

Research Article

Value of concept of operations analysis for digital transformation using digital twins

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Abstract

Structured sociotechnical approaches are increasingly important to digital transformation given digital technology not only changes the way companies operate, but also brings to light new business strategies. Indeed, companies have ramped up operational data collection opportunities and adopted digital practices to facilitate new flows of design information, enabling teams to interoperate in ways that might lead to better system performance. More structured approaches are needed to overcome challenges faced in digital transformation, as present efforts are often rather ad-hoc and poorly structured. Such approaches better enable tying transformation to the organization's strategic objectives, and leverage operational strengths while mitigating limitations. As digital transformation occurs under certain sociotechnical contexts and with specific purposes, success can critically depend on the ability to unambiguously describe this context and the intended transformation as new operational scenarios. This paper discusses digital transformation using digital twins as a transdisciplinary challenge, presents a sociotechnical system analysis framework for digital twins, and offers insight on the value of applying an existing method called Concept of Operations Analysis, producing operational scenarios. Our ongoing work shows that the aforementioned method may accelerate the sociotechnical system redesign cycle and generate actionable decisions aligned with strategic goals and operational strengths and limitations.

Keywords: digital transformation, digital twins, sociotechnical systems.

1. Introduction

A structured approach to digital transformation requires linking the digital transformation process to the organization's strategy and operational processes and capabilities. This is challenging due to the complex social and technical elements at play. While understanding the technical elements can be difficult, understanding the social ones can be daunting in large part because of the multiple and potentially diverse stakeholders that may be involved. Understanding the full nature and effects of interactions between technical and social elements in transformation process requires a transdisciplinary perspective. So far, the research effort dedicated to these matters is not commensurate with this observation. This paper attempts to address this imbalance by offering a transdisciplinary discussion behind digital transformations, and by sharing a sociotechnical system analysis framework for digital twins, still under active development. Preliminary results from ongoing research suggest that one particular element of this framework—Concept of Operations (ConOps) analysis—has the potential to accelerate the sociotechnical system redesign cycle and generate actionable decisions toward digital transformation. A particularly powerful artifact of the analysis is the development of operational scenarios that illustrate the envisioned transformation. This paper is structured as follows: section 1 reviews the literature on digital transformation and discusses the transdisciplinary nature of digital twins; section 2 introduces the aforementioned framework and discusses the value of a ConOps analysis for digital twin development; section 3 offers some examples of representative operational scenarios for different digital technology in the aerospace domain; finally, section 4 offers some concluding remarks and discusses future work.

2. Literature review

2.1. Digital transformation using digital twins

Presently, the area of digital transformation is rife with inconsistencies and ambiguous terminology (Abdallah et al., 2021). This situation is, to a great extent, due to several organizations pursuing varying levels of digital transformation sophistication, independent of past or current work on the subject. For the purposes of

Received: August 18, 2022. **Accepted:** September 12, 2022.

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this paper, and in keeping with the definition provided in (Govindarajan & Immelt, 2019), a digital transformation is defined as a value-creation mechanism whereby humans reimagine products and services as digitally enabled assets, and create a sociotechnical environment that makes this possible. This definition highlights the fact that a digital transformation is not so much about equipping organizations with the latest digital technology as it is about transformation of work processes, organizational structures and culture, and connecting all these elements using digital technologies (Bockshecker et al., 2018).

Some benefits that a digital transformation might bring about include operational efficiency, customer engagement, and competitive advantage (Jones et al., 2021). Nevertheless, digital transformation also encounters significant obstacles. The majority of the reported obstacles are technology-related (Abdallah et al., 2021); for example, data insufficiency and unreliability, lack of reference architectures, immature technology, cybersecurity attacks, and unfitting legacy infrastructure (Jones et al., 2021). There are also important social and cognitive barriers. For instance, should the people in an organization see the transformation as a threat to their jobs or doubt their ability to acquire new skills, resistance to change will be a likely barrier. The risk culture that prevails in an organization, the investment in digital training and talent, and an aging labor force are other important social obstacles (Abdallah et al., 2021).

A great deal of effort has been dedicated to address the technological challenges; however, the same cannot be said for the social and cognitive challenges which often remain underestimated factors to the success of a digital transformation (Jones et al., 2021). Although some relevant approaches advocate for experimental and incremental transitions toward digital maturity, these approaches do not directly tackle the human component of digital transformations. For this aspect not to be neglected, organizations need to make a conscious effort to understand their sociotechnical environment, assess their ability to grow, and listen to and act upon stakeholders' concerns and needs. Digital transformation truly calls for a holistic and transdisciplinary approach, as opposed to a silo mentality, incorporating a comprehensive set of digital technologies (Brown & Brown, 2019).

Digital transformation can leverage a plethora of digital technologies (Abdallah et al., 2021). Examples of common technologies include integrated product lifecycle management, simulation and modeling, digital threads, internet of things (IoT), additive manufacturing, artificial intelligence and machine learning, automation and robotics, and digital twins; this paper focuses on digital twins. The origins of digital twins have been extensively discussed and a myriad of digital twin definitions have been proposed in the literature (Grieves & Vickers, 2017) (Glaessgen & Stargel, 2012) (Barricelli et al., 2019) (Semeraro et al., 2021). Collectively, these definitions reveal some key features that a digital twin should—or is expected—to have. For example, a digital twin should replicate the behavior of a physical system, be able to follow its entire lifecycle, and have near real-time and closed loop links with it. Individually, these definitions expose some disagreement in the literature such as how to replicate a physical system in a virtual environment.

Digital twins are often confused with digital models and digital shadows. In line with (Kritzinger et al., 2018), a digital model is a digital representation of a physical object that relies on a manual exchange of data between the physical and digital objects. A digital shadow differs in that there is an automated one-way data flow from the physical to the digital object; this implies that a change in the state of the physical object results in a change of state in the digital object but not the opposite. Finally, a digital twin is different because there is a bi-directional and automatic data exchange between the physical and digital objects; in this case, a change in state of the physical object results in a change in state of the digital object and the other way around. This level of specificity is sufficient to enable a meaningful discussion into the nature of digital twins in this paper.

2.2. Transdisciplinary nature of digital transformation using digital twins

Digital transformations using digital twins are commonly used to better manage the lifecycle of one or more assets, while delivering key insights to stakeholders and inform their decisions (Bickford et al., 2020). Viewed in this way, a digital twin should answer different questions depending on which stage of the lifecycle its physical counterpart is in. For example, if the asset is in the design stage, a question of interest might be: *what are the key functional requirements for the asset given current market demands and customer preferences?* Or, *what system architecture performs best considering existing operational data?* If the asset is in the service phase, the nature of the question changes significantly, for example: *what is the best maintenance plan for the asset given its current condition?* Or, *what services should be offered to the client based on the client's usage of the system?* Digital twins could also answer “what-if” types of questions leading to better risk assessments (Rasheed et al., 2020). For example, *by perturbing the system in an unexpected way, how might it respond and how does that response inform current mitigation strategies?*

Being able to answer lifecycle-related questions using the same digital object is a transdisciplinary challenge that requires knowledge from a diverse set of disciplines—both technical and social—as well as buy-in from a multitude of stakeholders, both internal and external to the organization. The need for technical knowledge is

straightforward: just considering the questions above, knowledge from engineering, product, customer delivery, dependability and safety is needed, not to mention the domain expertise required to replicate the physical object in question. Social knowledge is also quite important. A common misconception is that humans play no role in digital twins other than during their design and development. While many low-level tasks—often referred to as dirty, dangerous, and dull—can be autonomously achieved without human intervention, highly adaptable tasks that require great levels of causal thinking are still performed by humans. In these cases, a digital twin can expose humans to an adequate number of relevant datasets and analyses to inform, and not overwhelm, their decisions. This is more a social design or human-factors decision than it is technical.

Transdisciplinary knowledge is therefore just as critical as stakeholder buy-in. Depending on their technical background and personal interests, different stakeholders are likely to support or oppose different design decisions involving the digital twin of a given asset. Buy-in from all stakeholders is necessary not only to guarantee that there is some consensus on why the digital twin is needed but also to have stakeholders collaborating and supporting the design efforts with their knowledge and perspectives. This way, the value of the digital twin throughout the lifecycle of its physical counterpart can be better leveraged. Getting consensus from different stakeholders can be extremely difficult to achieve though, as it is necessary to manage both their expectations and level of comfort with the technology. For instance, a safety engineer might not accept the case of commands being automatically sent to certain systems. If stakeholder buy-in is not properly addressed, it will negatively impact the value proposition of the digital transformation. This difficulty might in fact be one of the reasons why most digital twins only apply to a single phase (e.g., service) of an asset's lifecycle (Semeraro et al., 2021).

3. Sociotechnical system analysis framework for digital twins

Transformation of work processes, organizational structures and culture are viewed as essential activities in digital transformation, yet most organizations fail to take a sociotechnical perspective in digital twin design. Moreover, although the sociotechnical aspects of digital twins have been identified as important by some other authors, there is little evidence of research on the subject. It is often the case, however, that organizations developing digital twins that initially considered only the technical attributes discover that it is actually very necessary to consider a range of social and technical issues relating to how various stakeholders work, interact, and communicate. This has motivated our investigation of sociotechnical systems analysis applied to digital twins (Rebentisch et al., 2021).

Figure 1 shows the *Sociotechnical System Analysis Framework for Digital Twins* developed in our research that aims to guide an organization in developing its strategic approach for adopting digital twins to attain unique digital transformation goals. We believe design and implementation of a digital twin within a sociotechnical systems design context enhances the opportunity to achieve both organizational benefits (e.g., business performance goals, improved product lifecycle management) and broader societal benefits (e.g., social and environmental sustainability) of digital twins (Rebentisch et al., 2021).

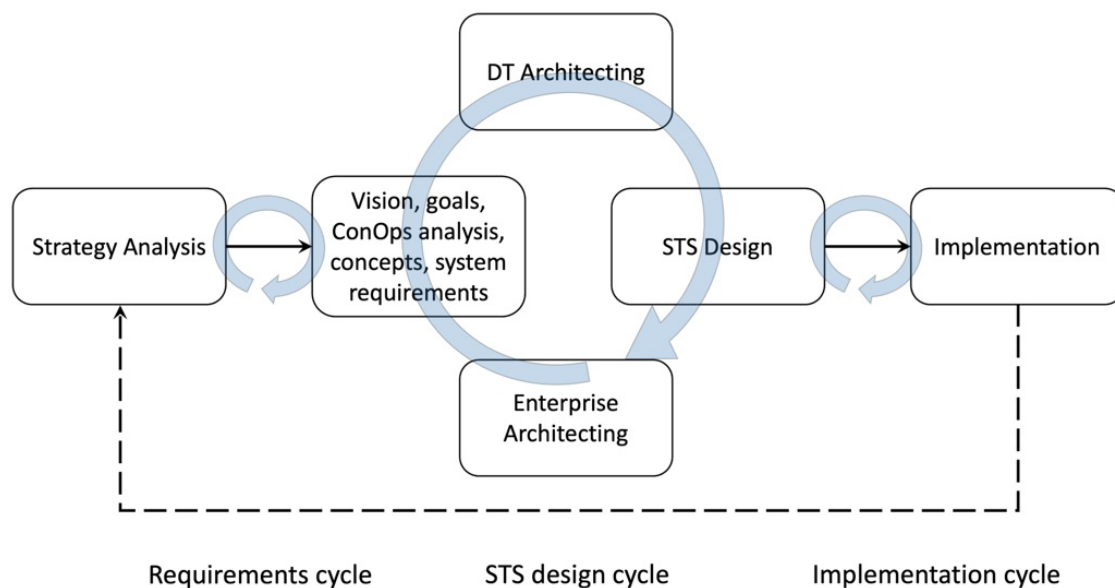


Figure 1. Sociotechnical system analysis framework for digital twins.

The framework includes three interactive cycles: the Requirements cycle, the Sociotechnical System (STS) design cycle and the Implementation cycle. The *Requirements cycle* begins with strategy analysis to assess the organization's strategic goals and objectives, and the role for digital twins as an enabler of digital transformation. The vision for the digital twin is clarified and elaborated, and specific goals are established for it in the context of the organization's goals and motivations respective to digital transformation. ConOps analysis is employed to identify the operating modes and capabilities, characterize key stakeholders activities and interactions, and assess existing capabilities and gaps between these and desired capabilities. The analysis uses structured, rigorous methods to progress from strategic objectives to operational capabilities needed to accomplish them. ConOps analysis promotes interaction with and between stakeholders as user stories are developed, through which operational needs of users are elicited. In developing user stories, the analyst helps the stakeholders better envision new capabilities enabled by the digital twin that may not have been considered, given stakeholders likely have limited knowledge of what could be possible with the digital twin. Similarly, the analyst may be able to better understand any constraints and limitations that should be considered when specifying requirements. This informs the definition of the digital twin requirements.

The second cycle, *Sociotechnical System (STS) design cycle*, is a recursive process that uses the ConOps analysis and requirements to perform digital twin (DT) architecting and enterprise architecting. The DT architecting decisions drive definition of technical attributes for providing digital twin capabilities. Enterprise architecting decisions drive definition of the sociotechnical attributes for desired enterprise capabilities. A holistic approach to enterprise architecting uses multiple lenses and investigates suitable organizational structures and desired behaviors, respective to enterprise strategy and ecosystem (Nightingale & Rhodes, 2015). Alternative architectures are defined and evaluated, and a preferred concept is selected that best satisfies the strategic goals for digital transformation and enables successful digital twin adoption. The STS design effort identifies combinations of social and technical elements that best satisfy the requirements derived in the previous cycle. These requirements may evolve over time as more is learned about what sociotechnical system decisions are feasible or preferred. The STS design cycle results in the overall sociotechnical systems design, with architecture concepts for both digital twin and the future enterprise, and specified capabilities to be developed.

The Implementation cycle iteratively implements the STS design. Implementation planning includes development of roadmaps, prioritization of planned capabilities and possible timelines or pathways for implementation. The execution of the implementation plan takes place over the defined timeline. Observations of the implementation activities and outcomes results in learning, and reveal emergent behavior that may not have been anticipated. The detailed requirements are then adjusted based on this new knowledge.

The sociotechnical systems analysis framework is not implemented as a linear process of sequential activities, as the activities in each cycle are performed iteratively. Significant learning and observed emergent outcomes may trigger a planned iteration back through the requirements cycle, STS design cycle and implementation cycle.

3.1. The value of concept of operations analysis for digital transformation

The complexity and uniqueness of the different stakeholder perspectives that surface during the requirements cycle illustrated in Figure 1 make this cycle extremely challenging to manage. This difficulty is exacerbated where communication between stakeholders is difficult for reasons such as extreme workload or time pressure. Walking stakeholders toward some shared mental model(s) of the digital twin concept becomes fundamental to manage their expectations and increase buy-in. In line with Rouse and Morris, a mental model is a "mechanism whereby humans generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of system states" (Rouse & Morris, 1986). The fact is that stakeholders are likely to have mental models of how the digital twin should operate even prior to starting the requirements cycle; oftentimes, these models are highly influenced by their domain knowledge and real-world experiences. The ConOps analysis brings about an opportunity to expose stakeholders to possible contradictions in their mental models triggered by active discussions with other stakeholders who might hold different opinions. Progressively, a shared mental model(s) among all stakeholders might emerge.

The literature on applied psychology suggests that shared mental models in expert team decision making can be viewed as reflections of task- and team-related characteristics of the activity at hand (Mathieu et al., 2000). This means that, during stakeholder discussions on what the digital twin should be about, any shared mental models that might emerge are likely to drift around technology and equipment, jobs or tasks, team interactions, and teams. Considering the IEEE 29148:2018 standard as reference for a ConOps analysis, the points of discussion suggested there overlap significantly with the aforementioned task- and team-related elements, which speaks for the appropriateness of using a ConOps analysis for walking stakeholders toward some shared mental model of the digital twin concept (International Organization for Standardization, 2018). Specifically, the standard suggests that the state of the system as it currently exists (the physical asset to be twinned) and as it is

envisioned (digital twin of the asset) be discussed; this encompasses a discussion of the key stakeholders (internal and external), their roles and activities, profiles, and interactions. In addition, the discussion should be extended to other relevant systems and their modes of operation, and to the operational environment at large, which includes, among other things, operational costs, risks, policies, and constraints.

In between discussing the system as it currently exists and as it is envisioned, there is a great effort in the ConOps analysis to understand and discuss stakeholders' needs, experienced obstacles, and desire for change. This effort is aligned with wanting to find evidence for what truly makes (or does not make) stakeholders gravitate toward the digital twin development (as opposed to something else). Depending on the stakeholder in question, this justification can be strategic, tactical, or operational. For example, a strategist might want to reach new markets (desire) while also handling competition better (need); a manager might want to automate certain processes (desire) but has no available resources to allocate to the automation effort (obstacle); an operator might want remote asset monitoring (desire) due to a constant personnel shortage (obstacle) but does not have the necessary technology for that (need). Learning where the key stakeholders stand on these matters is likely to reveal conflicting wishes and expectations that must be dealt with prior to any digital twin and enterprise architecting effort.

The last major element produced by a ConOps analysis and that results from combining the above efforts is a set of operational scenarios that, ideally, capture how the digital twin should operate and interact with its stakeholders under different circumstances. This is the main opportunity for the ConOps analyst to take what is reasonable for the organization, both financially and culturally speaking, combine with what motivates and discourages the different stakeholders, and form a very powerful message that cements any shared mental model(s) that might have emerged during the ConOps analysis and stakeholder discussions. In other words, this is the time for the analyst to unambiguously describe the sociotechnical context and the intended digital transformation, and linking it to the organization's strategy and operational processes and capabilities. In this way, the ConOps analysis creates a shared transdisciplinary mental model prior to the commitment to and expenditure of resources toward the creation of the digital twin. The next section offers some representative operational scenarios in the aerospace domain to illustrate the idea; the use of different technologies is emphasized.

4. Representative operational scenarios in the aerospace domain

With the desire to reduce the operating costs for its customers, a large aviation company makes a significant investment in the development of digital technologies that allow new engines to operate more efficiently and for longer periods of time, increasing the time between repairs. The investment involves a transdisciplinary team of people developing a range of new digital services that pair with the engine. Four different options are available to customers: the first option allows customers to purchase the engine without additional digital services; the second option allows customers to acquire the engine with the digital models used to design the engine; the third option gives customers the possibility of buying the engine together with its digital shadow; finally, the fourth option grants customers access to the engine's digital twin, in addition to the engine itself. Different customers—Airlines A, B, C, and D—decide to engineer their new fleet of aircraft with the new engine. However, given their financial positions and needs, the Airlines make different decisions in terms of the digital options to acquire. The following scenarios reflect how Airlines A, B, C, and D come to address the same problem of a faulty electronic engine control (EEC) module on one of their aircrafts' new engines.

4.1. The case of a faulty electronic engine control with no digital technology

Airline A opts for purchasing the engines alone and installing them in its new fleet of 30 long-haul aircraft. Almost a year after the engines are installed and become operational, the maintenance team of Airline A schedules the annual inspection of the aircrafts over a period of 30-45 days. Upon inspection, the maintenance team reports an excessive wear of a few components in one of the engines and replaces them. An inspection report is sent to the reliability team of Airline A who finds the situation intriguing given the fact that the engine is relatively new and is the only engine exhibiting abnormal wear. A discussion of what might be causing this damage follows and the reliability team recommends that the EEC module of the engine be reinspected. Specifically, the team wants to know what information the EEC is sending to the engine. The maintenance team schedules an unexpected reinspection of the engine, and manually collects and sends the EEC information requested to the reliability team. As suspected, the reliability team concludes that the EEC is defective and sending incorrect information to the engine; this incorrect information causes an increase in fuel flow and the excessive wear observed. The maintenance team repairs the faulty EEC by manually changing specific parameters on the EEC software; these parameters have a direct impact on the flow of fuel that is sent to the

engine and consequently, on how efficient the engine is. This failure results in Airline A incurring significant operational and environmental costs. Specifically, during the one year that the EEC was faulty, the engine was receiving approximately 45 kilos per flight hour more fuel than necessary to operate. Averaging 16 flight hours per day, this is equivalent to 263.7 tons of fuel wasted in a year or 52.6 flight hours missed. Importantly, considering that 3.15 tons of CO₂ are emitted per ton of fuel burned, 263.7 tons of fuel wasted in a year means an additional 828.45 tons of CO₂.

4.2. The case of a faulty electronic engine control with a digital model

Contrary to Airline A, Airline B decides to engineer its new fleet of 50 long-haul aircrafts with the new engine and acquire the digital models used to design it. Having installed quick access recorders (QAR) for routine monitoring of the aircrafts, Airline B believes that the models are fundamental to take full advantage of the QAR operational data and to proactively identify problems that might go unnoticed for a long period of time. Due to some design and logistical constraints, the ground operations crew for Airline B must manually download the QAR data, a routine that takes place every 2000 hours of recorded operating time or, approximately, every 4 months. After the first 4 months of operation, the QAR data of the entire fleet is sent to the reliability team of Airline B who feeds the data to the digital models purchased and runs these models on local machines. The reliability team spends over a month running the models and analyzing the results. Except for one dataset, the team concludes that all engines seem to be performing as expected with no signs of immediate problems. However, the team suspects that something unusual is happening to the engine whose QAR data shows a lower engine efficiency. The reliability team tunes a few parameters in the digital models and runs additional simulations. After analyzing the simulation results, the team now suspects that the engine in question might have a faulty EEC module that must be sending incorrect information to the engine. The reliability team sends a request for reinspection of the engine and the maintenance team of Airline B grounds the aircraft out of the planned maintenance cycle during the next opportunity available, which is 2 weeks ahead. Upon inspection, the maintenance team confirms the problem and repairs the faulty EEC by manually changing specific parameters on the EEC software. During the half a year that the EEC was faulty, Airline B incurs considerable operational and environmental costs of approximately 131.9 tons of fuel wasted and additional 414.23 tons of CO₂.

4.3. The case of a faulty electronic engine control with a digital shadow

Differently from the previous airlines, Airline C chooses to engineer its new fleet of 80 long-haul aircraft with the new engine and acquire the engines' digital shadows. Airline C believes that the monitoring and diagnostic capabilities of a digital shadow are worth the investment. Particularly, the Airline recognizes that having the telemetry logs being automatically sent from the engines to the engines' digital shadows facilitates ground-based diagnostics and timely maintenance recommendations. The reliability team of Airline C is very enthusiastic about having automatic fault codes and advisories of abnormal sensor readings being brought to the team's attention as early as possible. One of such advisories arrives shortly after the new engines are installed and become operational; specifically, the reliability team is alerted by one of the digital shadows for an abnormal shift in the fuel flow of one of the new engines. This shift is detected when comparing the telemetry data received from the engine and the predicted fuel flow outputted by the engine's digital shadow. The reliability team understands immediately that the shift is significant enough to translate itself into considerable operational and environmental costs. As the reliability team investigates the issue further and runs additional simulations locally, it informs the maintenance team of Airline C of a possible faulty EEC. The maintenance team starts working on a convenient schedule to take the aircraft out of service for inspection; this happens a week after the alert. Upon inspection, the maintenance team confirms that the EEC is sending incorrect information to the engine which results in an increase in fuel flow. The team proceeds to repair the EEC by manually changing specific parameters on the EEC software. A week after the digital shadow alerts for the abnormal fuel flow, the reliability team confirms that the maintenance actions were effective as it observes the fuel flow for that engine returning to expected values in the engine's digital shadow. The reliability team is pleased that it was able to limit the operational and environment costs to less than 2 weeks of operation.

4.4. The case of a faulty electronic engine control with a digital twin

Among the 4 airlines that acquire the new engine, Airline D is the only one that engineers its new large fleet of 100 long-haul aircraft with the new engine and acquires the engines' digital twins. Airline D is confident that the monitoring, diagnostic, and intervention capabilities of a digital twin can help the company reduce its operational costs and adopt a more effective maintenance strategy. As the technology is still maturing, Airline D understands that the digital twins that pair with the new engines can only intervene on a small set of well-understood engine faults by changing control laws in pre-determined ways. The Airline is reassured by the aviation company that sells the new engines that any change automatically made by a digital twin always takes

the engine to a safe state, often with the best performance available as driving force. The reliability team of Airline D welcomes the purchase of the new technology under this limited set of safe, automatic interventions; nevertheless, the team decides to review past interventions on a regular basis as precautionary measure. During one of these review opportunities, the reliability team discusses an automatic intervention made on one engine the day it became operational. Specifically, the team sees that the digital twin automatically intervened on the EEC module by sending a command that changed a few parameters on the EEC software and altered the fuel flow being sent to the engine. Additionally, the reliability team understands that this intervention occurred after the digital twin processed the telemetry logs received from the engine, detected an abnormal fuel flow being sent to the engine upon comparison with local model predictions, and found inefficient parameters coded into the EEC software for a set of safe regimes of operation simulated locally. The reliability team marks the intervention as safe and recognizes its positive impact on operational, maintenance, and environmental costs.

These examples illustrate how different approaches to digital transformation, and specifically the use of digital twins, shadows, or models, involve different solution architectures, invoke different patterns of interactions and behaviors between enterprise stakeholders, and produce different system performance outcomes. Unambiguously understanding the intended objectives (the requirements) and behavioral modes prior to the commitment to the design and implementation of a specific digital twin instance may help avoid creating capabilities that do not provide the desired system value outcomes. Based on our evolving research, we are increasingly confident that the STS analysis framework with ConOps analysis presented in this paper can play a positive role in helping to define, create, and implement the digital capabilities necessary and sufficient to achieve an organization's digital transformation objectives.

5. Conclusions

Structured sociotechnical approaches to digital transformation are increasingly important given the impact that such transformations might have on organizations. This paper discusses digital transformation using digital twins as a transdisciplinary challenge, presents a sociotechnical system analysis framework for digital twins, and offers some insights on the value of a ConOps analysis for digital twin development. Research is continuing on further investigation of this analysis as a catalyst for creating a sociotechnical environment suitable for envisioned digital transformations.

6. Acknowledgements

The project TRF4.0 - Transformer 4.0 leading to this work is co-financed by the European Regional Development Fund - ERDF, through COMPETE - Operational Program for Competitiveness and Internationalization (POCI) and by the Foundation for Science and Technology under the MIT Portugal Program under POCI-01-0247-FEDER-045926.

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