Received 15 October 2022
Revised 26 February 2023
Accepted 3 May 2023

Maintenance work management process model: incorporating system dynamics and 4IR technologies

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Abstract

Purpose – The purpose of this paper is to propose a system dynamic simulated process model for maintenance work management incorporating the Fourth Industrial Revolution (4IR) technologies.

Design/methodology/approach – The extant literature in physical assets maintenance depicts that poor maintenance management is predominantly because of a lack of a clearly defined maintenance work management process model, resulting in poor management of maintenance work. This paper solves this complex phenomenon using a combination of conceptual process modeling and system dynamics simulation incorporating 4IR technologies. A process for maintenance work management and its control actions on scheduled maintenance tasks versus unscheduled maintenance tasks is modeled, replicating real-world scenarios with a digital lens (4IR technologies) for predictive maintenance strategy.

Findings – A process for maintenance work management is thus modeled and simulated as a dynamic system. Post-model validation, this study reveals that the real-world maintenance work management process can be replicated using system dynamics modeling. The impact analysis of 4IR technologies on maintenance work management systems reveals that the implementation of 4IR technologies intensifies asset performance with an overall gain of 27.46%, yielding the best maintenance index. This study further reveals that the benefits of 4IR technologies positively impact equipment defect predictability before failure, thereby yielding a predictive maintenance strategy.

Research limitations/implications – The study focused on maintenance work management system without the consideration of other subsystems such as cost of maintenance, production dynamics, and supply chain management.

Practical implications – The maintenance real-world quantitative data is retrieved from two maintenance departments from company A, for a period of 24 months, representing years 2017 and 2018. The maintenance quantitative data retrieved represent six various types of equipment used at underground Mines. The maintenance management qualitative data (Organizational documents) in maintenance management are retrieved from company A and company B. Company A is a global mining industry, and company B is a global manufacturing industry. The reliability of the data used in the model validation have practical implications on how maintenance work management system behaves with the benefit of 4IR technologies' implementation.

Social implications – This research study yields an overall benefit in asset management, thereby intensifying asset performance. The expected learnings are intended to benefit future research in the physical asset management field of study and most important to the industry practitioners in physical asset management.

Journal of Quality in Maintenance Engineering
Vol. 29 No. 5, 2023
pp. 88-119
Emerald Publishing Limited
1355-2511
DOI 10.1108/JQME-10-2022-0063

Originality/value – This paper provides for a model in which maintenance work and its dynamics is systematically managed. Uncontrollable corrective maintenance work increases the complexity of the overall maintenance work management. The use of a system dynamic model and simulation incorporating 4IR technologies adds value on the maintenance work management effectiveness.

Keywords System dynamics, Process model, Predictive maintenance, Maintenance work management, 4IR technologies

Paper type Research paper

1. Introduction

The management of maintenance processes fosters a change from a functional orientation to an orientation toward processes. Maintenance managers' attitude in the early 1900s was "fix when equipment breaks," also known as corrective maintenance. Arguably, technology was not in an advanced state, with no alternative for equipment defect elimination (Parida and Kumar, 2006; Tsang, 2002). In the 1950–1980s, technology advanced, and maintenance management was then considered a critical function for manufacturing and production. Preventative maintenance through equipment condition monitoring changed the perception of "fix when equipment breaks" to "maintenance work can be planned and controlled" (Parida and Kumar, 2006; Tsang, 2002). In the 2000s, maintenance management is perceived as an integral part of business strategy and processes, with the perception of "maintenance work creates sustainable value," and this reinforced a perception of planning and control of maintenance work (Parida and Kumar, 2006; Tsang, 2002).

Maintenance management is an essential support function in organizations with significant investments in physical assets and adds value to achieving organizational goals. According to Parida and Kumar (2006), Al-Chalabi *et al.* (2014), and Vayenas and Peng (2014), maintenance cost account for 12–23% of total operating costs in the manufacturing industry, and 30 to 60% of total operating costs in the mechanized mining industry. Most maintenance departments consist of up to 30% of total staffing in refineries (Parida and Kumar, 2006; Tsang, 2002). The study by Parida and Kumar (2006) noted factors that are driving demands on maintenance performance measures, namely, the value created by maintenance, investment in maintenance justification, focus on knowledge management, organizational structural changes, new trends in operation and maintenance strategy adaption, and maintenance resource allocation revision. The study by O'connor and Kleyner (2012) and Organ *et al.* (1997) suggests that production losses in the mining industry are attributed to poor maintenance execution, resulting in equipment failures and excessive mean time to repair.

The investment in maintenance discussed in the preceding paragraph is significant, particularly in a changing environment because of advanced technologies. Nonetheless, the challenges of manpower and equipment utilization in maintenance management remain unresolved (Tsang, 2002). The expected value-adds from maintenance activities to company profits are yet to be effective and efficient (Tsang, 2002). In addition to these challenges, organizations still rely solely on the knowledge and skills of maintenance workers, and in line with the study of Marwala (2013a, b) on rationality and decision-making, this phenomenon is subjective, particularly in a high-production environment. As John D. Sterman states, *"Mental models in which the world is seen as a sequence of events and in which feedback, nonlinearity, time delays, and multiple consequences are lacking lead to poor performance when elements of dynamic complexity are present"* (Sterman, 2002). In a maintenance work management system, a measure of planned work versus unplanned work is referred to as maintenance mix or maintenance index, and according to several scholars, the best practice maintenance index aims at 85% planned work versus 15% unplanned (Planned Maintenance Percentage; Ventana Systems, 2022). Nonetheless, most maintenance departments do not achieve this maintenance index, more so because of the complexity commonly encountered in the context of maintenance work management.

The purpose of this research study is to investigate the impact of the dynamic behavior maintenance management system's variables, and the impact of advanced technologies on the maintenance management system. This research study aims to predict the maintenance work management system's future behavior to answer or resolve challenges of maintenance manpower subjectivity and utilization thereof. This research study further aims at yielding overall value-add to business performance through an effective maintenance work management system. This research study intends to serve as a novel extension (amongst other objectives) to the body of knowledge in maintenance management.

The main objective of this research study is to answer the following research question: How can an optimized maintenance work management system be modeled, simulated, and validated to replicate a real-world optimized maintenance management system to foster optimum internal business performance?

2. Literature review

This research study reviews literature in the field of maintenance, the applicability of 4IR technologies, process modeling, and system dynamics modeling. Literature gaps are highlighted for novel extension purposes.

2.1 Maintenance management

Maintenance management may simply be defined as a consolidation of technical, administrative, activities and management measures during the operational phase of the equipment life cycle to sustain that equipment's intended function (Algabroun *et al.*, 2022). Maintenance management is a framework for maintenance work execution. Maintenance management in most organizations has proven to be one of the most important aspects of asset management due to its complexity, requirements, and widespread use in all equipment employed for productivity (Naji *et al.*, 2019).

Maintenance management remains a challenge as companies are presented with cost reduction pressure (such as maintenance labor cost) and/or constraints to realize good profit margins. Maintenance management system is a pivotal tool to ensure system's availability and reliability. Planning and scheduling processes are part of improving maintenance work management performance (Palmer, 2013; Ismail, 2022). Maintenance managers require decision-making tools and models to plan resources effectively and efficiently to support physical assets. Effective planning and scheduling are viewed as part of the maintenance work management process (Sedghi *et al.*, 2021; Naji *et al.*, 2019; Palmer, 2013).

Several scholars modelled different elements of maintenance management aiming at cost reduction gains. Babaeimorad *et al.* used joint optimization approach to model the integrated maintenance scheduling inventory policy adjustment (Babaeimorad *et al.*, 2022). Furthermore, the mathematical model of Babaeimorad *et al.* determined the inventory level and preventive maintenance planning for a single equipment production system with increasing random failures. The scholars highlight that decision-makers can minimize the total operating cost using decision variables such as production capacity quantities, maintenance costs, and machine failure distribution (Babaeimorad *et al.*, 2022). Zul-Altfi Ismail conducted a case study on the requirements of maintenance management systems to improve ineffective maintenance management systems. Zul-Altfi Ismail's study suggests that conventional maintenance management methods lack defect diagnosis tools and strategic decision-making for information analysis in maintenance-related project outcomes. The proposed maintenance management system aimed at reducing the number of overhauls and repairs, thereby reducing cost (Ismail, 2022). Pant and Singh modeled a system subjected to random inspections with hidden failures (Pant and Singh, 2022). The study highlights the determination of the system availability and long-run average cost rate. The optimal inspection period is obtained thereby reducing costs (Pant and Singh, 2022).

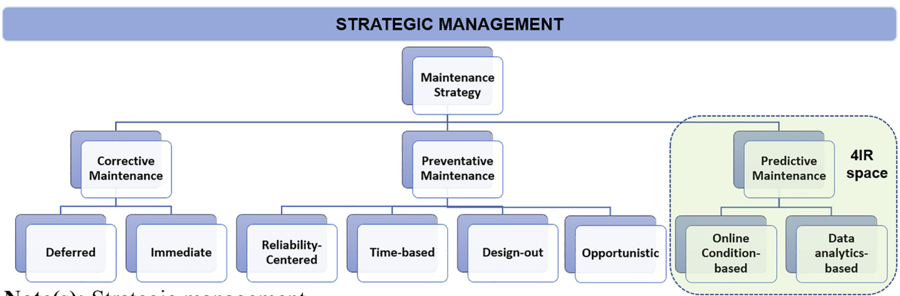
2.1.1 Maintenance strategies. A need for effective maintenance strategy that encompasses planning and scheduling activities, and digital technologies (4IR technologies) in a volatile environment is unavoidable. Cyber-Physical Systems (CPS) present the opportunity of monitoring physical assets in real-time in support of a quick and effective decision-making process (Sedghi *et al.*, 2021; Tortorella *et al.*, 2021; Zhe *et al.*, 2016). Equipment data collection and analytics opportunities have sparked an intelligent and objective way of maintenance decision-making (Sedghi *et al.*, 2021). A need for effective asset management and maintenance best practices to foster critical success factors in safety, product quality, speed of innovation, price, profitability, and reliable delivery (Naji *et al.*, 2019; von Thun and Maier, 2004). The 4th industrial revolution (4IR or Industry 4.0) is perceived as the answer to enhance and intensify asset performance (von Thun and Maier, 2004).

One of the common challenges in the manufacturing industry is the optimization of maintenance strategy that takes cost-effective initiatives into account as revealed by study referenced in Spendla *et al.* (2017) and Naji *et al.* (2019). Maintenance strategies differ based on the type of engineering equipment intended to be maintained (Kumral, 2009; Anderson and Neri, 1990; Alabdulkarim *et al.*, 2015). The following maintenance strategies are briefly discussed as per the illustration in Figure 1:

(1) *Corrective maintenance:* This strategy is based on equipment failure and the approach is "Fix when equipment breaks." Figure 1 illustrates that repairs are either executed immediately or deferred, resulting in a high cost of operation (Kumral, 2009; Anderson and Neri, 1990; Alabdulkarim *et al.*, 2015).

(2) *Preventive maintenance:* This strategy is based on regular intervals of work execution and the approach is "Work can be planned and controlled." Figure 1 depicts maintenance work based on equipment condition, proactive change-out of failing components, design-out for reliability improvement, and reliability-centered maintenance. Figure 1 further illustrates that the approach supports work execution at regular intervals or time-based (Kumral, 2009; Anderson and Neri, 1990; Alabdulkarim *et al.*, 2015).

(3) *Predictive maintenance:* The basis of this strategy is equipment condition, effectiveness, and efficiency, and the approach is "planned and controlled maintenance work creates sustainable value." Figure 1 depicts that work is carried



Note(s): Strategic management
Source(s): Created by Zhe *et al.* (2016) and modified by the authors

Figure 1.
Maintenance strategy

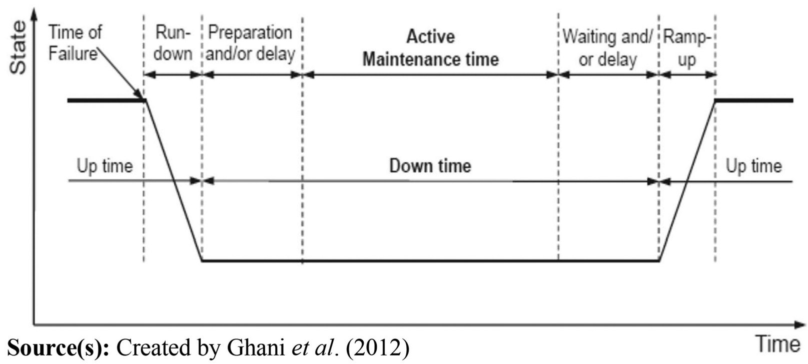
out based on equipment deteriorating condition, detected through online condition monitoring. For equipment effectiveness and efficiency, the data analytics approach is used to initiate maintenance work planning, control, and execution (Kumral, 2009; García and García, 2019).

Basic interventions in the maintenance of any engineering equipment are corrective and preventive. According to Anderson and Neri (1990), Alabdulkarim *et al.* (2015), and Zhe *et al.* (2016), reliability-centered maintenance (RCM) is the optimum combination of corrective maintenance, time or interval-based maintenance, and condition-based maintenance. The study of Anderson and Neri (1990), Alabdulkarim *et al.* (2015), and Zhe *et al.* (2016) further suggested that RCM is centered around equipment reliability through equipment failure analysis or defect elimination, the consequence for safety and production, and the benefits of preventative maintenance. Nonetheless, García and García (2019) suggested that the maintenance strategy in the digital lens is predictive, as illustrated in Figure 1. Scholars suggested that predictive maintenance reduces labor inefficiencies mainly because of reduced work requirements from a labor force perspective. This includes performing online inspections, where critical equipment condition is monitored online by 4IR technologies such as the use of predictive algorithms, sensors, and equipment data analytics to yield best practices in maintenance index (Planned Maintenance Percentage).

2.2 System time model for physical assets

The system's time model assists in the maintenance work management process, particularly when equipment is frequently taken down for both planned and unplanned maintenance (scheduled and unscheduled maintenance or maintenance index) (Manenzhe, 2018). The system time model is a systematic way of measuring the reliability of assets. In the digital transformation lens, enabling industry 4.0 technologies such as cloud computing combined with data analytics enables accurate measurements of asset reliability (García and García, 2019; Tortorella *et al.*, 2021; Zhe *et al.*, 2016).

Figure 2 represents some of the reasons why artisans' actual time to perform a task (wrench time) is low, suggested to be 3.5 h on a 10-h shift without the benefit of a planner (Palmer, 2013). Figure 2 illustrates that there is time allocated for the preparation and/or delay after the equipment is switched off before active maintenance time (wrench time or tool time) and a further waiting and/or delay towards the end of the downtime (Ghani *et al.*, 2012). The time of failure in Figure 2 may also be viewed as the time to run down equipment for scheduled maintenance.



Source(s): Created by Ghani *et al*. (2012)

Figure 2.
State of a system time model

2.3 4th industrial revolution

The past three industrial revolutions are characterized by the mechanization of manufacturing and the use of a steam engine, mass production and the use of electrical power, the use of electronics, information technology, and automation (García and García, 2019; Richardson *et al.*, 2022). The Fourth Industrial Revolution (4IR) is characterized by a combination of digital or cyber systems with physical systems. This combination produces intelligent systems or “agents” that can autonomously perform activities that in the past were primarily performed by humans (Balamurugan *et al.*, 2019; García and García, 2019; Tortorella *et al.*, 2021).

In maintenance management, cyber-physical systems can be used to monitor equipment conditions in real-time and eliminate equipment health status subjectivity, where for instance, an artisan would have been required to perform regular inspections (García and García, 2019; Tortorella *et al.*, 2021; Vaidya *et al.*, 2018).

Based on the abilities of industry 4.0 technologies and the study referenced in (García and García, 2019), the operative level of maintenance management can mostly be supported by these technologies as compared to tactical and strategic levels. Industry 4.0 technologies support manufacturing processes, processing, and/or condition monitoring. García S.G. and García M.G. (García and García, 2019) further argue that maintenance costs and system availability, seen as maintenance targets, are impacted by industry 4.0 technologies.

2.3.1 4IR technologies applicability in maintenance. Industry 4.0 technologies are the basis for the implementation of innovative maintenance strategies and foster the optimization of existing maintenance practices. This yields an overall predictive maintenance strategy as illustrated in Figure 1. Table 1 discusses the applicability of industry 4.0 technologies to maintenance management.

Ref no.	Industry 4.0 technologies	Applicability in maintenance
García and García (2019), Tortorella *et al.* (2021), Vaidya *et al.* (2018), Zhe *et al.* (2016), Nordal and El-Thalji (2021)	Cyber-Physical Systems (CPS) (Embedded systems)	Links different coexisting equipment and systems and the cyber computational space
García and García (2019), Tortorella *et al.* (2021), Vaidya *et al.* (2018)	Virtualization technologies (Virtual Realities (VR) and Augmented Realities (AR))	Offers better guidance for equipment diagnostics and inspection
García and García (2019), Tortorella *et al.* (2021), Vaidya *et al.* (2018)	Adaptive robotics	Provides autonomy to equipment, which in return fosters equipment reliability
García and García (2019), Tortorella *et al.* (2021), Vaidya *et al.* (2018), Zhe *et al.* (2016), Nordal and El-Thalji (2021)	Data analytics	Schedule planning and prediction of typical equipment life cycle stage
García and García (2019), Tortorella *et al.* (2021), Vaidya *et al.* (2018)	Cloud computing	Efficient monitoring of equipment operating conditions
García and García (2019), Tortorella *et al.* (2021), Vaidya *et al.* (2018)	Additive manufacturing	Supports quick turnaround time for customized spares that are required for maintenance
García and García (2019), Tortorella *et al.* (2021), Vaidya *et al.* (2018), Nordal and El-Thalji (2021)	Internet of things (IoT)	Mitigates waste resources in line with maintenance, repairable, and overhauls (MRO), leading to optimized decision-making. Supports maintenance scheduling and planning

Source(s): Created by authors

Table 1.
4IR technologies applicability in maintenance

A combination of traditional maintenance management concepts with industry 4.0 technologies changes current maintenance practices. This complex phenomenon is in line with digital transformation, in that these technologies reduce inefficiencies in maintenance management (García and García, 2019; Tortorella *et al.*, 2021). For this reason, maintenance management requires an effective conceptualization of the process model. Industry 4.0 technologies enable machines to be elf-aware and self-learning. 4IR technologies improve overall performance and maintenance management with the surrounding interaction (García and García, 2019; Tortorella *et al.*, 2021). Maintenance driven by Industry 4.0 technologies is gaining popularity as Maintenance 4.0 (Tortorella *et al.*, 2021).

Wesley Richardson *et al.* modeled a business process management for predictive maintenance and remote monitoring with 4IR technologies implementation. The study suggests how IoT sensors, IoT cloud, and business process management notation can benefit remote and rural areas (Richardson *et al.*, 2022). Hatem Algabroun *et al.* developed a concept for digital maintenance through 4IR technologies (Algabroun *et al.*, 2022). Acernese *et al.* describe a model for developing a condition-based maintenance strategy through the adaption of empirical and machine learning-based models for comparison purposes (Acernese *et al.*, 2021). The study reveals that the proposed predictive models support the maintenance team in equipment shutdowns through a reliable decision system (Acernese *et al.*, 2021).

2.4 Business process modeling in maintenance

A business process may simply be perceived as a logical and systematic way of working activities to achieve sustainable results, through a logical organization of people, equipment, energy, materials, and procedures (Zakarian and Kusiak, 2000; Entringer *et al.*, 2019; De Nicola *et al.*, 2007). A business process can be divided into three categories, namely, managing process focusing on strategy and direction setting to enhance business planning and control, operating process focusing on work execution, and supporting process mainly for support of both managing and operating processes. The maintenance work management process can be pinned from a point of the operating process. A flow chart is defined as a graphic presentation of the manufacturing process, program logic sequence, and/or organization chart (Cheng and Chiu, 2004; Zakarian and Kusiak, 2000).

Flow charts are characterized by flexibility and communication ability (De Nicola *et al.*, 2007; Cheng and Chiu, 2004). Although there are various modeling techniques such as data flow diagrams, action diagrams, role interaction diagrams, and colored Petri-net, this study aims at using flow charts to develop a maintenance work Management process model based on its simplicity and fit for purpose for the intended process model.

The work of Ghani *et al.* (2012) outlines the maintenance management process in two parts: strategy with objectives as input from a business plan. The maintenance management process can be used to determine the effectiveness of its department. The second part of the maintenance management process is the implementation of the maintenance strategy. The study of Ghani *et al.* (2012) further highlighted that process modeling of maintenance management is critical for determining both efficiency and effectiveness within a maintenance department.

There is a need to develop a process that is dynamically tested (system behavior testing) using empirically supported evidence and/or real-world data (organizational documents) and from literature findings particularly in maintenance management (Sterman *et al.*, 2015; Ghani *et al.*, 2012).

2.5 System dynamics: system thinking tool

Systems thinking is used for identifying interrelationships to determine patterns of change. In system thinking literature, systems thinking is explained as the understanding of a system and is the ability to determine how subsystems work together as one system (Mella and Gazzola, 2019). Most of the decision-makers in operations systems are boundedly rational, and at times irrational, influenced by stress levels and emotions, omitting interactions for system behavior and most feedback (Sterman, 2002; Marwala, 2013a, b; Sterman *et al.*, 2015).

Systems thinking is an effective tool for problem investigation, modeling, and simulating the dynamics of systems such as maintenance work management (Sterman, 2002). System dynamics (SD) modeling and simulation process consist of five stages, namely, problem identification and definition, system conceptualization, model formulation, model testing and evaluation, and policy analysis and design (Mella and Gazzola, 2019). SD represent the behavior of a system based on its structure. SD model encompasses feedback loops, stocks and flows, and nonlinearities because of the interaction between the physical and institutional structure of the model with the decision-making processes of the agents acting within a system (Sterman, 2002; Forrester, 2009; Sterman *et al.*, 2015). System dynamics, therefore, have commonalities with models in traditional operation behavior (Sterman *et al.*, 2015).

According to Sterman *et al.* (2015), SD have been used in project management, supply chain management, and human resources, process management, and the dynamics of improvement. This research study is in line with process management and the dynamics of improvement. The study of Sterman *et al.* (2015) suggests that scholars and practitioners are challenged in operations management because of challenges of continuous improvement. The role of workloads motivation is examined by several scholars using system dynamics according to Sterman *et al.* (2015). Scholars empirically identified (using system dynamics) nonlinear relationships between workload and performance over extended time in the context of quality improvement (Sterman *et al.*, 2015). In line with this research study, (Sterman *et al.*, 2015) further outlines that SD is used to determine a major line of work on capability traps in oil and chemical industries with an observation to reinforcing dynamics on short-run pressure to drive work output and found to lead to longer hours, taking short cuts, less maintenance, and bad safety record. The study referenced in Ghani *et al.* (2012) used SD modeling to evaluate maintenance work outsourcing and analyzed outsourcing profitability.

2.5.1 Maintenance-related system dynamics modeling and identified gaps. Maintenance-related SD modeling is limited in the literature, yet maintenance system dynamics are complex to solve with just a subjective model alone. Various scholars referenced in Table 2 predominantly covered maintenance-related SD conceptualization with little on model simulation and real-world scenario replication. The study of Ensafi and Thabet (2021) unpacks challenges that are faced by maintenance staff at large. According to Ensafi and Thabet, the following areas are gaps in the maintenance SD modeling (Ensafi and Thabet, 2021):

(1) Prioritization of work and schedule creation are two key areas of concern; and

(2) There is no effective approach for performing works orders processing through a dynamic behavioral simulation model.

Most scholars modeled maintenance systems using SD with little work on model validation using a calibration approach, wherein system optimization payoff is defined to replicate real-world scenarios. One such study used SD modeling to analyze the productivity of maintenance systems (Esmaeili *et al.*, 2019). Fang and Zhaodong used system dynamics simulation on corrective maintenance costs of aviation equipment with little model validation (Fang and Zhaodong, 2015). Khorshidi and Ibrahim observed RCM using SD with little model validation (Khorshidi *et al.*, 2015). The study of Jokinen and Ylén focused on modeling maintenance strategies of a generic plant with different performance measures, and

Table 2.
System dynamics modeling in maintenance subject

Maintenance variable	Used and/or recommended by
Maintenance cost	Liu Fang, Huang Zhaodong (2014)
Reliability of maintenance	Pegah Basirat, Hamed Fazlollahtabar (2010)
Green Maintenance Index	Sajad Kazemi (2013)
Improving maintenance operations	Jacqueline Ming-Shaih Ye (2007)
Reliability based decision-making	AkhsaniMF, Yuniato MN (2021) and J. Krogstie, Rudolph Brynn, Ahmed Abdeltawab Abdelgawad (2013)
Maintenance strategies	Tero Jokinen, Jean-Peter Ylen (2007)
Maintenance delay	Leandro Rosales, Jian-Bo Yang, Yu-Wang Chen (2014)
Added value of maintenance	Tero Jokinen, Peter Ylen, Jouni Pyotsia (2011)
Condition-based maintenance	Bjarne Brgquist, Peter Soderholm
Maintenance downtime	Thanapun Prasertrungruang, B.H.W. Hadikusumo (2008)
OEE	Ali zauashkan, Hazhir Rahmandad, Andrew K.S. Jardine (2011)
Preventive Maintenance	Jorn Henrick Thun (2009)

Source(s): Created by authors

sensitivity analysis; nonetheless, little is done on the payoff optimization for model validation (Jokinen and Ylén, 2007). Hosseinzadeh *et al.* focused on sustainable maintenance planning in the petroleum industry using SD modeling with the aim to reduce equipment downtime. The study categorized individual policies into three groups, namely, economic, social, and environmental (Hosseinzadeh *et al.*, 2023). Asim Tokgoz *et al.* modeled airline maintenance, repairable and overhauls (MRO) operations using system dynamics approach to analyze decision scenarios (Tokgöz *et al.*, 2018). The study suggests that MRO operations have a direct impact on the availability of aircraft fleet (Tokgöz *et al.*, 2018).

The extant literature is limited on the impact of the maintenance work management model incorporating 4IR technologies using system dynamics modeling particularly when its model validation considers more than just one equipment type to set the optimization payoff.

This research study is a novel extension to the body of knowledge in the field of asset management (maintenance work management) and system dynamics model validation of maintenance management. The expected learnings are intended to benefit future research in the physical asset management field of study and most important to the industry using physical and maintainable assets.

Table 2 illustrates recommended and/or used system dynamics modeling in the field of maintenance found in the reviewed extant literature.

The extant literature highlighted in Table 2 predominantly covers system dynamics causal loop diagram and to an extent stock and flows diagram. This study extends on the work previously done by the scholars referenced in Table 2, thereby covering both process flow and system dynamic modeling and simulation of the maintenance work management model, particularly in the context of 4IR.

3. Research method

To guide this research study in the direction of fulfilling the research team's objectives, the research method used is mixed (both qualitative and quantitative modeling), incorporating both process and SD modeling (Malina *et al.*, 2011). Chitongo and Pretorius (2018), Tokgöz *et al.* (2018), and Hosseinzadeh *et al.* (2023) successfully used mixed method incorporating system dynamics modeling to model projects execution dynamic behavior, airline MRO operations, and sustainability maintenance planning respectively. Qualitative modeling encompasses non-numerical data from literature findings and empirical information retrieved from companies, required for considerations in the provisional model formulation (Borrego *et al.*, 2009). On the other hand, quantitative modeling and simulation encompass numerical data from literature findings and retrieved data from companies required for considerations in the provisional model formulation and validation (Borrego *et al.*, 2009).

Different approaches other than SD modeling could be used to model system dynamic behavior such as Agent-Based Modeling (ABM). Several scholars have used ABM for modeling maintenance management-related systems. The study of Assaad *et al.* used ABM in optimizing maintenance strategies for a network of green infrastructure. The study of Lee *et al.* used ABM in analyzing emerging challenges for aircraft predictive maintenance. These studies represent ABM as a computational simulation approach where agents interact with one another and the environment with specified rules (Assaad *et al.*, 2023; Lee *et al.*, 2023).

SD modeling and ABM are the most prominent approaches in modeling nonlinear systems (Macal, 2010). Light-sights systems that produce similar results on SD modeling and ABM (Macal, 2010). This research study adapts SD modeling because of its emphasis on the importance of feedback effects on net stock levels as determinants of system behavior (Macal, 2010; Sterman, 2002).

3.1 Research technique: process modeling and simulation

Research methods are reinforced by techniques and/or step-by-step procedures on how each research question is answered (Borrego *et al.*, 2009). In this research study, the mixed method is reinforced by process modeling and simulation. Data is collected from current best practices in maintenance work management systems, captured from a combination of literature findings and two companies' documents in maintenance work management, and using systems thinking. In conceptual modeling terminology (qualitative modeling), this research study captures relevant data from literature findings and empirical observation (reviewed from organizational documents in maintenance work management), where for instance a subjective model could have been used particularly in maintenance work management (Martinez-Moyano and Richardson, 2013; Sterman, 2002; Chitongo and Pretorius, 2018). For this research study, two steps reinforcing the research method are discussed below.

Step 1: formulates a process model for maintenance work management (qualitative modeling) using Microsoft Visio as part of a subjective model caption to an extent recommended by Sterman (2002) and Martinez-Moyano and Richardson (2013). This model formulation captures key findings from literature and information from company documents to systematically address a way to effectively manage maintenance work to support overall gain in asset management and performance. According to Sterman (2002), Martinez-Moyano and Richardson (2013), Forrester (2009), unless the process model is simulated and validated, that model is considered subjective.

Step 2: formulates a Stock and flow diagram (quantitative modeling) using Vensim DSS to examine the dynamics of a system (maintenance work management) and analyze the effects of state variables together with flows, also recommended by Sterman (2002) and Martinez-Moyano and Richardson (2013).

This technique corroborates with five stages of system dynamics modeling suggested by Sterman (2002), Martinez-Moyano and Richardson (2013), Chitongo and Pretorius (2018), Forrester (2009):

(1) Problem identification and definition;

(2) System conceptualization;

(3) Model formulation;

(4) Model testing and validation; and

(5) Policy analysis and design.

This research study technique follows the first four stages (mentioned above) of system dynamics modeling incorporated in the system modeling of the maintenance work management process. The four stages considered for this research study are discussed below:

Stage 1: reviews (using critical thinking) existing literature and company documents to identify key elements affecting variables in maintenance work management;

Stage 2: captures concepts of maintenance work management from a combination of literature review and empirical observation (on company documents) and using system thinking, and conceptually models a maintenance work management process (system conceptualization);

Stage 3: makes use of Vensim DSS software to develop stock and flow diagram for model formulation with a lens to 4IR technologies identified as part of literature findings to formulate the provisional model; and

Stage 4: uses real-world data for model validation using calibration techniques and analysis on the impact made by 4IR technologies in the maintenance work management model on Vensim DSS software.

Figure 3 presents both qualitative data/information collection and quantitative data collection methods. Figure 3 illustrates a systematic research method process flow (summary of preceding paragraphs) depicting data collection for mixed method (both qualitative and quantitative) modeling.

3.2 Research data collection overview: triangulation

The term triangulation is first used by Denzin in 1978; Denzin outlined using complementary methods or data sources to offset weaknesses amongst data sources (Borrego *et al.*, 2009).

Figure 4 outlines data sources for this research study, aiming at triangulating between the literature reviewed, retrieved organizational documents addressing business processes, and real-world maintenance data both in maintenance work management to offset weaknesses, particularly in model validation (Forrester, 2009; Borrego *et al.*, 2009). The data sources referred to in Figure 4 are used either as a combination and/or individually for process model and simulation formulation and system behavior analysis. The maintenance real-world quantitative data is retrieved from two maintenance departments from company A, both for a period of 24 months, representing years 2017 and 2018. The maintenance quantitative data retrieved represent six various types of equipment used at underground Mines. The maintenance management qualitative data (organizational documents) in maintenance management are retrieved from company A and company B. Company A is a global mining industry, and company B is a global manufacturing industry.

4. Research study findings and formulation of provisional maintenance work management process

Research study findings for the maintenance work management process and dynamic behavior amongst its key elements/variables and relationship analysis to effects of decisions within the maintenance work management process are modeled (Sterman, 2002; Martinez-Moyano and Richardson, 2013). Findings from the literature reviewed and empirically

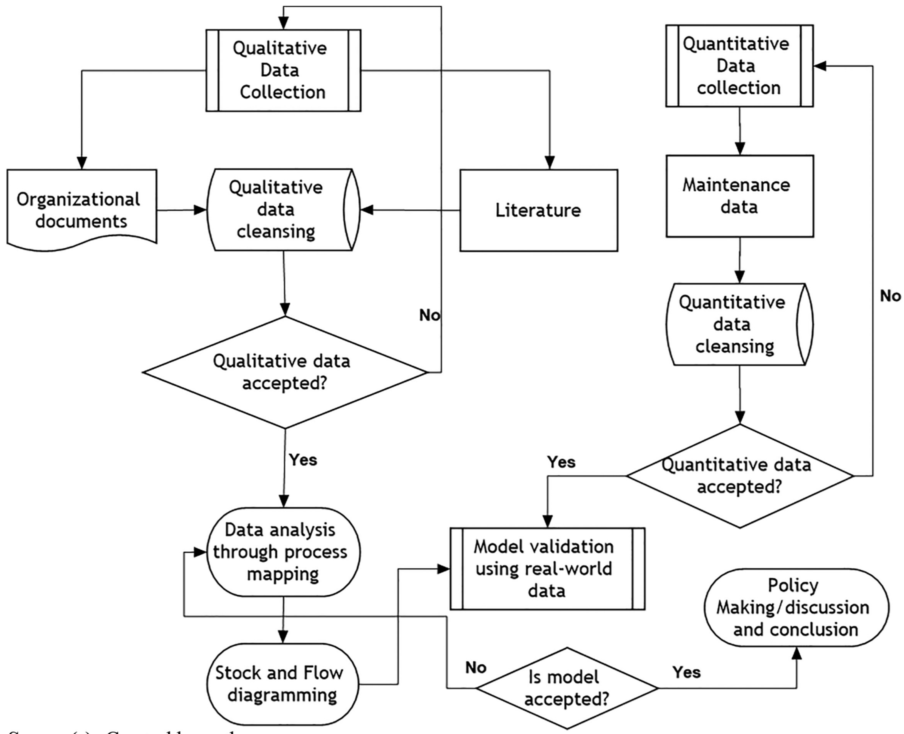


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Figure 3.
Research method process flow

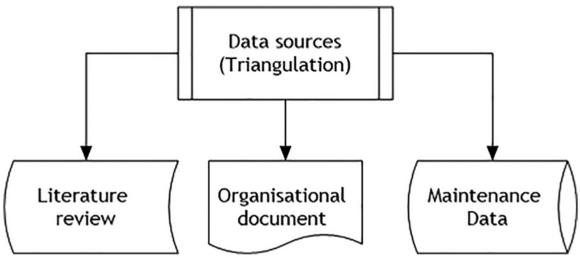

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Figure 4.
Data sources for modeling of this research study

supporting organizational documents in maintenance management using systems thinking are discussed. Relationships between key variables within the maintenance work management process are outlined.

4.1 Maintenance work management process model overview

Figure 5 represents formulated maintenance work management conceptual process flow using Microsoft Visio from a combination of literature findings and organization documents. Figure 5 outlines that for any maintenance work to be executed, identification and approval of that work is the initial step, this is conducted to prioritize work that is critical over work that

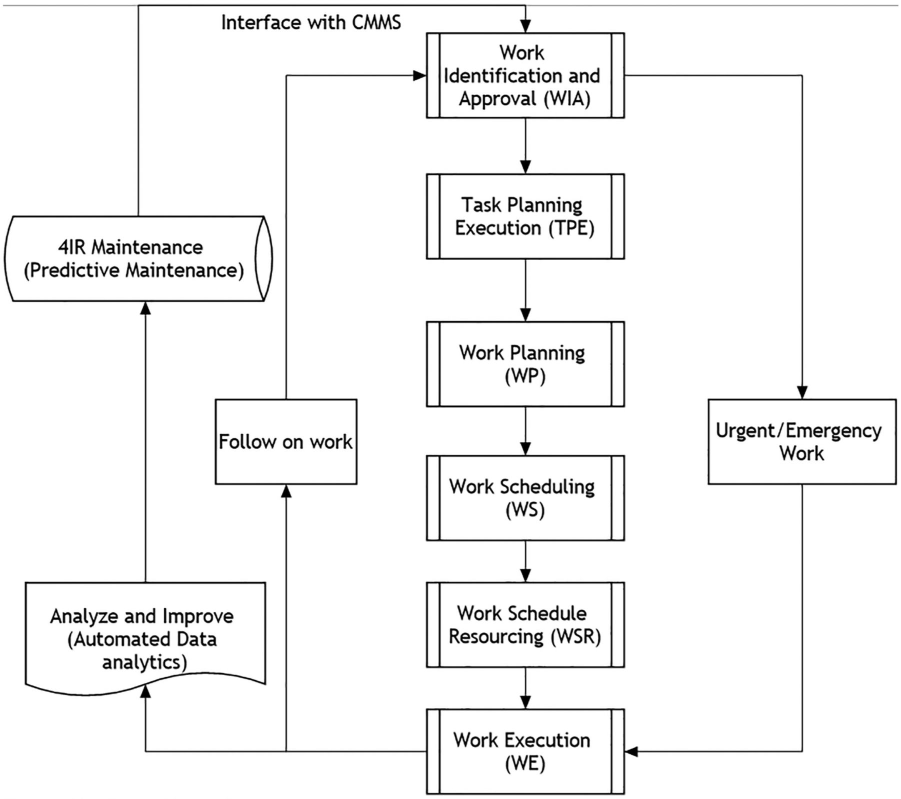

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Figure 5.
Overall maintenance work management process flow

may be executed in the next maintenance window, thereafter, step by step on how a task should be executed, a good way to benchmark on this is through maintenance manuals supplied by the original equipment manufacturer, in digital technologies context, cloud computing can accelerate this step. Thirdly, detailed planning commences with a lens on the specification of tools, special skills required, and any additional time or cost that would be required. Once the work is effectively planned, a schedule can be drafted covering at least 5–7 weeks of the forecast.

No work can be completed without the required resources as specified in the panning step, work resourcing aims at the effective acquisition of these resources to eliminate time wastage on the day of execution, this research study suggests that tool time or wrench time for artisans is mainly affected by upfront preparations and/or delays just before task execution (Ghani *et al.*, 2012), such delays include but not limited to the acquisition of tools or parts on the day of work execution. Work may effectively be executed with a minimal safety risk, and in this study, it is also found that detailed planned work yields safe and quality execution. The findings of this research study suggest that breakdown work may not be executed through WIA to WSR. These tasks move from WIA to WE and hence a maintenance index of 85/15 is critical. In simpler terms, minimization of unscheduled downtime supports unnecessary time wastage reduction. In the 4IR, the maintenance strategy is predictive. 4IR technologies yield an overall best practice maintenance mix, and more tasks are performed as planned work than unplanned work.

The next subsections discuss each step of the maintenance work management process as per Figure 5. Sections 4.2 and 4.3 discuss work identification and approval and task planning execution with respective formulated process model flow diagrams, as an example of how each step as per Figure 5 is modeled. Sections 4.4 to 4.7 discussions are without respective formulated process models and hence Figure 5 is used as a reference point.

4.2 Work identification and approval (WIA)

Figure 5 represented an overall formulated maintenance work management process model, illustrating both steps from WIA to WE overview, and is based on findings from data sources presented in Figure 4. Figure 6 illustrates details of the first step (Work Identification and Approval). In line with Figure 6, any maintenance task to be performed, and in line with equipment inspection, task identification and approval as an initial step are crucial for validation of that task allocation. In Figure 6, work identification is seen as an activity predominantly captured by online condition monitoring using online sensors such as vibration, temperature, etc. (4IR support). Furthermore, Virtualization technologies are seen as another 4IR technology that can be employed for the effective handling of equipment parameters as presented in Table 1 of this journal.

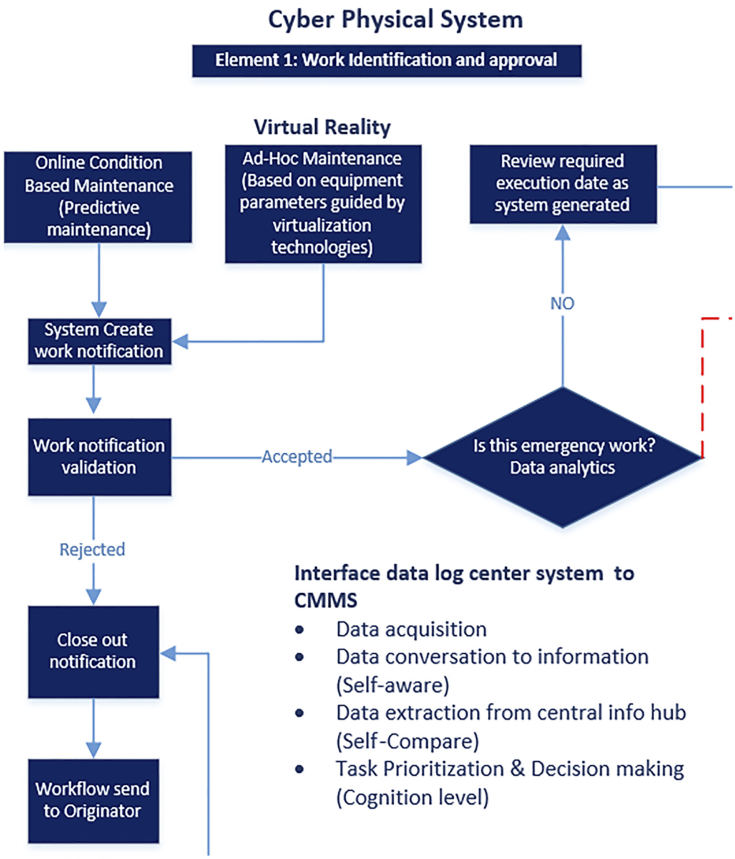

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Figure 6. Work identification and approval (WIA) process flow

Visualization technologies can inform the prediction of the exact time for ad hoc maintenance activity before equipment failure at the most opportune time for that equipment restoration. The findings of this research study suggest that should work be triggered by these 4IR technologies, an interface between these technologies and Computerized Maintenance Management System (CMMS) be implemented to support the automatic creation of work/task notification (Raouf *et al.*, 1993; García and García, 2019; Tortorella *et al.*, 2021). Based on the criteria set (i.e., Priority 1 tasks for illustrate stopper equipment and safety-related equipment, and Priority 2 for the second type of equipment), the system can be equipped with a tool for task/notification validation with a lens on labor compliment for that equipment.

In maintenance work management literature, there is evidence of some ineffective maintenance work management because of failure to categorize tasks thereby misusing human resources (also suggested by (Ensafi and Thabet, 2021)). Thus, the maintenance index (85/15 best practice) is somewhat to be desired in the industry. For tasks accepted through notification validation, the system can use data analytics technique to classify whether that notification constitute emergency work or not. Emergency work is seen as either breakdown work or health, safety, or environment threat avoidance or mitigation. This approach discussed herein is centered around cyber-physical systems (4IR enabling technology) (García and García, 2019). Figure 6 is a graphical representation of Work Identification and Approval.

4.3 Task planning execution (TPE)

Figure 7 unpacks the process developed for task planning execution. It starts with a need for defect elimination, which could be achieved through failure mode and effects analysis (FMEA) or failure mode, effects, and criticality analysis (FMECA). These processes assist in identifying potential problems that can occur and the effects thereof on the system. Secondly, for tasks required but no functional location is registered on the CMMS, the execution of maintenance tactics can only be done after such functional location is registered. Thereafter, system identifies tasks steps required for the task initiated; in the 4IR context, this is known as data mining through cloud computing. To put this into context, a similar task can be executed in one of the sister operations. Architecturally, there is a need for the information hub/data hub to reduce time wastage on developing tactics that already exist.

A high-level determination of labor requirements, time estimation, and potential delays can be specified. If functional location is registered in the CMMS, assets can be registered and confirmation of maintenance strategy, task tactics, and the approval thereof can then be executed, this includes additional changes to maintenance tactics (Palmer, 2013).

4.4 Work planning (WP)

The work planning step begins with scoping the work, addressing the maintenance task list, and required resources, and matching that against cost. Planned work can only be approved as such if the following criterion is met; the works order needs to be compiled and well understood by the executor, the upper-cost limit needs to be known and approved by the cost center owner, the specification of resources such as special tools, required tradesman and the specification of cranage.

As an example, consider three artisans working without the benefit of work planning, in a high-production environment. According to Palmer (2013), (a maintenance management handbook), combined productivity is equivalent to one artisan working without any time wastage.

i.e. $3 \times 35\% = 105\%$ total productivity (Without planning).

One planner, two artisans: $1 \times 0\% + 2 \times 55\% = 110\%$

Ratio planner to artisans (1:20–30 artisans).

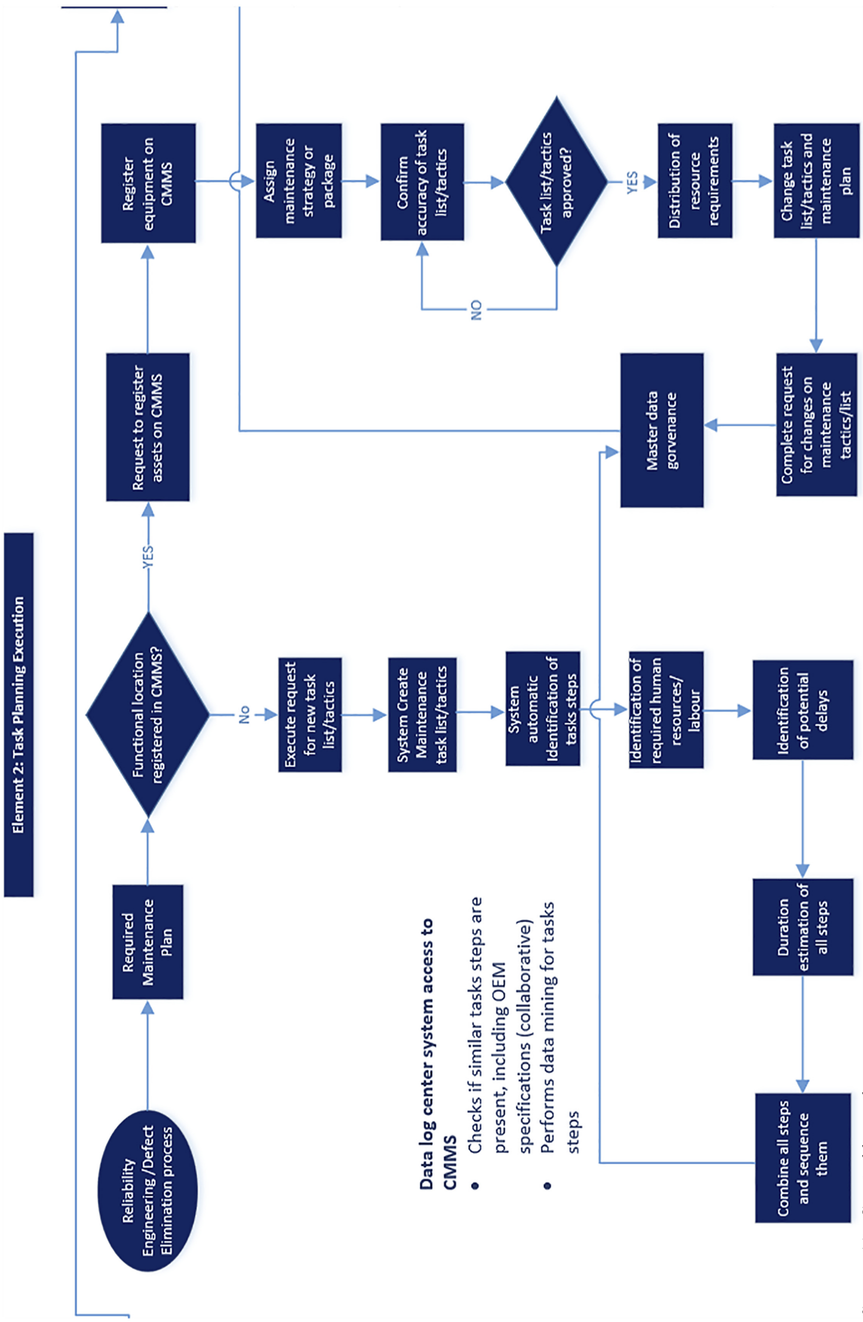

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Figure 7.
Task planning execution (TPE) process flow

Therefore, 55%/35% = 1.57 (This is a 57% improvement).

Thus, 30 artisans X1.57 = 47 artisans.

The example above represents the importance of work planning, reinforcing that at least 85% of work should be executed under scheduled work conditions.

4.5 Work scheduling (WS)

Work can only be scheduled once the plan is confirmed by both the maintenance and production departments. The findings of this research study suggest that a schedule should cover at least four weeks to allow the effective use of human resources, in this case, prioritization takes precedence. In the context of 4IR, data analytics and the Internet of things can assist in adequately predicting critical tasks that should be executed first.

4.6 Work resourcing (WR)

This research study found in the literature that an artisan's tool time in a 10-h shift is only 3.5 h, this is due to ineffective planning leading to failure to specify resources required for the task, this section looks at mitigating some of the time that can be wasted during execution stage (known as time optimization) (Palmer, 2013).

Artisans spend more time looking for spares, and special tools and figuring out how to execute the task adequately. This study proposes a need for work resourcing so that all required resources are acquired beforehand thereby eliminating time wastage, particularly when executing tasks.

4.7 Work execution (WE)

There is great emphasis in the literature in line with maintenance activities that, the right work should be done at the right time, by the right skilled person the right way. This can only be achieved should WIA to WR discussed in preceding subsections are executed effectively. Nonetheless, this study considers emergency work as any work emanating from a breakdown or deterioration of any health and safety equipment. Such work need not be taken through WIA to WR due to the requirement of restoring that equipment timely. In this study and according to the literature (Planned Maintenance Percentage), such work should not exceed 15% of the total work.

The next section discusses the dynamic behavior of the maintenance system incorporating the formulated maintenance work management process using system dynamics modeling and simulation. Forrester suggested that the system dynamics model's source of information must consider available databases from any institution, including modeled business processes just like the process model in this research study by Forrester (2009).

5. System dynamics quantitative modeling and simulation

5.1 Model formulation and simulation overview

This section converts the formulated qualitative maintenance work management formulated model in the preceding section to a quantitative system dynamics model. The conceptual model developed and represented in Figure 5 consists of six steps, namely, work identification and approval, task planning execution, work planning, work scheduling, work resourcing, and work execution. These steps are converted to a quantitative model with unintended effects and incorporating 4IR technologies.

5.1.1 System dynamics modeling and simulation motivation for this research study. The dynamic behavior of the maintenance work management system incorporating the formulated maintenance work management process discussed in the preceding section requires simulations. SD simulation is helpful to test the dynamic behavior of any system model. According to Sterman (2002), Martinez-Moyano and Richardson (2013), and Forrester (2009), a system model without any dynamics behavioral testing remains rationally bounded. This means that most decision-makers in operations systems are boundedly rational, influenced by stress levels and emotions, omitting interactions for system behavior and most feedback (Sterman, 2002; Marwala, 2013a, b; Sterman *et al.*, 2015). To mitigate bounded rationality, system dynamics can play a huge role in modeling system behavioral dynamics within the formulated business process model in maintenance management. SD present to an extent a flexibly bounded rational decision-making in that an element of future behavioral prediction can be simulated (Sterman, 2002; Martinez-Moyano and Richardson, 2013; Marwala, 2013a, b).

Figure 6 illustrates the formulated SD simulation model of the maintenance work management process (maintenance work management controls) and associated unintended effects, using Vensim DSS software incorporating WIA to WE as discussed in the preceding sections. The simulation uses stock and flow diagrams with feedback loops and is equipped with specified mathematical equations. These equations assist in ensuring dimensional consistency and depicts relationships amongst all variables, and initial conditions are specified as recommended by Sterman (2002), Martinez-Moyano and Richardson (2013), and Forrester (2009). This simulation intends to first understand the dynamics within a maintenance work management system. The graphical visualization of the quantitative model used is like the recommendation of Sterman (2002), Martinez-Moyano and Richardson (2013), and Forrester (2009).

5.1.2 Model simulation subscripts. The use of subscripts in Vensim DSS software assists in model validation using multiple types of equipment rather than having multiple models for each equipment type. This research study uses subscripts for model validation encompassing six types of equipment. Subscripts also cater to a single variable to represent multiple and different equipment types (Ventana Systems, 2022).

This research study uses subscripts on model equations named "Maintenance," each equipment type is assigned a code, M1 to M6 for six equipment types in the model simulation. Once the "Maintenance" subscript is set for the equipment type variable, Vensim DSS software automatically appends the subscript in the square bracket to each variable used in model equations. Equation (1) is an illustration of subscripted model variables and/or parameters:

$$PM\ Tasks\ Planning[Maintenance] = INTEG\ (planning[Maintenance] - scheduling[Maintenance], 50 \tag{1}$$

where:

INTEG is an integral function; and

[Maintenance] represents that the variable or parameter is subscripted.

5.1.3 Microsoft Excel for imported data illustration. The data acquired for both equipment for this research study is captured, cleansed, and repackaged in a Microsoft Excel file named "data.xlsx". This research study uses Vensim DSS software functions to read data parameters from the "data.xlsx" Microsoft Excel file presented in Table 3 for model simulation (Ventana Systems, 2022). The Microsoft Excel data file in Table 3 serves as an example of data arrangement for readability in Vensim DSS software and covers the first 9 months out of 24 months of the time series used.

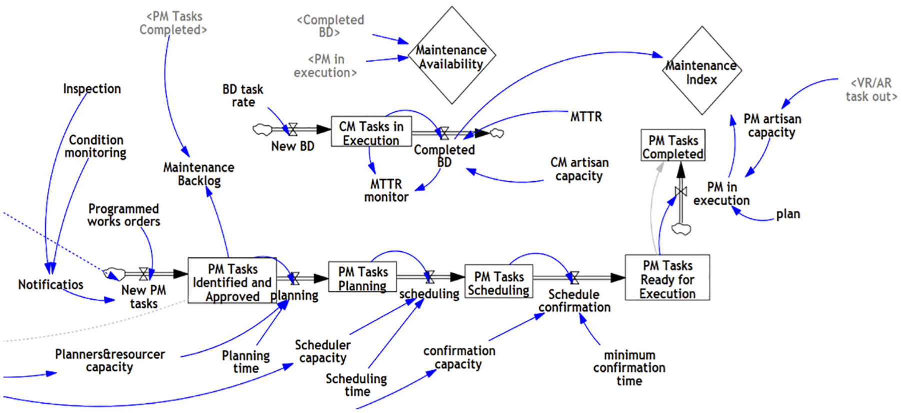
Time (Month)	1	2	3	4	5	6	7	8	9
Maintenance Index [M1]	86	79	83	97	85	99	99	82	72
Maintenance Index [M2]	80	86	93	91	95	88	91	87	92
Maintenance Index [M3]	71	18	93	83	92	75	98	65	84
Maintenance Index [M4]	94	99	96	84	98	95	100	92	96
Maintenance Index [M5]	98	99	95	100	64	78	75	96	98
Maintenance Index [M6]	93	93	92	91	91	93	94	97	96
CM Tasks in Execution [M1]	10	12	20	3	16	11	12	6	13
CM Tasks in Execution [M2]	11	17	7	4	3	3	5	3	4
CM Tasks in Execution [M3]	1	7	2	2	2	6	1	9	4
CM Tasks in Execution [M4]	1	2	1	2	2	2	1	2	2
CM Tasks in Execution [M5]	3	1	4	1	9	10	5	2	2
CM Tasks in Execution [M6]	49	41	38	40	64	43	54	15	25
Maintenance availability [M1]	600	507	403	306	394	372	423	398	383
Maintenance availability [M2]	556	527	643	481	590	608	647	625	590
Maintenance availability [M3]	598	532	430	323	388	407	413	412	399
Maintenance availability [M4]	550	510	413	316	395	381	432	404	388
Maintenance availability [M5]	610	502	412	317	390	374	431	399	384
Maintenance availability [M6]	608	499	391	301	361	372	398	349	385

Source(s): Created by authors

Table 3.
Imported Microsoft excel data file

5.2 System dynamics model formulation

Figure 8 is a graphical illustration of a stock and flow diagram (SFD), representing discrete events for maintenance tasks processed through the formulated maintenance work management process. For preventative tasks, programmed works orders, condition monitoring, and inspections are viewed as the drivers for work identification. This follows through to a point where tasks are executed with a defined maintenance department capacity. In SD terms, identified and approved tasks are seen as stock accumulation reinforced by inspections, condition monitoring, and programmed works orders (reinforcing loop). Activities in the planning phase, resourcing, scheduling, and task execution balance or deplete identified and approved tasks (balancing loop) (Sterman, 2002). The model conforms with extant literature in that it allocates one planner per 20 artisans with a wrenching time of



Note(s): Incorporating developed maintenance work management process
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Figure 8.
Formulated system dynamics simulation

3.5 h per 9-h shift (Palmer, 2013), allowing tasks identified to undergo planning and scheduling processes.

In Figure 8, although tasks identified in any given month may exceed the work capacity in the maintenance department in that month, the only tasks that can be planned by the maintenance department capacity at a level of planning and scheduling. Furthermore, prioritization for tasks to be planned is given to critical equipment and that on its present subjectivity without the benefit of 4IR technologies. Unintendedly, some of these critical tasks are omitted and end up resulting in a breakdown, and dynamically reinforcing corrective maintenance tasks in execution (reinforcing loop). Subsequently, tasks that are left out in the planning phase due to capacity constraints and that have resulted in breakdowns unintendedly impact the intended maintenance mix negatively. Another unintended effect resulting from tasks that are omitted in the planning phase due to constraints increases the maintenance backlog as per the illustration in Figure 8. Table 4 encompasses key mathematical model equations for the formulated system dynamics simulation with subscripts "[Maintenance]".

Figure 8 is a partial representation of the system dynamics model structure, with mathematical formulas presented in Table 4. In Figure 8, no 4IR technologies have been implemented, and simulations and system behavior are executed as the first step for analysis.

To control the complex phenomenon discussed in the preceding paragraph, the second part of the formulated model in Figure 9 incorporates 4IR technologies as a balancing loop for critical assets. The study referenced in García and García (2019) suggested that virtual reality (VR) and augmented reality (AR) offer a unique opportunity in critical asset inspections to detect defects and adapted as such in this research study. This alleviates time spent by artisans on the inspection with overall gain to hands-on tasks rather than on inspections. Another subjectivity is observed particularly when artisans are to judge whether a defect requires work to be executed timeously. Using cyber-physical systems (CPS), equipment deterioration or degradation is detected, analyzed (using data analytics), planned, and scheduled digitally and in real-time without human intervention as per Figures 5 and 7 (recommended by (Tortorella *et al.*, 2021)). Digital planning and scheduling add to tasks that are planned and scheduled

Variable/parameter	Formulations/Equations	Units
Planning[Maintenance]	Planning = MIN(PM Tasks Identified and Approved [Maintenance]/Planning time[Maintenance], "Plannersandresourcer capacity[Maintenance]")	Task/Month
scheduling[Maintenance]	Schedule confirmation = MIN(confirmation capacity [Maintenance], PM Tasks Scheduling[Maintenance]/minimum confirmation time[Maintenance])	Task/Month
PM Tasks Scheduling [Maintenance]	Schedule confirmation = MIN(confirmation capacity [Maintenance], PM Tasks Scheduling[Maintenance]/minimum confirmation time[Maintenance])	Task/Month
PM in execution [Maintenance]	PM in execution = MIN(PM artisan capacity[Maintenance], PM Tasks Ready for Execution[Maintenance]/plan [Maintenance])	Task/Month
Completed BD [Maintenance]	Completed BD = MIN(CM artisan capacity[Maintenance], (CM Tasks in Execution[Maintenance]/MTTR[Maintenance])	Task/Month
PM Tasks Completed [Maintenance]	PM Tasks Completed = INTEG (PM in execution[Maintenance], PM Tasks Ready for Execution[Maintenance])	Task
DA tasks out (data analytics tasks-auto planning) [Maintenance]	DA tasks Out = Tasks Data Analytics in scheduling and planning[Maintenance]*digital system planning and scheduling rate[Maintenance]	Task/Month

Source(s): Created by authors

Table 4. Key mathematical model equations

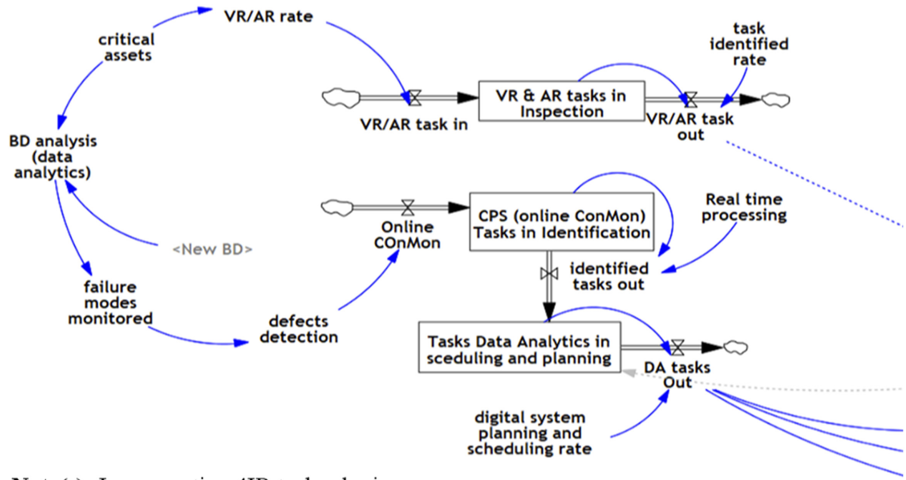


Figure 9. Formulated system dynamics simulation

Note(s): Incorporating 4IR technologies
Source(s): Created by authors

manually for assets not deemed critical. Table 4 details mathematical equations used for key stocks and flows represented in Figures 8 and 9.

Figure 10 is a graphical representation of the overall model for maintenance work management (a combination of Figures 8 and 9).

6. System dynamics model validation of maintenance work management process

SD model Validation compares model behavior to time series data collected in the real world. The system dynamics simulation model incorporated key subsystems: maintenance work management process (WIA to WE) following the discrete event from task identification to

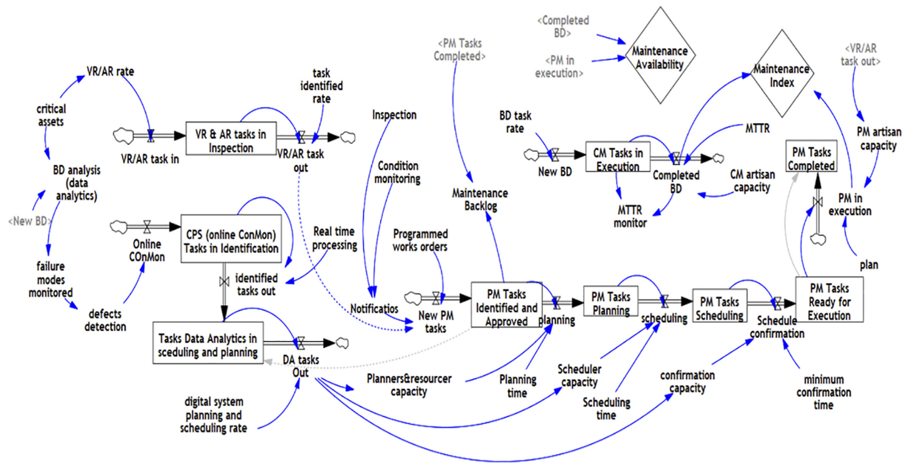


Figure 10. Formulated overall system dynamics simulation

Note(s): Work management incorporating 4IR technologies
Source(s): Created by authors

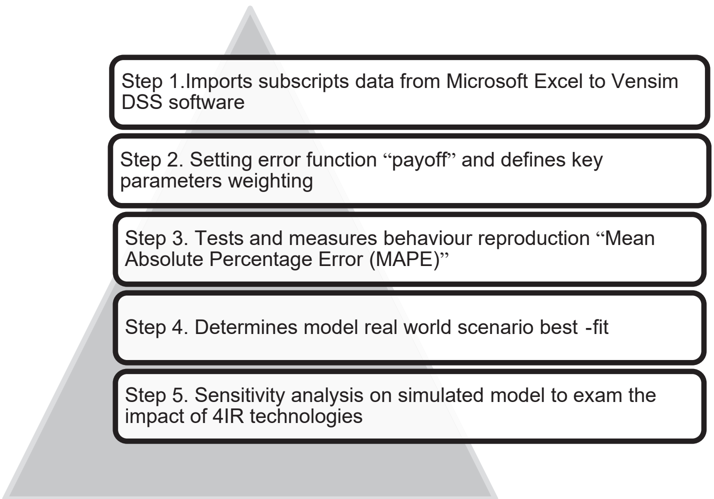
execution, with its unintended effect, looked at as maintenance backlog, maintenance availability controls, and maintenance index controls with close view on corrective maintenance tasks in execution.

6.1 Model validation and testing overview

Figure 11 is an overview of this research study model validation and testing. Step 1 involves importing real-world data from a Microsoft Excel data file named "data.xlsx" to Vensim DSS software (Sterman, 2002; Ventana Systems, 2022; Martinez-Moyano and Richardson, 2013), and (Chitongo and Pretorius, 2018). The baseline model for this study captured subscripts named [Maintenance] to ease simulation iterations rather than having each model simulation for each equipment type (Ventana Systems, 2022; Chitongo and Pretorius, 2018). Vensim DSS software automatically appends subscripts to model variables and/or parameters (Ventana Systems, 2022). Step 2 captures the optimization setting using the model error function "payoff" and defines model parameter weighting. Step 3 captures behavior reproduction test measuring "Mean Absolute Percentage Error (MAPE)" for calibration error descriptive statistic (Ventana Systems, 2022). Step 4 determines the model's real-world scenario best fit, or replication based on equipment type captured on the model subscripts (Ventana Systems, 2022; Sterman, 2002; Martinez-Moyano and Richardson, 2013; Chitongo and Pretorius, 2018). Lastly, step 5 uses experiments to analyze the impact of 4IR technologies on the model structure in line with sensitivity analysis (Christopher Frey and Patil, 2002; Hekimoğlu and Barlas, 2010; Kleijnen, 1995).

6.2 Model validation and testing

Model calibration forms part of system dynamics model testing and validation. According to Sterman (2002), Martinez-Moyano and Richardson (2013), and Forrester (2009), model constants may be altered manually to achieve the best fit between real-world data and simulation output. Using optimization, Vensim DSS automatically varies chosen constants for the best fit between simulation output and real-world data. This study adapts this concept of model validation using calibration techniques as part of model validation as suggested by Sterman (2002) and Martinez-Moyano and Richardson (2013). This research study uses six



Source(s): Created by authors

Figure 11. Model validation overview

different types of production equipment (M1 to M6 discussed below) for analysis of the impact of the maintenance work management process (WIA to WE) from experiments simulation.

The intent for six different types of equipment is to enhance model validity and conclusions derived therefrom. Real-world data is retrieved from two unique maintenance departments managing production machines that comprise Continuous Miners (M1), Shuttle Cars (M2), Feeder Breakers (M3), Roof Bolters (M4), Section Conveyor Belts (M5), and Trunk Conveyor Belts (M6). Data is imported to Vensim DSS as M1 to M6 and is defined as such in the subscripts of the model simulation. This way of calibration conducted for this study model provides a novel extension to the extant system dynamics simulation model testing and validation body of knowledge, more so because the extant literature reviewed is limited to either a generic maintenance model with just one type or class of equipment or machine. Furthermore, the extant literature in maintenance system dynamics modeling is limited in modeling a process for work management (WIA to WE) viewed as discrete events (Karnon *et al.*, 2012). Lastly, the experimental simulation of this study enhances future system dynamics modeling and physical asset management research studies. Most importantly, it can be used as a provisional answer to challenges encountered in complex maintenance work management systems.

The problem for this research study model calibration is expressed by a single optimization problem having an error function known as the objective function or payoff. This model calibration starts by setting the initial payoff; secondly, real-world data is imported to the model for comparison purposes, thereafter, model calibration is executed.

Key maintenance management system parameters used for payoff settings are Maintenance Index (MI) and Maintenance Availability (MA) both weighted at 0.4985 and CM tasks in execution (CM) weighted at 0.003 (weight setting recommended by Ventana Systems (2022)). These three parameters a chosen because they represent a discrete event of the model (from task identification to execution). Equations (2) and (3) are mathematical expressions of payoff calculation used for this study (adapted from Ventana Systems (2022)). According to Vensim Ventana systems, the payoff is defined as a comparison of model variables with actual data, or as a combination of model variables. Two types of payoffs are calibration payoff and policy payoff. This research study used calibration payoffs for model validation (Ventana Systems, 2022).

$$\text{Equipment type Payoff}m = w_{MI}\left(\frac{MI_{sim,m}-MI_{act,m}}{|MI_{sim,m}|+|MI_{act,m}|}\right)^2 + w_{MA}\left(\frac{MA_{sim,m}-MA_{act,m}}{|MA_{sim,m}|+|MA_{act,m}|}\right)^2 + w_{CM}\frac{1}{t_{sim,m}}\int_0^{t_{sim,m}}\left(\frac{CM_{sim,m}(t)-CM_{act,m}(t)}{|CM_{sim,m}(t)|+|CM_{act,m}(t)|}\right)^2 dt \tag{2}$$

where:

w_{MI} = weight for the maintenance index component;

$MI_{sim,m}$ = simulated maintenance index for equipment type m;

$MI_{act,m}$ = actual maintenance index for equipment type m;

w_{MA} = weight for the maintenance availability component;

$MA_{sim,m}$ = simulated maintenance availability for equipment type m;

$MA_{act,m}$ = actual maintenance availability for equipment type m;

w_{CM} = weight for the correct maintenance component;

$t_{sim,m}$ = simulation final time for equipment type m;

$CM_{sim,m}(t)$ = simulated corrective maintenance for equipment type m; and

$CM_{act,m}(t)$ = actual corrective maintenance for equipment type m.

$$\text{All Equipment type Payoff} = \sum_{m=1}^{n} \text{Equipment type Payoff} m \quad (3)$$

where:

n = number of equipment types considered.

In line with recommendations from Sterman (2002) and Martinez-Moyano and Richardson (2013), the calibration used payoff optimization in Vensim DSS using Powell conjugate search algorithm for parameters estimation as first step of the calibration (Ventana Systems, 2022). A total of 432 real-world data points is used for parameters estimation purposes. Thereafter optimization for all equipment type, class, or group (M1 to M6) is conducted and the payoff for all equipment type is calculated as the objective function for minimization similarly to the study of Chitongo and Pretorius (2018).

The second step of calibration for this study is also in line with both (Sterman, 2002) and (Martinez-Moyano and Richardson, 2013). Behavior reproduction test measure known as the mean absolute percentage error (MAPE) is used for calibration error descriptive statistic for this study (Ventana Systems, 2022). Four calibration errors are deduced for each equipment type (MI, MA, CM as discussed in preceding section), thus determining MI MAPE (Maintenance Index calibration error), MA MAPE (Maintenance Availability calibration error) and CM MAPE (Corrective Maintenance in Execution calibration error) using equation (4) for this study.

O MAPE (Overall calibration error) is calculated using equation (5) with weighted MA, MI, and CM (depicted as W_{MI}, W_{MA}, and W_{CM} in equation 5) the same as when used to calculate equipment type payoff (equation 2). This approach is supported by Ventana Systems (2022).

$$MAPE_m = \frac{1}{n}\Sigma_{m=1}^{n} \frac{|D_{sim,m} - D_{act,m}|}{D_{act,m}} \quad (4)$$

where:

n = number of iterations considered (n = 24 for both MI MAPE, MA MAPE, and CM MAPE).

$$O\,MAPE = W_{MI}(MI\,MAPE) + W_{MA}(MA\,MAPE) + W_{CM}(CM\,MAPE) \quad (5)$$

where:

W_{MI} = weight for maintenance index component;

W_{MA} = weight for maintenance availability component; and

W_{CM} = weight for corrective maintenance.

The dataset used in the calibration consists of actual maintenance availability, actual maintenance index, and actual corrective maintenance tasks in execution (all per time series data of 24 months).

6.3 Model validation results (maintenance work management process)

Table 5 is a representation of calibration results; four different calibration errors denoting dimensionless MAPE values for each equipment type with an O MAPE viewpoint are discussed. Equipment type M4 and M6 are the best fit for real-world data both with least overall calibration error (O MAPE) of 0.065, followed by equipment type M2 at O MAPE of 0.071. M3 is observed with the largest overall calibration error of O MAPE accounting for 0.098, denoting the worst fit.

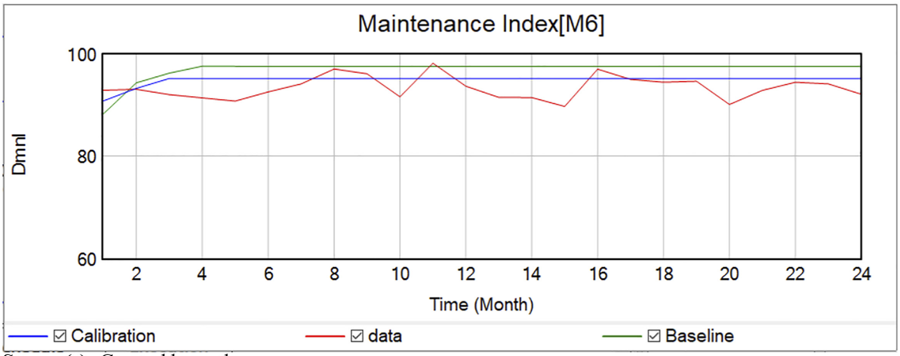
Table 5 summarizes key results of system dynamics simulation model after calibration, illustrating the unintended effect of random equipment breakdowns on intended overall maintenance index of a world class 85/15 ratio is unavoidable with just a subjective model alone. Nonetheless, this study reveals great insights due to its control in mapping out a process model for maintenance work management. This research study observed from CM MAPE in Table 5 that due to randomness of breakdown events, modeling random breakdowns is complex and is not easy to replicate real-world scenarios. Thus, the focus for this research study is more on what can be done to produce industry benchmark on maintenance work management process that accounts for a dynamic maintenance complexity presented by random equipment breakdowns. MI MAPE and MA MAPE denote best fit between model parameters and real-world parameters, thus representing an overall mean percentage error supporting the validity of the model and random breakdown events controls.

6.3.1 Model validation results: maintenance index best fit. Figure 12 is a graphical representation of the system dynamics simulation. Real-world data is compared to calibrated results for equipment type (M6), denoting the best fit amongst the six equipment types as

Equipment type	Mean absolute percentage error (MAPE) (dimensionless) MI MAPE	MA MAPE	CM MAPE	O MAPE
M3	0.124	0.068	0.553	0.098
M1	0.104	0.074	1,587	0.093
M5	0.098	0.073	0.625	0.087
M2	0.088	0.051	0.618	0.071
M4	0.047	0.080	0.625	0.065
M6	0.048	0.080	0.249	0.065

Note(s): Maintenance work management process
Source(s): Created by authors

Table 5.
Calibration errors per equipment type



Source(s): Created by authors

Figure 12.
Calibrated results vs real-world data for maintenance index: best fit (M6)

calibrated. In Figure 12, calibration denoted by the blue line represents calibrated results, and data denoted by a red line represent real-world data. The key parameter represented in Figure 12 is the Maintenance Index (between 85 and 97% for both calibrated and real-world values, achieving best practice of 85%/15%). The green line is a representation of baseline model before calibration.

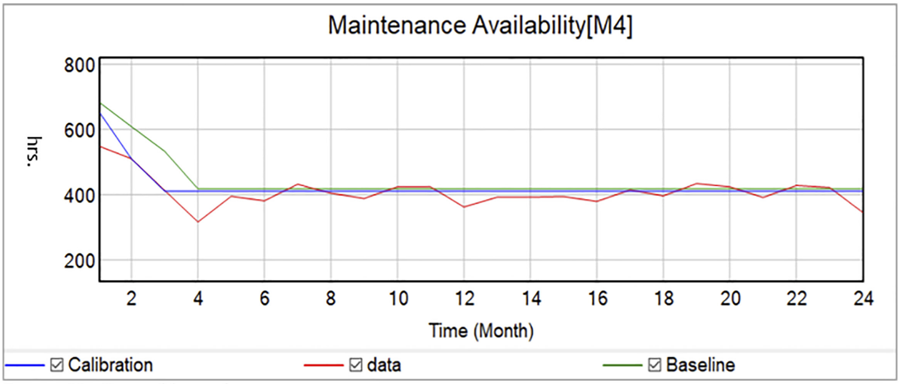
6.3.2 Model validation results: maintenance availability best fit. Figure 13 is a graphical representation of the system dynamics simulation like Figure 12. Real-world data is compared to calibrated results for equipment type (M4), denoting best fit amongst the six equipment types as calibrated. In Figure 13, calibration denoted by the blue line represent calibrated results, and data denoted by a red line represent real-world data. Key parameter represented in Figure 13 is maintenance availability and is found mostly around 400 h per month for both real-world and calibrated values. Like Figure 12, the green line demotes baseline of the model before calibration.

6.4 4IR technologies sensitivity analysis on validated system dynamics model

Sensitivity analysis is used to understand the effects and/or impact of input variables in system dynamics models (Kleijnen, 1995). The preceding section illustrated system dynamics simulation to solve real-world maintenance work management complex phenomenon. Simulations are based on experimentation of modeling real-world scenarios (Christopher Frey and Patil, 2002; Kleijnen, 1995). Statistical design of experiments (DOE) is adopted in this research study in the attempt to investigate the optimization of maintenance work management using 4IR technologies (Kleijnen, 1995).

6.4.1 Sensitivity analysis overview. The 4IR technologies sensitivity analysis for this research study adapts descriptive statistical method to examine the impact of 4IR technologies on the model structure (Christopher Frey and Patil, 2002; Hekimoğlu and Barlas, 2010). Firstly, an analysis of maintenance index descriptive statistical simulation without the benefit of 4IR technologies is performed in experiment 1. Secondly, a partial implementation of 4IR technologies is analyzed next in experiment 2. Thirdly, all 4IR technologies considered for this research study are implemented on just 50% of critical assets in experiment 3. Lastly, all 4IR technologies considered for this study implemented on 100% of critical assets and the impact thereof is analyzed in experiment 4.

In all sensitivity analysis experiments for this research study discussed in the preceding section, standard deviation is used to examine tasks predictability, to corroborate what mean



Source(s): Created by authors

Figure 13. Calibrated results vs real-world data for maintenance availability: best fit (M4)

is denoting according to the expected 4IR technologies impact. Standard deviation measures the dispersion of dataset relative to its mean (average amount of variability relative to the mean) according to Leys *et al.* (2013). High value of standard deviation imply that values are generally far from the mean, while low value of standard deviation imply that values are clustered close to the mean (Leys *et al.*, 2013; Lee *et al.*, 2015). In this research study, values close to zero suggest that the maintenance strategy is predictive.

6.4.2 Sensitivity analysis experimental simulation results. Experiment 1: Table 6 outlines the descriptive statistics simulation for maintenance index without the benefit of 4IR technologies, with a viewpoint to the impact of 4IR technologies (included in experiment 2 to 4) on the developed and simulated maintenance work management process. Maintenance index is the ratio between scheduled vs unscheduled maintenance work and is observed to be the lowest without the benefit of 4IR technologies and below best practice of 85% (Planned Maintenance Percentage), at a mean of 68.05% yielding toward scheduled maintenance. In maintenance strategy terms discussed in the preceding section, this means that the maintenance strategy is not predictive, based on the observed 31.95% yielding towards unscheduled maintenance. Furthermore, the same phenomenon is corroborated by a higher standard deviation observed at 4.51, representing a lack of tasks predictability before failure.

Experiment 2: Table 6 further represents descriptive statistics simulation for maintenance index with partial 4IR technologies implementation (VR/AR for inspections, supported by CPS sensors). Scheduled vs unscheduled maintenance (Maintenance Index) is observed at a mean of 78.92% yielding toward scheduled maintenance, but below best practice of 85%. This yields a 10.87% benefit relative to maintenance work management process model formulated without 4IR technologies. Furthermore, standard deviation is observed at 2.07%, representing an improved defect detection before failure when compared to experiment 1, thus yielding partial predictive maintenance strategy.

Experiment 3: This experiment represents descriptive statistics simulation for maintenance index with full implementation of 4IR technologies at 50% of critical assets. Table 6 illustrates the maintenance index at a mean of 85.79%, above best practice of 85%. This yields a 17.74% benefit relative to maintenance work management process model formulated without 4IR technologies, and up by 6.87% from experiment 2. Furthermore, standard deviation is observed at 2.10, representing an improved defect detection before failure when compared to experiment 1, thus yielding partial predictive maintenance strategy and reinforcing 4IR technologies implemented in experiment 2.

Experiment 4: This experiment represents descriptive statistics simulation for maintenance index with full implementation of 4IR technologies at 100% of critical assets. Table 6 illustrates simulated maintenance index at a mean of 95.51%, above best practice of 85% by 10.51%. This yields a 27.46% benefit relative to maintenance work management process model formulated without 4IR technologies, and up by 16.59% and 9.72% from experiment 1 and 2, respectively. Furthermore, standard deviation is observed at 1.77% improved by 2.74% from maintenance

Table 6. Descriptive statistics simulation for maintenance index

Descriptive statistics for maintenance index based on 4IR technologies implementation 4IR technologies benefit	Min	Max	Mean	Median	SD	(Norm)
Without 4IR technologies	66.67	88.24	68.05	66.67	4.51	0.07
Partial 4IR technologies implementation (VR/AR Inspections)	78.26	88.24	78.92	78.26	2.07	0.03
4IR technologies deployed at 50% of critical assets	77.02	88.24	85.79	86.26	2.10	0.02
4IR technologies deployed at 100% of critical assets	88.24	96.18	95.51	96.09	1.77	0.02

Note(s): Focusing on 4IR technologies' benefits
Source(s): Created by authors

work management process model formulated without 4IR technologies, representing an improved defect detection before failure when compared to experiment 1, 2, and 3, thus yielding overall predictive maintenance strategy and intensifying overall asset performance.

7. Discussion

The research study aimed at developing a maintenance work management simulated process using process modeling from a combination of extant literature, empirical observation (organizational documents), and using systems thinking. The research study considered modeling maintenance work management using a non-complex flow chart approach, from extant literature and direct analysis of organizational documents for maintenance work management processes. The formulated maintenance work management process was then subjected to complex modeling techniques, using a system dynamics modeling approach (hybrid approach). To achieve the objectives of this study, a mixed method approach was used incorporating system dynamics modeling.

In line with Sterman (2002), Martinez-Moyano and Richardson (2013), and Chitongo and Pretorius (2018), the first stage unpacked the dynamic hypotheses of the impact of the maintenance work management process incorporating 4IR technologies on best practice maintenance index (at least 85%/15% ratio) and to an extent the conceptual model emanating from a maintenance work management process model formulation and its attempt to address subjectivity observed empirically and supported by the extant literature. The process modeling of maintenance work management suggested that for any emergency work identified and approved for execution, such work can be subjected to execution without any detailed prior planning, hence a need to achieve the maintenance Index of at least 85%/15%. Furthermore, the 4IR technologies adoption assisted in achieving the world-class maintenance index discussed in the preceding sections, particularly when combined with the structured process of maintenance work management (WIA to WE) as discussed in preceding sections.

The second stage of SD unpacked model simulation of the maintenance work management process formulated using Vensim DSS software (Ventana Systems, 2022). The process model for maintenance work management was then subjected to complex dynamic modeling to examine its behavior with the gradual implementation of 4IR technologies to yield a predictive maintenance strategy. To examine this phenomenon (predictive maintenance), the study used two descriptive statistics, namely, mean values to determine best practice maintenance mix, and standard deviation to determine defects detection predictability. This research study revealed that 4IR technologies intensify asset performance with an overall gain of 27.46% yielding the best maintenance index. This research study also revealed that a standard deviation of 1.77, improved by 2.74 when compared to a model without the benefit of 4IR technologies can be used to represent the overall predictive maintenance strategy achieved through the implementation of both the maintenance work management process and 4IR technologies.

Maintenance performance data used for calibration, experimental simulations, and analysis of 4IR technologies impact or sensitivity analysis was gathered from six types of equipment used at underground coal mines from two unique maintenance departments. The results from calibrations, simulations, and impact analysis suggested that although M4 and M6 equipment types are the best fit for real-world data at 0.065 O MAPE, random equipment breakdowns remained a challenge to replicate real-world data, particularly without the benefit of 4IR technologies. The phenomenon of randomness on equipment breakdowns impacts negatively CM MAPE represented in the preceding section. Various scholars indicated the prevalence of controlling equipment defects through both corrective and preventative maintenance (Manenzhe, 2018; von Thun and Maier, 2004).

8. Conclusion

This study concludes that SD modeling can be used to model the maintenance work management system dynamic behavior. The unintended effect of corrective maintenance task execution that impacts negatively on the maintenance index can be controlled using 4IR technologies for prior work identification, yielding an overall maintenance strategy benefit that is predictive. 4IR technologies positively impacts the overall maintenance work management system thereby reducing the unintended subjective approach in decision-making.

In the extant literature, there is a lack in addressing the impact of the maintenance work management model incorporating 4IR technologies using SD modeling, particularly when its validation and testing consider more than just one equipment type and multiple maintenance departments. The work carried out in this study serves as a novel extension to the body of knowledge in the field of asset management (maintenance work management), SD model validation, and testing through calibration techniques of maintenance management. The benefits of this research study are expected to support future research in asset management studies, implementation of 4IR technologies in maintenance management, SD model calibration, and most importantly, industry practitioners using physical assets.

The authors of this research study intend to (among other objectives) incorporate other subsystems such as cost of maintenance, production process, human resources, and supply chain management process to the subsystem (maintenance) presented in this research study to further understand the dynamic behavior of maintenance work management when such subsystems are subjected to multiple variables amongst them. The authors further aim at intensifying overall business performance through asset management system behavior best practices.

References

Acernese, A., Del Vecchio, C., Tipaldi, M., Battilani, N. and Glielmo, L. (2021), "Condition-based maintenance: an industrial application on rotary machines", *Journal of Quality in Maintenance Engineering*, Vol. 27 No. 4, pp. 565-585, doi: 10.1108/JQME-10-2019-0101.

Al-Chalabi, H.S., Lundberg, J., Wijaya, A. and Ghodrati, B. (2014), "Downtime analysis of drilling machines and suggestions for improvements", *Journal of Quality in Maintenance Engineering*, Vol. 20 No. 4, pp. 306-332.

Alabdulkarim, A.A., Ball, P. and Tiwari, A. (2015), "Assessing asset monitoring levels for maintenance operations: a simulation approach", *Journal of Manufacturing Technology Management*, Vol. 26 No. 5, pp. 632-659.

Algabroun, H., Bokrantz, J., Al-Najjar, B. and Skoogh, A. (2022), "Development of digitalised maintenance – a concept", *Journal of Quality in Maintenance Engineering*, Vol. 28 No. 2, pp. 367-390, doi: 10.1108/JQME-04-2019-0039.

Anderson, R.T. and Neri, L. (1990), *Reliability-centered Maintenance: Management and Engineering Methods*, Elsevier Applied Science, London.

Assaad, R.H., Assaf, G. and Boufadel, M. (2023), "Optimizing the maintenance strategies for a network of green infrastructure: an agent-based model for stormwater detention basins", *Journal of Environmental Management*, Vol. 330, 117179.

Babaeimorad, S., Fattahi, P. and Fazlollahtabar, H. (2022), "Integrated maintenance scheduling inventory policy adjustment considering back order disruptions using joint optimization approach", *Journal of Quality in Maintenance Engineering*, Vol. 28 No. 4, pp. 748-767.

Balamurugan, E., Flaih, L.R., Yuvaraj, D., Sangeetha, K., Jayanthiladevi, A. and Kumar, T.S. (2019), "Use case of artificial intelligence in machine learning manufacturing 4.0", *2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, IEEE, pp. 656-659.

Borrego, M., Douglas, E.P. and Amelink, C.T. (2009), "Quantitative, qualitative, and mixed research methods in engineering education", *Journal of Engineering Education*, Vol. 98 No. 1, pp. 53-66.

Cheng, C. and Chiu, M.S. (2004), "A new data-based methodology for nonlinear process modeling", *Chemical Engineering Science*, Vol. 59 No. 13, pp. 2801-2810.

Chitongo, A.M. and Pretorius, L. (2018), "Unintended negative effects of client project cost controls: a system dynamics approach", *South African Journal of Industrial Engineering*, Vol. 29 No. 3, pp. 121-131.

Christopher Frey, H. and Patil, S.R. (2002), "Identification and review of sensitivity analysis methods", *Risk Analysis*, Vol. 22 No. 3, pp. 553-578.

De Nicola, A., Lezoche, M. and Missikoff, M. (2007), "An ontological approach to business process modeling", ISBN-978, *3th Indian International Conference on Artificial Intelligence 2007*.

Ensafi, M. and Thabet, W. (2021), "Challenges and gaps in facility maintenance practices", *EPiC Series in Built Environment*, Vol. 2, pp. 237-245.

Entringer, T., Nascimento, D., Ferreira, A., Siqueira, P., Boechat, A., Cerchiaro, I., Mendonça, S. and Ramos, R. (2019), "Comparative analysis main methods business process modeling: literature review, applications and examples", *International Journal of Advanced Engineering Research and Science (IJAERS)*, Vol. 6 No. 5, pp. 446-455.

Esmaeili, E., Karimian, H. and Najjartabar Bisheh, M. (2019), "Analyzing the productivity of maintenance systems using system dynamics modeling method", *International Journal of Systems Assurance Engineering and Management*, Vol. 10 No. 2019, pp. 201-211, doi: 10.1007/s13198-018-0754-5.

Fang, L. and Zhaodong, H. (2015), "System dynamics based simulation approach on corrective maintenance cost of aviation equipments", *Procedia Engineering*, Vol. 99, pp. 150-155.

Forrester, J.W. (2009), *Some Basic Concepts in System Dynamics*, Sloan School of Management, Massachusetts Institute of Technology, USA, pp. 1-17.

García, S.G. and García, M.G. (2019), "Industry 4.0 implications in production and maintenance management: an overview", *Procedia Manufacturing*, Vol. 41, pp. 415-422.

Ghani, U., Monfared, R.P. and Harrison, R. (2012), "Machine Utilisation and breakdown modelling for measuring productivity using virtual engineering simulation modelling", *Proceedings of the 10th International Conference on Manufacturing Research ICMR 2012*, September 11-13, 2012, Birmingham, UK, Vol. I, ISBN: 9781905866601.

Hekimoğlu, M. and Barlas, Y. (2010), "Sensitivity analysis of system dynamics models by behavior pattern measures", *The Journal of the System Dynamics Society*, Vol. 18, p. 2015.

Hosseinzadeh, M., Samadi Foroushani, M., Ghayem, H. and Mehregan, M.R. (2023), "Sustainable maintenance planning in the petroleum industry: an application of system dynamics approach", *International Journal of Quality and Reliability Management*, Vol. ahead-of-print No. ahead-of-print, doi: 10.1108/IJQRM-08-2022-0255.

Ismail, Z.A. (2022), "The requirements for maintenance management systems (MMS) at Malaysian polytechnic: a case study", *Journal of Quality in Maintenance Engineering*, Vol. 28 No. 4, pp. 768-790, doi: 10.1108/JQME-09-2020-0101.

Jokinen, T. and Ylén, P. (2007), "Dynamic modeling of maintenance strategies", *Proceedings of the 6th EUROSIM Congress on Modeling and Simulation*.

Karnon, J., Stahl, J., Brennan, A., Caro, J.J., Mar, J. and Möller, J. (2012), "Modeling using discrete event simulation: a report of the ISPOR-SMDM modeling good research practices task force–4", *Medical Decision Making*, Vol. 32 No. 5, pp. 701-711.

Khorshidi, H.A., Gunawan, I. and Ibrahim, M.Y. (2015), "Reliability centered maintenance using system dynamics approach", *2015 IEEE International Conference on Industrial Technology (ICIT)*, IEEE, pp. 1932-1936.

Kleijnen, J.P. (1995), "Sensitivity analysis and optimization of system dynamics models: regression analysis and statistical design of experiments", *System Dynamics Review*, Vol. 11 No. 4, pp. 275-288.

Kumral, M. (2009), "Mine maintenance time as a non-linear optimization problem under uncertainty", *Journal of Quality in Maintenance Engineering*, Vol. 15 No. 3, pp. 297-307.

Lee, D.K., In, J. and Lee, S. (2015), "Standard deviation and standard error of the mean", *Korean Journal of Anesthesiology*, Vol. 68 No. 3, pp. 220-223.

Lee, J., Mitici, M., Blom, H.A., Bieber, P. and Freeman, F. (2023), "Analyzing emerging challenges for data-driven predictive aircraft maintenance using agent-based modeling and hazard identification", *Aerospace*, Vol. 10 No. 2, p. 186.

Leys, C., Ley, C., Klein, O., Bernard, P. and Licata, L. (2013), "Detecting outliers: do not use standard deviation around the mean, use absolute deviation around the median", *Journal of Experimental Social Psychology*, Vol. 49 No. 4, pp. 764-766.

Macal, C.M. (2010), "To agent-based simulation from system dynamics", *Proceedings of the 2010 winter simulation conference*, IEEE, pp. 371-382.

Malina, M.A., Nørreklit, H.S. and Selto, F.H. (2011), "Lessons learned: advantages and disadvantages of mixed method research", *Qualitative Research in Accounting and Management*, Vol. 8 No. 1, pp. 59-71.

Manenzhe, M.T. (2018), *Maintenance Strategy Optimization for Load Haul Dumpers Operating at an Underground Mine*, University of Johannesburg Repository, Johannesburg, South Africa.

Martinez-Moyano, I.J. and Richardson, G.P. (2013), "Best practices in system dynamics modeling", *System Dynamics Review*, Vol. 29 No. 2, pp. 102-123.

Marwala, T. (2013), "Flexibly-bounded rationality and marginalization of irrationality theories for decision making", *arXiv Preprint arXiv: 1306.2025*.

Marwala, T. (2013), "Semi-bounded Rationality: a model for decision making", *arXiv Preprint arXiv: 1305.6037*.

Mella, P. and Gazzola, P. (2019), "Improving managers' intelligence through systems thinking", *Kybernetes*, Vol. 48 No. 1, pp. 58-78.

Naji, A., El Oumami, M., Bouksour, O. and Beidouri, Z. (2019), "A mixed methods research toward a framework of a maintenance management model: a survey in Moroccan industries", *Journal of Quality in Maintenance Engineering*, Vol. 26 No. 2, pp. 260-289.

Nordal, H. and El-Thalji, I. (2021), "Modeling a predictive maintenance management architecture to meet industry 4.0 requirements", *A Case Study. Systems Engineering*, Vol. 24 No. 1, pp. 34-50.

Organ, M., Whitehead, T. and Evans, M. (1997), "Availability-based maintenance within an asset management programme", *Journal of Quality in Maintenance Engineering*, Vol. 3 No. 4, pp. 221-232.

O'connor, P. and Kleyner, A. (2012), *Practical of Reliability Engineering*, 5th ed., John Wiley & Sons, Hoboken, NJ.

Palmer, R.D. (2013), *Maintenance Planning and Scheduling Handbook*, McGraw-Hill Education, New York City.

Pant, H. and Singh, S.B. (2022), "Availability and cost assessment of systems with dormant failure undergoing sequential inspections", *Journal of Quality in Maintenance Engineering*, Vol. 28 No. 3, pp. 533-544, doi: 10.1108/JQME-10-2020-0112.

Parida, A. and Kumar, U. (2006), "Maintenance performance measurement (MPM): issues and challenges", *Journal of Quality in Maintenance Engineering*, Vol. 12 No. 3, pp. 239-251.

Planned Maintenance Percentage (PMP), explained (upkeep.com), available at: https://www.upkeep.com/learning/planned-maintenance-percentage/ year (accessed 2022).

Raouf, A., Ali, Z. and Duffuaa, S.O. (1993), "Evaluating a computerized maintenance management system", *International Journal of Operations and Production Management*, Vol. 13 No. 3, pp. 38-48, doi: 10.1108/01443579310026005.

Richardson, W.B., Meyer, J. and Von Solms, S. (2022), "A business process management model for predictive maintenance and remote monitoring of rural infrastructure supported by 4IR technologies", University of Johannesburg Repository.

Sedghi, M., Kauppila, O., Bergquist, B., Vanhatalo, E. and Kulahci, M. (2021), "A taxonomy of railway track maintenance planning and scheduling: a review and research trends", *Reliability Engineering and System Safety*, Vol. 215, p. 107827.

Spendla, L., Kebisek, M., Tanuska, P. and Hrcka, L. (2017), "Concept of predictive maintenance of production systems by industry 4.0", *2017 IEEE 15Th International symposium on applied machine intelligence and informatics (SAMI)*, IEEE, pp. 000405-000410.

Sterman, J. (2002), "System dynamics: systems thinking and modeling for a complex world", MIT repository.

Sterman, J., Oliva, R., Linderman, K.W. and Bendoly, E. (2015), "System dynamics perspectives and modeling opportunities for research in operations management", *Journal of Operations Management*, Vol. 39, p. 40.

Tokgöz, A., Bulkan, S., Zaim, S., Delen, D. and Torlak, N.G. (2018), "Modeling airline MRO operations using a systems dynamics approach: a case study of Turkish Airlines", *Journal of Quality in Maintenance Engineering*, Vol. 24 No. 3, pp. 280-310, doi: 10.1108/JQME-05-2017-0037.

Tortorella, G.L., Fogliatto, F.S., Cauchick-Miguel, P.A., Kurnia, S. and Jurburg, D. (2021), "Integration of Industry 4.0 technologies into total productive maintenance practices", *International Journal of Production Economics*, Vol. 240, 108224.

Tsang, A.H. (2002), "Strategic dimensions of maintenance management", *Journal of Quality in Maintenance Engineering*, Vol. 8 No. 1, pp. 7-39.

Vaidya, S., Ambad, P. and Bhosle, S. (2018), "Industry 4.0–a glimpse", *Procedia Manufacturing*, Vol. 20, pp. 233-238.

Vayenas, N. and Peng, S. (2014), "Reliability analysis of underground mining equipment using genetic algorithms: a case study of two mine hoists", *Journal of Quality in Maintenance Engineering*, Vol. 20 No. 1, pp. 32-50.

Ventana Systems (2022), "Vensim manuals", available at: https://www.vensim.com/documentation/usr18.html

von Thun, J.H. (2004), "The dynamics of maintenance — a system thinking view of implementing total productive maintenance", in Maier, F. (Ed.), *Komplexität und Dynamik als Herausforderung für das Management*, Deutscher Universitätsverlag.

Zakarian, A. and Kusiak, A. (2000), "Analysis of process models", *IEEE Transactions on Electronics Packaging Manufacturing*, Vol. 23 No. 2, pp. 137-147.

Zhe, L., Kesheng, W. and Yafei, H. (2016), "Industry 4.0-potentials for predictive maintenance", *Proceedings of the 6th International Workshop of Advanced Manufacturing and Automation*, University of Manchester, pp. 10-11.

Further reading

Kaveh Pishghadam, H. and Esmaeeli, H. (2021), "A system dynamics model for evaluating the firms' capabilities in maintenance outsourcing and analyzing the profitability of outsourcing", *Scientia Iranica*, Vol. 30 No. 2, pp. 712-726.

Manenzhe, M. and Telukdarie, A. (2021), "Maintenance management conceptual model: a system dynamics approach", *2021 International Conference on Maintenance and Intelligent Asset Management (ICMIAM)*, IEEE, pp. 1-6.

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