the same time, supporting the essential activities of construction management. The proofs of concept aligned with the change in data culture have two components: technology and people. The first consists mainly of intelligent automation and process optimization. The second component involves sensitization, training and developing solutions together with the company's employees. The results involve a reduction in workload since some activities have been partially or totally transferred to the software. Greater assertiveness in estimating numerical data, such as prices and budgets. Increased reliability by reducing human intervention and complex calculations. Greater controllability by monitoring multiple activities and sectors, simplifying management. Finally, the integration of technology and people has shown significant advances in organizational culture, enabling employees to have a greater understanding of advanced tools and methods and to be able to identify opportunities and share solutions within the company.

Keywords: data culture; proof of concepts; construction management; artificial intelligence; machine learning.

INTRODUCTION

A Data Culture encompasses the shared behaviours and beliefs of individuals who value, engage in, and advocate for the utilization of data to enhance decision-making. Consequently, data becomes intricately woven into the operations, mindset, and identity of an organization [1].

However, large organizations have a large volume of data which, combined with the need for information security, makes cultural change more challenging. Changing the data culture may seem intimidating and unattainable at first, but it is not only necessary for improving processes, it also matures teams and empowers the organization as a whole. In this way, people and companies become resilient to technological change and embark on a path of continuous improvement [2].

Another characteristic present in large companies is the vast number of computer systems. In this scenario, the overall complexity of the environment increases, posing greater challenges for maintenance and management, in addition to cybersecurity challenges. Depending on the complexity of the environment, the benefits of computer systems may not be realized. Extensive training for users is necessary, and there may be resistance to the adoption of new technologies, especially if the systems are not intuitive or lack proper support [2].

Therefore, with big data being generated by a large volume of different software, some companies tend to avoid acquiring new systems. In this sense, the path to organizational data culture lies not in new platforms but rather in implementing methodologies for integration among existing systems and collaborative teams [3].

One way to generate value for the company considering the integration of multiple teams and systems is through the implementation of Proof of Concepts [4]. A Proof of Concept (POC) is the practical implementation of methods or ideas with a view to exploiting them in a practical and useful way. It therefore becomes a decisive step towards innovation and data culture.

Real Case in Energy Sector

One of the most critical processes in a company in this sector is construction management. New ventures must be brought into operation as quickly as possible, meeting all technical and safety aspects. These works include new facilities, improvements, expansions or reinforcements to existing facilities. From high complexity and uncertainties in the process, large-scale works become a to prioritizing and managing challenges. The multidisciplinary nature of the teams and their dependence on several agents, such as equipment manufacturers, contractors and technical public bodies, increase the difficulties and time involved in carrying out the work. Therefore, the integration of internal and external teams is fundamental to assure the success of the project and its rapid commissioning.

In this context, ‘COPEL Geração e Transmissão’ (COPEL GeT) together with the Gnarus Institute are carrying out a research and development (R&D) project under the ANEEL (the Brazilian National Electric Energy Agency) R&D program, which includes intelligent computer methodologies to increase the efficiency of construction management.

In this project, POCs are implemented through intelligent computer methodologies applied to specific employee tasks, with the aim of globally optimizing the Construction Management process. In addition, the POCs play a very important role, enabling the use of proven technical results and also guiding strategic actions aimed at success in innovation and applicability. In this sense, intelligent algorithms in conjunction with software robots play a fundamental role as they minimize purely operational activities and optimize communication, culminating in good, organized joint working.

This way, the aim of this paper is to present a form of Data Culture and Governance by presenting applications implemented through proofs of concept. For POCs to be understood, a culture and governance journey must be presented. Therefore, this paper is organized as follows: (2) describing the foundations for intelligent management (3) data culture and POCs; (4) presenting cases researched, developed and implemented, looking at their results, and finally (5) conclusions and future works.

GOVERNANCE: THE BASIS FOR INTELLIGENT MANAGEMENT

Given that the scope of this project is based on applications for process management, it is necessary to lay the foundations for developing the solutions. This foundation is described by corporate governance. Figure 1 illustrates the relationship between governance and management.

Figure 1. Governance and Management relationship.

The relationship between governance and management is crucial for the smooth functioning and success of an organization. While corporate governance sets the guidelines, policies, and structures that define the balance of power, accountability, and shareholder interests, management focuses on efficiently implementing these guidelines to achieve the operational and strategic objectives of the company. Governance provides the high-level framework and direction, outlining the boundaries within which management can operate. In turn, management deals with day-to-day activities, makes operational decisions, and seeks to optimize organizational performance. An effective relationship between governance and management implies cohesive collaboration, where governance sets expectations, and management fulfils them, ensuring integrity, transparency, and effectiveness in the organization's operation [5].

The massive presence of information systems within organizations has led to the creation of policies aimed at this segment, giving rise to Information Technology Governance. Over time, computer systems have evolved beyond tools that help processes and have come to be characterized as instruments for collecting data on the behavior of individuals and organizations. At this point, there was an alert about information security, prompting the creation of Data Governance [6].

Today, the applications provided by Artificial Intelligence have had disruptive effects on society as a whole. At the forefront of technological evolution, some organizations have implemented intelligent systems in various sectors, culminating in the need for AI Governance [7].

Figure 2 depicts AI governance as a subset of corporate governance, partially overlapping IT and data governance. The rationale for this position is that corporate governance provides the overarching governance structure within an organization, and AI systems, as IT systems with specific capabilities, are governed by mechanisms that fall under IT governance. The focus is to give autonomy to AI governance, while still remaining under the corporate governance.

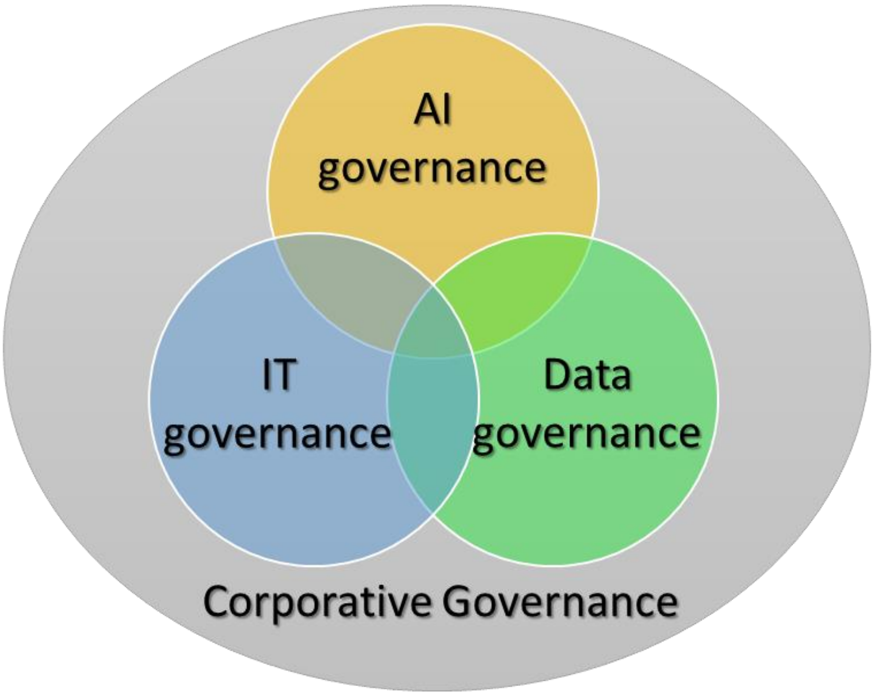

Figure 2. Governance from the perspective of the R&D project.

Therefore, the corporative governance, in the context of this work, will cover aspects of IT (Information Technology), AI (Artificial Intelligence), and Data, which directly impact the applicability of POCs. The following literature review describes the governance tripod in the context of research and development and its relationship with the environment.

IT governance

There are several widely recognized frameworks for Information Technology (IT) governance that are used by organizations worldwide. Each framework has its own objectives, principles, and practices, but they all share the common purpose of improving the management and use of technology in organizations. Some of the main IT governance frameworks include:

- *COBIT (Control Objectives for Information and Related Technologies):* Developed by the Information Systems Audit and Control Association (ISACA), COBIT is a globally recognized framework that provides a comprehensive set of practices for IT governance and management, aligning IT objectives with business objectives [8].

- *ITIL (Information Technology Infrastructure Library):* Focused on IT service management, ITIL offers a set of best practices for planning, delivering, and supporting IT services [9].

- *ISO/IEC 27001 (International Organization for Standardization/International Electrotechnical Commission):* This is an international standard for information security, including specific practices for managing security risks. While not exclusively an IT governance framework, it is widely used to ensure information security in IT management [10].

- *TOGAF (The Open Group Architecture Framework):* This framework is used to enhance efficiency through the standardization of enterprise architecture. It provides methods and tools to help organizations develop and manage IT architectures [11].

These frameworks are often used in a complementary manner, depending on the specific needs of the organization. The choice of the most suitable framework depends on the organization's objectives, industry, regulations, and individual characteristics.

Data governance

There are several frameworks and standards specifically for data governance, which help organizations manage, protect, and utilize their data assets efficiently. Some of the most well-known frameworks in the field of data governance include:

- *DAMA-DMBOK (Data Management Body of Knowledge):* This framework is maintained by the Data Management Association (DAMA) and provides a comprehensive structure that describes best practices and fundamental concepts in data management [12].

- *DCAM (Data Management Capability Assessment Model):* Developed by DAMA International, DCAM offers an approach to assess and improve data management capabilities within an organization [13].

- *GDPR (General Data Protection Regulation):* While not exclusively a data governance framework, GDPR is a European Union regulation that sets strict rules for the protection of personal data, directly impacting data governance practices [14].

- *CMMI-Data Management Maturity (CMMI-DM):* An extension of the Capability Maturity Model Integration (CMMI), CMMI-DM focuses on data management capabilities, providing a framework to assess and improve maturity in this area [15].

- *ISO 8000 (Data Quality):* The ISO 8000 series addresses data quality and provides guidelines for standardizing, specifying, and controlling data quality [16].

These frameworks are designed to assist organizations in building robust structures for data governance, ensuring the quality, security, and compliance of data throughout its lifecycle. The choice of framework may depend on the specific needs of the organization, industry, and applicable regulations.

Because AI systems rely on data to operate and learn, certain aspects of data governance are also central to AI governance. Based on his review of data governance literature, Abraham [17] conceptualizes data governance as comprising four elements. In his conception, first, data governance is a cross-functional effort, enabling collaboration across functional boundaries and data subject areas. Second, data governance is a framework that defines a structure and formalization for data management. Third, data governance considers data a strategic business asset and views it as a representation of facts in different formats. Fourth, data governance specifies decision rights and responsibilities for an organization's decision-making about its data.

Data governance elements are relevant to AI governance, particularly in relation to the technical layers related to specific algorithmic systems. Doneda and Almeida [18] argue that governing datasets is one of the most fundamental ways of governing algorithms. However, AI governance goes beyond data control because data represents just one element in algorithmic systems. So, while data governance is necessary for effective AI governance, it is not sufficient on its own.

AI governance

Unlike the previous cases, the massive use of artificial intelligence in organizations is not yet a reality and therefore there are no well-defined frameworks for this governance. On the other hand, a number of authors recognize the importance of creating them.

Some authors direct this importance, in part, to the so-called “third wave of studies on ethical AI”, which focuses on transforming AI principles into applicable practice and governance [19]. This wave even aims to promote practical mechanisms of liability [20]. To structure this complex domain, researchers in the field presented layered AI governance structures, which include, for example, ethical and legal layers and levels ranging from AI developers to regulation and supervision in the field [21], [22]. At the social level, AI regulation and policy, and particularly human rights laws, have also been raised as critical considerations [23], [24].

Despite this academic attention, there have been few explicit attempts to define AI governance. In their global overview, Butcher and Beridze [25] characterize AI governance as “a variety of tools, solutions, and levers that influence AI development and applications.” In its broad scope, this definition is closer to Floridi’s concept of digital governance [26] defined as “the practice of establishing and implementing policies, procedures and standards for the appropriate development, use and management of the infosphere”. Along the same line, Gahnberg [27] operationalizes AI governance as “intersubjectively recognized rules that define, constrain, and shape expectations about the fundamental properties of an artificial agent.” The focus on rules is useful, but Gahnberg's definition focuses on the making of social rules, such as standards and legislation, rather than organizational AI governance. Overall, these macro-level conceptions remain silent on how organizations should govern their AI systems.

Schneider and coauthors [28] define AI governance for enterprises as “the framework of rules, practices, and processes used to ensure that the organization’s AI technology sustains and advances the organization’s strategies and objectives.” This paper conceptualizes the scope of AI governance for enterprises as including the machine learning (ML) model, the data used by the model, the AI system that contains the ML model, and other components and functionality (depending on the use and system context). While AI governance for enterprises is a promising starting point, the concept presented largely omits ethical and regulatory issues present in previous literature on AI governance. In doing so, such concept contrasts with AI ethics literature and downplays established AI-specific ethical and regulatory issues arisen from the organization's environment.

Additionally, none of the conceptualizations of AI governance researched by the projects team could explain the role of technologies used to manage and govern AI systems. These include, for example, tools for data governance [29], explainable AI [30] and bias detection [31].

Bringing together the ethical, organizational and technological aspects, and considering the definitions of related governance fields, we propose the following definition of AI governance at the organization level:

Proposition 1. *“AI governance is a system of rules, practices, processes and technological tools that are employed to ensure that an organization use of AI technologies is aligned with the organization strategies, objectives, and values, meets legal requirements, and meets the ethical AI principles followed by the organization”.*

Therefore, the key elements to define AI governance plan are four:

1. Be a system whose constituent elements must be interconnected to form a functional entity;
2. Have rules, practices, processes and technological tools, which essentially are all methods of regulating behavior to keep it within acceptable limits and enable the desirable behavior;
3. These elements exist to govern an organization use of AI technologies. In other words, AI governance needs to address the entire lifecycle of the AI system;
4. Finally, the use of AI technologies is governed to ensure multiple alignments, both in internal operations and with external requirements.

This section has presented the relationship between governance and management, as well as the particular aspects of each of the aforementioned governance subgroups. With this, it should be clear that IT, Data and AI governance have a direct impact on the company's construction management process since the aim is to develop technologies within this scope to optimize the process in question. Once strategic policies have been defined by governance, the next step is to put them into practice through data culture, the subject of the next section.

DATA CULTURE

Data culture refers to the set of behaviors, values, and practices within an organization that emphasize the use of data to inform decision-making and drive business outcomes. It reflects the extent to which data is integrated into the everyday operations and decision processes of a company, and how well employees understand, value, and leverage data in their roles [1].

Building a data culture is an ongoing process that involves leadership commitment, employee engagement, and the integration of data-related practices into the organization's overall strategy. It's a crucial aspect of becoming a more agile, adaptive, and competitive entity in today's data-driven business environment [2].

Every organization must start somewhere into their journey to adopting a true data culture. The Figure 3 shows one possible journey for an organization moving from using just data analytics to build a solid data culture.

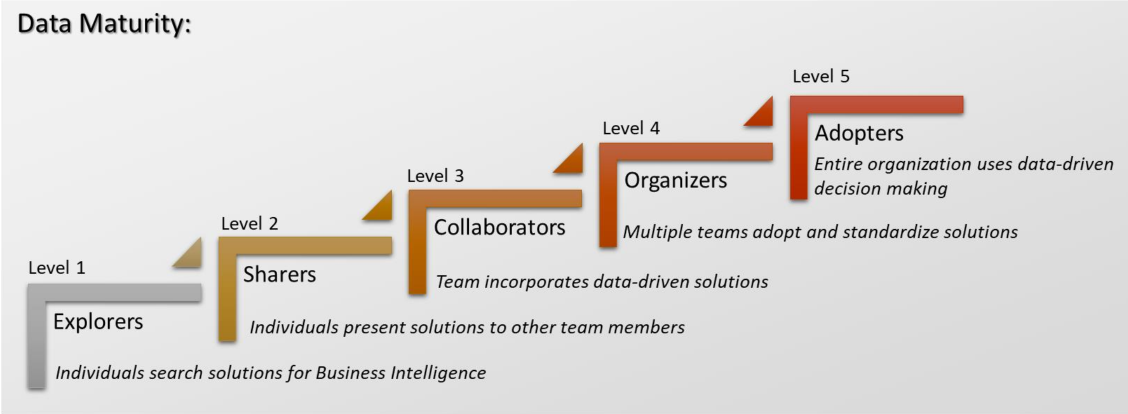

Figure 3. Five (5) progressive steps to data maturity (adapted from [32]).

- *Level 1 - Explorers:* At this level, individuals within the organization are just scratching the surface of data analysis visualization. They are starting to discover solutions for Business Intelligence (BI).
- *Level 2 - Sharers:* This is when data culture in the organization begins to go beyond the individual. Team members have experienced the benefits of BI and want to share their reports and findings with other team members who haven't tried it yet.
- *Level 3 – Collaborators:* At this stage, entire teams are using BI and have incorporated self-service data reporting into their standard operations as a team.
- *Level 4 – Organizers:* Level where data analysis and reporting has become such a standard practice that multiple teams are using these tools, requiring data sharing and collaboration to become more organized.
- *Level 5 - Data Culture Adopters:* This is the end state of the data culture maturity model and the objective for any organization. The individuals and teams are calling for data-driven decision-making, using reporting, analytics and including standardized data processes. The organization has successfully adopted a data-driven culture.

In this sense, success depends on two fundamental aspects: technology and people [1],[2]. These aspects are discussed below, followed by proofs of concept and how they are used to break down paradigms within the organization.

Technology and People

The Technology component are the solutions that organize and extract meaning and insights from your data, replacing or assisting slow manual processes traditionally associated with data analysis and visualization. Data technology is what allows the organization to truly understand the meaning of its data and provide manageable and useful insights to the business [33].

The Technology component alone cannot create a true data culture for the organization, thus the need for the People component arises. Team members must be prepared to innovate due to Technology. Creating a data-focused cultural shift involves an intensive effort to help the team members, regardless of their roles, since data insights are needed to keep analytics moving forward to the business [32].

It is noteworthy that when addressing data culture, especially when explored by a research project, having flexibility is a relevant factor. This so-called flexibility must accommodate the organization's ever-changing data needs and compliance regulations, besides it can provide lasting and extraordinary benefits, some of which can be described as follows [34]:

1. Provides clarity on the mission of data as an asset for each stakeholder;
2. Increases confidence in organizational data and, thus, leverages its use to obtain better results [35];
3. Clearly articulates the roles and responsibilities of each stakeholder, outlining the portfolio of responsibilities to minimize conflicts [36];
4. Prioritizes what is strategic and important, even if it faces constant changes;

5. Defines data-related metrics in measurable terms and establishes a clear roadmap for monitoring and achieving success;
6. Facilitates the execution and/or surpassing of conformities, goals and regulatory requirements;
7. Creates better structures for timely data retrieval and retention, leading to better decision making and stronger relationships with customers and internal and external stakeholders.

It was in relation to this flexibility which was evidenced by this research project that the results of POCs are so valuable. Therefore, at this point it was essential to create the different forms of integration so that the continuation of the research could occur fully and without the obstacles and limitations that happen when trying to carry out these integrations [37].

POCs (Proofs of Concepts)

A Proof of Concept (PoC) is a demonstration or prototype that provides evidence or validation of a certain concept or idea. It is a tangible representation of a concept that allows stakeholders to evaluate its feasibility, functionality, and potential success before committing resources to full-scale development or implementation. The main goal of a Proof of Concept is to test the viability of a solution or innovation in a real-world scenario and to verify whether it can meet the intended objectives [38].

The proof of concept or POC (Proof of Concept) is presented as a 'critical step' in the research and innovation process, being widely used by companies and their ecosystems [39]. A POC can be described as “a step towards innovation and value creation, a learning step that is often decisive if well managed” [4]. This type of proof has been little used in the strategic management of companies, probably because it is considered an exclusively technical milestone [40]. However, these milestones in POCs are extremely important for a research and development project, which can have its technical results confirmed, but also to direct or to redirect strategic actions in order to the project could be successful in its innovation and applicability [37].

A POC is a strategic and critical moment in the evolution of a research and development project because, in addition to testing innovative methodologies, it also involves breaking technological and functional barriers that will be used in the sequence of the project [37].

IMPLEMENTATIONS AND RESULTS

As described in the previous section, the fundamental components for changing the data culture are based on technology and people. The first of these is covered by the project execution team, i.e. an external team specializing in the technology component. The second is represented by the team within the organization. These are the individuals who receive the technology being developed. In this sense, the success of the project depends fundamentally on the contribution of the people who are directly or indirectly responsible for the construction management process.

Therefore, in order to begin the journey of maturing the data culture, as summarized in Figure 1, it is necessary to put people-focused strategies into practice with the aim of breaking down some technological barriers and changing the inertial state of the POCs. The proposed strategy has four pillars, which are developed throughout the project:

- *Leadership:* This involves identifying individuals with an inspiring vision, solid interpersonal skills and strategic positions within the construction management process. The aim is to mediate the teams involved and drive implementation of the POCs.
- *Sensitization:* is used in the context of making people aware, informed, or responsive to a particular issue or topic. Sensitization involves creating an understanding and fostering a positive attitude toward selected POCs.
- *Training:* This involves orientation and education about the technologies that are being implemented within the company. This makes people more receptive to maturing in the data culture and also makes them agent developers within the company.
- *Engagement:* The implementation of technology is carried out together with the company's employees rather than delivering a ready-made product. The aim is to enable employees to maintain and further develop the technologies that have been implemented.

Through the leadership of the organization, some cases were carefully selected and are described below.

Overview of selected cases

As stated in the Introduction, it was taken into account that Construction Management teams already use too much computer systems, therefore, there is no room for one more system. Thus, this R&D project was defined to assist teams with intelligent computing tools implemented from two perspectives: application of proofs of concepts (POC) and integration methodologies, both between existing systems and with collaborative teams.

In order for the research project team could be able to put into practice everything that was described about data culture, technology and people, four POCs were researched and developed. To not create a new systems, but rather back-office algorithms, information was used from the most relevant systems which are part of the four POCs initially developed, these being:

- POC1: Prices update for materials and services;
- POC2: Budgetary control;
- POC3: Financial monitoring;
- POC4: Intelligent activities monitoring.

A basic system architecture was need to be defined so that there was adequate sensitization and involvement of people from other areas in the company. This architecture defined flows between the computational tools used, computational methods, interactions with the team and provision of results. Figure 4 illustrates the architecture and its relationships with the created POCs.

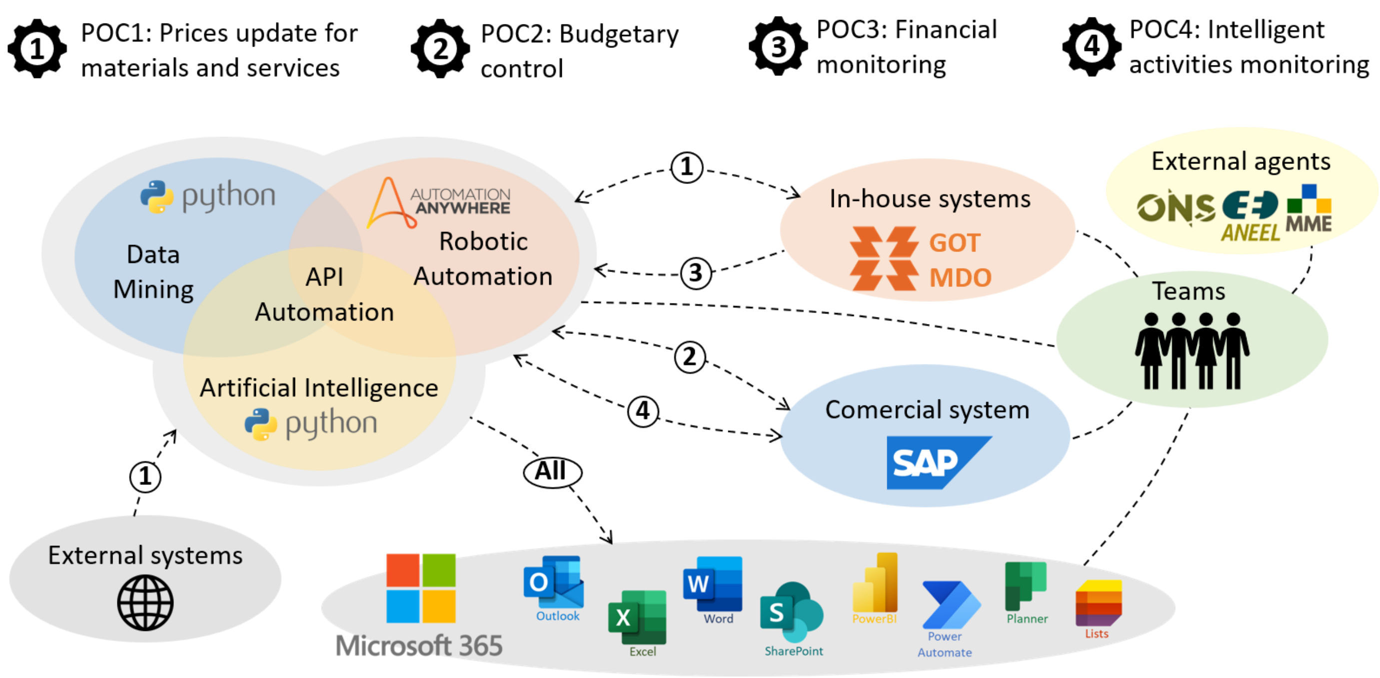

Figure 4. General architecture of the R&D project with the initial POCs.

POC1: Prices update for materials and services

For POC1 entitled “prices update for materials and services for construction works in transmission system, it was necessary to collect information from a single internal system called Transmission and Construction Works Management (GOT). This system has the composition of items of a construction work with their respective market prices. The intelligent algorithms developed aimed to search for information in external databases, whether structured or not, such as SINAPI (National System for Research on Civil Construction Costs and Indices) [41]. The end result is to update the prices of items in the construction works composition intelligently and on demand from the works team so that the bidding process was as close to market reality. In addition to updating the GOT system database, outputs were created for the construction management team in Microsoft 365 (SharePoint, PowerBI and Excel) [42].

POC2: Budgetary control

POC2, called "Budgetary Control", aims to obtain several information from the 'SAP interfaces' to create a budget monitoring report and analyze its history. Many hours of highly qualified people were involved in this activity and each construction manager had their own way of monitoring the execution of the work. Thus, an algorithm was created based on budget similarities that properly grouped and standardized such information. This POC, in addition to avoiding hours of work of a qualified team, also avoided errors when dealing with large financial volumes. The interface with the construction management team was also carried out through Microsoft 365 via Lists, SharePoint and Excel [42].

POC3: Financial monitoring

POC3 named "Financial monitoring" aims to monitor the physical and financial evolution of the construction works carried out. As a result, a table is presented with the estimated and actual cost values of the works, so that those responsible can monitor the development and evolution of each phase of their projects on a monthly basis. Similarly to POC2, the number of working hours and the diversity of the form of monitoring meant that this POC was developed.

The process of creating this monitoring task consists of two steps. The first stage is prepared by the manager responsible for the construction work and is carried out before it begins. Its objective is to organize a schedule, which has the monthly costs involved predicted from the beginning to the end of the projects. These costs include equipment, materials, outsourced services and labor. The second stage is carried out throughout the project and according to progress in the execution of each work, which consists of obtaining a monthly report that contains all the effective costs indicated by the people involved, materials, equipment and other services obtained by the management systems. In this case, it was necessary to create an intelligent database comparison algorithm to display differences in the posting of the same costs. The result of this POC3 was the correct posting of costs in the SAP system under their appropriate heading, depicting the organization of this information within Microsoft 365 through Excel and PowerBI.

POC4: Intelligent activities monitoring

And finally, in POC4 "Intelligent activities monitoring", the main objective is to create an intelligent analysis of activities planned in a given project versus what was actually carried out. But before even predicting anything, an intense debate was necessary to standardize activities, not processes, which generated 64 standard activities. With these in hand, a method for inserting activity forecasts was created via Microsoft 365. This forecast is made by managers and impacts the execution of works. Thus, the information was organized in a PowerBI that will receive the activities actually carried out so that it could be possible to insert machine learning algorithms for the analysis of data from forecast and achieved activities, in order to optimizing the allocation of teams with greater financial return.

CONCLUSION

This text depicted the conception and implementation of a research and development project whose objective is to develop a methodology for the management of complex construction works with an increase in reliability, traceability and agility through methodologies based on optimization techniques, process robotization, treatment of uncertainties, machine learning, and support for collaborative work.

With the implementation of this research project, a more comprehensive discussion emerged about data culture and IT, AI and corporate governance models, which is an important result of the project allowing reflection and review of the company's internal processes under a more efficient and modern approach. It was found that only the implementation of advanced solutions based, for example, on AI and Machine Learning techniques, without due evolution in data culture, cannot guarantee perpetuity and complete absorption of new technologies in the business environment.

In this context, a strategy focused on the teams was developed and implemented to promote mastery of the technologies and raise people's awareness to enable them to effectively absorb the new data culture. In addition, as a way of facilitating the introduction of technology, the construction management process was segmented into smaller tasks and focused on the activities of the teams. With this, the proof-of-concept model was applied as a testing and validation tool. The implemented proofs of concept are based on automating tasks using robotization in conjunction with machine learning and data mining to improve processes.

The future points to the implementation of other methodologies, always using POCs as a testing and validation method, as well as special attention being paid to the integration between the tools and methodologies developed to support the construction management teams of power utilities. Another axis of constant, long-term activities concerns raising sensibilization among people in the company, using the results of the implementation of cases in POCs as examples.

Acknowledgments: This work was financed by the program for research and technological development of Companhia Paranaense de Energia - COPEL, through the project PD-06491-0565/2019, regulated by Agência Nacional de Energia Elétrica - ANEEL. The authors would like to thank COPEL and ANEEL for the opportunity and support.
Conflicts of Interest: The authors declare no conflict of interest.

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