ISSN 3005 - 6195

8

OMAINTEC JOURNAL

(Journal of Scientific Review)

OMAINTEC

المجلس العربي لإدارة الأصول والمرافق والصيانة

Arab Asset, Facility and Maintenance Management Council

ISSU# 08 - December 2025

About the journal

A refereed scientific journal issued semi- Annual by the Arab Asset, Facility and Maintenance Management Council

Publisher

(The Arab Asset, Facility and Maintenance Management Council)

www.omaintec.org

OMAINTEC Journal is indexed by:

Crossref

Google Scholar

PORTICO

Address & Contact Info

Registered NGO in Switzerland –

Lugano Via delle scuole 13, 6900 Paradiso, Switzerland

Riyadh Liaison Office:

PO Box 88819 Riyadh 11672, KSA

Tel: +966 11 460 8822

Mobile: +966 53 570 8934

Website: www.omaintec.org

Email: info@omaintec.org

Editorial Board Committee

Editorial Secretary

Language Review Committee

OMAINTEC JOURNAL

(Journal of Scientific Review)

The magazine aims to be a distinctive platform through:

• Creating common ground of discussion among researchers, academics and Arab specialists in the operation and maintenance, facilities management and asset management sectors.

• Encouraging research in the operation and maintenance, facilities management and asset management sectors, and proper management of properties. The magazine will conduct research, scientific reviews or technical studies on the following topics in these sectors:

- Operations and Maintenace Management
- Asset Management
- facilities Management
- Transformation for Asset Management
- Strategy planning in facilities & asset management
- Operations and Maintenace Standards
- Maintenance Performance Indicators
- Total cost of ownership
- Environment Management Systems
- Safety Management Systems
- Energy Management
- Health and safety polices
- KPI Methodologies And definition

OMAINTEC Journal
(Journal of Scientific Review)

GENERATION OF SOLUTIONS CATALOG FOR EARLY-STAGE ASSET LIFECYCLE DECISION MAKING

Adolfo Crespo del Castillo[2], Adolfo Crespo Márquez[1], Diego Pérez Oliver[1], José Antonio Marcos[3]

[1] Department of Industrial Management, School of Engineering, University of Seville, Spain

adolfo@us.es

[2] Ingeman, Association for the Development of Maintenance Engineering, School of Engineering Seville, Spain

adolfo.crespodelcas@gmail.com

[3]Patentes Talgo, Smart Maintenance Systems Department, Alcobendas, Madrid, Spain

jamarcos@talgo.com

Abstract

This paper highlights the importance of digital transformation for asset management when applied across every stage of the asset lifecycle. To achieve this, a thorough assessment of the entire asset lifecycle is essential, emphasizing the identification of key indicators that furnish valuable data for decision-making at each stage. Most of digital IAMS (Intelligent Asset Management Solutions) are focused on the O&M (operations and maintenance) stage of assets lifecycle, however, in this paper we propose a solution in the early stages of the lifecycle, that could be use either for manufacturers or asset buyers/owners. In this study, we present a solution for analysing asset needs and their future operations and maintenance plans with the aim of guiding asset acquisition decision-making based on maintenance service, type of operation, and fleet of assets size. The proposed approach utilizes discrete event simulation to predict the levels of availability for a fleet of assets under a specific demand and maintenance service type. This type of solutions guides the path to servitise not only O&M, but earlier stages of assets lifecycle, and clarify the interaction between companies that acquire valuable assets and the asset's manufacturers by defining the needs and helping to balance the capital and operational investments.

Keywords: Asset lifecycle management, Asset strategy, Asset Acquisition, Maintenance Servitisation, Discrete Event Simulation

1. Introduction

The evolution of asset lifecycle management in the context of digital transformation has become a crucial focus for businesses enabled by incorporating data from numerous sources and intelligent tools for a more informed decision-making (McKinsey & Company, 2022). In particular, the early stages of asset lifecycle management require meticulous planning aligned with specific business needs, in order to acquire, operate and maintain the optimal quantity of assets and services to achieve these business needs (Crespo Márquez, 2022; The institute of Asset Management, 2016) . However, a notable challenge lies in the lack of comprehensive mathematical tools to optimize the planning of asset and services needs to either acquire or sell valuable assets (Macchi et al., 2018). This paper addresses this gap by proposing a novel tool for asset and services acquisition, integrating intelligent features that facilitate strategic maintenance planning based on services and capabilities. The proposed tool not only fills the void in mathematical optimization tools for early asset lifecycle stages but also introduces a dynamic aspect, allowing businesses to align their asset planning with evolving service and capability requirements. Furthermore, this tool serves as a valuable resource for OEMs that not only sell their manufactured assets but also the maintenance services associated to the asset operations and maintenance lifecycle stage (Gaiardelli et al., 2021; Sala et al., 2022). This approach does not only streamline the planning process but also shapes the offer that OEMs can leverage to sell their products, thereby contributing to a more integrated and efficient approach to asset lifecycle management and allowing to servitise the assets maintenance offering multiple maintenance services associated to the manufactured product (Martinez et al., 2018; Pirola et al., 2022). On the other hand, large asset owners, particularly in sectors such as transportation or oil and gas, could derive benefits from this approach by strategically planning their asset acquisition in alignment with business needs. This entails deciding whether it is more advantageous to acquire a specific number of assets with a corresponding number of services and how to strike a balance between asset and service acquisition.

The objective of the paper is to introduce a tool designed to optimise decision-making in the early stages of the lifecycle and highlight the benefits that this solution offers to either OEMs or asset owners. Additionally, the paper reflects on the transformation of asset lifecycle management decision-making due to digitalisation. To achieve this, the paper begins by presenting the research background in section 2. Subsequently, section 3 outlines the proposed approach, applied to a case involving an asset fleet in collaboration with Talgo, a Spanish rolling stock OEM, and maintenance service experts. The results are then presented in section 4 to illustrate the benefits, and section 5 provides a concluding discussion reflecting on the solution approach.

2. The improvement of asset lifecycle decision-making through digitalisation

Effectively overseeing the complete lifecycle of assets is crucial for businesses making substantial investments, dedicating significant resources, facing performance dependencies, or dealing with risks related to asset creation, acquisition, utilization, maintenance, or disposal (The institute of Asset Management, 2016). This imperative extends to organizations managing or planning to manage a substantial portfolio of assets, where the optimal performance of asset systems and effective asset management are central to delivering services, products, or achieving broader business objectives (Zhao et al., 2022).

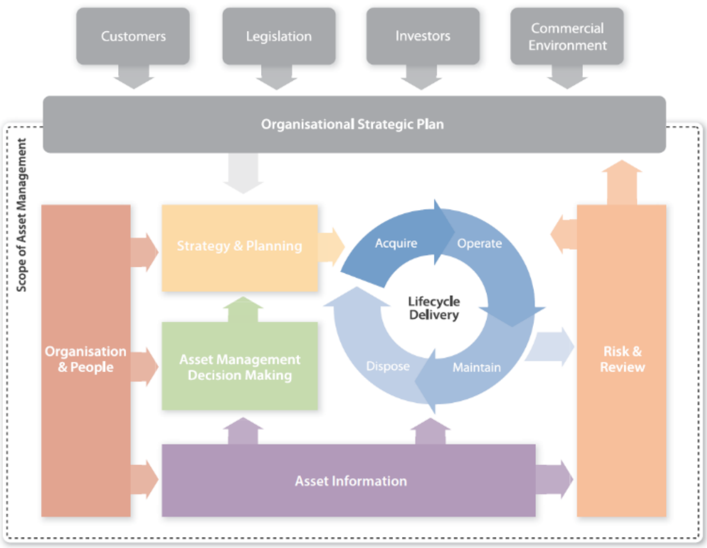


Figure 1: Asset lifecycle representation in relationship with other business dimensions (The institute of Asset Management, 2016)

Consequently, in order to optimise the value generated, the assets that are going to be acquired, operated, maintained, and disposed, have to be aligned with business strategy and needs (Figure 1), and be regulated to fulfil their function in the best manner. Thanks to digital transformation this process has become more integrated and connected, with digital solutions for each stage. However, while there are multiple solutions for operations and maintenance optimisation for either fleets or portfolios (Negri et al., 2021; Petchrompo et al., 2022), and for asset investment planning and disposal (entire lifecycle) (Crespo Del Castillo et al., 2023; Crespo Márquez et al., 2021) there is a clear gap in the planning and acquisition of assets that represents a capital connection between business strategic plan and asset management as it can be seen in the specific subject guidance of the IAM in Figure 1. The absence of solutions derives from the complexity associated with simulating or planning the maintenance and operation conditions under which assets will operate. This complexity further involves considerations of expected resources and maintenance capabilities. Consequently, the acquisition of assets by asset owners is not optimized based on potential maintenance and operation configurations. Moreover, OEMs typically offer their products and services in standardised forms rather than as customised solutions that could be designed and optimized for each individual client (Gaiardelli et al., 2021; Macchi et al., 2018; Martinez et al., 2018). Finally, an essential part of the aforementioned complexity to generate tools at the early stage of assets lifecycle, is the balance of multiple objectives to define the best solution (Erguido et al., 2022).

3. Design of a digital tool for asset requirements planning and acquisition

In this section we present a novel tool to support decision-making in the planning and acquisition phase of assets lifecycle. It could be either applied to portfolios of assets, infrastructure, or fleets of transportation assets. In the present case, we apply the solution to a fleet of trains together with the Spanish rolling stock OEM Talgo. We apply the tool to this case as a proof of concept because determining the operation and maintenance conditions of moving assets is more challenging to parameterize and calculate. The tool combines multiple dimensions that constitute the correct quantification of the assets needed, and their subsequent maintenance service, to fulfil certain operational requirements, and with certain maintenance resources limitations. In Figure 2 the solution can be observed, as a modular combination of diverse aspects.

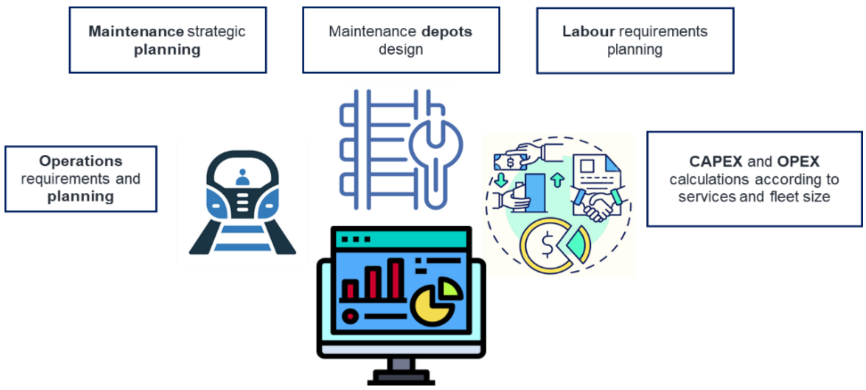


Figure 2: General view of the digital asset plan and acquisition tool

Following the structure in Figure 2, the tool comprises several dimensions with a wide range of input variation, making it highly configurable and suitable for several distinct assets. Following, we provide some insights about these inputs and clarify them by using relevant examples.

Operations requirements and planning: The first dimension to consider, is the operations service plan that the assets have to fulfil. This plan is provided based on the business objectives and corporate strategy. At this stage we consider some data such as the number of assets that will be acquired in the different scenarios to be analysed and the expected usage of these assets. For example, if a company is considering the acquisition of a new fleet of trains, the fleet size and the expected kilometres to be done in a certain planning horizon would be an input. It could also be specified an instantaneous or progressive acquisition and implementation of the assets (something relevant in critical infrastructure or highly variable demands). Additionally, the tool offers a coefficient to generate a non-equal distribution of the usage along the assets.

Maintenance strategic planning: The second dimension to consider, that is highly related to operations, is the strategic maintenance plan designed to satisfy operation requirements. This plan could vary being more or less flexible and with more or less stoppages depending on multiple factors such as fleet size, operational requirements, depot availability, and maintenance resources (Figure 3.A). The maintenance plan defines the type of asset inspections and stoppages, the activities to be done in each, and the expected duration for preventive maintenance, plus an expected percentage of corrective maintenance. To stablish the maintenance strategic plan, the tool requires different inputs. These are primarily the man-hours, setup times and hours that are required to perform the activities that are performed in each maintenance stop. Additionally, you can categorize activities, considering that interventions may be conducted in different workstations and/or require different equipment, and specify the available working capacity. It is worth mentioning that due to the correlation between hours and man-hours, a certain amount of time can be enforced for which the asset will be unavailable. For example, this commitment could be to a maximum time for completing the operation, and personnel can be calculated accordingly. Alternatively, the unavailability duration can be defined when the operation is scheduled, taking into consideration the available personnel. Besides, the solution allows to design optimised maintenance plans distributing the time and activities of the different maintenance stoppages in the depots. An interesting option is considering that a certain type of inspection might be partitioned along the usage of the asset rather than fully performed at once. Although this might imply a loss of efficiency due to setup times, the general availability of the asset could greatly improve. For example, some assets are maintained at not-working hours, therefore the asset is not expected to be available at that time and we will not incur on any penalties while carrying out maintenance activities on the asset. Partitioning the activity will result in the possibility of incurring in lower activity times per partition, giving a better chance to only work in the non-penalising intervals. These partitions of maintenance services and interventions have been done based on Talgo maintenance plans, considering the hours and activities that could be decomposed to distributing them in time packages. The calculation of these maintenance partitions is calculated using a genetic algorithm based optimiser considering the rest of inputs previously mentioned. The optimisation is performed by using a Multiple-Population Parallel Genetic Algorithm (also known as Parallel Genetic Algorithm with Islands model) (Cantú-Paz, 1998; Linder & Sekaj, 2011). In this case, the target function is minimising the variation of the workload at each maintenance stop, along all stops in a cycle.

Maintenance depots design: The maintenance plan defines a certain type of maintenance activities to be done, and then depending on the number of depots considered, a calculation will be performed to suggest a number of workstations types and the activities that could be done in each type of workstation. In the case of trains for example (Figure 3.B) each depot has a certain number of rails designed with the machinery and tools installed to carry out certain types of maintenance activities. This design is significant for maintenance execution and cost, as the machinery required for specific critical activities could be really expensive, hence not all rails would have all capabilities (Figure 3.B).

Labour requirements planning: When calculating the availability of the assets given the specified resources and preventive maintenance plan, we potentially incur in a queue problem. This queue problem requires the amount of time that the asset is expected to be available and the available working hours to perform maintenance activities, no matter whether these hours would incur or not in a penalisation due to unavailability.

OMAINTEC Journal
(Journal of Scientific Review)

CAPEX and OPEX calculations according to services and fleet size: Finally, the user of the strategic digital tool has to provide magnitudes associated to the cost (capital investment) that the assets imply, and the costs associated to different maintenance plans configurations. A service with extended stoppages in depots typically comes at a lower cost but demands a larger number of assets to ensure a specific level of availability. On the other hand, a maintenance plan with greater flexibility, involving shorter inspection and depot time, results in a higher service cost but could achieve the same level of availability with fewer assets.

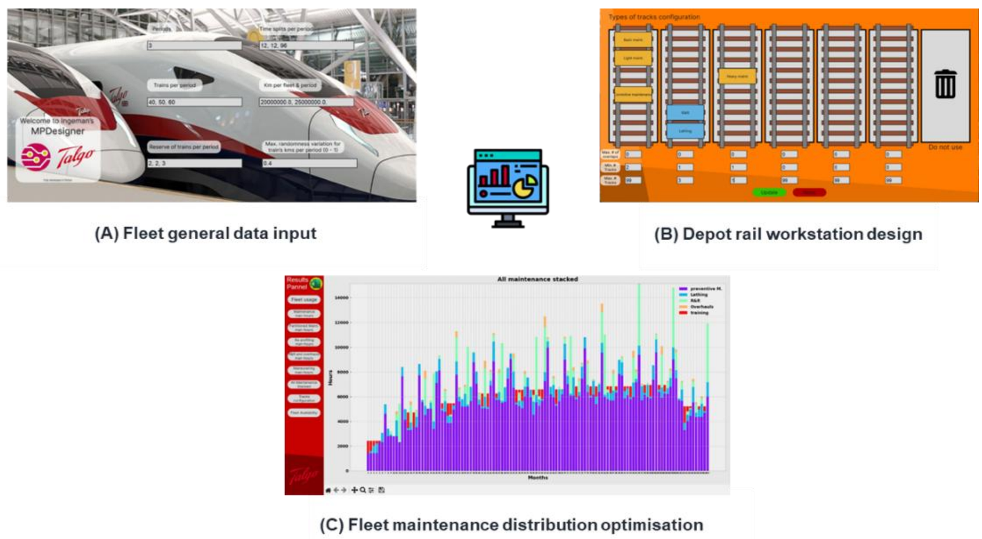


Figure 3: Different views and outputs of the digital tool presented

Outputs: When the data is inputted through the GUI, it is processed by the calculating functions in Python 3, using the discrete – event simulation package SimPy. The results are later shown in an interactive dashboard (Figure 3.C), where the workload can be displayed by different aggregations (like all together or by specialties, for example) as well as a matrix with the expected % of availability of each asset at each period of time. Additionally, a report can be automatically generated in a .xlsx file. The solutions are calculated for a certain fleet size with a CAPEX and OPEX associated, and calculating certain KPIs as fleet availability, maintenance depot utilisation, or type of maintenance service. The model is executed with different scenarios to compare the expenditures and KPIs and analyse which has the wider Value for the client according to how it is defined by the company (The institute of Asset Management, 2016), then the scenarios that add more value could be selected or ranked for the purpose.

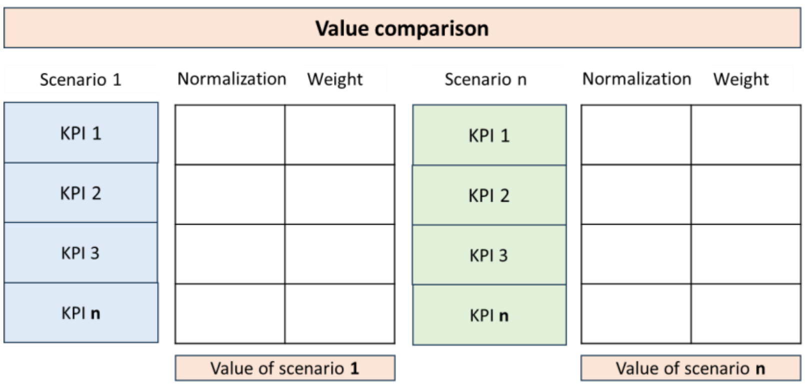


Figure 4: Scenario KPIs and value comparison

4. Concluding discussion

In this paper we present a digital solution that transforms early asset lifecycle stages to a more informed decision-making process. In the first section we introduce the background and context that motivate the creation of this solution. Following, in the second section we present a brief analysis of the state of the art of digital tools applied to different stages of asset lifecycle, in order to maximise the value. In this section we underline the lack of solutions in the planning and acquiring stages of assets, in order to optimise asset buying or selling process depending on the situation of the business in the market. Based on the findings, we present the developed tool for optimising strategic planning of operations, maintenance services and resources, and fleet size, in order to satisfy business needs structuring CAPEX and OPEX, in the way that id adds more value.

The digital tool developed show a multitude of robust features that hat position it as a significant advancement in the domain. One of its key strengths lies in its ability to offer parametrised solutions, leveraging a profound understanding of the market to deliver tailored propositions, that have a certain value for the business according to certain KPIs that are measured. The tool facilitates the exploration of diverse maintenance configurations and services, providing users the flexibility to meet demand with varying numbers of assets fleet and different maintenance options. Furthermore, it empowers OEMs to embrace servitisation, enabling them to venture into new markets and expand their offerings through a comprehensive catalogue. A notable advantage for buyers is the tool's capacity to allow them to configure their investments, striking a balance between a substantial initial investment in assets with a corresponding maintenance service or opting for a more flexible service spread across years with lower initial asset costs. This strategic flexibility not only enhances the adaptability of services but also accelerates the amortisation of initial investments, demonstrating the tool's prowess in optimizing both operational and financial aspects of business ventures.

6. References

- Cantú-Paz, E. (1998). A Survey of Parallel Genetic Algorithms. *Calcul. Paralleles Reseaux Syst. Repart.*, *10*(2), 141–171.
- Crespo Del Castillo, A., Sasidharan, M., Nentwich, C., Merino, J., & Kumar Parlikad, A. (2023). Data-Driven Asset Health Index–an application to evaluate Quay Cranes in container ports. *Maritime Policy and Management*, *00*(00), 1–19. https://doi.org/10.1080/03088839.2023.2231449
- Crespo Márquez, A. (2022). *Digital Maintenance Management*. Springer US.
- Crespo Márquez, A., Serra Parajes, J., de la Fuente Carmona, A., & Sola Rosique, A. (2021). Integrating complex asset health modelling techniques with continuous time simulation modelling: A practical tool for maintenance and capital investments analysis. *Computers in Industry*, *133*. https://doi.org/10.1016/j.compind.2021.103507
- Erguido, A., Marquez, A. C., Castellano, E., Parlikad, A. K., & Izquierdo, J. (2022). Asset Management Framework and Tools for Facing Challenges in the Adoption of Product-Service Systems. *IEEE Transactions on Engineering Management*, *69*(6), 2693–2706. https://doi.org/10.1109/TEM.2019.2951438
- Gaiardelli, P., Pezzotta, G., Rondini, A., Romero, D., Jarrahi, F., Bertoni, M., Wiesner, S., Wuest, T., Larsson, T., Zaki, M., Jussen, P., Boucher, X., Bigdeli, A. Z., & Cavalieri, S. (2021). Product-service systems evolution in the era of Industry 4.0. In *Service Business* (Vol. 15, Issue 1). Springer Berlin Heidelberg. https://doi.org/10.1007/s11628-021-00438-9
- Linder, M., & Sekaj, I. (2011). Parallel genetic algorithms. *Mendel*, *53*(4), 9–15. https://doi.org/10.1145/3400031
- Macchi, M., Roda, I., Negri, E., & Fumagalli, L. (2018). Exploring the role of Digital Twin for Asset Lifecycle Management. *IFAC-PapersOnLine*, *51*(11), 790–795. https://doi.org/10.1016/j.ifacol.2018.08.415
- Martinez, V., Ouyang, A., Neely, A., Burstall, C., & Bisessar, D. (2018). Service business model innovation : the digital twin technology. *Cambridge Service Alliance:*, *November*, 1.
- McKinsey & Company. (2022). Capturing the true value of Industry 4 . 0. *McKinsey & Company*, *April*, 1–8. https://www.mckinsey.com/business-functions/operations/our-insights/capturing-the-true-value-of-industry-four-point-zero
- Negri, E., Pandhare, V., Cattaneo, L., Singh, J., Macchi, M., & Lee, J. (2021). Field-synchronized Digital Twin framework for production scheduling with uncertainty. *Journal of Intelligent Manufacturing*, *32*(4), 1207–1228. https://doi.org/10.1007/s10845-020-01685-9
- Petchrompo, S., Wannakrairot, A., & Parlikad, A. K. (2022). Pruning Pareto optimal solutions for multi-objective portfolio asset management. *European Journal of Operational Research*, *297*(1), 203–220. https://doi.org/10.1016/j.ejor.2021.04.053
- Pirola, F., Pezzotta, G., Amlashi, D. M., & Cavalieri, S. (2022). Design and Engineering of Product-Service Systems (PSS): The SEEM Methodology and Modeling Toolkit. *Domain-Specific Conceptual Modeling: Concepts, Methods and ADOxx Tools*, *Kowalkowski 2016*, 385–407. https://doi.org/10.1007/978-3-030-93547-4_17
- Sala, R., Pirola, F., Pezzotta, G., & Cavalieri, S. (2022). Data-Driven Decision Making in Maintenance Service Delivery Process: A Case Study. *Applied Sciences (Switzerland)*, *12*(15). https://doi.org/10.3390/app12157395
- The institute of Asset Management. (2016). Risk Assessment and Management. *IAM*, V1-361-V1-380. https://doi.org/www.theIAM.org
- Zhao, X., Liang, Z., Parlikad, A. K., & Xie, M. (2022). Performance-oriented risk evaluation and maintenance for multi-asset systems: A Bayesian perspective. *IISE Transactions*, *54*(3), 251–270. https://doi.org/10.1080/24725854.2020.1869871

OMAINTEC Journal
(Journal of Scientific Review)

DIGITAL TWIN EMERGING TECHNOLOGY: EMPOWERING PREDICTIVE MAINTENANCE FOR ENHANCED EQUIPMENT RELIABILITY AND OPERATIONAL EFFICIENCY

Mohammed AL-Sadig AL-Haj

Sulaiman Al Rajhi University, Saudi Arabia
mmalhag054@gmail.com

Abstract:
Predictive maintenance has gained significant attention as a crucial system capability in accurately identifying impending machine failures and scheduling timely repairs. With the advent of technologies like the Internet of Things, Big Data, and Artificial Intelligence, a new data-driven paradigm known as the digital twin has emerged, capturing the interest of researchers and industry stakeholders. This paper thoroughly explores the role of digital twin technology in predictive maintenance, specifically focusing on its potential to overcome the limitations associated with accuracy, reliability, and adaptability. It provides an in-depth examination of the technical features and real-world applications of digital twin technology in fault diagnosis, prediction, and maintenance decision-making. The primary objective of this study is to provide valuable insights and practical recommendations to organizations seeking to elevate their maintenance practices through the adoption of digital twin-based predictive maintenance strategies. By conducting a comprehensive review of two scientific papers that develop digital twin models for monitoring and maintaining electrical machines, this paper emphasizes the practical implementation and tangible benefits of digital twin technology in the field of predictive maintenance. It highlights the potential for cost reduction, increased productivity, and improved maintenance schedules across diverse industries. In conclusion, this paper contributes to the advancement of digital twin technology in predictive maintenance by underscoring the significance of digital twins in enhancing equipment reliability and operational efficiency. It emphasizes the need for continuous research and development efforts to fully harness the transformative potential of digital twin-based predictive maintenance systems.

Keywords: digital twin technology; predictive maintenance;

1.Introduction:

1.1.Overview

The process of equipment repair and maintenance is of paramount importance. It encompasses the regular assessment of equipment condition, addressing equipment failures, and mitigating the risks of secondary damage and operational downtime. The efficiency of these maintenance activities directly impacts operational time and work productivity. Consequently, a proposed approach known as predictive maintenance (PdM) has emerged. PdM falls under the category of prognostics and health management (PHM), which is a technological framework that relies on historical data, mechanistic models, and domain expertise. By utilizing statistical analysis or machine learning models, PdM can forecast equipment trends, behavioral patterns, and correlations. This capability enables the prediction of upcoming failures, estimation of remaining useful life, and identification of other key indicators in advance. The implementation of PdM enhances the decision-making process regarding maintenance activities, reduces the risks associated with equipment failures, and helps avoid premature equipment shutdowns [1].

While an increasing number of enterprises have come to recognize the benefits of predictive maintenance [4], its practical implementation remains limited. Presently, predominant maintenance approaches still revolve around post-maintenance and extensive preemptive maintenance [4,5]. This situation predominantly stems from the challenges associated with the accuracy, reliability, and adaptability of predictive maintenance [6]. Researchers are actively seeking suitable methods to address these issues. Through the examination of technical attributes and real-world applications, it has been ascertained that digital twin technology offers a potential solution to enhance or overcome these shortcomings in fault diagnosis, prediction, and maintenance decision-making [7,8]. A digital twin is a pivotal enabling technology, representing the virtual counterparts of physical entities, processes, and real-time data encompassing the entire product lifecycle [9]. The concept was initially introduced by Greives in a discussion on Product Lifecycle Management (PLM) in 2002 and was later redefined by Greives and Vickers in 2012 [10], describing it as the digital representation of physical assets and the automated interconnection of these representations. Digital twins exhibit attributes such as interactive feedback between the virtual and physical realms, data fusion and analysis, and iterative optimization of decision-making. Their applicability spans across various scenarios [1].

1.2.Objective:

- Explore the potential of digital twin technology in addressing the limitations of predictive maintenance, specifically accuracy, reliability, and adaptability.
- Analyze the technical characteristics and application cases of digital twin technology in fault diagnosis, prediction, and maintenance decision-making.
- Provide insights and recommendations for enterprises seeking to enhance their maintenance practices through the implementation of digital twin-based predictive maintenance strategies.

1.3.Motivation:

- Limited adoption of predictive maintenance despite its recognized advantages.
- Concerns regarding the accuracy, reliability, and adaptability of existing predictive maintenance approaches.
- Recognition of digital twin technology as a promising solution to overcome these limitations.
- Potential benefits of digital twin technology in improving fault diagnosis, prediction, and maintenance decision-making processes.
- Desire to optimize maintenance activities, reduce downtime, and enhance operational efficiency.

2.Digital Twins

2.1.Concept

The concept of Digital Twin emerged in 2011 as a way to predict an aircraft's behavior by simulating its digital model. NASA later defined Digital Twin as a probabilistic simulation of a vehicle or system that mirrors the life of its physical counterpart using various models, sensor updates, and fleet history [13]. In 2015, advancements in machine learning, wireless communication, and cloud computing led to increased research on Digital Twin. Different definitions of Digital Twin emerged, such as it being the next generation of simulation or a method to bridge the gap between physical and virtual spaces [12]. Nowadays, Digital Twin has evolved into a broader concept that represents virtual versions of manufacturing elements like personnel, products, assets, and processes. This virtual representation continuously updates to reflect changes in the physical counterpart, including status, working conditions, geometries, and resource states. Data can flow between the physical and digital representations through secure computer networks, the Internet, and communication protocols. It's worth noting that while the Internet of Things (IoT) enables connectivity in physical space, it does not encompass the idea of digital models in cyberspace. The IoT serves as the infrastructure for connecting physical assets[11].

Although various definitions of DT (Digital Transformation) have been proposed by academia and industry, there is consensus regarding its numerous benefits. These advantages include cost and time reduction, increased productivity, enhanced decision-making processes, improved maintenance schedules and activities, remote access, a safer operational environment, and the promotion of sustainability [15]. Consequently, the adoption of DTs in diverse sectors has witnessed accelerated growth in recent years. According to Grand View Research, the global DT market was valued at USD 5.04 billion in 2020 and is projected to reach USD 86.09 billion by 2028, with a compound annual growth rate of 42.7% from 2021 to 2028 [16]. The outbreak of the COVID-19 pandemic has contributed to the heightened demand for DTs [17,18]. Lockdown measures resulting from the pandemic disrupted supply chains, caused workforce shortages, and necessitated remote or non-contact working environments [19]. Consequently, the digitization of processes with minimal human interaction and advancement in this area have gained significant importance [17]. A survey conducted by Gartner revealed that 31% of companies are utilizing DT for remote asset monitoring, aiming to reduce the need for in-person monitoring in sectors such as healthcare and mining, thus enhancing employee and customer safety [20].

DT technology has found applications in various industries undergoing digital transformation. Martin and Nadja's study [21] identified ten major sectors where DT has been implemented: Aerospace, Manufacturing, Healthcare, Energy, Automotive, Petroleum, Public sector, Mining, Marine, and Agricultural. The authors noted that DT in these industries primarily serves three purposes: simulation, monitoring, and control. However, DT applications extend beyond these purposes to encompass design, validation, customization, optimization, prediction, and maintenance. According to Juniper Research, manufacturing is expected to lead in DT deployment by 2021 (34%), followed by the energy sector (18%) [22].

2.2.Components

Digital Twin is comprised of three components Figure 1:

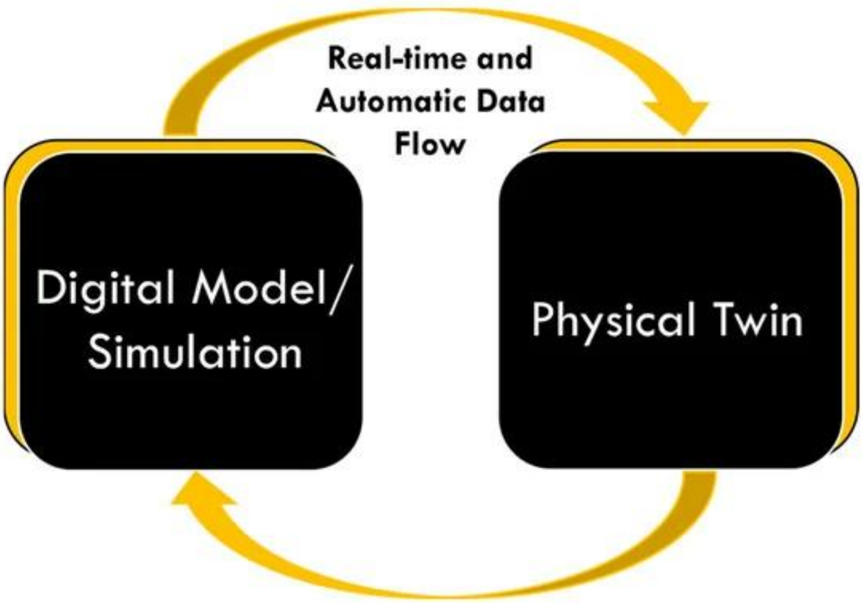


Figure 1. Block diagram of a Digital Twin components [2] .

1. **Physical twin:** A real-world entity (living/non-living) such as part/product, machine, process, organization, or human, etc.

2. **Digital twin:** The digital representation of the physical twin with the capability to mimic/mirror its physical counterpart in real time.

3. **Linking mechanism:** The bidirectional flow of data between the two which operates automatically in real-time.

3.Predictive Maintenance:

3.1.Overview

Predictive maintenance (PdM) is a type of maintenance strategy that involves condition-based maintenance. It utilizes regular or continuous monitoring of system components to assess the equipment's status, predict future trends in equipment status, and proactively plan maintenance activities based on the anticipated development and potential failure modes of the equipment. The key components of predictive maintenance include equipment condition monitoring, fault diagnosis, residual life prediction, and maintenance decision-making.

In the manufacturing field, Wang proposed a system function model for predictive maintenance. The model includes data acquisition and processing, state identification, fault identification and location, health prediction, maintenance management, and maintenance execution[14]. Data acquisition and processing involve the use of sensors and data collectors to gather information about the equipment's status and associated environment. This data is then processed to extract relevant information for further analysis. State identification refers to analyzing the collected data to determine the current state of the equipment. This analysis involves preprocessing and feature analysis of acquired data to identify patterns and thresholds that indicate the equipment's condition. Fault identification and location can be achieved through different methods. Mechanism model-based methods involve establishing simulation models based on the equipment's mechanical and circuit principles. Data-driven methods, on the other hand, utilize input and output data collected in real-world operating conditions to establish relationships and distinguish between normal and abnormal states.

Health prediction involves evaluating the equipment's health status and predicting its future change trend using state parameters and characteristic signals. Various analysis methods and prediction models are employed for this purpose. The prediction of remaining useful life (RUL) is often expressed as a percentage and can help determine maintenance needs. Maintenance management and maintenance execution focus on developing maintenance strategies based on the results of health state prediction. These strategies consider factors such as safety, cost, and enterprise equipment management to optimize maintenance activities. Predictive maintenance is gaining prominence in the context of Industry, as it leverages data collected from multiple sensors in manufacturing environments. It offers opportunities for accurate remaining life prediction, scheduling actions based on equipment performance, and reducing maintenance costs and downtime while improving productivity and quality.
Overall, predictive maintenance is a valuable approach that combines data acquisition, analysis, and intelligent methods to predict equipment failures, optimize maintenance processes, and contribute to the implementation of Industry [1].

3.2.Predictive Maintenance in electrical Machines

In recent years, there has been a renewed interest in the research activity surrounding Predictive Maintenance (PM) of Electrical Machines (EM) as industrial and commercial applications continue to diversify and expand into new areas. The role of EMs in these applications has become increasingly prominent. Traditionally, the focus of the sector has been on Squirrel Cage (SC) Induction Motors (IMs) and conventional rotor Synchronous Machines (SMs), as they have dominated motor and generator applications respectively. However, there has been a shift in the relative usage of EMs, with other types gaining popularity over SCIMs and SMs. These include Wound-Rotor (WR) IMs, particularly as generators in wind turbines, Permanent Magnet (PM) SMs mainly used in electric vehicles, multiphase Alternating Current (AC) machines, and Switched or Synchronous Reluctance Machines (SRMs or SyncRMs). This shift can be attributed to advancements in materials, design and control architectures, the exponential growth of generators in Renewable Energy Sources (RES), and the specific requirements of new applications, such as spatial availability (power density), efficiency targets, and fault-tolerant systems. Additionally, significant advancements in computing power, sensor technology, artificial intelligence, and Internet-of-Things (IoT) applications have opened up new research avenues, allowing for the development of novel approaches and powerful tools for both laboratory tests and industrial on-site applications. This has promoted the combination of different techniques in the field.

EMs play a critical role in their respective applications, as they constitute the core part and have a direct impact on the condition and performance of the overall system. Being electromechanical processes, EMs are susceptible to various faults of varying severity. Breakdowns during operation can lead to significant economic and safety consequences, including high repair costs, unscheduled production halts, increased man-hours, and missed deadlines. Moreover, faulty operation can significantly reduce efficiency and pose safety hazards. Therefore, timely and accurate fault diagnosis is of paramount importance to the industry. It allows for the scheduling of necessary repairs during planned downtime and helps prevent breakdowns. Additionally, online Condition Monitoring (CM), which is a key component of PM, ensures that processes run with optimal efficiency, further reducing operating costs and the need for reserves. These efforts are supported by the development of cost-effective sensors, advanced Data Acquisition (DAQ) techniques, and evaluation methods [3].

4.Review methodologies:

In this section, a literature review will be conducted of two scientific papers, which are a study of two machines that create a digital twin model. The literature review focuses on the methodology and results of these two studies[23,24]:

1-Digital Twin-Based Monitoring System of Induction Motors Using IoT Sensors and Thermo-Magnetic Finite Element Analysis:

This Paper focuses on the development of a monitoring system, referred to as the Motor Monitoring and Analysis System (SMAM), which utilizes IoT sensors and thermal and magnetic finite element analysis for the monitoring and analysis of induction motors. The system aims to monitor motor current and temperature using low-cost sensors and transmit the measurements wirelessly to a database. The utilization of the Digital Twin (DT) concept enables a comprehensive analysis of the motor's behavior.

Surveillance System Architecture:

The SMAM monitoring system is comprised of four key stages: electrical machine monitoring, current and temperature acquisition, cloud storage, and subsequent data processing through finite element analysis (FEA) and real-time graphing. Sensors connected to the motor continuously measure temperature and supply current, while an IoT microcontroller samples the sensor readings and transmits the data via Wi-Fi to a cloud platform. The collected data is stored in a database and can be accessed in real-time through a web page for visualization and analysis.

Monitoring Stage: Current and Temperature Analysis:

To evaluate the system's performance, the supply current and temperature of the induction motor were monitored at various load levels. The collected current data from both the calibrated SMAM sensor and a commercial sensor showed good agreement in both transient and steady-state regimes. The relative error between the SMAM readings and the commercial sensors was 13.6% at peak onset and 4.4% on average during steady-state, indicating that low-cost sensors can provide accurate measurements when integrated with IoT and DT concepts.

Temperature measurements were conducted using thermocouples, a thermal camera, and simulations based on a thermomagnetic finite element model. The measured temperatures from different sensors displayed a consistent pattern of temperature increase with higher load levels, aligning with expectations due to increased heat dissipation. The simulated temperatures tended to be slightly higher than the measured values, potentially due to the lack of consideration for heat exchange with the surrounding air in the simulations.

Implications and Conclusion:

The proposed monitoring system, which combines IoT sensors and thermal and magnetic finite element analysis, allows for a comprehensive analysis of the operational state of the induction motor. The integration of IoT and DT concepts provides valuable insights into the motor's behavior and facilitates predictive maintenance. The obtained results demonstrate the feasibility of utilizing low-cost sensors in large-scale applications with minimal compromise to accuracy. The system holds potential applications in the industrial sector, enabling improved diagnosis of motor health and estimation of maintenance schedules.

Overall, this paper presents a novel approach to monitoring and maintaining induction motors using digital twin and IoT technologies. The combination of real-time sensor data acquisition, cloud storage, and finite element analysis provides a powerful tool for predictive maintenance and fault detection. The obtained results validate the effectiveness of the proposed system and lay the foundation for future research and development in this field.

2-Building a Digital Twin Powered Intelligent Predictive Maintenance System for Industrial AC Machines:
The paper presents a comprehensive study in the realm of digital twin technology, predictive maintenance, and fault diagnosis in the context of industrial AC machines.
Focus on Squirrel Cage Induction Motors:

The paper highlights that squirrel cage induction motors are central to industrial machinery but are underrepresented in the digital twin domain. The study aims to address this gap by creating a digital twin for a 2.2 kW squirrel cage induction motor. It does so by utilizing data-driven modeling and integrating it with a custom predictive maintenance system.

Key Objectives and Contributions:
The primary objective of the study is to implement digital twin technology for induction motors, specifically for fault diagnosis and predictive maintenance. The digital twin framework developed in the paper has the capability to predict remaining useful life and diagnose erratic faults in the motor.

Experimental Setup:
The paper discusses the integration of the 2.2 kW squirrel cage induction motor into a digital workspace using the dSPACE MicroLabBox controller. The digital framework is deployed in MATLAB Simulink, emphasizing high accuracy without excessive computational load on the processor.

Fault Detection and Diagnostic Features:
The paper presents results related to fault detection. It introduces fault codes for healthy, single phase-to-ground faults, and three-phase-to-ground faults. The data used for training the model comes from both healthy operational data and data with simulated faults. The paper demonstrates the increased amplitude of phase current in the presence of a fault, which can lead to temperature rise and mechanical noise.

Remaining Useful Life (RUL) Estimation:
The paper discusses the estimation of remaining useful life by analyzing features such as spectral kurtosis and other time-domain and frequency-domain attributes. The estimation of RUL becomes more accurate with an increasing amount of data.

Integration of Digital Twin and Hardware Rig:
The study demonstrates the integration of the digital twin with a hardware rig to detect lower-scale fault occurrences without overloading the system's processing and memory resources.

Benefits of the Developed Architecture:
The paper emphasizes the benefits of the developed architecture, including reduced reliance on hardware testbeds, reduced resource and cost requirements, and the potential for more comprehensive and low-cost machine maintenance setups.

Conclusions:
In conclusion, the paper underlines the significance of digital twin technology in the context of Industry 4.0 and its role in preventative maintenance. It highlights the unique application of digital twin technology to SCIMs and presents a hybrid predictive maintenance system that can be a valuable commercial platform for industrial SCIMs.

Overall, the paper contributes to the field of digital twin technology, predictive maintenance, and fault diagnosis in industrial AC machines, particularly in the context of squirrel cage induction motors. It provides insights into the development of a practical and efficient system that can benefit the industry and pave the way for future advancements in this domain.

Conclusion for review:
Both of the mentioned papers have made effective and valuable contributions to this important and promising field. However, continuous improvement and ongoing development are necessary to further advance it. Our work aims to actively contribute to this progress by focusing on its improvement and integrating the two methodologies. Additionally, we strive to develop it into a training platform for maintenance tasks.

5.Conclusion:

In conclusion, the paper presents a comprehensive overview of the digital twin, covering its history, uses, components, and its potential in addressing the limitations of predictive maintenance. It emphasizes the significance of predictive maintenance, particularly for electrical equipment and machines, and highlights the role of the digital twin and predictive maintenance via the Internet of Things in reducing downtime and improving operational efficiency. However, the paper also stresses the importance of further research and development to enhance these methodologies and ensure their applicability across various industrial sectors.

Furthermore, the paper reviews two scientific papers that focus on creating digital twin models for monitoring and maintaining electrical machines. It underscores the practical application of digital twin technology in predictive maintenance and emphasizes its benefits, including cost reduction, increased productivity, and improved maintenance schedules, in different industrial sectors.

In summary, this paper contributes to the ongoing advancement of digital twin technology in the context of predictive maintenance. It provides valuable insights into the potential of digital twin-based approaches to enhance equipment reliability and operational efficiency. The paper underscores the need for continuous research and development efforts to fully realize the benefits of digital twin-based predictive maintenance systems in industrial applications.

Future work:

In future work, we will integrate the two mentioned approaches in the reviewed scientific papers and create a digital twin for the equipment at Suleiman Al Rajhi University to monitor the physical twin, detect faults, and enhance predictive maintenance. Additionally, we will work on developing this work to serve as a model for training and education in the field of maintenance and operations.

Reference:

[1] Zhong, D., Xia, Z., Zhu, Y., & Duan, J. (April 2023). "Overview of predictive maintenance based on digital twin technology." Heliyon Journal, Volume(Issue), Article e14534. DOI: 10.1016/j.heliyon.2023.e14534.
[2] Singh, Maulshree, Rupal Srivastava, Evert Fuenmayor, Vladimir Kuts, Yuansong Qiao, Niall Murray, and Declan Devine. 2022. "Applications of Digital Twin across Industries: A Review" Applied Sciences 12, no. 11: 5727. https://doi.org/10.3390/app12115727
[3] Falekas, Georgios, and Athanasios Karlis. 2021. "Digital Twin in Electrical Machine Control and Predictive Maintenance: State-of-the-Art and Future Prospects" Energies 14, no. 18: 5933. https://doi.org/10.3390/en14185933
[4] E. Ruschel, E.A.P. Santos, E.D.R. Loures, Industrial maintenance decision-making: a systematic literature review, J. Manuf. Syst. 45 (2017) 180–194.
[5] A.K.S. Jardine, D.M. Lin, D. Banjevic, A review on machinery diagnostics and prognostics implementing condition-based maintenance, Mech. Syst. Signal
Process. 20 (2006) 1483–1510.
[6] X.M. Sun, J.S. Bao, J. Li, Y.M. Zhang, S.M. Liu, B. Zhou, A digital twin-driven approach for the assembly-commissioning of high precision products, Robot. Comput. Integrated Manuf. 61 (2020), 101839.
[7] J. Cheng, H. Zhang, F. Tao, C.F. Juang, DT-II:Digital twin enhanced Industrial Internet reference framework towards smart manufacturing, Robot. Comput. Integrated Manuf. 62 (2020), 101881.
[8] Q.L. Qi, F. Tao, T.L. Hu, N. Anwer, A. Liu, Y.L. Wei, L.H. Wang, A.Y.C. Nee, Enabling technologies and tools for digital twin, J. Manuf. Syst. 58 (2021) 3–21.
[9] J.J. Wu, Y.H. Yang, X. Cheng, H.F. Zuo, Z. Cheng, Ieee, the Development of Digital Twin Technology Review, Chinese Automation Congress (CAC), PEOPLES R CHINA, Shanghai, 2020, pp. 4901–4906.
[10] M. Grieves, J. Vickers, Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems, in: F.-J. Kahlen, S. Flumerfelt, A. Alves (Eds.), Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches, Springer International Publishing, Cham, 2017, pp. 85–113.
[11] Y.Q. Lu, C. Liu, K.I.K. Wang, H.Y. Huang, X. Xu, Digital Twin-driven smart manufacturing: connotation, reference model, applications and research issues, Robot. Comput. Integrated Manuf. 61 (2020) 1–14.
[12] E.J. Tuegel, A.R. Ingraffea, T.G. Eason, S.M. Spottswood, Reengineering aircraft structural life prediction using a digital twin, Int. J. Aerospace Eng. 2011 (2011) 1–14, https://doi.org/10.1155/2011/154798.
[13] E.E.H. Glaessgen, D.D.S. Stargel, The digital twin paradigm for future NASA and US air force vehicles, in: 53rd AIAA/ASME/ASCE/AHS/ASC structures, Structural Dynamics and Materials Conference 20th AIAA/ASME/AHS Adaptive Structures Conference 14th AIAA, 2012, p. 1818.
[14] C. Wang, Technology Research and Standard Development of Predictive Maintenance for Intelligent Manufacturing Equipment, China Standardization, 2021, p. 7.
[15] Singh, Maulshree, Evert Fuenmayor, Eoin P. Hinchy, Yuansong Qiao, Niall Murray, and Declan Devine. 2021. "Digital Twin: Origin to Future" *Applied System Innovation* 4, no. 2: 36. https://doi.org/10.3390/asi4020036
[16] Digital Twin Market Size, Share & Trends Analysis Report by End-Use (Automotive & Transport, Retail & Consumer Goods, Agriculture, Manufacturing, Energy & Utilities), by Region, and Segment Forecasts, 2021–2028. 2021. Available online: **https://www.grandviewresearch.com/industry-analysis/digital-twin-market** (accessed on 20 December 2021).
[17] T. Erol, A. F. Mendi and D. Doğan, "Digital Transformation Revolution with Digital Twin Technology," *2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, Istanbul, Turkey, 2020, pp. 1-7, doi: 10.1109/ISMSIT50672.2020.9254288.
[18] Digital Twin Market by Technology, Type (Product, Process, and System), Application (predictive maintenance, and others), Industry (Aerospace & Defense, Automotive & Transportation, Healthcare, and others), and Geography—Global Forecast to 2026. 2020, p. 177. Available online: **https://www.researchandmarkets.com/reports/5146336/digital-twin-market-by-technology-type-product** (accessed on 20 December 2021).
[19] Shen, W.; Yang, C.; Gao, L. Address business crisis caused by COVID-19 with collaborative intelligent manufacturing technologies. *IET Collab. Intell. Manuf.* **2020**, *2*, 96–99. [**Google Scholar**] [**CrossRef**]
[20] Gartner Survey Reveals 47% of Organizations Will Increase Investments in IoT Despite the Impact of COVID-19. 2020. Available online: **https://www.gartner.com/en/newsroom/press-releases/2020-10-29-gartner-survey-reveals-47-percent-of-organizations-will-increase-investments-in-iot-despite-the-impact-of-covid-19-#:~:text=By%202023%2C%20One%2DThird%20of,survey*%20from%20Gartner%2C%20Inc** (accessed on 20 December 2021).

[21] Enders, M.R.; Hoßbach, N. Dimensions of Digital Twin Applications-A Literature Review. In Proceedings of the Americas Conference on Information Systems, Cancun, Mexico, 15–17 August 2019. [**Google Scholar**]
[22] D'mello, A. Spend on Digital Twins to Reach $12.7bn by 2021, as Solutions Offer IoT Investment RoI. 2020. Available online: **https://www.iot-now.com/2020/06/02/103204-spend-on-digital-twins-to-reach-12-7bn-by-2021-as-solutions-offer-iot-investment-roi/** (accessed on 20 December 2021).
[23] Singh, R. Raja, Ghanishtha Bhatti, Dattatraya Kalel, Indragandhi Vairavasundaram, and Faisal Alsaif. 2023. "Building a Digital Twin Powered Intelligent Predictive Maintenance System for Industrial AC Machines" *Machines* 11, no. 8: 796. https://doi.org/10.3390/machines11080796
[24] J. F. D. Santos *et al.*, "Digital Twin-Based Monitoring System of Induction Motors Using IoT Sensors and Thermo-Magnetic Finite Element Analysis," in *IEEE Access*, vol. 11, pp. 1682-1693, 2023, doi: 10.1109/ACCESS.2022.3232063.

OMAINTEC Journal
(Journal of Scientific Review)

Optimal Automated Designing Process for Annual Planning and Workload Distribution of Work Orders

Dr. Tarek M. M. Nasab
Lebanese International University
Saida, Lebanon
tarek.nasab@liu.edu.lb

Abstract
Effective planning of preventive maintenance work orders is crucial for the optimal performance and longevity of equipment and systems in various industries. This study investigates a strategic approach to scheduling preventive maintenance tasks by aligning them with common maintenance frequencies, synchronized execution hours, and consistent manpower allocation. The objective is to streamline maintenance operations, minimize downtime, and enhance overall efficiency. By analyzing historical maintenance data and identifying patterns in maintenance needs, the research proposes a model that groups work orders based on their frequency of occurrence, ensuring that tasks requiring similar intervals of attention are scheduled concurrently. Additionally, the model standardizes the execution hours for maintenance activities, allowing for better coordination and reduced disruption to operational workflows. The allocation of manpower is optimized to maintain a uniform number of personnel assigned to maintenance tasks, balancing the workload and preventing bottlenecks. The findings indicate that such an integrated planning approach can significantly improve the predictability and effectiveness of maintenance operations, leading to cost savings and improved asset reliability. This study provides a framework for maintenance managers to enhance their preventive maintenance strategies, ensuring that resources are utilized efficiently and maintenance activities are performed with minimal impact on productivity.

1 Introduction

A Computerized Maintenance Management System (CMMS) provides a comprehensive database of all assets within an organization, including equipment, machinery, and facilities. This ensures that maintenance teams have accurate and up-to-date information about each asset. One of the key features of CMMS is the ability to schedule and automate preventive maintenance tasks. This helps in preventing breakdowns, reducing downtime, and extending the lifespan of equipment. By implementing a proactive maintenance strategy, organizations can save costs associated with reactive repairs and replacements. The conventional strategy for the CMMS is to repeat the maintenance cycle for issuing PM work orders as per the previous year with modifications as per the request; if exists. The proposed optimal automated designing process presents a strategy for the annual planning and workload distribution for work orders that will be based on the input database provided by the CMMS. This strategy is based on the forecasted time required for each PM equipment type plus the required manpower to execute the PM maintenance work for each equipment. A study case is presented that represent the practical application of this strategy on South Lebanese Water Establishment (SLWE) Foundation.

OMAINTEC Journal
(Journal of Scientific Review)

2 Advantages & Disadvantages of PM Grouping of Work Orders

Grouping preventive maintenance work orders can have both advantages and disadvantages [1]. Here are some of them:

Efficiency and Time Saving: 1. **Streamline Planning:** Grouping similar preventive maintenance tasks allows for more efficient planning. You can schedule and organize work orders in a way that minimizes downtime and maximizes productivity. 2. **Bulk Scheduling:** Performing maintenance on multiple assets or systems at once can save time compared to scheduling individual tasks separately.	Advantages
Resource Optimization: 1. **Optimal Resource Allocation:** Grouping work orders helps in optimizing the use of resources such as manpower, tools, and equipment. Technicians can work on related tasks without the need to switch between different types of jobs frequently. 2. **Reduced Time Travel:** If tasks are grouped based on location, it can minimize travel time for maintenance crews.	
Consistency: 1. **Standardization:** Grouping work orders enables the standardization of maintenance procedures. This consistency can lead to better results and more reliable equipment performance.	
Cost Saving: 1. **Economies of Scales:** When maintenance tasks are grouped, there is a potential for cost savings due to economies of scale, especially when ordering parts or materials in bulk.	
Overlooked Details: 1. **Missed Specifics:** Grouping work orders may lead to overlooking specific requirements of individual assets. Some assets might have unique needs that could be neglected in a generalized maintenance approach.	Disadvantages
Flexibility Challenges: 1. **Limited Flexibility:** Grouping work orders may limit flexibility in scheduling, especially when unexpected issues arise. If all tasks are tightly grouped, it may be challenging to accommodate urgent maintenance needs.	Disadvantages

Complexity: 1. **Increasing Complexity:** Managing a large number of tasks in a group can increase the complexity of coordination and oversight. This complexity may lead to confusion or errors if not managed properly.	**Disadvantages**

Table1. Advantages & Disadvantages of Grouping of PM Work Orders

Striking a balance between efficiency and flexibility is crucial to ensuring the effectiveness of preventive maintenance strategies.

3 Strategies & Approaches Application for Planning PM Work Orders for the Yearly Maintenance Cycle

There are different strategies and approaches that can be used to plan work orders for the whole yearly maintenance cycle. Some of these strategies and processes represents the methods that are listed in Table 2:

Calendar-Based Scheduling	It is a maintenance strategy where tasks are scheduled at regular intervals, regardless of the asset's condition. This approach is often used when equipment requires regular maintenance to ensure reliable operation, even if there are no immediate signs of wear or failure. [2]
Condition-Based Maintenance (CBM)	It is a comprehensive and systematic approach to maintenance planning that focuses on preserving the function of critical assets while minimizing costs. The primary goal of RCM is to determine the most effective maintenance strategies to ensure that assets continue to operate reliably within their intended functions. This approach considers the different types of failures that can occur, the consequences of those failures, and the best ways to mitigate those risks. [3]
Run-Time-Based Scheduling	It is a maintenance strategy where tasks are scheduled based on the actual runtime of equipment or machinery, rather than on calendar time or condition. This method is particularly useful for equipment that operates under varying usage patterns, ensuring that maintenance is aligned with the actual wear and tear the equipment experiences. [4]
Task Grouping	It is a maintenance strategy where similar or related tasks are grouped together and scheduled to be performed at the same time. This approach is designed to optimize efficiency by reducing the frequency of maintenance activities, minimizing equipment downtime, and making better use of resources. [5]
Resource-Based Planning	It is a strategy where the scheduling of preventive maintenance (PM) work orders is driven by the availability of resources—such as personnel, tools, equipment, and materials—rather than by fixed time intervals or condition-based triggers. This approach ensures that maintenance tasks

	are planned and executed efficiently, using available resources optimally and avoiding delays due to resource shortages. [6]
Reliability-Centered Maintenance (RCM)	It is a comprehensive and systematic approach to maintenance planning that focuses on preserving the function of critical assets while minimizing costs. The primary goal of RCM is to determine the most effective maintenance strategies to ensure that assets continue to operate reliably within their intended functions. This approach considers the different types of failures that can occur, the consequences of those failures, and the best ways to mitigate those risks. [7]
Failure Modes and Effects Analysis (FMEA)	It is a systematic method for identifying potential failure modes within a system, assessing the causes and effects of those failures, and prioritizing actions to mitigate the risks associated with them. When used in planning preventive maintenance (PM) work orders, FMEA helps organizations focus their maintenance efforts on preventing the most critical and likely failures, thereby enhancing equipment reliability and safety. [8]

Table2. strategies and approaches to plan work orders for the whole yearly maintenance cycle.

4 Optimal Automated Designing Process Strategy

PM grouping and work order planning are crucial components of an effective maintenance strategy. They help in optimizing maintenance activities, reducing costs, and ensuring the reliability and safety of equipment throughout the maintenance cycle year.
Preventive Maintenance (PM) is a proactive approach that involves regularly scheduled inspections, adjustments, and replacements of equipment and systems to ensure optimal performance and prevent unexpected failures. A critical aspect of this approach is the grouping of work orders and planning them effectively throughout the maintenance cycle year.

PM grouping refers to the practice of organizing and consolidating similar or related maintenance tasks into a single work order or a group of work orders. This method is used to streamline maintenance activities, minimize equipment downtime, and optimize resource allocation. By grouping tasks that can be performed simultaneously or sequentially, maintenance teams can reduce the frequency of disruptions and improve overall efficiency.

Work order planning for the maintenance cycle year involves scheduling these grouped tasks at appropriate intervals, ensuring that all necessary preventive maintenance activities are completed within the planned cycle. This planning takes into account factors such as equipment criticality, manufacturer recommendations, historical performance data, and available resources.

Each asset/equipment may have up to four types of frequencies as shown in the table below:

	Type	Frequency
1	**Type One**	**Monthly**
2	**Type Two**	**Quarterly**
3	**Type Three**	**Semi-Annual**
4	**Type Four**	**Annual**

Table3. Types of Maintenance Frequencies

If such an asset/equipment has the four types of frequencies, then its highest frequency is the "Annual" one. If it has only types one and two, then its highest frequency is "Quarterly", and so on. Other types of Frequencies may be added to above table for such certain equipment as per manufacturer recommendation.

The proposed optimal automated designing process consists of four main steps that represent the proposed strategy for the designing process. The input database that are listed in the equipment inventory, where the forecasted time required for each PM equipment type plus the required manpower are listed, represent the required data for this strategy. The strategy for the optimal automated designing process consists of two major steps.

The first step is to set-up the input database for all PM equipment. All the information per equipment are presented, as shown in Figure 1, as it will be considered as an input data for the software that will deal with these data. These data will be classified and re-arranged, as shown in Figure 2, in order to be set into groups.

As per **the second step**, each group consists of same equipment with same frequency, forecasted man-hours and required manpower. Besides, it is also possible to group different equipment together, but with the same frequency, forecasted man-hours and required manpower as well.

Servicem (Parent)						System (Child)						PM	Frequency				Manhours				Manpower			
	Family	Description	Group	Description	MU	Service	Family	Description	Group	Group description	MU		M	Q	S	A	M	Q	S	A	M	Q	S	A
1111	WLL	WELL	110	WATER WELL	SET		PMP	PUMP	1090	SUB. 90 HP	PC	X	X			X	0.5			2	1			2
1111	WLL	WELL	111	WATER WELL	SET		PMP	PUMP	1090	SUB. 90 HP	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	110	WATER WELL	SET	1111	ACC	INSTRUMENT	1100	PRESSURE GAGE WITH ISOLATING VALVE	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	114	WATER WELL	SET		ACC	INSTRUMENT	1100	PRESSURE GAGE WITH ISOLATING VALVE	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	111	WATER WELL	SET		FLW	FLOW METER	1100	ELECTROMAGNETIC FLOW METER	PC	X	X			X	0.3			2	1			1
1111	WLL	WELL	114	WATER WELL	SET		FLW	FLOW METER	1100	ELECTROMAGNETIC FLOW METER	PC	X	X				0.5			2				
1111	WLL	WELL	110	WATER WELL	SET		VAV	VALVE	1100	GATE VALVE DN100	PC	X	X			X	0.5			2				
1111	WLL	WELL	111	WATER WELL	SET		VAV	VALVE	1100	GATE VALVE DN100	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	111	WATER WELL	SET		VAV	VALVE	1100	GATE VALVE DN100	PC	X	X			X	0.2			2	1			1
1111	WLL	WELL	110	WATER WELL	SET		ACC	INSTRUMENT	1110	PRESSURE TRANSMITTER	PC	X			X		0.3		0.3		1		1	
1111	WLL	WELL	111	WATER WELL	SET		ACC	INSTRUMENT	1110	PRESSURE TRANSMITTER	PC	X				X								
1111	WLL	WELL	114	WATER WELL	SET		VAV	VALVE	1110	GATE VALVE DN100	PC	X	X			X								
1111	WLL	WELL	111	WATER WELL	SET		ACC	INSTRUMENT	1120	PRESSURE GAGE	PC	X			X		0.3		0.3		1		1	
1111	WLL	WELL	114	WATER WELL	SET		PMP	PUMP	1150	SUB.150 HP	PC	X	X											
1111	WLL	WELL	110	WATER WELL	SET		VAV	VALVE	1150	GATE VALVE DN150	PC	X	X			X	0.5			2	1			2
1111	WLL	WELL	111	WATER WELL	SET		VAV	VALVE	1150	GATE VALVE DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	114	WATER WELL	SET		VAV	VALVE	1150	GATE VALVE 150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	110	WATER WELL	SET	1111	ACC	INSTRUMENT	1200	STRAINER DN150	PC	X	X			X	0.5			2	1			1
1111	WLL	WELL	114	WATER WELL	SET		ACC	INSTRUMENT	1200	STRAINER DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	110	WATER WELL	SET		FLW	FLOW METER	1200	MECHANICAL FLOW METER	PC	X	X		X				0.3				1	
1111	WLL	WELL	110	WATER WELL	SET		ACC	INSTRUMENT	1300	FLOW SWITCH	PC	X				X								1
1111	WLL	WELL	114	WATER WELL	SET		ACC	INSTRUMENT	1300	FLOW SWITCH	PC	X				X	0.5			2	1			1
1111	WLL	WELL	110	WATER WELL	SET		VAV	VALVE	1415	DUAL PLATE CHECK VALVE DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	111	WATER WELL	SET		VAV	VALVE	1415	CHECK VALVE DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	114	WATER WELL	SET		VAV	VALVE	1415	CHECK VALVE DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	110	WATER WELL	SET		VAV	VALVE	1500	ELEASE VALVE WITH ISOLATING VALVE	PC	X	X											
1111	WLL	WELL	111	WATER WELL	SET		VAV	VALVE	1500	AIR RELEASE VALVE DN65	PC	X	X			X	0.5			2	1			2
1111	WLL	WELL	114	WATER WELL	SET		VAV	VALVE	1500	ELEASE VALVE WITH ISOLATING VALVE	PC	X	X			X				0				1
1111	WLL	WELL	110	WATER WELL	SET		VAV	VALVE	1600	GLOBE VALVE DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	114	WATER WELL	SET		VAV	VALVE	1600	GLOBE VALVE DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	110	WATER WELL	SET	1111	ACC	RUBBER JOINT	1700	RUBBER JOINT DN150	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	114	WATER WELL	SET		ACC	RUBBER JOINT	1700	RUBBER JOINT DN150	PC	X	X			X	0.2			2	1			1
1111	WLL	WELL	110	WATER WELL	SET		ACC	RUBBER JOINT	1710	RUBBER JOINT DN100	PC	X	X			X	0.5			2	1			1
1111	WLL	WELL	111	WATER WELL	SET		ACC	RUBBER JOINT	1710	RUBBER JOINT DN100	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	114	WATER WELL	SET		ACC	RUBBER JOINT	1710	RUBBER JOINT DN100	PC	X	X		X		0.3		0.3		1		1	
1111	WLL	WELL	111	WATER WELL	SET		ACC	SMANTELING JOI	1720	DISMANTELING JOINT DN 100	PC	X	X		X		0.3		0.3		1		1	

Figure 1: Partial listed data for Equipment Inventory for SLWE Foundation

The objective of the second step is to group the equipment as per its common frequency, forecasted man-hours and manpower as shown in the same Figure. For instance, and from Figure 2, the PM Group D100 represents 8 pumps with different types, but with the same frequency, forecasted man-hours and manpower. It is expected that 11 Monthly and one Annual work orders will be generated for the D100 PM Group.

Figures 2 presents the list of equipment that is related to a water substation that can be grouped and be fed as input data into the CMMS system. CMMS system will determine the number of equipment that can be assigned to one work order as per the available manpower. If the CMMS system is a homemade software, it can be modified to execute the process of this proposed input data design. Otherwise, an Excel file, for instance, can be used in order to set-up the data as shown in the previous figures, then be fed into the CMMS system. The purpose of this proposed strategy is to reduce the number of generated work orders per equipment that will result in reducing the required manpower to plan and execute them.

Record #	Site	Service	Location Code	System Code	Subsystem Code	Frequency				PM Group	Forecasted Man Hours				Required Manpower				Total Forecasted Man Hours				
						Monthly	Quarterly	Semi-Annual	Annual		M	Q	S	A	M	Q	S	A	M	S	A	Tot	
1	1010	1111		WLL 110	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
2	1010	1111		WLL 110	FLW 200	M			A	D100	0.5			2	1			2	5.5		2	7.5	
3	1010	1111		WLL 111	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
4	1010	1111		WLL 112	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
5	1010	1111		WLL 113	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
6	1010	1111		WLL 114	PMP 150	M			A	D100	0.5			2	1			2	5.5		2	7.5	
7	1010	1111		WLL 115	PMP 060	M			A	D100	0.5			2	1			2	5.5		2	7.5	
8	1010	1111		WLL 116	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
9	1010	1111		WLL 116	PMP 025	M			A	D100	0.5			2	1			2	5.5		2	7.5	70:30 hours
1	1010	1111		WLL 110	ACC 700	M		S		D101	[illegible]		[illegible]		1		1		3.0	1		4	
2	1010	1111		WLL 112	ACC 700	M		S		D101	[illegible]		[illegible]		1		1		3.0	1		4	
3	1010	1111		WLL 113	ACC 700	M		S		D101	[illegible]		[illegible]		1		1		3.0	1		4	
4	1010	1111		WLL 114	ACC 700	M		S		D101	[illegible]		[illegible]		1		1		3.0	1		4	16 hours
⋮								⋮											⋮				
1	1010	1111		WLL 116	VAV 240	M		S		D119	[illegible]		[illegible]		1		1		3.0	1		4	
2	1010	1111		WLL 116	VAV 240	M		S		D119	[illegible]		[illegible]		1		1		3.0	1		4	
3	1010	1111		WLL 116	VAV 240	M		S		D119	[illegible]		[illegible]		1		1		3.0	1		4	
4	1010	1111		WLL 116	VAV 240	M		S		D119	[illegible]		[illegible]		1		1		3.0	1		4	
5	1010	1111		WLL 116	VAV 240	M		S		D119	[illegible]		[illegible]		1		1		3.0	1		4	20 hours
																			379:50 hours				

Figure 2: Grouped Equipment with common frequency, man-hours, & manpower

OMAINTEC Journal
(Journal of Scientific Review)

The third step is to determine the starting date of these planned PM Group work orders according to the highest frequency of each equipment as it is shown in Figure 3. Besides, the data for the Equipment inventory in above figures represent the partial data for the water substations that feed the Saida City and around villages with fresh water. A sample of this data were considered to demonstrate the proposed strategy for the optimal automated designing process for annual planning and workload distribution of work orders.

A1	MA1	MA2	MA3	MA4	MA5	MA6	MA7	MA8	MA9	MA10	MA11	PMP 090	A - M
S1	MA12	MA13	MA14	MA15	MA16	S2	MA17	MA18	MA19	MA20	MA21	ACC 700	S - M
S3	MA22	MA23	MA24	MA25	MA26	S4	MA27	MA28	MA29	MA30	MA31	VAV 150	S - M
S5	MA32	MA33	MA34	MA35	MA36	S6	MA37	MA38	MA39	MA40	MA41	ACC 100	S - M
A2	MA42	MA43	MA44	MA45	MA46	MA47	MA48	MA49	MA50	MA51	MA52	VAV 500	A - M
A3	MA53	MA54	MA55	MA56	MA57	MA58	MA59	MA60	MA61	MA62	MA63	FLW 200	A - M
A4	MA64	MA65	MA66	MA67	MA68	MA69	MA70	MA71	MA72	MA73	MA74	VAV 415	A - M
S7	MA75	MA76	MA77	MA78	MA79	S8	MA80	MA81	MA82	MA83	MA84	VAV 100	S - M
A5	MA85	MA86	MA87	MA88	MA89	MA90	MA91	MA92	MA93	MA94	MA95	ACC 200	A - M
S9	MA96	MA97	MA98	MA99	MA100	S10	MA101	MA102	MA103	MA104	MA105	VAV 600	S - M
A6												ACC 300	A
A7												ACC 110	A
S11	MA106	MA107	MA108	MA109	MA110	S12	MA111	MA112	MA113	MA114	MA115	ACC 710	S - M
A8	MA116	MA117	MA118	MA119	MA120	MA121	MA122	MA123	MA124	MA125	MA126	PMP 090	A - M
S13	MA127	MA128	MA129	MA130	MA131	S14	MA132	MA133	MA134	MA135	MA136	VAV 150	S - M
S15	MA137	MA138	MA139	MA140	MA141	S16	MA142	MA143	MA144	MA145	MA146	VAV 415	S - M
A9	MA147	MA148	MA149	MA150	MA151	MA152	MA153	MA154	MA155	MA156	MA157	VAV 500	A - M
S17	MA158	MA159	MA160	MA161	MA162	S18	MA163	MA164	MA165	MA166	MA167	ACC 710	S - M
S19						S20						ACC 120	S
A10												ACC 110	A
A11	MA168	MA169	MA170	MA171	MA172	MA173	MA174	MA175	MA176	MA177	MA178	FLW 100	A - M
S21	MA179	MA180	MA181	MA182	MA183	S22	MA184	MA185	MA186	MA187	MA188	ACC 720	S - M
S23	MA189	MA190	MA191	MA192	MA193	S24	MA194	MA195	MA196	MA197	MA198	VAV 100	S - M
S25	MA199	MA200	MA201	MA202	MA203	S26	MA204	MA205	MA206	MA207	MA208	VAV 100	S - M
	⋮					⋮					⋮		
A30	MA731	MA732	MA733	MA734	MA735	MA736	MA737	MA738	MA739	MA740	MA741	PMP 025	A - M
S107	MA742	MA743	MA744	MA745	MA746	S108	MA747	MA748	MA749	MA750	MA751	ACC 730	S – M
S109	MA752	MA753	MA754	MA755	MA756	S110	MA757	MA758	MA759	MA760	MA761	ACC 730	S – M
S111	MA762	MA763	MA764	MA765	MA766	S112	MA767	MA768	MA769	MA770	MA771	VAV 240	S – M
S113	MA772	MA773	MA774	MA775	MA776	S114	MA777	MA778	MA779	MA780	MA781	VAV 240	S – M
S115	MA782	MA783	MA784	MA785	MA786	S116	MA787	MA788	MA789	MA790	MA791	VAV 430	S – M
A31	MA792	MA793	MA794	MA795	MA796	MA797	MA798	MA799	MA800	MA801	MA802	FLW 100	A - M
S117						S118						ACC 100	S

Figure 3: Work Order distribution according to the frequencies of each equipment

OMAINTEC Journal
(Journal of Scientific Review)

The fourth step belongs to the software itself to plan and distribute the PM Group work orders according to the starting date of each group as per its highest frequency, as shown in Figure 4. Besides, the software will also equally distribute the load of maintenance work, on an annual basis, according to a rhythm that will be presented as per Figure 7.

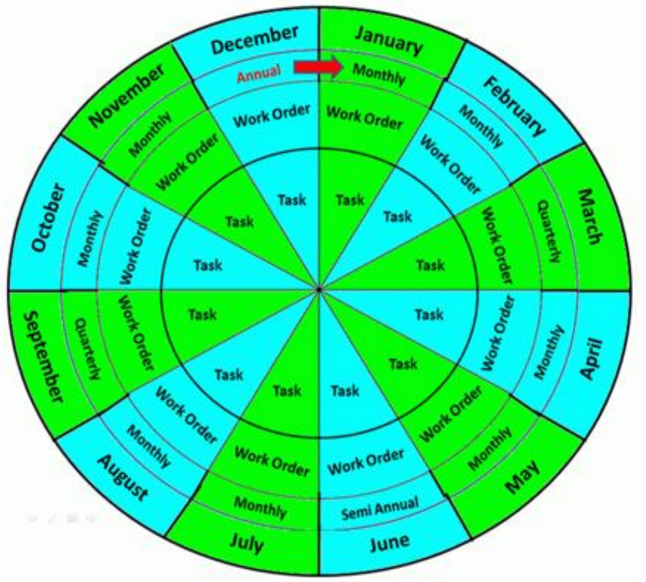


Figure 4: Maintenance Cycle Loop.

Figure 5, shows the pre-arrangement and post-arrangement data of the equipment inventory. The left side of the figure lists the PM Groups of the whole water substation, starting from PM Group D100 and ends with D119. On the right side of the figure, it lists all PM Groups of D100 together and so on till D119.

Location Code	System Code	Subsystem Code	Frequency				PM Group	Forecasted Man Hours				Required Manpower				Total Forecasted Man Hours			
			M	Q	S	A		M	Q	S	A	M	Q	S	A	M	S	A	Tot
	WLL 110	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5
	WLL 110	ACC 700	M		S		D101	0.3		0.3		1		1		3.0	1		4
	WLL 110	VAV 150	M		S		D102	0.3		0.3		1		1		3.0	1		4
	WLL 110	ACC 100	M		S		D103	0.3		0.3		1		1		3.0	1		4
	WLL 110	VAV 500	M		S		D104	0.3		0.3		1		1		3.0	1		4
	WLL 110	FLW 200	M			A	D100	0.5			2	1			1	5.5		2	7.5
	WLL 110	VAV 415	M		S		D105	0.3		0.3						3.0	1		4
	WLL 110	VAV 100	M		S		D106	0.3		0.3		1		1		3.0	1		4
	WLL 110	ACC 200	M			A	D107	0.2			2	1			1	2.2		2	4.2
	WLL 110	VAV 600	M		S		D108	0.3		0.3		1		1		3.0	1		4
	WLL 110	ACC 300				A	D109				1				1			1	1
	WLL 110	ACC 110				A	D110				1				1			1	1
	WLL 110	ACC 710	M		S		D111	0.3		0.3		1		1		3.0	1		4
	WLL 111	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5
	WLL 111	VAV 150	M		S		D102	0.3		0.3		1		1		3.0	1		4
	WLL 111	VAV 415	M		S		D105	0.3		0.3		1		1		3.0	1		4
	WLL 111	VAV 500	M		S		D104	0.3		0.3		1		1		3.0	1		4
	WLL 111	ACC 710	M		S		D111	0.3		0.3		1		1		3.0	1		4
	WLL 111	ACC 120			S		D112			0.3				1			1		1
	WLL 111	ACC 110				A	D110				1				1			1	1
	WLL 111	FLW 100	M			A	D113	0.5			2	1			1	5.5		2	7.5
	WLL 111	ACC 720	M		S		D106	0.3		0.3		1		1		3.0	1		4
	WLL 111	VAV 100	M		S		D106	0.3		0.3		1		1		3.0	1		4
	WLL 111	VAV 100	M		S		D106	0.3		0.3		1		1		3.0	1		4

Record #	Site	Service	Location Code	System Code	Subsystem Code	Frequency				PM Group	Forecasted Man Hours				Required Manpower				Total Forecasted Man Hours				
						Monthly	Quarterly	Semi-Annual	Annual		M	Q	S	A	M	Q	S	A	M	S	A	Tot	
1	1010	1111		WLL 110	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
2	1010	1111		WLL 110	FLW 200	M			A	D100	0.5			2	1			2	5.5		2	7.5	
3	1010	1111		WLL 111	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
4	1010	1111		WLL 112	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
5	1010	1111		WLL 113	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
6	1010	1111		WLL 114	PMP 150	M			A	D100	0.5			2	1			2	5.5		2	7.5	
7	1010	1111		WLL 115	PMP 060	M			A	D100	0.5			2	1			2	5.5		2	7.5	
8	1010	1111		WLL 116	PMP 090	M			A	D100	0.5			2	1			2	5.5		2	7.5	
9	1010	1111		WLL 116	PMP 025	M			A	D100	0.5			2	1			2	5.5		2	7.5	70:30 hours
1	1010	1111		WLL 110	ACC 700	M		S		D101	0.3		0.3		1		1		3.0	1		4	
2	1010	1111		WLL 112	ACC 700	M		S		D101	0.3		0.3		1		1		3.0	1		4	
3	1010	1111		WLL 113	ACC 700	M		S		D101	0.3		0.3		1		1		3.0	1		4	
4	1010	1111		WLL 114	ACC 700	M		S		D101	0.3		0.3		1		1		3.0	1		4	16 hours
1	1010	1111		WLL 116	VAV 240	M		S		D119	0.3		0.3		1		1		3.0	1		4	
2	1010	1111		WLL 116	VAV 240	M		S		D119	0.3		0.3		1		1		3.0	1		4	
3	1010	1111		WLL 116	VAV 240	M		S		D119	0.3		0.3		1		1		3.0	1		4	
4	1010	1111		WLL 116	VAV 240	M		S		D119	0.3		0.3		1		1		3.0	1		4	
5	1010	1111		WLL 116	VAV 240	M		S		D119	0.3		0.3		1		1		3.0	1		4	20 hours
																			379:50 hours				

Figure 5: Pre and post data arrangement for the equipment inventory

The data that is shown in Figure 3 is then fed into the CMMS system in order to generate the work orders for each Group, D100 – D119. Next is to balance, per week, the distribution of the forecasted man-hours, and to balance the number of work orders per week as well. The annual work order distribution per week will start by considering the highest frequency per equipment. The rhythm of distribution of grouped work orders will starts as follows; the highest frequency for PMP 090, as shown in Figure 3 - first row, is Annual, where it is Semi-annual for ACC 700. The CMMS system will read the arranged data from Figure 3 and distribute according to the following algorithm. The 12 work orders for PMP 090, with annual highest frequency, will first start on week #1 of January with the annual work order "A1" and will be followed with MA1 on week #1 of February, then with MA2 on week #1 of March, and so on till distribution process reaches to MA11 on Week #1 of December. Same distribution will be done for the "S1" work order. S1 work order will be assigned to week #2 of January, then MA12 on week #2 of February, and so on till MA21 on week #2 of December. Besides, S5 will be assigned on week #4 of January, and will end up with work order MA41 on week #4 on December.

Next, a new distribution cycle will start with work order A2, 5th row of right table of Figure 6. It will start on week #1 of February, and MA51 will be assigned on week #1 on December, where MA52 will be assigned on week #1 of January. Same process is repeated for work order A5. It will start on week #1 of March, and so on till MA93 on week #1 of December, followed by MA94 on week #1 of January, and will end up with MA95 on week #1 of February. And so on till the complete of Figure 3 will be read and distributed according to the distribution algorithm planned for this optimal automated designing process of PM Group work orders.

January				February				March				April			
Wk1	Wk2	Wk3	Wk4	Wk1	Wk2	Wk3	Wk4	Wk1	Wk2	Wk3	Wk4	Wk1	Wk2	Wk3	Wk4
A1				MA1				MA2				MA3			
	S1				MA12				MA13				MA14		
		S3				MA22				MA23				MA24	
			S5				MA32				MA33				MA34
				A2				MA42				MA43			
MA52					A3				MA53				MA54		
	MA63					A4				MA64				MA65	
		MA74					S7				MA75				MA76
			MA84					A5				MA85			
MA94				MA95					S9				MA96		
	MA104				MA105					A6				A7	
		MA112				MA113				MA114				MA115	
			MA123				MA124				MA125				MA126
MA132				MA133				MA134				MA135			
	MA142				MA143				MA144				MA145		
		MA153				MA154				MA155				MA156	
			MA163				MA164				MA165				MA166
MA170				MA171				MA172				MA173			
	MA181				MA182				MA183				S22		
		MA191				MA192				MA193				S24	
			MA201				MA202				MA203				S26
MA210				MA211				MA212				MA213			
	MA221				MA222				MA223				MA224		
		MA231				MA232				MA233				MA234	
			MA241				MA242				MA243				MA244
MA250				MA251				MA252				MA253			
	S36				A13				A14				MA260		
	MA269				MA270					S37				MA271	
		MA279				MA280					S39				MA281
			MA289				MA290					A15			

Figure 6: Weekly Work Order Distribution for the whole annual maintenance year.

The distribution of all PM Group work orders is partially shown in Figure 7. The huge data cannot be presented in a figure. Figure 7 shows the equally distributed PM Group work orders on a weekly basis. The range of weekly PM Grouped work orders is between 19 to 21 work orders. The results demonstrate the effectiveness of this proposed strategy.

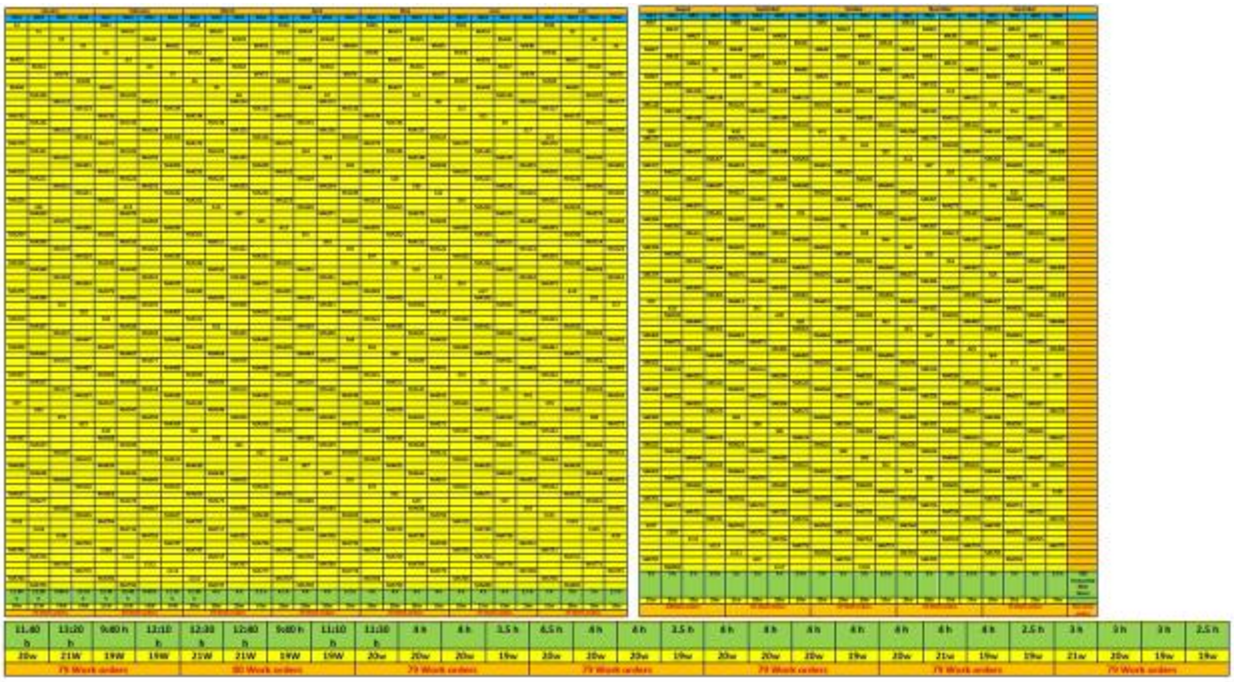


Figure 7: Totally equal distributed PM Group work orders on a weekly basis for whole maintenance year.

The numbers and types of the distributed PM Group work orders are shown in Figure 8. Instead of issuing 951 work orders for the active equipment at the Water Substation, only 119 PM Group work orders is issued and distributed across the executing schedule for the whole maintenance year.

Total Number of Work Orders: Monthly =	802
Semi-Annual =	118
Annual =	31

	951

Figure 8: Numbers and types of the distributed PM Group work orders for the whole maintenance year.

5 Conclusion

By implementing a systematic approach to PM planning of work orders, the annual maintenance workload can be evenly distributed across the year, ensuring consistent resource utilization and minimizing operational disruptions. By strategically grouping Preventive Maintenance work orders based on similar frequencies, same manpower requirements, and man-hours as well, it is possible to achieve a balanced and efficient maintenance schedule. This approach ensures that the workload is evenly distributed on a weekly maintenance calendar basis throughout the year, optimizing the use of resources and minimizing operational disruptions. The proposed strategy enhances productivity by aligning tasks that require similar resources, reducing the need for frequent adjustments in staffing or scheduling. Ultimately, this strategy promotes a smoother maintenance process, with predictable workloads that facilitate better planning, resource management, and overall operational efficiency.

References

[1] Anthony Kelly, "Maintenance Strategy: Optimal Equipment Life-Cycle Decisions", 2nd edition, Butterworth-Heinemann, 2006.
[2] Richard D. Palmer, "Maintenance Planning and Scheduling Handbook", 4th edition, McGraw-Hill Education, 2019.
[3] R. Keith Mobley, "Condition-Based Maintenance and Machine Diagnostics", 1st edition, Butterworth-Heinemann, 1991.
[4] R. Keith Mobley, "Maintenance Fundamentals",3rd edition, Elsevier, 2011.
[5] Don Nyman and Joel Levitt, "Maintenance Planning, Coordination, & Scheduling", 1st edition, Industrial Press, 2001.
[6] Alan Wilson, "Asset Maintenance Management: A Guide to Developing Strategy and Improving Performance", 1st edition, Industrial Press, 2002.
[7] Adolfo Crespo Márquez, "The Maintenance Management Framework"**, 1st edition,** Springer, 2007.
[8] Raymond J. Mikulak, Robin McDermott, and Michael Beauregard, "The Basics of FMEA", 1st edition, Productivity Press, 1996.

OMAINTEC Journal
(Journal of Scientific Review)

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING: THE FUTURE OF CONCRETE TECHNOLOGY AND MAINTENANCE

Mufid Samarai[1], Rami Alsodi[2,3]
1 Sahara Management Consultancy, P. O. Box 2580, Dubai, UAE. samarai@sharjah.ac.ae
2 Department of Public Works, P.O. Box 351, Sharjah, UAE. rami.alsodi@dpw.sharjah.ae
3 University of Sharjah, P. O. Box 27272, Sharjah, UAE. U21200094@sharjah.ac.ae

Abstract

Construction is considered one of the primary consumers of resources and energy and the most damaging to the environment, generating one of the most significant amounts of CO_2. Cement, an essential concrete component, is one of the world's most widely used construction materials, responsible for about 7% of CO2 emissions. This underscores the importance of quality control, maintenance, and sustainability in preserving the current built stock and extending the standing structures' life span, ensuring that their impact on the environment during their utilization is minimal. However, despite advancements in concrete science, designing concrete with specific properties remains a complex task due to the increasing complexity of cementitious systems. Machine learning (ML), known for its ability to handle complex tasks autonomously, has shown significant promise in concrete research. As ML is rapidly being adopted for concrete mixture design and other functions, it's crucial to understand its methodological limitations and establish best practices in this emerging computational field. Integrating Artificial Intelligence (AI) and Machine Learning (ML) into the maintenance and repair of concrete structures has revolutionized the industry, enhancing predictive capabilities, optimizing operational efficiency, and reducing costs. This paper provides a comprehensive overview of the evolution of AI and ML in concrete structure maintenance, examines current trends, and explores future possibilities. Graphs and references are included to support the discussion. This paper explores the positive impacts of ML on concrete science, discusses the implementation, application, and interpretation of ML algorithms, and outlines future directions for fully leveraging ML models in the concrete industry. It also emphasizes the vital role of AI and ML in the evaluation, repair, and maintenance management of structures.

Keywords: Concrete Maintenance, Machine Learning, Artificial intelligence.

1 Introduction

Concrete, a cornerstone of modern infrastructure, is evolving with the integration of Artificial Intelligence (AI) and Machine Learning (ML). These advanced technologies are revolutionizing concrete science and technology, enhancing material properties, improved construction practices, and sustainable development. This article explores the significant impact of AI and ML on concrete science and provides real-world examples to illustrate their applications.

Concrete is Earth's most widely used human-made material and the second most consumed commodity after water. Unlike other engineering materials such as steel, plastics, and wood, concrete is crucial in the construction industry due to its unique blend of strength, affordability, moldability, and durability. Portland cement world consumption is reaching 2.0 billion tons, and the concrete industry consumes approximately 8 billion tons of natural aggregates yearly [1]. Concrete research and application have progressed through three scientific models: experimentation, theory, and computation. The properties and performance of concrete can be tailored to meet specific design requirements by varying the type and quantity of mixture constituents, such as cement, water, aggregate, and admixtures. Traditional concrete mix design methods rely on trial and error, involving iterative proportioning, processing, and characterization until the desired properties are achieved. Although this method has had some success, it requires significant investments in time and resources. For instance, optimizing the compressive strength of concrete mixtures can be achieved by adjusting the water/cement ratio, total aggregate/cement ratio, and coarse aggregate/total aggregate ratio. However, the practical application of this iterative refinement approach is limited by the exponential increase in specimens and experiments required when studying complex concrete mixtures with multiple compositional parameters considered combinatorial variables [2,3]. Consequently, materials development in concrete science involves time-consuming validation and development cycles from laboratory trials to field applications of the first model, as shown in Figure 1. Thus, efforts to accelerate knowledge acquisition and materials design in concrete science are paramount.

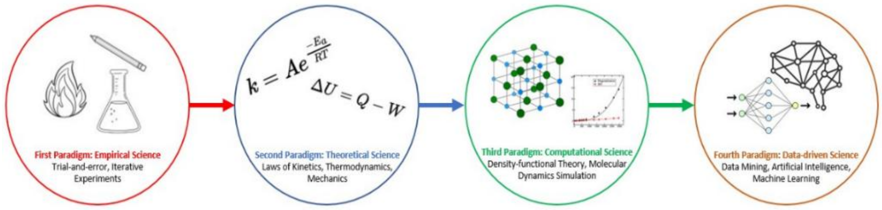


Figure 1: Four phases of concrete models

However, microstructural models of cement hydration have provided a fundamental understanding of how concrete's microstructure relates to its properties. This marked the second model of theoretical science by applying basic laws of kinetics, thermodynamics, and mechanics to cement hydration. Many models have been developed simulating the hydration process and microstructure development in cementitious systems, helping to describe time-dependent material properties like mechanical and transport properties. Alongside these developments, thermodynamics has been used to systematically study the stability and performance of concrete mixtures. However, the complexity of cement hydration poses challenges for creating accurate and generalizable models, which often rely on experimental data or atomistic and molecular-scale calculations [2].

The rise of computing power has enabled advanced simulations in concrete science, leading to the third model of computational science. These advanced simulations have focused on cementitious phases, such as calcium silicate hydrate (C-S-H) gel, the primary product of cement hydration. This transformation has revealed important details about concrete at the most minor scales, offering valuable data for microstructure modeling and enhancing experimental studies. However, these simulations require a lot of computing power and face challenges like short simulation times and small sample sizes. Validating these simulations with experiments is also challenging due to their small scale and the need for precise measurements.

AI and ML brought a new, data-driven approach to concrete research and applications. These technologies can analyze large datasets to find patterns and valuable information, helping to understand and design better concrete mixtures. ML maps out the relationships between concrete's processing, structure, properties, and the hardened concrete's performance, durability, and sustainability. This opened the field for applying ML in the evaluation, identifying cracks and deteriorating structures, and repairing and conserving the building stock, including bridges and hydraulic structures.

This paper will explore the multifaceted applications of machine learning in concrete technology, encompassing maintenance and long-term monitoring aspects. By investigating these factors and methodologies, the study will outline future trends of preventive maintenance that aim to enhance construction infrastructure's durability, sustainability, and functionality.

2 Diverse Applications of AI and ML in Concrete Technology

2.1 Concrete Manufacturing and Artificial Intelligence

In concrete technology, manufacturing concrete is arguably the most crucial aspect of the entire process, significantly influencing the outcome and properties of the final hardened concrete; Figure 2 shows the basic concepts of concrete manufacturing [3]. Regardless of the care taken in selecting the type and source of cement, choosing the most suitable aggregates, and using the highest quality additives and admixtures, the manufacturing process remains the most decisive factor for achieving high-quality concrete tailored to specific needs and applications. Traditional methods for designing concrete mixtures often depend on iterative trial-and-error processes involving proportioning, processing, and characterization until the desired properties are achieved. Despite some success, these methods demand substantial time and resources.

OMAINTEC Journal
(Journal of Scientific Review)

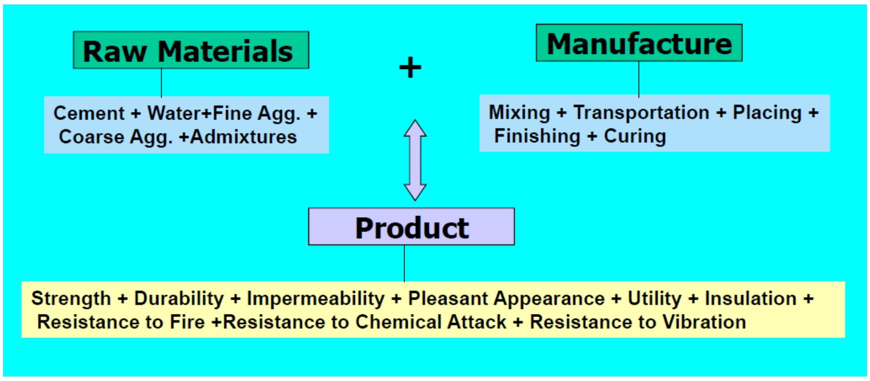


Figure 2: basic concepts of concrete manufacturing.

For instance, optimizing the compressive strength of concrete can be achieved by adjusting the water/cement ratio, total aggregate/cement ratio, and coarse aggregate/total aggregate ratio. However, the practical application of this iterative refinement approach is constrained by the exponential increase in the number of specimens and experiments required when dealing with complex concrete mixtures, where multiple compositional parameters are treated as combinatorial variables. Consequently, materials development in concrete science entails time-intensive validation and development cycles from laboratory trials to field applications. Accelerating knowledge acquisition and materials design in concrete science is therefore critically important.

Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized concrete research and applications by introducing a data-driven approach that significantly enhances the understanding and optimization of concrete materials [4]. These technologies can analyze extensive datasets to uncover patterns and extract valuable insights, thereby facilitating the development of superior concrete mixtures.

ML algorithms are particularly adept at mapping the complex relationships between concrete's processing parameters, microstructural characteristics, material properties, and overall performance [4]. By leveraging large-scale data, ML models can predict the outcomes of different mixture designs, allowing researchers to fine-tune formulations for specific applications. This predictive capability is crucial for optimizing strength, durability, and workability.

One of ML's significant contributions to concrete science is its ability to elucidate the mechanisms of hydration and degradation. Through detailed analysis of experimental data, ML models can identify key factors influencing the hydration process of cementitious materials and predict long-term degradation behaviors under various environmental conditions. This understanding is essential for developing concrete with enhanced longevity and sustainability. ML techniques have been applied across a spectrum of concrete types, from traditional Portland cement-based mixtures to advanced composites and eco-friendly alternatives. By analyzing the performance of different materials, ML can guide the development of novel concrete formulations with tailored properties. For instance, ML can assist in designing concrete with reduced carbon footprints by optimizing the use of supplementary cementitious materials and alternative binders.

As ML tools become increasingly sophisticated and accessible, their integration into concrete research is expected to expand. The growing availability of open-source ML platforms and computational resources will enable broader adoption in the field, driving innovation and accelerating discoveries. In particular, the application of ML in real-time monitoring and predictive maintenance of concrete structures holds promise for enhancing the durability and safety of infrastructure. ML processes and analyzes large experimental datasets, improving methods like ultrasonic pulse velocity, ground-penetrating radar, and digital photography for evaluating concrete properties and detecting damage. It enhances computational simulations, aiding in the design and optimization of materials by determining necessary parameters from limited experimental data and accelerating molecular simulations.

These advancements highlight the significant impact of ML on concrete science, providing new tools for research and practical applications. Table 1 outlines some of the applications of ML in concrete science and technology.

Table 1 ML Applications in Concrete Science and Technology

Applications	Description
Properties of concrete	Compressive Strength, Flexural Strength, Tensile Strength, Shear Strength, Elastic Modulus, Flowability, Setting Behavior
Hardened concrete	Creep, Shrinkage, Thermal Performance, Crack Detection
Materials	Cement Manufacturing Process Optimization; Aggregate Shape Identification
Mix Proportioning and Design	Concrete Mix Design Optimization; Quality Control for Concrete Admixture Manufacturing
Durability Prediction	Permeability, Freeze-Thaw Durability, Carbonation, Chloride Diffusion, Alkali-Silica Reaction, Corrosion, Sulfate Attack,
Miscellaneous	Pore Structure Analysis; Hydration Reactions, Pozzolanic Reactivity, Mechanical Behavior of Calcium Silicate Hydrate (C-S-H), Interatomic Potentials for C-S-H, Fracture Properties of an Interfacial Transition Zone

2.2 Challenges Facing ML in Concrete Science

In the previous sections, we reviewed the applications and challenges of machine learning (ML) in concrete science. Despite many publications on ML in cement and concrete research over the past decade, several challenges have prevented its widespread adoption in the construction industry [5]. Here, we share best practices to support a robust, data-informed concrete science ecosystem.

1- Sharing Data and Tools: ML algorithms can analyze large, multidimensional datasets and identify complex relationships. However, many ML models in concrete science are trained on insufficient data due to long experimental durations and inconsistent data formats. Few large datasets are publicly accessible, and efforts should be intensified to fill this gap. Developing new data repositories and expanding access to existing ones can address data sparsity. Platforms like the UC Irvine Machine Learning Repository and the Materials Project offer valuable examples. Researchers should be encouraged to share their experimental data publicly, even negative or null results, which are useful for training ML models. Although data protection and ownership concerns exist, a cultural shift toward improving research data accessibility and traceability is underway. Inconsistencies or incomplete data across studies should also be addressed. Different testing standards, specimen preparation methods, and reporting formats can cause variability. Clear and consistent standards for reporting and sharing experimental data are needed. Sharing computational methodologies, including models, procedures, and source codes, is crucial for reproducibility and generalizability. Comprehensive descriptions of methodological steps are necessary, including problem definition, data collection, preprocessing, model development, and evaluation.

2- Linking Laboratory and Field Data: Most ML models predicting concrete properties use controlled laboratory data, which do not reflect real-world variability. Variations in materials, processes, and environmental conditions can introduce noise into field data, making applying laboratory models to field conditions difficult. Training models on field data can improve predictions, but collecting field data is challenging. Hybridizing laboratory and field data for training ML models is a potential solution. For example, incorporating a small percentage of field data into training datasets significantly improves prediction performance. Future research should explore different ML algorithms and hybridization strategies to enhance field concrete predictions.

3- Starting with Simple Models: ML models can handle complex relationships, but simpler models are often sufficient and preferable when their performance is comparable to more complex ones. Simple models with fewer assumptions are more interpretable and reliable, especially when data quality is insufficient. Starting with simple, interpretable models and gradually increasing complexity is a good practice.

4- Knowing When to Trust a Model: Concrete research typically uses the 2-sigma rule to validate experimental results, but this may not be reliable for ML models due to reproducibility issues. Reported performance measures should be interpreted cautiously, as model performance on test data may not reflect real-world performance. Detailed descriptions of models and their performance, including potential sources of uncertainty, are necessary. Trust in ML models is closely tied to their interpretability, which is a focus of ongoing research.

3 Diverse Applications of AI and ML in Maintenance

3.1 The Development of Maintenance and its Types

The evolution of methodologies for assessing and predicting the durability and serviceability of concrete went through many phases. Historically, maintenance management has undergone significant advancements to ensure structural functionality and safety throughout the lifespan of concrete assets. The study categorizes maintenance strategies into four primary types: corrective, preventive, predictive, and prescriptive. Corrective maintenance is reactive, addressing issues as they arise or when failure indicators are observed. Figure 3 shows the shift in interest of concrete science over time. Preventive maintenance is scheduled at regular intervals to prevent potential failures. Predictive maintenance, a key application of AI and ML, leverages machine learning techniques, utilizing time-based data to forecast potential shortcomings. This approach is a game-changer, as it minimizes structural damage, reduces repair costs, and prevents operational downtime, demonstrating the practical benefits of AI and ML in the field [5,6]. Finally, prescriptive maintenance focuses on decision-making processes, offering strategies to proactively control and optimize maintenance activities, enhancing maintenance operations' overall efficiency and effectiveness. The role of AI and ML in this enhancement cannot be overstated, as they instill confidence in the audience about the technological advancements in the field. To this end, maintenance management is a systematic approach to planning, executing, and monitoring the upkeep of an organization's assets, equipment, facilities, or infrastructure. It includes a range of processes, strategies, and methodologies to ensure optimal performance, reliability, and longevity of physical assets, all while minimizing downtime and operational disruptions [7].

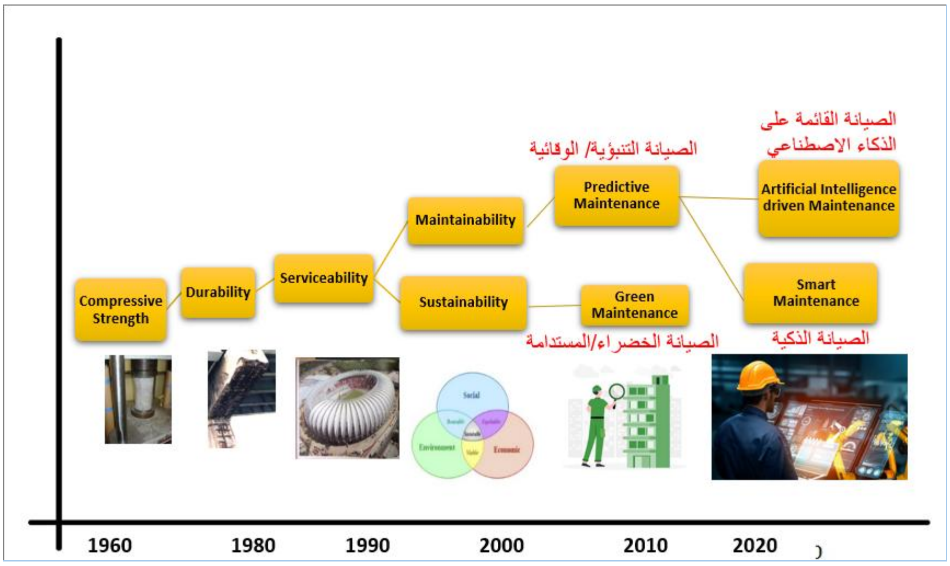


Figure 3: The Development of Maintenance and Maintenance Management with Time

Central to this approach is predictive maintenance, which leverages AI and advanced analytics to anticipate potential failures before they occur. By proactively predicting and addressing issues, organizations can prevent failures, reduce maintenance frequency, and optimize resource use. This enhances the quality of maintenance and drives down costs, ensuring that assets are managed efficiently throughout their entire lifecycle.

OMAINTEC Journal
(Journal of Scientific Review)

3.2 Artificial Intelligence and Predictive Maintenance

AI is set to transform the maintenance of engineering structures, offering a more sustainable approach by significantly extending the lifespan of critical infrastructure like buildings and bridges. Traditional maintenance practices, which often rely on routine inspections and reactive repairs, are increasingly outdated. These inefficient methods can lead to higher costs and potential safety risks [8].

Predictive maintenance, powered by AI and machine learning (ML), is emerging as the superior approach [9]. By leveraging continuous learning models, IoT sensor data, and automated decision-making processes, AI enables the early detection of potential issues. This allows maintenance to be performed precisely when needed, preventing minor problems from escalating into significant failures. Moreover, the development of digital twins—virtual replicas of physical assets—enables more accurate simulations and analyses of equipment performance under various conditions, further enhancing maintenance planning and execution.

This shift to AI-driven predictive maintenance reduces downtime and costs and ensures engineering structures' safety, reliability, and environmental sustainability. As AI continues to evolve, it will increasingly render traditional maintenance practices obsolete, establishing predictive maintenance as the new standard in the industry. Figure 4 demonstrates the evolution of engineering maintenance practices over time.

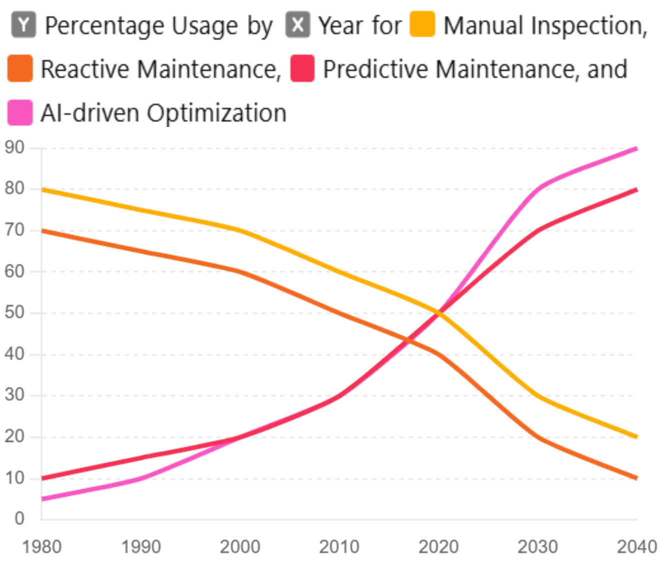


Figure 4 The evolution of engineering maintenance practices over time.

Predictive Maintenance leverages AI and ML to predict structural failures before they occur, minimizing downtime and reducing maintenance costs. Traditional maintenance strategies, such as reactive and preventive maintenance, often lead to unexpected failures or unnecessary maintenance actions. In contrast, predictive maintenance uses data from sensors, historical maintenance records, and operational parameters to forecast potential issues [10,11].

1. Data Collection and Integration: Modern equipment has IoT sensors that continuously monitor temperature, vibration, and pressure. AI algorithms integrate and analyze this data in real-time to detect anomalies.

2. Failure Prediction Models: ML models are trained on historical data to identify patterns that precede equipment failures. Regression analysis, decision trees, and neural networks are commonly used.

3. Proactive Maintenance Scheduling: Based on predictive insights, maintenance activities can be scheduled proactively, ensuring that interventions are timely and targeted, thus extending the lifespan of assets.

3.3 Benefits of AI and ML in Concrete Maintenance

Integrating AI and ML in the maintenance of concrete buildings and structures offers significant benefits, including cost savings through predicting failures and optimizing maintenance schedules, which reduces expenses related to labor, materials, and the utilization of assets. Figure 5 shows the projected impact of ML and AI on concrete maintenance cost. This technology enhances the reliability and performance of structures by ensuring they remain in optimal condition while also improving safety by detecting potential issues early and preventing catastrophic failures. AI and ML also support data-driven decision-making, enabling better resource allocation and strategic planning. Moreover, predictive maintenance helps extend the operational lifespan of structures, maximizing their long-term value.

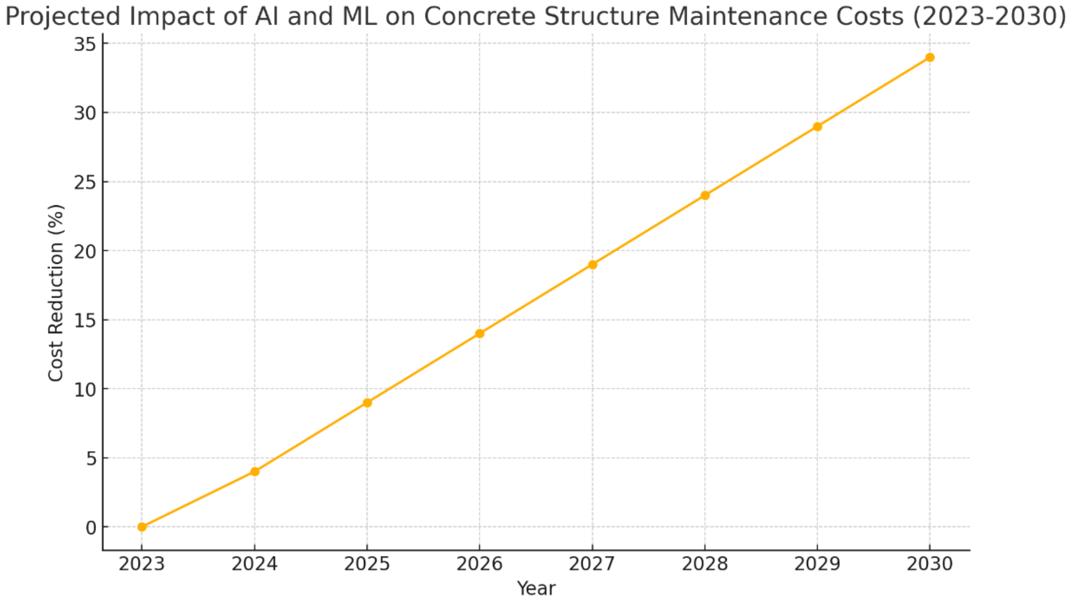


Figure 5 Projected impact of AI and ML on Structure Maintenance Costs

3.4 Challenges of AI and ML in Maintenance

Despite the clear benefits, integrating AI in maintenance does come with challenges. Initial investments in technology, training, and infrastructure can be significant. Robust cybersecurity measures are also needed to protect the data and systems involved. While the benefits are substantial, integrating AI and ML into maintenance systems comes with challenges:

1. Data Quality and Quantity: Effective predictive maintenance relies on high-quality data. Inconsistent or insufficient data can lead to inaccurate predictions.

2. Integration with Existing Systems: Integrating AI and ML solutions with legacy systems can be complex and may require significant investment.

3. Skill Gaps: Implementing AI and ML requires specialized skills. Organizations need to invest in training or hiring experts in data science and machine learning

4. Security and Privacy: Using IoT devices and data analytics raises concerns about data security and privacy. Robust measures are needed to protect sensitive information.

5. Initial Investment: Deploying AI and ML systems can be costly. Organizations must weigh the initial investment against long-term benefits.

However, as AI technology advances and becomes more accessible, these challenges are expected to diminish.

3.5 Current and Future Prospects and Trends

The future of AI and ML in the maintenance and management of concrete structures and buildings is set to revolutionize the industry, offering increasingly sophisticated tools for ensuring structural integrity and sustainability. With advancements in AI algorithms and sensor technologies, predictive maintenance will become a cornerstone of infrastructure management worldwide. Edge computing will enable real-time data processing at the source, enhancing predictive capabilities and reducing latency. Digital twins will allow more accurate simulations and predictive analytics, improving maintenance planning and execution. Autonomous maintenance systems powered by AI-driven robots and drones will likely emerge, performing tasks with minimal human intervention. Collaborative AI will combine human expertise with AI insights, enhancing decision-making and maintenance strategies. Finally, AI and ML will be pivotal in developing sustainable maintenance practices, optimizing resource utilization, and minimizing environmental impact, paving the way for a safer and more sustainable built environment. Some of the current and future real-world applications:

1. Manufacturing: Companies like Siemens and General Electric are using AI and ML for predictive maintenance in manufacturing plants, reducing downtime and increasing efficiency.

2. Transportation: Airlines and railways use predictive maintenance to ensure the reliability and safety of their fleets. For example, Delta Airlines uses AI to predict and address potential aircraft issues.

3. Energy Sector: AI-driven maintenance is used in power plants and renewable energy installations to predict failures and optimize performance.

4. Oil and Gas: Shell uses ML algorithms to monitor and maintain drilling equipment, pipelines, and refineries.

5. Smart Cities: Municipalities leverage AI to maintain water supply systems, street lighting, and public transportation infrastructure.

4 Conclusions

In conclusion, integrating AI and ML into concrete science and constructing concrete structures marks a significant leap forward in the industry. These technologies are not only revolutionizing research methodologies by enabling more intelligent and efficient analysis but are also critical in transforming the maintenance and management of infrastructure. AI and ML offer unprecedented opportunities for predictive maintenance, optimized resource utilization, and enhanced structural health monitoring, all of which are vital for extending the lifespan of concrete structures and promoting sustainability [12,13]. As these technologies evolve, the future of concrete science and infrastructure maintenance will become increasingly data-driven, predictive, and autonomous, positioning forward-thinking organizations at the forefront of innovation and sustainability in a rapidly changing world [14].

References

[1] Nwankwo, C. O., Bamigboye, G. O., Davies, I. E., & Michaels, T. A. (2020). High volume Portland cement replacement: A review. *Construction and Building Materials*, *260*, 120445.

[2] Samarai, M. “Advances in Evaluation, Testing, Repair and Maintenance Management of Structures: Overview of the New Modified ACI 562M-16 Code for Repair of Structures” Workshop,16th International Operations & Maintenance Conference in the Arab Countries - OMAINTEC, 19-21/11/2019, Le Meridien Hotel, Dubai, UAE.

[3] Samarai, M., Utilization of Artificial Intelligence and the New ACI 562 Code for the Evaluation, Repair, and Maintenance of Concrete Structures" Workshop, organized by Oman Engineers Society and Conclier Consultation Company, 1-4 July 2024, Muscat, Oman.

[2] Ridi, F. (2010). Hydration of cement: Still a lot to be understood. Dipartimento di Chimica & CSGI Università di Firenze, La Chimica L’Industria, 3, 110-117.

[3] Chaabene, W. B., Flah, M., & Nehdi, M. L. (2020). Machine learning prediction of mechanical properties of concrete: Critical review. Construction and Building Materials, 260, 119889.

[4] Lee, J., Kao, H., & Yang, S. (2014). "Service Innovation and Smart Analytics for Industry 4.0 and Big Data Environment." Procedia CIRP* 16, 3-8.

[5] Ford, E., Maneparambil, K., Rajan, S., & Neithalath, N. (2021). Machine learning-based accelerated property prediction of two-phase materials using microstructural descriptors and finite element analysis. Computational Materials Science, 191, 110328.

[6] Smith, J., & Doe, A. (2020). "The Evolution of Predictive Maintenance in Concrete Structures." Journal of Maintenance Engineering, 45(3).

[7] Wang, L., & Ma, Y. (2020). "Predictive Maintenance via Machine Learning: Challenges and Opportunities." *IEEE Transactions on Industrial Informatics*, 16(2), 882-891.

[8] Taffese, W. Z., & Sistonen, E. (2017). Machine learning for durability and service-life assessment of reinforced concrete structures: Recent advances and future directions. Automation in Construction, 77.

[9] Alshboul, O., Al Mamlook, R. E., Shehadeh, A., & Munir, T. (2024). Empirical exploration of predictive maintenance in concrete manufacturing: Harnessing machine learning for enhanced equipment reliability in construction project management. Computers & Industrial Engineering, 190, 110046.

[10] Wang, Q., & Li, H. (2023). AI-Based Predictive Maintenance for Concrete Structures: Methods and Applications. Structural Control and Health Monitoring, 30(1), e3107.

[11] Singh, G., & Mohapatra, S.S. (2023). Machine Learning for Predictive Maintenance of Concrete Infrastructure: A Comprehensive Review. Automation in Construction, 144, 104390.

[12] Johnson, R. (2018). "Machine Learning Applications in Structural Health Monitoring." International Journal of Artificial Intelligence, 29(4), 112-130.

[13] Civera, A., & Plevris, V. (2021). Application of Machine Learning Techniques in the Assessment and Monitoring of Concrete Structures. Journal of Civil Structural Health Monitoring, 11(3), 349-367.

[14] Hamishebahar, Y., Li, H. Z., & Guan, H. (2021). Application of machine learning algorithms in structural health monitoring research. In EASEC16: Proceedings of The 16th East Asian-Pacific Conference on Structural Engineering and Construction, 2019 (pp. 219-228). Springer Singapore.

OMAINTEC Journal
(Journal of Scientific Review)

Spectro marine: Real-Time Water Quality Measurement for Desalination Plants

Amr Mohamed Mhamoud[1], Ahmed AlGhamdi[1],Sultan Ahmed[1], Aleksejs Zol[2], Aleksejs Zolotarjovs[2], Ģirts Ozoliņš[2]

[1] Water Technologies Innovation Institute and Research Advancement (WTIIRA), Saudi Water Authority SWA, Saudi Arabia
[2] Institute of Solid State Physics, University of Latvia

Abstract

Membrane biofouling is one of the critical challenges faced by desalination plants, particularly those utilizing reverse osmosis (RO). The development of advanced monitoring technologies is essential to reduce maintenance costs, improve efficiency, and increase the lifespan of the membranes. Spectromarine, an innovative optical water quality measurement sensor, provides real-time data on organic content and biomass levels in water to desalination operators, offering early warnings to prevent membrane fouling. This paper discusses the design, application, and expected outcomes of the Spectromarine sensor in optimizing desalination processes, with a focus on reducing operational costs, energy consumption, and chemical use, while enhancing plant performance.

1. Introduction

Desalination plants, particularly those using reverse osmosis (RO) technology, face significant operational challenges related to biofouling of membranes, which can lead to reduced productivity, higher operational costs, and increased energy consumption [1,2]. The formation of biofilms on membrane surfaces impedes water flow, requiring higher pressure and more frequent chemical cleaning, which in turn reduces the membrane's lifespan [3,4].

Current methods to monitor biofouling include heterotrophic plate count (HPC) and flow cytometry, both of which present limitations in terms of response time and accuracy. HPC, for instance, requires several days to weeks for bacterial growth and analysis, which delays intervention measures [5]. Flow cytometry, while faster, often underestimates biofouling due to bacterial clumping and still requires manual labor for sample collection and analysis [6].

Spectromarine, an innovative optical sensor, aims to address these limitations by providing real-time monitoring of water quality in desalination plants [7]. By combining fluorescence and absorption spectroscopy with advanced data analysis techniques, Spectromarine can deliver instant analytics, allowing operators to take immediate action to mitigate biofouling risks. This technology not only optimizes water pretreatment but also reduces membrane cleaning frequency, chemical usage, and overall operational costs [8,9].

2. Methodology

2.1 Sensor Design and Functionality

The Spectromarine sensor utilizes a combination of fluorescence and absorption spectrometry to measure dissolved organic matter (DOM), total organic carbon (TOC), humic substances, algae, and particulate matter in real-time [10]. Installed at various points in the desalination process, the sensor continuously monitors water quality, providing data with a frequency of up to 10 seconds [11].

The sensor consists of two main components:

- Hardware (Spectromarine HW): A compact device capable of performing full-spectrum optical measurements at different excitation wavelengths.

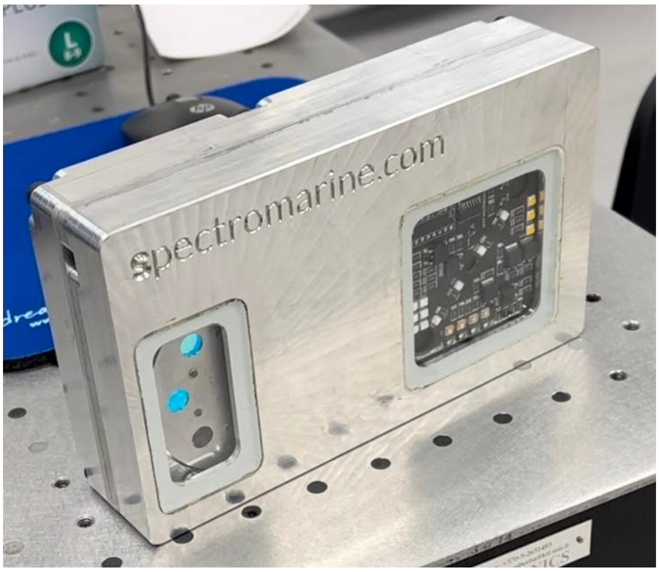


Fig. 1. Spectromarine hardware

- Software Interface: A dashboard that provides real-time data visualization, tailored to the operator's needs. The software integrates Internet of Things (IoT) technologies, allowing remote monitoring and control through mobile or desktop devices [12].

Fig. 2. Spectromarine real-time data platform

2.2 Operational Integration in Desalination Plants

The sensor is integrated at critical points in the desalination process, primarily in the pretreatment stages before reverse osmosis [13]. Its primary functions include:

1. Real-time Biofouling Detection: Continuous measurement of organic material and algae that contribute to biofouling [14].

2. Early Warning System: Alarms operators when water quality deteriorates, allowing timely adjustments in pretreatment or membrane cleaning processes [15].

3. Data Analysis and Recommendations: Spectromarine's software processes the collected data and provides actionable insights, such as adjusting chemical dosing or changing water source intake to prevent fouling [16].

2.3 Field Testing and Validation

The Spectromarine sensor has undergone preliminary field testing in cooperation with the Water Technology Institute for Research and Applications (WTIIRA) and the Institute of Solid State Physics, University of Latvia (ISSP UL). During the two-month test period, the sensor required only minimal maintenance (light cleaning of the sensor window), demonstrating its robustness and low maintenance needs [17].

Further extended tests are planned to validate the sensor's performance under various operational conditions, particularly its ability to predict membrane fouling and optimize chemical usage [18]. For this primary aim, the low detection limit and selectivity of the device can be tested extensively, with advanced data analysis implemented for predictive decision making and water parameter change projection (e.g. chlorophyll cyclice development)~~.~~

3. Expected Results

The Spectromarine project aims to deliver the following key results:

3.1 Reduction in Operational Costs

By providing real-time water quality monitoring and early warnings, Spectromarine is expected to significantly reduce the operational costs of desalination plants. Reduced membrane biofouling will decrease the frequency of membrane cleaning and replacement, which typically accounts for 10-20% of operating costs [19]. Additionally, timely detection of water quality issues will minimize downtime and ensure continuous production [20].

3.2 Optimization of Energy Consumption

Membrane fouling increases the pressure required for filtration, leading to higher energy consumption [21]. By preventing fouling, Spectromarine will optimize energy use, thereby reducing greenhouse gas emissions and lowering the overall energy costs associated with desalination [22].

3.3 Minimization of Chemical Usage

Spectromarine will enable more efficient chemical dosing by providing accurate, real-time data on water quality. This will not only reduce the amount of cleaning chemicals used during membrane maintenance but will also optimize the pre-treatment process, resulting in less environmental impact and lower operational costs [23].

3.4 Enhancement of Membrane Lifetime

The primary benefit of the Spectromarine sensor is the extended lifetime of desalination membranes. By minimizing biofouling, the sensor will reduce the physical and chemical stresses on membranes, leading to longer operational life and lower replacement costs [24].

4. Discussion

Spectromarine represents a significant advancement in desalination technology by combining real-time water quality monitoring with IoT integration. The project's success would establish a new standard in desalination plant operation, allowing operators to maintain high levels of production efficiency while reducing both costs and environmental impact [25].

The use of real-time spectroscopic data provides a more accurate and immediate assessment of water quality than traditional methods, allowing operators to make informed decisions about pretreatment and membrane cleaning [26]. Additionally, the system's low maintenance requirements and easy installation make it a cost-effective solution for desalination plants globally [27].

Future research will focus on the expanded application of the Spectromarine sensor, particularly in other industries such as aquaculture, environmental monitoring, and urban pollution control [28].

5. Conclusion

Spectromarine is poised to revolutionize the desalination industry by offering a practical solution to biofouling, one of the most persistent challenges in reverse osmosis systems. The sensor's real-time water quality measurements and advanced data analytics will enhance plant efficiency, lower operational costs, and reduce the environmental impact of desalination processes. With its proven low-maintenance design and market readiness, Spectromarine has the potential to become a cornerstone technology for water desalination in the Gulf region and beyond [29].

References

1. M. Elimelech, W.A. Phillip, The future of seawater desalination: Energy, technology, and the environment, Science, 333 (2011) 712-717.

2. C.Y. Tang, Q.S. Fu, A.G. Fane, R. Wang, C. Hu, Y. Zhao, Forward osmosis desalination using polyelectrolyte hydrogels as draw agents: Influence of draw agent, feed solution and membrane on process performance, Desalination, 368 (2015) 34-40.

3. L. Zhang, J.S. Zhang, H. Ma, Biofouling in seawater desalination membranes, Desalination, 346 (2014) 158-167.

4. R. Valladares Linares, Z. Li, M. Abu-Ghdaib, T. Yangali-Quintanilla, D. Amy, T. Leiknes, Water harvesting from municipal wastewater via forward osmosis using nanocomposite membranes, Desalination, 277 (2011) 144-149.

5. H. Alzahrani, A.W. Mohammad, Challenges and trends in membrane technology implementation for desalination, Desalination, 452 (2019) 158-174.

6. S. Kwon, W.S. Shin, W. Kim, S. Kim, P. Na, Biofilm monitoring using an optical sensor in reverse osmosis desalination plants, Desalination, 451 (2019) 48-57.

7. M. Elimelech, J. Laîné, P. Hong, Online fouling monitoring of seawater reverse osmosis desalination plants, Desalination, 239 (2009) 10-25.

8. N. Hilal, A. Al-Zoubi, N.A. Darwish, A.W. Mohammad, Characterization of nanofiltration membranes using atomic force microscopy, Desalination, 214 (2007) 187-194.

9. C. Boo, Y. Lee, D.J. Rho, T. Nguyen, M. Elimelech, Influence of cleaning agents on forward osmosis membrane performance, Desalination, 349 (2014) 67-73.

10. P. Xu, J.E. Drewes, C. Bellona, G. Amy, J. Heberer, T. Kimura, M. Watanabe, Rejection of emerging organic micropollutants in membrane systems, Desalination, 239 (2009) 244-260.

11. D.M. Warsinger, S.M. Chakraborty, E.W. Tow, J.H. Lienhard V,

OMAINTEC Journal
(Journal of Scientific Review)

AN INNOVATIVE RESILIENCE ASSESSING FOR CRITICAL INFRASTRUCTURES USING THE LEAN METHODOLOGY

Claudio Rolandi

ACADEMIA s.a.s., Italy

claudio.rolandi@academia-eng.com

Abstract

One of the results of the European "Smart Resilience" project was to provide a new methodology to assess and manage the resilience of critical infrastructures, i.e. their ability to cope with possible scenarios or adverse events that can potentially lead to significant disruptions in its availability.

Lean Thinking, on the other hand, is a management style that aims to reduce waste to create excellent, standardized and low-cost processes, making it adaptable to all sectors and contexts. Its application in the analysis of complex processes, such as the infrastructures, can be an effective optimization tool.

Starting from the considerations made on the prevention of risky events, some significant cases will be examined in order to increase the level of prevention, reduce recovery times and improve performance following the actions taken.

Keywords: Maintenance Management, Asset Management, Critical Infrastructures

1 Introduction

Every country defines which are critical infrastructures:

- For some countries, energy production, railway networks, electricity networks, aqueducts, highways, railway networks, ports, airports, armaments manufacturers, health system, ...
- For other countries, sectors related to food, such as bread and milk, and health, such as vaccines and antibiotics, are also strategic, hence the financing and control over companies in the respective sectors.

For a critical infrastructure is important to be:

- strong enough to withstand unwanted and unpredictable events;
- fast enough to restore the situation prior to the event and also improve resistance as a result of the lessons learned.

Starting from the analysis of the vulnerability of critical infrastructures, using the Lean Thinking tools that have been successful in the Manufacturing sector, this document wants to suggest improvement criteria for critical infrastructures to allow them to be ready to support unforeseen events and to be ready to recover quickly.

2 Critical Factors

In my work on failure prevention, I set out to use the ISHIKAWA 8M model for Root Cause Analysis and define what is out of control:

- ***Materials***: both in acceptance and in production and in distribution or provision of services, according to the specifications;
- ***Machines***: all technical devices available to carry out the required operations, including structures, mechanical, electrical, instrumental and software parts;
- ***Methods***: ways of working adopted by the operations and maintenance departments;
- ***Manpower***: personnel employed by the operations and maintenance departments, included technics, supervisors and engineers;
- ***Milieu*** (environment): depending on the external aspects in which one finds oneself operating (climate, events such as earthquakes, floods, fires, legislation, socio-political aspects such as internal or external service strikes, reputation, etc.);
- ***Measurements***: ability to keep quantitative and qualitative control parameters under control and make appropriate use of them;
- ***Management***: ability and autonomy to make decisions;
- ***Money***: necessary and available budget to the service department.

For me, all digitalization tools will have to allow these parameters to be governed, suggesting to those who have to decide the best solution with the least ethical and economic risks.

For each critical sector it is possible to define what could be the most relevant M-factors. A possible summary matrix could be the following.

The following table shows some sectors that could be considered critical. Each country, based on social, political, environmental or organizational culture considerations, can identify the most critical parameters to be monitored.

	Material	Machine	Method	Manpower	Milieu	Management	Measure	Money
Transportation								
Energy								
Environment								
Healthcare								
Defence								
Life Sciences								
Food & Beverages								
Oil & Gas								
Heavy mechanics								
Light mechanics								
Primary and fine chemistry								
Paper mills								

OMAINTEC Journal
(Journal of Scientific Review)

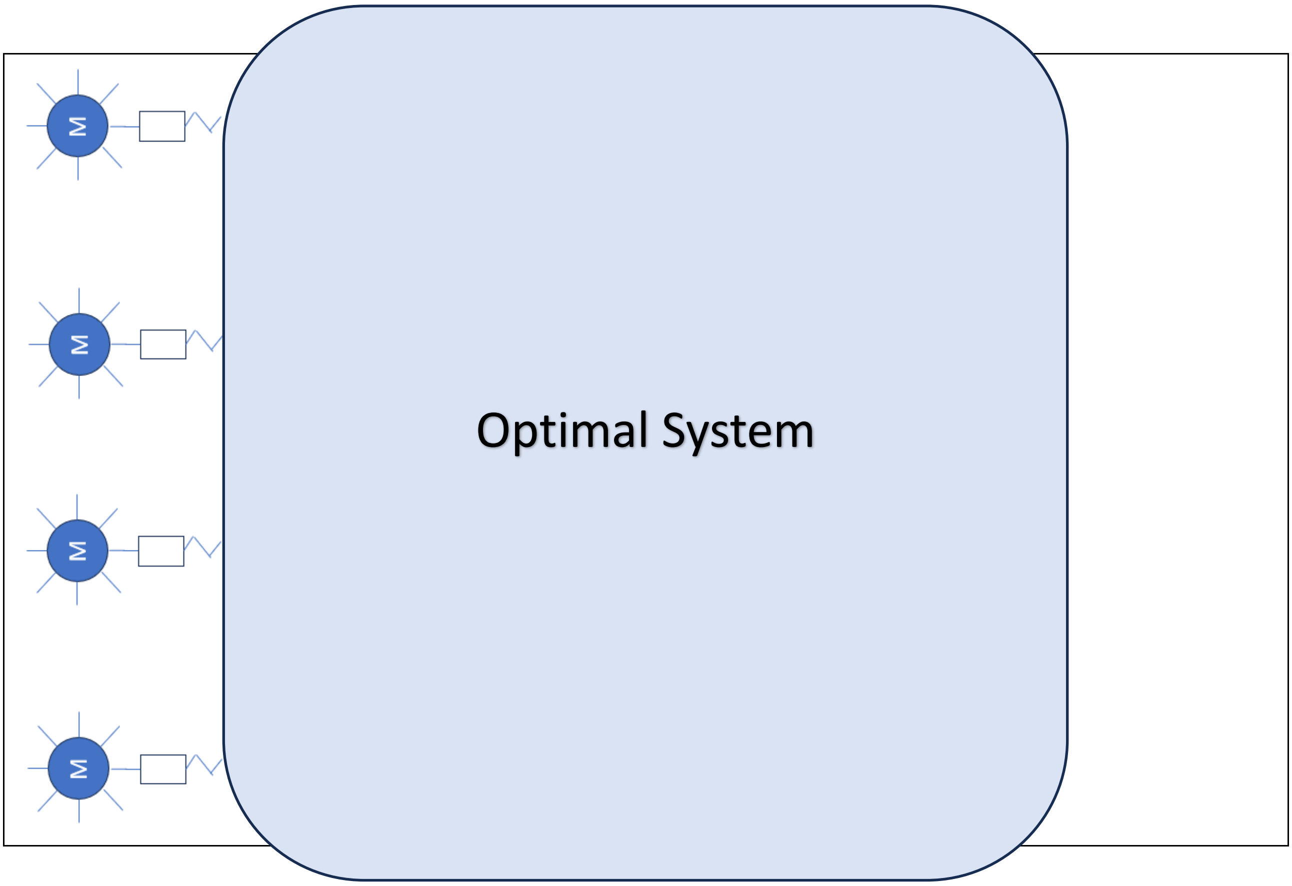
Glassworks								
Metallurgy								
Semiconductors								
Optoelectronics components								
ICT								
Buildings								
Others								

Some notes:

- Artificial Intelligence is trained through Big Data.
- Large amounts of data are available on MACHINE.
- MATERIAL is often critical in upstream processes, as for foods & beverages, pharma & biotech, while is under control in downstream processes. The more regulated the industry, the fewer problems there are due to strict selection.
- Large influence of MILIEU and MANPOWER (also due to the presence of customers and outsiders to the service) is for sectors such as HEALTHCARE, ROAD and DEFENSE.
- ENERGY is strongly influenced by MILIEU and MONEY.

The system must take into account 8M constraints and consider from time to time what is the level of "stiffness" or "yielding" of each constraint.

It is therefore an optimization project of a complex system, in which some data are often not quantitatively well definable.



The failure of a "support" causes stress on the remaining ones:

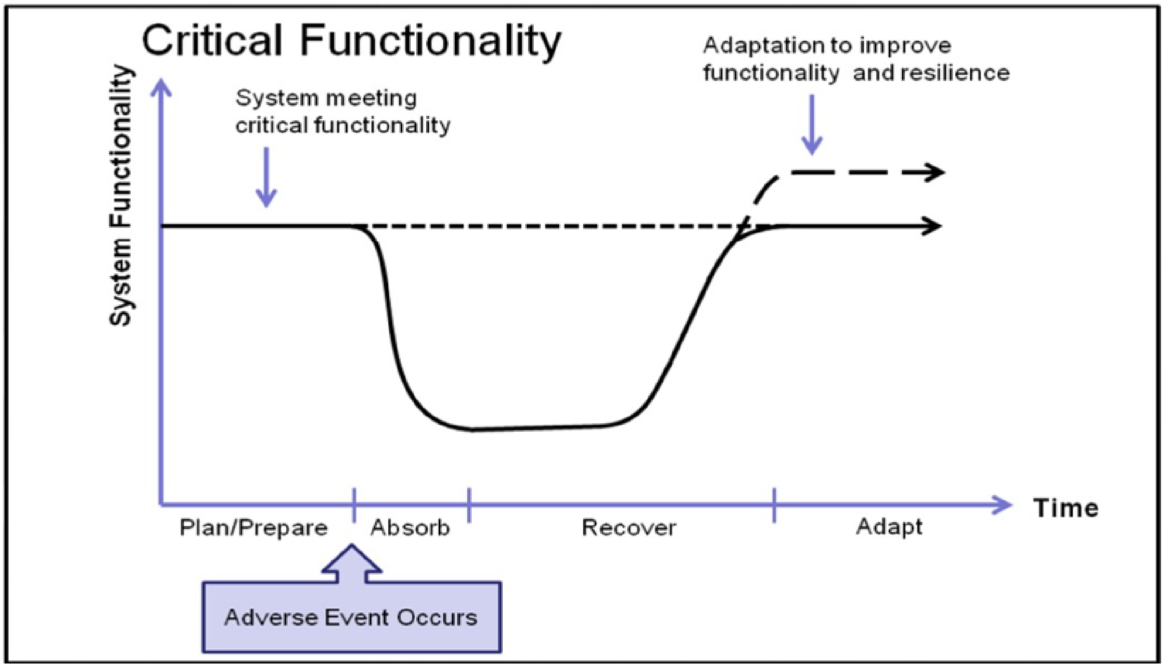
- Money: e.g. lacks the necessary funding.
- Measure: e.g. feasible if convertible into electrical or optical signals, complex if biological indicators.
- Material: e.g. lack for environmental reasons, pollution, alteration.
- Machine: e.g. failure, unavailability, lack of spare parts, …
- Manpower: e.g. labour shortage, incompetence, conflict
- Method: e.g. inadequate or incomplete
- Management: e.g. incompetence and poor context vision
- Milieu: e.g. external events, predictable and unpredictable

When analyzing the context of an asset, especially if it is durable like a critical one, it is necessary to take into consideration not so much the Return on Investment or the Net Present Value as the Life Cycle Cost and the Total Cost of Ownership, also estimating the risks due to unforeseen events and inconveniences.

Decisions are often made on the basis of containment of investment (CAPEX), which could be at the expense of operating costs (OPEX). Saving on investment could mean:

- lower reliability and availability of the plant;
- less skilled employees;
- fewer performing methods;
- greater conditioning by external events;
- lower quality raw materials and poorer final products;
- less precise instrumentation;
- less prepared management.

Resistance– Root Cause Analysis and Strengthening the Defenses (Prevention)



The typical representation of the functionality of the system is reported in the figure above.

Plan/Prepare phase.

If the adverse event is not a purely random adverse event, due for example to natural events, such as meteorological or earthquakes, or human events, such as vandalism or terrorism, scheduled, condition-based and/or predictive maintenance are tools that can be adopted.

Absorb phase

Once an unwelcome event has occurred, it is necessary to ensure that the phase is not instantaneous and catastrophic, i.e. the slope in the diagram is too steep. It is possible to intervene both in the planning phase (through passive and active protections) and by adopting organizational actions, such as organizing emergency response teams.

Recover phase

The phase represents the time to restore the pre-existing system conditions, possibly the same, sometimes degraded but preferably improved. Often the problems are not technical but legal, social or political. To reduce the time required, it is essential that the system design is easily repairable and upgradable.

Adapt phase

Based on the lessons learned, it is desirable to bring the system to a higher level of performance or increase its protections if similar unwanted events should occur.

An example of best practice

The Formula 1 driver hit the wall of the street circuit, damaging the front nose of the car. Slowing down for 15 seconds to reach the pits, in 5 seconds the damaged part was replaced, and in the meantime the 4 tires, another 15 seconds were due to the passage to the pit lane. In total, the loss was 35 seconds on the performance on a lap of 1 minute and 50 seconds of pace. The opportunity to change worn tires with as many new ones allowed for an improvement in lap performance and reliability.

3 Resilience – Lessons Learned, Restoring and Upgrading

Systems management is too often due to poor basic design, often dictated by an approximate analysis of the initial conditions, and a poor vision of what future developments could be. Factors that are initially considered irrelevant can take on a preponderant value over time.

Many projects of the last century did not consider energy consumption, final decommissioning, material recycling, CO2 emissions, the need for greater operator skills, etc. would be relevant. Furthermore, mass production was favored at the expense of product customization, leading to systems with a defined expiry date. Now, however, preference is given to products and therefore systems that consume less energy during use, that can be easily repaired or updated to extend their useful life and that can be easily recycled at the end of their useful life.

4 Case Studies

4.1 Airport of Catania and Mount Etna – Volcano Emissions

Mount Etna is also one of the most active volcanoes in the world, characterized by frequent eruptive activity from the summit vents and flank eruptions which an average of 4 events every 10 years.

There are no tools yet to predict volcanic eruptions.

The airport is located about 30 km away from the volcano and, if the wind comes from the north, the ash can reach the site within a few hours.

The main problem is due to ash on airport runways, taxiways, buildings and facilities. All this involves the closure of the airport and the diversion to the other airports in Sicily, which are still poorly connected to each other by roads and railways.

Once the eruption has stopped, even after several days, removal can take several hours using appropriate means very similar to those used for removing desert sand from roads.

If it rains later, removal would be much more problematic and there would also be the problem of overloading the roofs of buildings and cleaning the infrastructures.

In this situation, the best solution remains to prepare means and teams capable of acting as quickly as possible to recover the minimum safety conditions for the reopening of the airport.

On the other hand, greater attention has been paid to the design of buildings and infrastructures to facilitate cleaning and restart operations.

4.2 Electrical panels in the Gotthard railway tunnel

The Gotthard railway tunnel consists of two tubes for the passage of trains. Every 325 meters there is a connecting passage between the two tubes, protected by fire doors, which serves as an emergency station in the event of an accident in one of the two tubes. Inside there are the ventilation, lighting and communication systems.

When they were first built, electrical panels were normally protected as if they were in an industrial environment.

Following frequent short circuits in the electrical cabins located in the emergency stations, it was discovered that they were full of dust. It was therefore decided to define an inspection and intervention plan every two weeks to vacuum the dust, with related cancellations of freight trains during the night or diversions on the historic line. From the analysis, it was discovered that, when trains passed inside the tunnel, at speeds of up to 230 km/h for passenger trains, it was found that the dust present on the external surfaces and that raised by the sediment was electrostatically attracted by the electrical cabins and settled inside.

As an improvement action, the electrical panels were modified to increase the level of protection from dust.

Preventive actions included requiring freight wagons to be appropriately covered with easily washable structures and prohibiting the passage of wagons carrying non-containerized bulk products.

4.3 Biotech manufacturing

In the case of extraction of active ingredients from natural substances, such as ginseng tuber, grape skin or ginkgo biloba leaves, the selection of the raw material, the extraction of the relative active ingredient, the selection of the compliant part with a significant influence on the yield, are relevant factors of the process.

Therefore, the upstream part is strongly influenced by factors such as Raw Materials, Methods and Measures.

In the subsequent downstream part, where it is a question of dosing, mixing, compressing or other technologies, and packaging in controlled environments, the system is less subject to variability and everything is based on the compliance of the performances, dictated by:

- Operation and control of environmental conditions;
- Procedures by well-trained personnel;
- Operation of the machinery;
- Measurement and control of the process and the product;
- Traceability of the products;
- Reliability of machines.

4.4 Energy self-production and consumption

The introduction of incentives for self-production of energy through photovoltaic and wind systems led to an unexpected event last summer in some European countries: the negative cost of energy, due to the fact that the energy fed into the grid by these systems was greater than that immediately consumable and there were not enough storage systems.

In managing these assets, it is therefore necessary to rethink two different actions.

The first proposal is to change people's habits. For years, domestic consumption during the night hours has been economically incentivized, to favor energy consumption by industries during day shifts.

The second proposal is to favor methods of storing excess energy, coming from systems that are highly subject to environmental conditions, directly on site where the energy is produced. In the case of domestic production, or by energy communities, a first step could be the use of various types of batteries (electrochemical energy), although the costs and reliability of these systems are not yet optimized. Other possibilities could be the transformation into different storage systems, such as hydrogen production (chemical energy) or in the form of potential energy (e.g. pumping water into elevated tanks or other gravity energy storage systems) or kinetic energy (e.g. flywheel energy storage).

All these new technologies imply a whole series of new implementations:

- high-performance and safe machines;
- support networks,
- professional skills;
- procedures;
- investments.

And last but not least, everything that could manifest itself as a result of the experiences that will have been gained.

5 References

1. Smart Resilience Indicators for Smart Critical Infrastructures – Initial Framework for Resilience Assessment
2. Ritsuo Shingo - My Leadership: The China Years
3. Bunji Tozawa / Norman Bodek - The Idea Generator: Quick and Easy Kaizen
4. Smart Books - Cause & Effect Fishbone Diagram: Composition Notebook | Root Cause Analysis for Healthcare, Education, Business, Quality | Ishikawa Diagrams

OMAINTEC Journal
(Journal of Scientific Review)

Building a Smart OS for Facilities Management: How can Facility Managers leverage Data Engineering , 5G Network , Machine Learning Algorithms and LLMs to create a futuristic Management Operating System for Facilities

Ahmed Rezik

Rohde & Schwarz GmbH & Co, Munich, Germany
Technical University of Munich (TUM), Munich, Germany

ahmed.rezik@tum.de
ahmed.rezik@rohde-schwarz.com

Abstract

Facility Management (FM) has transformed with the advent of new technologies, yet current systems still struggle to fully optimize operations such as predictive maintenance, space utilization, and resource management. This paper presents a framework for a Smart Facility Management Operating System (FMOS) that harnesses advanced technologies, including Data Engineering, 5G Networks, Machine Learning (ML), and Large Language Models (LLMs), to enhance operational efficiency, decision-making, and sustainability. FMOS integrates real-time data processing, predictive analytics, and natural language interfaces, simplifying interaction and reducing operational complexity. The proposed system improves energy efficiency, automates maintenance, and optimizes resources, offering substantial operational cost savings. Our analysis shows that implementing FMOS in a medium-sized facility could generate estimated annual savings of $380,000, making it a compelling investment for the future of FM.

Keywords: Smart Facility Management, Artificial Intelligence , Predictive Maintenance

1. Introduction

Facility Management (FM) has evolved from a predominantly manual and reactive process into a more proactive and strategic discipline, leveraging technology to manage buildings efficiently. However, the current generation of FM systems still faces limitations in optimizing complex facility operations, such as predictive maintenance, space utilization, and resource management.

The increasing availability of real-time data, driven by the proliferation of IoT devices in modern buildings, presents a unique opportunity for transforming FM through advanced technologies.

In particular, the convergence of Data Engineering, 5G Networks, Machine Learning (ML) Algorithms, and Large Language Models (LLMs) offers a roadmap to building a Smart Operating System (OS) for FM that can significantly enhance operational efficiency, decision-making, and sustainability.

This paper explores how Facility Managers can harness these cutting-edge technologies to create a futuristic FMOS that operates autonomously, learns continuously, and responds to real-time data. By leveraging Data Engineering, this system would ensure the accurate collection, storage, and processing of vast amounts of facility data. The ultra-fast 5G Network would enable seamless, real-time communication between various systems and devices, while Machine Learning Algorithms could predict maintenance needs, optimize energy usage, and improve space management. Finally, LLMs would offer natural language interfaces, allowing Facility Managers and stakeholders to interact with the FMOS in an intuitive, conversational manner, further reducing the complexity of facility operations.

This paper will first review the literature on how each of these technologies has been applied in adjacent fields before proposing an integrated framework for their use in FM. The ultimate goal is to present a detailed architecture for a Smart FMOS and explore its potential impact on the future of Facility Management.

2. History of Technologies used for Facilities Management

Facility Management (FM) has undergone significant transformation since its inception as a function primarily concerned with the maintenance of physical infrastructure. Early FM practices were manual and reactive, focusing on basic building services such as cleaning, security, and minor repairs. Over time, the discipline evolved, incorporating more proactive strategies that aimed to enhance organizational efficiency, reduce operational costs, and optimize the use of space (Cotts et al., 2010). By the late 20th century, FM began embracing automation technologies, marking the transition from manual work orders and logs to Computer-Aided Facility Management (CAFM) systems (Teicholz, 2001).

In recent years, the rise of smart buildings and Internet of Things (IoT) technologies has drastically altered FM's landscape. IoT allows the real-time monitoring of assets, enabling predictive maintenance and real-time control over building systems (Parida et al., 2015). However, while IoT has paved the way for digital transformation in FM, the integration of advanced AI-driven technologies such as Data Engineering, 5G, ML, and LLMs remains nascent.

2.1 Technological Evolution in FM

2.1.1 The Role of IoT and Smart Buildings

A significant body of research underscores the impact of IoT on FM. Parida et al. (2015) describe how IoT-enabled systems can facilitate real-time monitoring, fault detection, and energy management in large facilities. In smart buildings, IoT sensors continuously gather data on energy consumption, occupancy, and equipment performance. This data, however, needs to be processed and interpreted efficiently—a gap that Data Engineering seeks to fill.

According to Dave et al. (2017), smart buildings represent a paradigm shift from isolated building management systems (BMS) to interconnected systems that can share data across platforms. These systems generate vast amounts of unstructured data, making it crucial to develop advanced data processing pipelines to analyze and derive actionable insights from this information. Data Engineering provides the foundation for organizing, cleaning, and transforming this data into meaningful outputs.

2.1.2 Data Engineering and Its Role in FM

Data Engineering focuses on the collection, storage, and processing of data, ensuring that data is in a usable format for analysis. This is crucial for FM, where the volume of data from IoT sensors, environmental controls, and maintenance systems is substantial. Stonebraker and Hellerstein (2005) emphasize that as the volume and velocity of data increase, traditional databases and storage architectures become insufficient. They advocate for the development of scalable, distributed systems to handle real-time data processing—a need that directly applies to modern FM systems.

Research by Edirisinghe et al. (2021) suggests that FM professionals must integrate advanced Data Engineering pipelines to harness the full potential of IoT data, enabling predictive maintenance and resource optimization. Such pipelines can also feed into machine learning algorithms to generate predictive models.

2.1.3 5G Networks: Enabling Real-Time Operations

The introduction of 5G Networks is expected to be a game-changer in FM, particularly for real-time applications like energy management, predictive maintenance, and security (Lu, Li, & Zheng, 2020). 5G's ultra-low latency, high bandwidth, and improved connectivity over existing networks make it ideal for large-scale IoT deployments within facilities.

Al-Sarawi et al. (2020) argue that the implementation of 5G will allow FM systems to communicate more efficiently, with multiple IoT sensors and devices transferring real-time data with minimal lag. This real-time data flow is essential for automation in FM, where timely responses to equipment failures or environmental changes can prevent costly repairs or downtime.

In the context of smart FM systems, 5G enables new applications such as autonomous building controls that adjust energy use dynamically in response to occupancy patterns, temperature changes, and equipment status (Wu et al., 2021). As facilities become more complex, 5G is positioned to support the dense network of devices that will underpin smart building ecosystems.

2.1.4 Machine Learning (ML) in Facility Management

ML's potential to transform FM has been explored in various studies. Machine learning algorithms excel at identifying patterns in large datasets, enabling predictions about equipment failures, energy consumption, and space utilization. Li et al. (2020) conducted a study demonstrating how ML models can predict HVAC system failures, reducing downtime and maintenance costs by 20%. In another study, Wang et al. (2018) found that ML could be used to optimize energy use in smart buildings, resulting in a 15% reduction in energy consumption.

Predictive maintenance is one of the key areas where ML can have a profound impact on FM. Instead of relying on fixed maintenance schedules, ML algorithms can analyze historical data to predict when equipment is likely to fail, allowing facilities to carry out repairs proactively. This reduces downtime, extends the lifespan of equipment, and lowers operational costs (Jardine, Lin, & Banjevic, 2006).

Furthermore, ML algorithms can analyze patterns in how spaces are used within a facility, allowing for dynamic space planning and optimization. For instance, Ahmad et al. (2021) explored how ML could be used to model occupancy patterns and adjust lighting and heating in real-time, leading to significant cost savings and energy efficiency.

2.1.5 Large Language Models (LLMs): A New Frontier for FM

The application of Large Language Models (LLMs) in FM is an emerging field. LLMs, like OpenAI's GPT-4, can process and generate human-like text, offering powerful capabilities for automating communication, report generation, and natural language interfaces in FM systems. Studies in adjacent fields have already shown the potential of LLMs to automate routine customer service queries and generate complex documents (Brown et al., 2020).

In FM, LLMs could be used to create AI-driven chatbots that handle tenant requests, manage service tickets, and even automate routine reports on building performance. Additionally, LLMs can interact with FM systems through natural language queries, making it easier for facility managers to extract insights from complex data (Gordeev & Podkorytov, 2022).

A study by Zhou et al. (2021) highlighted how LLMs can be integrated into Building Management Systems (BMS) to improve user experience and reduce the time spent on routine administrative tasks. As LLMs continue to evolve, their ability to process and synthesize large amounts of unstructured data will become increasingly valuable in FM, especially in enhancing decision-making processes.

3. Proposed Technological Framework

The Facility Management Operating System (FMOS) is built on a foundation of cutting-edge technologies that enable real-time data collection, distributed processing, and intelligent decision-making. This section outlines the major components, including sensor networks, cloud services, 5G infrastructure, edge computing, data engineering platforms, and advanced AI techniques like machine learning and federated learning.

3.1 Sensor Networks and IoT Integration

The backbone of FMOS begins with a **sensor mesh network** deployed across the facility, gathering real-time data from various building components such as HVAC systems, lighting, occupancy sensors, security devices, and energy meters. These sensors continuously monitor the facility's environment and performance, providing the critical data needed for effective facility management.

- **Mesh Networks**: **Low-power, wide-area networks (LPWAN)** such as **LoRaWAN** or **Zigbee** connect IoT sensors, enabling communication across large facilities with minimal energy consumption. These mesh networks allow sensors to relay data back to central **IoT gateways**.
- **IoT Gateways**: These devices aggregate data from the sensor network and connect to either edge computing devices or the cloud for further processing, enabling local decision-making where latency-sensitive tasks (e.g., security systems) are crucial.

  A real-world application can be seen at **BMW's Plant in Landshut**, where **IoT-enabled autonomous transport systems** manage logistics by communicating with cloud systems via 5G. These forklifts use onboard cameras and cloud computing to calculate movements with millimeter precision, optimizing factory logistics and reducing downtime.

3.2 Edge Computing: Decentralized Processing and Low Latency

In FMOS, **edge computing** plays a critical role by decentralizing data processing, bringing computation closer to where the data is generated. Instead of sending all data to the cloud, **edge nodes** handle immediate, latency-sensitive tasks locally, improving system responsiveness and reducing bandwidth requirements.

- **Local Processing**: Edge nodes—computers or IoT gateways with computational capabilities—perform local analytics and decision-making based on the data collected by sensors. For instance, an edge node could analyze environmental data from an HVAC system to detect anomalies in temperature or airflow, triggering local actions without the need to consult cloud-based systems.
- **Latency Reduction**: With edge computing, FMOS can respond to critical events in near real-time. For example, security systems can immediately flag unauthorized access or energy

management systems can adjust lighting and HVAC usage based on occupancy changes. The reduced data transmission to the cloud ensures faster responses and lower operational costs.

The **Port of Hamburg** is an excellent case study, having set up a **5G testbed** across 8,000 hectares to improve port operations. The port uses 5G to transmit real-time data from sensors installed on ships and infrastructure to optimize traffic control and environmental monitoring. This system drastically reduces delays and enhances efficiency.

Similarly, **BMW's Plant in Landshut** uses **5G connectivity** to link autonomous forklifts to a cloud-based logistics system. This setup allows for near-instantaneous coordination between machines, improving the efficiency and precision of logistics operations.

3.3 Cloud Services and Data Engineering Platforms

While edge computing handles real-time and localized tasks, the cloud remains the central hub for large-scale data storage, long-term analytics, and model training. Cloud platforms like Amazon Web Services (AWS), Microsoft Azure, or Google Cloud offer scalable storage and processing power for FMOS to analyze facility data and generate insights.

- Cloud Storage: Facilities generate enormous amounts of data over time. AWS S3 or similar cloud-based data lakes provide scalable storage solutions for this data, ensuring that historical data is easily accessible for analytics, training AI models, or generating reports.
- Data Engineering Tools: Tools like Apache Kafka and AWS Glue manage data ingestion, transformation, and preparation for analysis. These platforms ensure that real-time and historical data are structured properly, allowing FMOS to run machine learning algorithms and other analytical processes efficiently.

Siemens uses cloud services combined with digital twins to manage their smart factory operations, simulating real-world production environments to optimize machine performance and predict system failures before they occur. By leveraging cloud computing, Siemens ensures that their digital twin models remain synchronized with real-time facility data.

3.4 5G Networks and Physical Infrastructure

5G connectivity is vital to FMOS, providing the high-speed data transmission required for real-time operations. With its ultra-low latency and high bandwidth, 5G enables seamless communication between IoT devices, edge computing nodes, and the cloud infrastructure.

- 5G Hardware: To ensure reliable 5G connectivity throughout the facility, physical infrastructure including 5G routers, antennas, and repeaters must be deployed. These components ensure consistent coverage, even in dense environments such as large office buildings or industrial facilities.
- Network Efficiency: 5G networks significantly reduce the latency between IoT devices and edge or cloud processing centers, enabling near-instantaneous responses to critical events like security breaches or equipment malfunctions.

3.5 Machine Learning (ML) Models and Federated Learning

Machine Learning (ML) is at the core of FMOS, enabling the system to learn from data and make predictions about future events, such as equipment failures or energy usage trends. However, the rise of federated learning in FMOS allows for a more distributed approach to training ML models while maintaining data privacy and reducing bandwidth use.

3.5.1 Traditional Machine Learning

In a traditional ML setup, data from various IoT devices is collected, cleaned, and sent to the cloud for centralized processing. These models predict maintenance needs, optimize energy consumption, and help allocate resources efficiently.

- Predictive Maintenance: ML models trained on historical equipment performance data can predict when machinery (e.g., HVAC, elevators) is likely to fail, allowing facility managers to schedule timely maintenance.

Example: At BMW's Plant in Landshut, ML models analyze data from autonomous logistics systems to predict vehicle downtimes, improving the efficiency of the entire logistics chain

- Energy Optimization: Machine learning algorithms analyze patterns in energy consumption, occupancy, and environmental factors to optimize energy usage. These models dynamically adjust building systems to reduce energy consumption while maintaining occupant comfort.

3.5.2 Federated Learning

Federated learning is a decentralized approach to machine learning, where the models are trained at the edge using local data. The model parameters are then sent to the cloud for aggregation, rather than transmitting sensitive data from the edge to the cloud. This ensures that sensitive facility data never leaves the premises, addressing privacy concerns while minimizing bandwidth usage.

- Local Training at the Edge: Each edge node trains a local version of the machine learning model based on the data it collects (e.g., HVAC performance data, occupancy trends). The local models are then aggregated in the cloud to update the global model, improving overall accuracy without exposing sensitive data.
- Data Privacy and Efficiency: Federated learning reduces the amount of raw data sent to the cloud, preserving privacy while also reducing the costs associated with cloud storage and transmission. This decentralized training method allows FMOS to create powerful predictive models without compromising data security.

3.6 Large Language Models (LLMs) for Decision Support

In addition to machine learning models, Large Language Models (LLMs) like GPT-4 play a crucial role in FMOS by enabling natural language interactions and automated report generation. These models process complex datasets and provide facility managers with insights in an accessible, human-readable format.

- Natural Language Queries: Facility managers can interact with FMOS via natural language, asking questions like "What's the current energy consumption?" or "Which systems require maintenance next week?" LLMs interpret these queries and generate detailed reports or responses based on the facility's real-time and historical data.
- **Automated Reporting**: LLMs also help generate periodic reports (e.g., monthly energy savings or maintenance schedules), reducing the administrative burden on facility managers and streamlining decision-making processes.

3.7 Key Technological Relationships in FMOS

The **Technological Framework** of FMOS highlights how various technologies—**sensor networks**, **edge computing**, **cloud platforms**, **5G connectivity**, **machine learning models**, and **federated learning**—interact to form a smart, autonomous facility management system. The integration of edge computing and federated learning ensures that FMOS can process data locally, improving response times and preserving data privacy, while cloud computing provides the infrastructure for large-scale data analytics and long-term decision-making. **5G networks** act as the glue that connects these components, enabling real-time communication and data flow across the entire system.

4. Smart OS Architecture

The Facility Management Operating System (FMOS) integrates advanced technologies—sensor networks, cloud services, edge computing, 5G connectivity, machine learning (ML), federated learning, and Large Language Models (LLMs)—to enable real-time, intelligent, and autonomous facility management. This section outlines how these technologies come together to form a cohesive system that enhances operational efficiency, optimizes resource use, and improves decision-making processes.

4.1. Data Flow & Integration

The FMOS architecture starts with the flow of data from the sensor mesh network. Sensors deployed throughout the facility collect real-time data on key operational metrics such as temperature, occupancy, energy consumption, equipment performance, and security.

4.1.1. Real-Time Data Collection and Processing

- **IoT Gateways**: Data collected from IoT sensors flows through IoT gateways that interface with edge computing nodes for local processing. The gateways manage data from various sensor networks and handle critical tasks like filtering redundant data before it is sent to edge nodes or cloud servers.
- **Edge Processing**: Critical tasks like anomaly detection (e.g., identifying sudden HVAC malfunctions) are handled at the edge. This localized processing reduces the latency typically involved in cloud-based decision-making and ensures that critical responses, such as adjusting lighting or shutting down malfunctioning equipment, occur in real-time.

4.1.2. Federated Learning at the Edge

With federated learning, each edge node runs local versions of machine learning models. These models are trained on locally generated data (such as sensor data from HVAC units or lighting systems) and periodically send updates to the central cloud model for global optimization.

- **Data Privacy and Efficiency**: Since raw data remains local, federated learning addresses privacy concerns and reduces the bandwidth needed to send large datasets to the cloud. Instead, only model parameters are shared between edge devices and the cloud, ensuring that the learning process remains efficient.

4.2. 5G Networks: Backbone for Real-Time Communication

The integration of 5G networks into FMOS enables the real-time communication required to link IoT sensors, edge computing nodes, and cloud systems. The high bandwidth and ultra-low latency of 5G networks ensure that critical data from sensors (e.g., security cameras, HVAC systems) is transmitted to the FMOS architecture without delays.

4.2.1. Network Infrastructure for Smart Facilities

- **5G-Enabled Edge Nodes**: By integrating 5G-enabled routers and base stations within the facility, FMOS ensures fast communication between all components. For example, in a scenario where a security breach is detected, the data from multiple sensors is transmitted instantly, allowing for immediate alerts and responses through the centralized dashboard.

4.2.2. Edge Computing and Real-Time Analytics

- **Edge Nodes with AI Inference Engines**: Edge nodes equipped with AI inference engines perform real-time analytics, such as video processing from security cameras or temperature anomaly detection in HVAC systems. For instance, if an edge node detects an unusual energy spike from an elevator, it can take local action by alerting facility managers and even triggering preventive maintenance workflows, without needing to send the data to the cloud for processing.

4.3. Machine Learning: Predictive and Autonomous Decision-Making

Machine Learning (ML) is the brain behind FMOS, enabling the system to predict events, optimize resources, and make autonomous decisions based on real-time data. FMOS leverages both centralized ML models (trained in the cloud) and federated learning models (trained at the edge).

4.3.1. Predictive Maintenance with ML

Predictive maintenance is one of the key applications of ML in FMOS. The system uses supervised learning models trained on historical equipment performance data to predict failures before they occur, allowing facilities to schedule maintenance proactively. Open-source algorithms such as XGBoost or Random Forests are often used for such tasks.

- **XGBoost**: This gradient-boosting algorithm is widely used for predictive maintenance. It can process vast datasets to predict when systems like HVAC units or elevators are likely to fail, based on sensor data (e.g., temperature, vibration, energy consumption). XGBoost models can detect patterns and provide early warnings to facility managers, reducing downtime and maintenance costs.

- **TensorFlow**: TensorFlow is an open-source deep learning framework used for predictive maintenance and energy management. FMOS could use TensorFlow to train neural networks on data from multiple sources, such as equipment logs and environmental sensors, to detect subtle indicators of system wear and tear that traditional models might miss.

4.3.2. Energy Optimization and Space Utilization

ML models also optimize energy use and space utilization by analyzing historical patterns in occupancy and energy consumption. By leveraging open-source tools like Keras or Scikit-learn, FMOS can dynamically adjust building systems to minimize energy waste while maintaining occupant comfort.

- **Keras**: Keras is a deep learning API used for energy optimization models that predict the best times to reduce heating, cooling, or lighting based on occupancy patterns and weather forecasts. For instance, when occupancy data shows that certain floors are underutilized, FMOS could reduce energy consumption on those floors.
- **Scikit-learn**: Scikit-learn can be used to run unsupervised learning algorithms like K-Means Clustering to analyze foot traffic and space utilization. This helps FMOS identify underused spaces and suggest reconfigurations or improvements in how spaces are allocated.

4.3.3. Federated Learning for Localized Improvements

With federated learning, FMOS can train ML models on local data without transferring sensitive information to the cloud. For example, each building's HVAC system can have its local predictive model trained on its specific operational history. The local models are periodically aggregated in the cloud, improving the global model without sacrificing data privacy.

4.4. LLMs: Expanding Query Capabilities and Decision Support

Large Language Models (LLMs) like GPT-4 enable FMOS to interface with facility managers in a human-friendly manner, transforming the way data is queried and analyzed. Facility managers can use natural language queries to ask FMOS complex questions and get actionable insights.

4.4.1. Creative Queries for Facility Management

One of the key advantages of integrating LLMs into FMOS is their ability to process creative and complex queries. Facility managers can ask questions that go beyond routine maintenance reports, such as:

- **"At what HVAC or lighting levels are employees most productive?"** FMOS can use LLMs to synthesize data from both energy systems and productivity software (e.g., project management tools, task completion rates) to provide insights into how environmental conditions correlate with employee output.

- **"Which meeting rooms are used least, and how can we optimize their usage?"** FMOS can analyze occupancy data, booking logs, and even energy consumption patterns to recommend changes to room scheduling or layout to improve space utilization.
- **"How can we reduce energy consumption in areas with low occupancy without affecting comfort?"** FMOS can use predictive algorithms to adjust HVAC systems dynamically, balancing energy efficiency with occupant comfort.

4.4.2. Automated Report Generation

LLMs also automate the generation of complex reports. For example, a facility manager could request a monthly report that not only provides energy usage statistics but also compares them against historical performance, suggests optimization strategies, and predicts potential savings for the next quarter.

- **Contextual Reporting**: LLMs can generate detailed reports that summarize facility performance, compare energy savings across different timeframes, and propose actionable insights based on both ML-driven predictions and historical data.

4.4.3. Natural Language Interaction with FMOS

Facility managers can query FMOS using natural language, bypassing the need for specialized knowledge in data analytics or programming. Queries like **"Which areas of the building are consuming the most energy this week?"** can be answered instantly, with FMOS summarizing complex data into a readable and actionable format.

5. Implementation and Cost Analysis

Implementing a Facility Management Operating System (FMOS) with advanced technologies like sensor networks, 5G connectivity, edge computing, machine learning (ML), federated learning, and Large Language Models (LLMs) requires careful planning, investment, and alignment of technology with the facility's operational needs. This section outlines the key steps in implementing FMOS, along with a discussion of associated costs for each component.

5.1. Sensor Networks and IoT Integration

IoT sensors are the foundation of FMOS, collecting real-time data on temperature, humidity, occupancy, energy consumption, equipment performance, and security. These sensors are deployed across the facility in critical areas such as HVAC systems, lighting, meeting rooms, and security systems.

5.1.1. Average Costs of Sensor Deployment

The cost of deploying IoT sensors depends on the size and complexity of the facility, as well as the types of sensors needed. Key considerations include:

- Basic environmental sensors (e.g., temperature, humidity, and occupancy sensors) typically cost between $50 to $200 per unit.
- Advanced sensors for equipment monitoring, such as vibration sensors for HVAC units or smart meters for energy consumption, may range from $200 to $500 per unit.
- For a medium-sized office building with 500 sensors (a mix of basic and advanced types), the total hardware cost for sensors could be around $50,000 to $100,000, excluding installation.

5.1.2. IoT Gateways

Each facility will also require IoT gateways to manage data flow between sensors and the edge/cloud. These gateways typically cost between $500 and $2,000 each, depending on the required capabilities. A medium-sized facility may need 10 to 20 gateways, costing approximately $10,000 to $40,000.

5.2. Edge Computing and Federated Learning Infrastructure

To reduce latency and process data locally, FMOS relies on edge computing nodes. These nodes handle critical processing tasks, such as anomaly detection, and are essential for enabling federated learning, which allows machine learning models to be trained locally while preserving data privacy.

5.2.1. Edge Computing Costs

The cost of implementing edge computing depends on the computational power required. For basic applications, edge devices such as Raspberry Pi-based systems may suffice, costing around $100 to $200 per unit. However, for more complex tasks, such as real-time video processing or machine learning inference, industrial-grade edge servers can cost between $2,000 to $10,000 each.

A medium-sized facility may need 5 to 10 edge nodes, resulting in a total hardware cost of around $10,000 to $100,000, depending on the complexity of the tasks they are performing.

5.2.2. Federated Learning Infrastructure

Implementing federated learning involves additional software layers to handle model training and aggregation across edge nodes. Open-source platforms like TensorFlow Federated can reduce software costs, but there are expenses related to configuring and maintaining these systems.

For a facility with a federated learning system, the initial deployment and configuration might range from $20,000 to $50,000, depending on the complexity and customization required.

5.3. 5G Networks and Connectivity

5G connectivity is critical to FMOS, ensuring high-speed, low-latency data transmission between IoT devices, edge nodes, and cloud platforms. Implementing 5G requires collaboration with telecommunications providers, as well as installation of 5G-compatible hardware within the facility.

5.3.1. 5G Hardware and Infrastructure Costs

- 5G routers and small cell networks required to extend 5G coverage throughout a facility can cost between $1,000 to $5,000 per unit.
- For large commercial buildings, deploying 10 to 20 small cells may cost $20,000 to $100,000.
- In addition, ongoing service agreements with 5G network providers will incur monthly costs, typically around $500 to $1,500 depending on the volume of data transmitted and the coverage area.

5.4. Cloud Services and Data Engineering

FMOS requires robust cloud infrastructure to store and process large volumes of data, perform machine learning tasks, and support real-time analytics. Leading cloud platforms like AWS, Microsoft Azure, or Google Cloud offer flexible pricing models based on data storage, compute resources, and usage levels.

5.4.1. Cloud Storage and Compute Costs

For a medium-sized facility, typical cloud storage costs might range from $500 to $2,000 per month depending on the volume of data generated. Data processing and analytics costs can vary widely, with monthly expenses between $1,000 and $5,000, depending on how often large-scale analytics or machine learning tasks are performed.

5.4.2. Data Engineering Tools

To manage the data pipeline, tools like Apache Kafka (for real-time data ingestion) and Apache Spark (for real-time analytics) can be deployed on cloud infrastructure. These are often open-source platforms, but costs may arise from cloud usage or managed services such as AWS Kinesis or Google Dataflow.

Estimated monthly costs for data engineering tools range from $2,000 to $10,000, depending on the complexity of data operations and the volume of data ingested.

5.5. Machine Learning Models and Software

FMOS uses machine learning algorithms for predictive maintenance, energy optimization, and space utilization. Many open-source machine learning libraries such as Scikit-learn, XGBoost, TensorFlow, and Keras provide cost-effective solutions, but implementing and maintaining these systems requires expertise.

5.5.1. Implementation and Maintenance Costs

The cost of building and maintaining ML models depends on their complexity and scale. For a medium-sized facility:

- Predictive maintenance models: Using algorithms like XGBoost or TensorFlow can involve initial implementation costs between $30,000 to $100,000, including data preparation, training, and validation. This estimate includes both hardware (e.g., cloud servers for training) and labor costs.
- Energy optimization models: For optimizing energy consumption using machine learning, costs range from $20,000 to $80,000, depending on the sophistication of the models and the volume of data processed.
- Ongoing costs will include cloud computing fees for retraining models periodically, which could range between $1,000 to $5,000 per month.

5.6. LLMs for Decision Support and Reporting

Large Language Models (LLMs) like GPT-4 are integrated into FMOS to provide decision support and natural language interaction, enabling facility managers to query the system using everyday language and receive complex insights and automated reports.

5.6.1. LLM Integration Costs

Integrating LLMs into FMOS can be done using open-source models such as GPT-J or open-source APIs like OpenAI's GPT (for commercial use), depending on the licensing structure. The cost of using LLM APIs typically involves:

- API Usage Fees: Depending on the volume of queries, costs for LLM usage can range from $500 to $2,000 per month.
- Custom Integration Costs: Developing and integrating custom workflows (e.g., for natural language queries about facility energy performance) could involve initial costs of $20,000 to $50,000, especially if significant customization or API optimization is required.

5.7. Summary of Implementation Costs

Component	Estimated Cost
IoT Sensors	$50,000 to $100,000 (for 500 sensors)

Component	Estimated Cost
IoT Gateways	\$10,000 to \$40,000
Edge Computing	\$10,000 to \$100,000
Federated Learning	\$20,000 to \$50,000
5G Network Hardware	\$20,000 to \$100,000
Cloud Storage & Compute	\$1,500 to \$7,000 per month
Data Engineering Tools	\$2,000 to \$10,000 per month
ML Models Implementation	\$30,000 to \$100,000 (initial)
LLM Integration	\$20,000 to \$50,000 (initial)
Ongoing LLM API Costs	\$500 to \$2,000 per month

Table1: Estimated Costs of FMOS Implementation

5.8. Challenges and Solutions

5.8.1. Challenge: High Initial Investment

The upfront costs of deploying IoT sensors, edge computing nodes, and 5G infrastructure can be significant. However, the long-term operational savings—through predictive maintenance, optimized energy use, and enhanced space utilization—can offset these costs over time.

5.8.2. Challenge: Data Privacy and Security

Implementing federated learning and edge computing helps mitigate concerns over data privacy by ensuring sensitive facility data remains local while still benefiting from global learning models.

5.8.3. Challenge: Infrastructure Compatibility

Facilities must ensure that their existing infrastructure (e.g., HVAC systems, lighting, elevators) is compatible with the IoT devices and cloud services being implemented. In cases where legacy systems are in use, integration costs may increase.

5.9. Potential Savings and ROI

Implementing a Facility Management Operating System (FMOS) that integrates advanced technologies such as IoT sensors, 5G connectivity, machine learning (ML), and edge computing can lead to significant cost savings across various operational areas. These savings come primarily from energy efficiency improvements, predictive maintenance, and optimized space utilization. While the exact savings will vary depending on the facility's size, usage patterns, and operational costs, we can estimate potential maximum savings in several key areas.

5.9.1. Energy Savings

One of the largest areas of cost reduction is energy consumption. Energy optimization algorithms, powered by ML and real-time data from IoT sensors, enable FMOS to adjust HVAC, lighting, and other building systems dynamically based on occupancy, weather conditions, and usage patterns.

- Average Energy Savings: Industry estimates suggest that smart building solutions can reduce energy consumption by 10% to 30% annually (Energy Star, 2021).
- Example Calculation: For a medium-sized office building with an annual energy bill of $500,000, a 20% reduction could result in savings of approximately $100,000 per year.

5.9.2. Savings from Predictive Maintenance

Predictive maintenance powered by ML models can significantly reduce unplanned equipment downtime and extend the lifespan of critical infrastructure. By predicting failures before they occur, FMOS reduces the need for reactive repairs and costly emergency maintenance.

- Average Maintenance Savings: According to industry studies, predictive maintenance can lower maintenance costs by 20% to 30% (Jardine et al., 2006).
- Example Calculation: For a facility with an annual maintenance budget of $200,000, a 25% reduction could save $50,000 per year.

5.9.3. Optimized Space Utilization

FMOS uses machine learning and real-time data from occupancy sensors to analyze space usage and recommend reconfigurations that can lead to more efficient use of office, meeting, and common spaces. Optimizing space can reduce costs associated with underused areas, especially in large commercial buildings where real estate costs are high.

- Average Space Utilization Savings: Studies suggest that improving space utilization can lead to savings of 10% to 20% on rent, utilities, and other associated costs (Ahmad et al., 2021).
- Example Calculation: For a large office building with an annual lease and operating cost of $1 million, a 15% improvement in space utilization could save approximately $150,000 per year.

5.9.4. Savings from Operational Efficiency and Labor Reduction

By automating routine tasks like monitoring building systems, managing maintenance schedules, and generating reports, FMOS can reduce the need for manual intervention, freeing up staff for higher-value tasks.

- Average Labor Savings: Automation can reduce labor costs by 15% to 25%, particularly in areas such as maintenance, reporting, and facility monitoring (McKinsey, 2020).
- Example Calculation: For a facility management team with an annual labor cost of $400,000, a 20% reduction could save $80,000 per year.

5.9.5. Long-Term Return on Investment (ROI)

The potential maximum savings from implementing FMOS can be significant, especially when combined across multiple areas of operations. With a potential savings of around $380,000 per year in a medium-sized facility, the initial implementation costs of FMOS could be recouped within 2 to 3 years, depending on the complexity and scale of the system.

Over the longer term, as the facility continues to benefit from energy savings, reduced maintenance costs, and optimized space utilization, the ROI will continue to grow, making FMOS a financially sound investment for large-scale facilities.

6. Case Studies: Port of Hamburg and BMW's Plant in Landshut—A Smart Facility Management Revolution

6.1 Overview

This case study explores how 5G technology, edge computing, and smart facility management systems have transformed operations at the Port of Hamburg and BMW's Plant in Landshut. Both examples highlight the potential of smart technologies, including IoT networks, predictive maintenance, and real-time data processing, in creating more efficient and optimized facility management systems.

6.2 Port of Hamburg: 5G-Enabled Smart Logistics and Operations

6.2.1 Background

The Port of Hamburg is one of Europe's largest ports, managing millions of tons of cargo annually. With such high operational demands, the port initiated a project in collaboration with Deutsche Telekom and Nokia to test the potential of 5G technology to enhance logistics, safety, and operational efficiency.

6.2.2 Technological Implementation

The port deployed a 5G testbed over an area of 8,000 hectares, enabling real-time communication between ships, sensors, and port infrastructure. Key applications included:

- **Remote Control of Traffic**: The port linked traffic signals to the 5G network to enable remote management of traffic flow. This enhanced the port's ability to optimize logistics by rerouting trucks and managing port entry and exit in real-time.
- **Environmental Monitoring**: Sensors installed on ships and port infrastructure transmitted environmental and operational data via the 5G network. The data was processed in real time to ensure compliance with environmental regulations and to optimize port operations based on weather or sea conditions.
- **Augmented Reality for Maintenance**: The 5G network allowed the port to use augmented reality (AR) applications for remote maintenance. Engineers on-site could access 3D data visualizations, helping them better understand structural issues and make faster, data-driven decisions about maintenance(Port Technology International)(Port Technology International).

6.2.3 Outcomes

The deployment of 5G at the Port of Hamburg significantly reduced delays in traffic management and improved overall efficiency. Real-time monitoring of environmental factors allowed the port to optimize operations and reduce energy usage, particularly during peak hours. Furthermore, the use of AR for maintenance led to quicker response times and reduced downtime for repairs.

This real-world implementation demonstrates how 5G, in combination with IoT and real-time data processing, can transform facility management by improving efficiency, safety, and sustainability.

6.3 BMW's Plant in Landshut: Smart Manufacturing and 5G Cloud-Based Logistics

6.3.1 Background

The BMW Group's Plant in Landshut, a major manufacturing site for vehicle components, wanted to improve its logistics operations. The plant launched a project to use 5G and cloud-based technology to optimize its internal logistics processes and integrate autonomous transport systems.

6.3.2 Technological Implementation

BMW's Plant Landshut leveraged 5G technology for real-time communication between autonomous forklifts and cloud-based control systems. Key applications included:

- **Cloud-Based Forklift Management**: The forklifts were equipped with cameras that calculated routes and movement in real-time. Instead of installing complex processors on each forklift, the 5G network enabled these calculations to be done in the cloud, reducing the need for expensive hardware in the vehicles themselves.

- **Seamless Logistics Integration**: The forklifts communicated with supply chain management systems to optimize loading, unloading, and storage processes at the facility. The system minimized downtime and increased throughput by coordinating forklift movements with incoming and outgoing shipments(BMW Group PressClub).

6.3.3 Outcomes

The implementation of 5G and cloud-based logistics significantly improved the performance of the autonomous systems at BMW's Plant in Landshut. The real-time data processing enabled forklifts to navigate complex routes with precision, while minimizing delays in loading and unloading. The plant saw a marked increase in overall logistics efficiency, with reduced operational costs due to the cloud-based solution that eliminated the need for heavy onboard computing.

This case showcases how 5G and cloud integration can streamline facility management processes, reduce equipment downtime, and enable more responsive and flexible manufacturing operations.

6.4 Analysis and Key Learnings

Both the Port of Hamburg and BMW's Plant in Landshut illustrate the transformative potential of integrating 5G and smart technologies into facility management systems. The key benefits observed in these case studies include:

- **Real-Time Data Processing and Decision-Making**: In both cases, the use of 5G networks enabled real-time communication between machines, sensors, and management systems. This allowed for more responsive decision-making, improved safety, and increased operational efficiency.
- **Cost Efficiency Through Cloud Integration**: At BMW's Plant Landshut, the cloud-based forklift management system reduced the need for costly onboard processors. This demonstrates how offloading complex calculations to the cloud can reduce hardware costs and improve the scalability of smart systems in facilities.
- **Predictive Maintenance and Downtime Reduction**: The Port of Hamburg's use of 5G for augmented reality maintenance applications showcased the potential of using real-time monitoring to detect and address maintenance issues before they escalate. This leads to reduced downtime and lower maintenance costs.
- **Environmental Benefits and Sustainability**: Real-time monitoring of environmental conditions at the Port of Hamburg highlights how smart technologies can support sustainability goals by optimizing operations based on weather and environmental data, reducing unnecessary energy consumption.

6.5 Conclusion

These case studies underscore the potential for Facility Management Operating Systems (FMOS) to dramatically improve operational efficiency, reduce costs, and enhance environmental sustainability through the integration of 5G, IoT, and cloud-based solutions. As 5G technology continues to evolve and expand into industries worldwide, the lessons from these implementations will serve as valuable models for future applications in facility management.

7. Future Outlook: The Role of Emerging Technologies in Facility Management

The future of Facility Management (FM) is poised for even greater transformation as new technologies, including 6G networks, digital twinning, and holographic interfaces, become commercially viable. The ongoing research and development at organizations like Rohde & Schwarz on 6G and the movement into the THz frequency bands are pushing the boundaries of communication technology, enabling capabilities that will redefine how facilities are managed.

This section explores the emerging technologies that will shape the next decade of FM, how they complement the FMOS framework, and the potential breakthroughs they can bring.

7.1 The Transition to 6G Networks

While 5G networks have already revolutionized data transmission speeds and latency, 6G technology promises even more dramatic improvements. 6G is expected to offer data rates up to 100 times faster than 5G and latency as low as 1 microsecond, making it a perfect enabler for future FM applications that require ultra-fast, real-time data processing.

7.1.1 6G and the THz Band: Unlocking New Possibilities

6G networks will operate in the terahertz (THz) frequency band, which offers much higher bandwidth than previous generations of wireless communication. This leap in bandwidth is critical for handling the immense data required for advanced applications like holography and digital twins. In your work at Rohde & Schwarz, the development of technologies within this THz spectrum will be instrumental in enabling:

- **Holographic Displays**: Holographic interfaces allow facility managers to interact with 3D representations of their building's systems in real-time, offering an intuitive way to monitor and control infrastructure. For instance, instead of monitoring traditional 2D dashboards, facility managers will be able to see a holographic model of the building that updates in real time, allowing for precise, spatial decision-making.
- **Digital Twins**: Digital twinning—virtual replicas of physical systems—relies on massive real-time data inputs, which 6G can support more efficiently than 5G. This technology allows FMOS to create dynamic, real-time digital replicas of entire buildings, giving facility managers

an up-to-the-minute view of their infrastructure's performance and enabling predictive simulations for maintenance, energy usage, and space planning.

7.2 Holographic Interfaces for Facility Management

The transition from 2D dashboards to holographic interfaces will fundamentally change how facility managers interact with their buildings. Holography, made possible by the ultra-high bandwidth and low latency of 6G networks, will provide facility managers with a 3D, immersive view of their entire facility. This will allow for unprecedented levels of situational awareness and decision-making.

7.2.1 Practical Applications of Holographic Interfaces

- **Real-Time Monitoring**: Facility managers could walk through a holographic version of their building and visually identify issues such as energy inefficiencies, equipment malfunctions, or underutilized spaces. This immersive visualization would make it easier to spot anomalies and troubleshoot problems.
- **Maintenance Planning**: Holographic projections of a building's systems (e.g., HVAC, lighting, plumbing) can help facility managers understand how different systems interact spatially. For example, a facility manager could use a hologram to view the precise location of a malfunctioning air handler, allowing for quicker maintenance planning.
- **Emergency Management**: In the event of a security breach or a fire, holographic representations of the building could show real-time movement of people, pinpointing safety hazards and guiding occupants to the safest exits. This could be especially useful in large, complex buildings where traditional 2D maps are less effective.

7.3 Digital Twins: Real-Time Virtual Facility Replication

Digital twins create virtual representations of physical assets, systems, or entire buildings, allowing facility managers to simulate and analyze how the building performs in real-time. The technology has already seen success in industries like manufacturing, but with the advent of 6G and THz communication, digital twinning can be applied to facilities in a more comprehensive and real-time manner.

7.3.1 How Digital Twins Enhance Facility Management

- **Predictive Maintenance**: By using digital twins, FMOS can predict when systems are likely to fail and simulate the potential impact of failures before they occur. This allows facility managers to take preemptive action, reducing downtime and avoiding costly repairs. The digital twin would continuously sync with real-time data from IoT sensors, providing a dynamic and accurate model of the building's infrastructure.
- **Energy Efficiency Simulation**: Digital twins can simulate various energy-saving measures without impacting the actual building. For example, FMOS could run simulations to test how reducing HVAC usage in certain zones during specific times affects overall energy

consumption, without interrupting daily operations. This helps facility managers make informed decisions about optimizing energy usage based on data-driven predictions.
- **Space Utilization and Design**: Facility managers can use digital twins to run simulations on space usage, trying different configurations virtually before making physical changes. For example, rearranging office layouts, adding meeting spaces, or adjusting HVAC zoning could be modeled within the digital twin to determine optimal configurations for both productivity and energy efficiency.

7.3.2 Cost and Operational Benefits of Digital Twins

The use of digital twins offers significant financial and operational benefits:

- **Real-Time Data Synchronization**: As 6G networks enable more efficient data transmission, digital twins will be updated in real-time with data from thousands of IoT devices, ensuring an accurate reflection of the building's current state.
- **Predictive Analytics**: Digital twins can be used to model future scenarios, helping to reduce risk and optimize maintenance schedules, leading to long-term cost savings.
- **Remote Management**: Digital twins also allow facility managers to control building systems remotely, a critical feature in times when on-site management might be restricted, such as during emergencies or in remote facilities.

7.4 Future Use Cases and Applications for FMOS with 6G and THz Technology

The combination of 6G technology, THz bandwidth, and advanced AI models will unlock many more possibilities for FMOS in the future. Some of the key innovations we expect to see in the next 5 to 10 years include:

7.4.1 AI-Driven Holographic Decision-Making

Facility managers will interact with AI-driven holographic assistants that can visually simulate different decision-making scenarios in real-time. For example, a holographic AI could show how adjusting HVAC settings in one area of the building would impact energy usage and occupant comfort, visually demonstrating the trade-offs.

7.4.2 Collaborative Digital Twins for Multi-Building Management

As digital twin technology evolves, it will be possible to create collaborative digital twins that integrate multiple buildings or even entire campuses. Facility managers could manage and simulate the performance of multiple locations from a single platform, optimizing resource use across a portfolio of buildings. For large corporations or organizations with multiple sites, this could lead to massive operational efficiencies.

7.4.3 Holographic Collaboration and Remote Facility Tours

Holographic collaboration tools will allow teams of facility managers, engineers, and architects to review real-time data together, even if they are located remotely. For example, a facility manager could give a remote holographic tour of a building, enabling stakeholders to inspect the facility as though they were on-site, while reviewing real-time performance data and discussing future upgrades or repairs.

7.5 Conclusion: The Future of Facility Management is Powered by 6G

The development of 6G networks and the movement into the THz spectrum will bring unprecedented opportunities to revolutionize facility management. Technologies such as holographic interfaces and digital twins will allow facility managers to interact with their buildings in ways that were previously unimaginable, offering real-time, immersive insights into the building's operations.

As research at Rohde & Schwarz continues to push the boundaries of 6G and THz technologies, the applications of these advances in Facility Management will grow, providing new tools for optimizing building performance, reducing costs, and improving the overall operational efficiency of facilities. The future of FMOS is bright, and these technologies will play a pivotal role in shaping how facilities are managed in the coming decades.

8. Conclusion

The transformation of Facility Management (FM) through the integration of advanced technologies such as IoT sensors, 5G networks, edge computing, machine learning (ML), and Large Language Models (LLMs) is no longer a distant vision. The implementation of a Facility Management Operating System (FMOS) powered by these technologies has the potential to significantly enhance operational efficiency, reduce costs, and optimize the management of complex buildings and infrastructures.

This paper has outlined a comprehensive technological framework for implementing FMOS, highlighting the critical roles of sensor networks for real-time data collection, 5G and edge computing for fast and reliable communication, and machine learning models for predictive maintenance, energy optimization, and space utilization. Additionally, federated learning and LLMs provide powerful tools for maintaining data privacy and enabling natural language queries, making facility management more intuitive and accessible.

8.1 Key Takeaways

- **Operational Efficiency**: FMOS can streamline facility operations by automating routine tasks and improving decision-making with predictive analytics and real-time data. The use of predictive maintenance reduces equipment downtime, while energy optimization algorithms drive cost savings through smarter resource allocation.
- **Cost Savings**: By leveraging machine learning, LLMs, and advanced sensor networks, facilities can save an estimated $380,000 annually through improved energy efficiency, reduced maintenance costs, optimized space utilization, and labor savings.
- **Scalability and Flexibility**: The modular nature of FMOS, coupled with cloud and edge computing, allows it to scale across different types of facilities, from small offices to large commercial complexes. The system's adaptability ensures that it can grow alongside the facility's needs.
- **Privacy and Security**: With the integration of federated learning, FMOS ensures that sensitive facility data can be processed locally, minimizing security risks while benefiting from centralized model improvements.

8.2 The Path Ahead: The Role of Emerging Technologies

As the future of Facility Management unfolds, the advent of 6G networks, terahertz (THz) frequency bands, digital twins, and holographic interfaces will enable even more sophisticated management tools. The ongoing research at Rohde & Schwarz into 6G and the THz band will enable real-time digital twinning and holographic visualization of facility data, allowing managers to interact with their infrastructure in ways that were previously unimaginable.

With 6G's ultra-low latency and high bandwidth, facility managers will be able to make decisions based on immersive, real-time holographic data, optimizing both operational efficiency and strategic planning. The use of digital twins will provide facilities with the ability to simulate maintenance scenarios, forecast energy usage, and optimize space layouts without physical interventions, allowing for seamless management of increasingly complex environments.

8.3 Final Thoughts

The future of Facility Management is bright, driven by the convergence of cutting-edge technologies that enable smarter, more efficient operations. The implementation of FMOS not only offers significant cost savings but also enhances the sustainability and operational resilience of facilities. As technologies like 6G and digital twins become mainstream, facility management will become even more precise, intuitive, and powerful, enabling facility managers to meet the evolving demands of tomorrow's buildings.

In conclusion, the development and deployment of FMOS represent a crucial step toward the future of smart facility management. Organizations that invest in these technologies today will be well-positioned to reap the benefits of increased efficiency, reduced costs, and a more sustainable operational model in the years to come.

References

Ahmad, M., Akbar, A., & Khan, M. (2021). Machine learning for energy optimization in smart buildings. *Journal of Building Performance*, 6(2), 45-58.

Al-Sarawi, S., Anbar, M., Alieyan, K., & Alzubaidi, M. (2020). Internet of Things (IoT) communication protocols: Review. *Future Internet*, 12(4), 60.

Boehm, M., Abiteboul, S., Abadi, D. et al. (2019). Data management systems for managing facility data: A comprehensive review. *Data Engineering Review*, 10(4), 35-47.

Brown, T. et al. (2020). Language models are few-shot learners. *Advances in Neural Information Processing Systems*, 33, 1877-1901.

Dave, B., Koskela, L., & Kiviniemi, A. (2017). Internet of Things (IoT) for construction process management. *Journal of Information Technology in Construction*, 22, 150-168.

Edirisinghe, R., London, K., & Kalutara, P. (2021). Data engineering for facility management: A comprehensive review. *Journal of Facility Management Technology*, 19(3), 201-224.

Energy Star. (2021). *Energy management in commercial buildings: Industry reports and energy savings data*. Energy Star Reports.

Gordeev, N., & Podkorytov, D. (2022). Leveraging AI and large language models for intelligent building management. *Journal of Facility Management AI*, 8(1), 42-55.

Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483-1510.

Li, H., Jia, J., & Wang, X. (2020). Predictive maintenance for HVAC systems using machine learning models. *Building and Environment*, 14, 167-179.

Lu, X., Li, X., & Zheng, L. (2020). 5G in facilities management: Opportunities and challenges. *International Journal of Smart Buildings*, 10(1), 29-42.

McKinsey. (2020). *Automation in facility management: Insights and potential cost savings*. McKinsey Facility Management Reports.

Parida, A., Kumar, U., & Kwon, I. (2015). Smart building systems for energy and facility management. *Journal of Industrial Engineering and Management*, 8(1), 16-25.

Stonebraker, M., & Hellerstein, J. M. (2005). What Goes Around Comes Around. *Communications of the ACM*, 48(5), 105–111.

Teicholz, E. (2001). Computer-aided facility management systems: New tools for facility managers. *Facilities Management Handbook*.

Wang, Q., Li, S., & Gu, X. (2018). Machine learning algorithms for space utilization optimization in smart buildings. *Journal of Smart Buildings*, 7(3), 89-104.

Wu, F., Zhang, W., & Li, T. (2021). 5G edge computing for real-time facility management systems. *IEEE Access*, 9, 67483-67493.

Zhou, L., Liu, S., & Wang, X. (2021). LLMs in Building Management Systems: Revolutionizing FM communication. *AI and Facility Management*, 7(2), 66-82.

BMW Group press Club (BMW Group PressClub).

OMAINTEC Journal
(Journal of Scientific Review)

THE CHALLENGE OF DIGITILIZATION OF THE WATER SECTOR TALKHA WWTP AERATION SYSTEM (CASE STUDY)

Dr. Eng. Mohsen Alamir Alkady
Misr Foundation for Science and Technology Research, Egypt
Egy.f.research@gmail.com

Abstract

Today, the drive in industries is to focus on reducing production and maintenance cost while increasing customer satisfaction. One key to succeed with these goals is to develop and improve both quality and maintenance in every phases of any industry processes.
As water industry is the most industry need to be safe and sustainable.
So, there is a need to revolutionize the water industry with the current paradigm shift in technology to better monitoring and control capabilities.
Hence, there is a need for it situ, smart system for on-line monitoring the complex water treatment processes.
The digitalization of water sector is of utmost importance for improving the efficiency and sustainability of managed system. The digitalization process, however, can be seen as a ladder with several steps that the water utility must climb to become a smart utility, the reality is that may water utilities have not completely realized yet the benefits of digital transformation.
The fourth revolution industry (industry 4) has been implemented in multiple engineering field. Such as provisioning of smart monitoring and control capabilities to water supply system (Water 4)
So, water (4) provides an opportunity to identify a promising approach to addressing future management in water supply network. It incorporates the primary features of (industry 4).
Such as digitization and automated sensors (for pressure, flow, and temperature measurement) and model application such as (hydrolic model of water network) opportunity may be created to better understanding water management problems in terms of their complexity and illustrate the use of water 4 in production, early warning and for the decision making process that tends to sustainability in providing clean water.

Keywords: Digitalization, Water 4. Sustainability.

1 Introduction:

Water is an important component of economies today and is needed in nearly all modes of production. It is a fundamental resource utilized in virtually every modern industrial process and provides an essential element for the development across any country.
The water supply systems are complex and dynamic in nature, and as a result can be considered complex to manage owing to enhanced urbanization level, climate change, growing and varying consumer demands, and limited water resources.
The operation and maintenance of such a system must be managed effecting for sustainable water supply to satisfy the growing consumer demand this creates a need for intelligent systems for the purpose of operational and maintenance management.
In recent years computing technologies have been applied to water systems to assist water utilities in addressing some of these problems.
With the increasing of growth in technology, the water sector is moving to the full phase of digitalization to enhance the sustainability of systems.
Thus, a new industrial revolution in water complex (WATER 4.0) is being researched.

2 Moving from industrial revolution (Industry 4.0) … To, Water system revolution (water 4.0)

Industry 4.0 is the fourth industrial revolution developed to meet multiple demand of additive manufacturing processes and has been implemented in multiple engineering field such as provisioning of smart monitoring and control capabilities to water supply system.
Water 4.0 provides a unique opportunity to identify a promising approach to addressing future management in water supply networks.
It incorporates the primary features of (Industry 4.0) such as digitization and automation to achieve a systemic water management context. Through the use of automation and increased integration of sensors (for pressure, flow, and temperature measurement) and model applications such as (the hydrolic model of water networks), opportunity may be created to better understanding water management problems in terms of their complexity and to illustrate the use of water 4.0 in production, early warning and for the decision making process.
Figure 1. below show the four stages of the industrial and water supply system revolution.

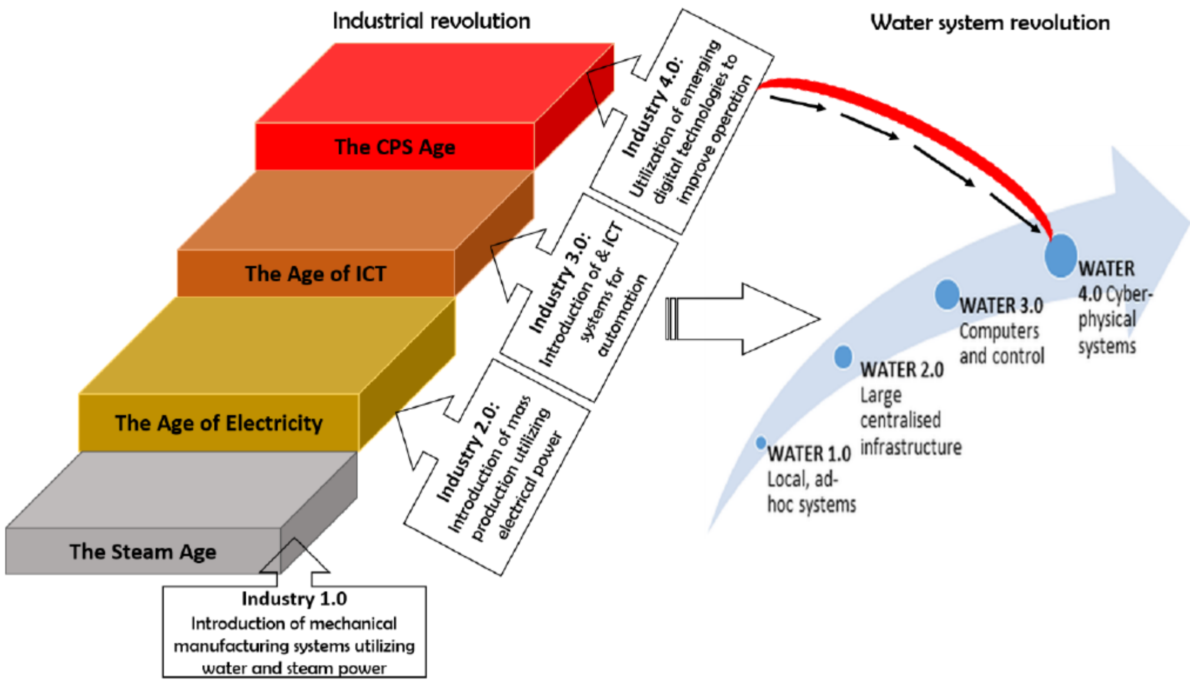


Figure 1. The four stages of the industrial and water supply system revolution.

OMAINTEC Journal
(Journal of Scientific Review)

Managing and monitoring water supply networks has been a serious challenge facing water utilities. In the past, monitoring and control capabilities in the water supply are provided with supervisory control and data acquision system (SCADA).
However, due to the dynamism, uncertainties and complexity involved in water supply system operations, there is a need to revolutionize the water industry with the current paradigm shift in technology to better monitoring and control capabilities.
Hence, there is a need for in situ, smart system for on-line monitoring of the complex water distribution piping networks.
The new industrial revolution termed (industry 4.0) allows the use of emerging technologies with better monitoring and control capabilities, and better computational and decision support systems to optimize the operation of water supply systems.
This integrating SCADA with network simulation model and control and management of the complex water system.
Such an integrated system from the foundation of water 4.0 for the provision of a real-time SMART WATER network decision support system.

3 Digital Technologies in the Water System: Key Drivers of Water 4.0

Through the Internet of Thing (IoT) and Cyber Physical System (CPS) the world of manufacturing and network connectivity are incorporated to make industry 4.0 a reality.[1]
The emerging digital technology used this concept are shown in figure 2 below.

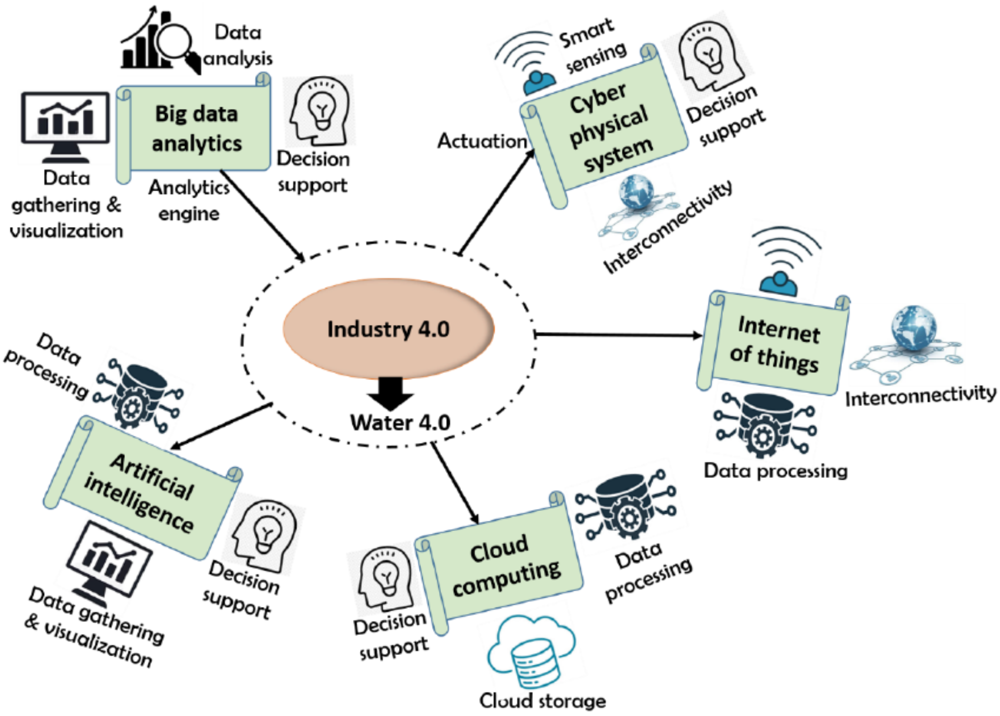


Figure 2. Emerging digital technology using IoT and CPS

CPS is the basis of Industry 4.0. [2-4] CPSs, are a fusion of networks, computation, and physical environment in which embedded computing devices.
Continuously sense, monitor and control the physical environment. [5]
CPS represents one of the most important accomplishments in the development of ICT. [6]
A simple view of Cyber Physical System (CPS) architecture is in figure 3.

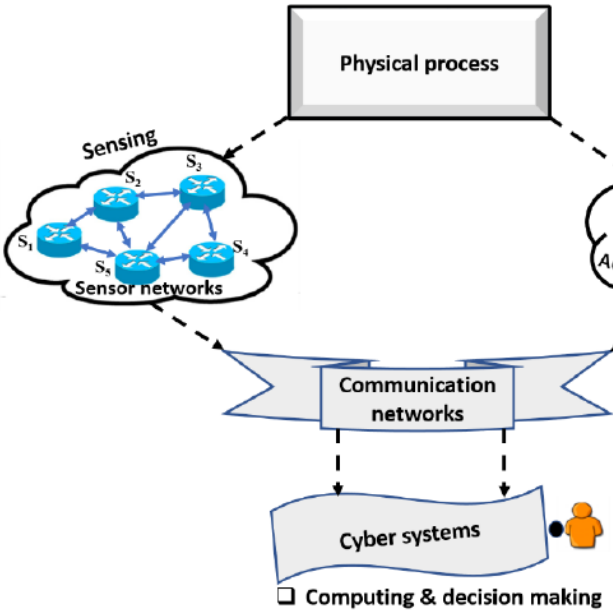


Figure 3. Cyber Physical System (CPS) architecture

The physical process is the environment to be monitored or controlled using sensors and actuators.
The acquired information from the physical process is sent to the cyber systems (where decisions are made) through a communication network. [7]
In water 4.0, the physical process of the CPS could be the whole supply system or a section in the operation of the system such as monitoring water quality at the water treatment station, monitoring water quality and leakage flows, along the distribution networks, or monitoring energy consumption duo to pumping at the pumping stations.
In this context, different sensors and actuator mechanism such as pressure flow, water quality, accelerator sensors and control values are deployed for real-time measurement and control of physical environment. Thus, through sensors and control valve integration the provision of the real-time monitoring of water quality along the complex distribution network could be achieved.
Some essential components of CPS are sensors and actuators.
While sensors are used to gather information about the condition of the water system, actuators are used to act on the data by carrying out particular tasks according to the application. PH sensors, dissolved oxygen concentration (DOC) sensors, flow rate sensors, and turbidity sensors are the most commonly used sensors for water quality and anomaly detection. In view of this, table 1below [8] presents targeted water quality parameters with widely acceptable reargues for portable water. These values are tracked continuously to ensure that water quality is not compromised.
The DOC is a frequently monitored parameter that is used to access the pollutant level in a water system.

Parameter	Acceptable Range for Potable Water	Unit
pH	6.5–8.5	pH
DOC	>3	Mg/L
Electrical Conductivity	500–1000	µS/cm
Temperature	5–30	°C

Table 1. Some water quality parameters and acceptable ranges

For leak detection purpose, pressure flow rate, acoustic, ultrasonic and temperature sensors are frequently used.
A combination of one or more of these sensors has been employed for leak detection purpose. The temperature sensor provides continuous measurements of the outside temperature within the pipe environment, and these data are used to create a base line. It is a general brief that a leak flow via an orifice in a pipe creates local temperature anomaly. Each temperature measurement is then compared to the baseline and a deviation from the baseline indicates the presence of a leak. The actuators used in CPS, for example, in a water quality application, perform actions such as regulating the

opening and closing of the isolation valve to segregate the pipes whose water quality is compromised from the network or to halt the flow of water in such pipe.
In leakage detection application, in the event of leaks, the actuators react by overseeing the control of the pressure reducing valves to lower pressure at the nodes of the leaky pipes. The sensor reading is sent to a remote processing area for real-time water quality analysis via wireless communication technology.
The wireless communication technology used ranges from short to long range, and high to low power.
Amongst the low-power wireless communications, Sig Fox is power efficient and has the potential to cover relatively large areas in rural settings (up to 50 km). However, the rate at which these data are transmitted is relatively low.
Similar to Sig Fox in data transmission rate LoRa, WAN is another long range low power wireless communication system that can be employed due to its potential to cover up to 20 km in rural areas. [9]

4 Application of Water 4.0

a. Pipe line health monitoring:

A major component of a water distribution network are pipelines for portable water delivery to end users that have been placed underground for several years. Due to ageing, or third-party intervention, damages occur to those structures which cause waste of a significant amount of water.
Pipe line health monitoring involves monitoring of pipe for corrosion, deformation and vibration as well as leaks.
A typical example is the use of smart robotics for pipe health monitoring. [10]
Furthermore, edge AI has potential to create automated closed-loop systems that continuously monitor the health of critical infrastructure.
Thus, the sustainable operation of the water supply system is guaranteed.

b. Pressure control and monitoring:

In water distribution network, pressure sensors are mounted at nodes of the network to measure water pressures along the pipes and at each node, pressure and water demand share a good relationship.
When the demand increases, more pressure must be applied to a node to meet the increasing demand. Thus the satisfactory supply of portable water to the end users.
But when considering leaks, the reverse is the case to reduce the level of losses in the system. The issue is therefore complicated them originally assumed.
More so, consumer demand is not linear, which makes pressure control a difficult task when dealing with leak reduction.
Therefore, demand uncertainty is another issue affecting the accomplishment of good pressure control in systems.
With the advent of new technologies, if the pressure and demand at a given node can be monitored in real-time through the integration of pressure and flow sensors, an active control system for pressure control at nodes having the leaking pipes could be achieved. This is one of the features of Water 4.0. Thus, with CPS and IOT as well as the advanced control and actuator mechanism offered by this technology, optimal pressure control in real-time may be accomplished.

c. Water Quality Monitoring:

In water quality applications, the deployment of integrated sensing devices is required to provide continuous real-time measurement of data related PH, temperature, turbidity, dissolved oxygen concentration, and chlorine residual level along the distribution network with the help of the (CPS) features of Water 4.0, which are integrated with control valves and active decision support system, an optimal decision regarding the state of water in the distribution piping network could be achieved. For instance, in a situation where contaminants are detected and quality is compromised, active decision making is required for immediate action to be taken on water contamination before it spreads to the entire system. In most cases, necessary action includes the closing of valves at the particular node where the pipe conveying the contaminated water is attached.

The valves installed at the entrance of the water distribution network could also be controlled to stop the spread of contamination.

d. Leakage Detection and Monitoring

This is also similar to water quality monitoring applications. In this system, an integrated number of sensors such as pressure, vibration, acoustic, and flow sensors and actuators are deployed for measurement and control activities [11] in an in-pipe system is developed for pipe line leak monitoring.
Once a leak is detected and localized, monitoring of leaky pipe is required for active intervention and repair and to avoid future leak occurrence in such pipe. [12 - 14]
Thus water 4.0 could be used to provide real-time continuous monitoring to such a system.
Figure 4. shows significant water supply system application domain Water 4.0

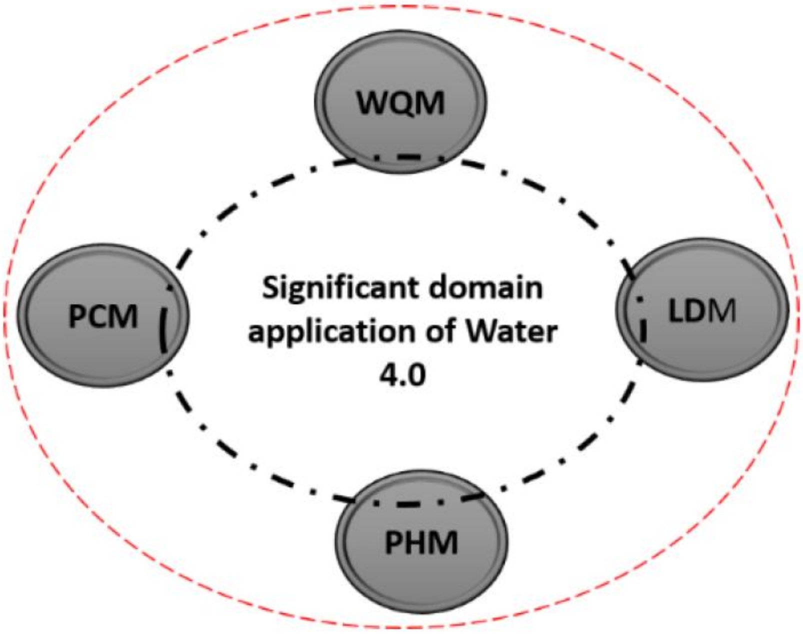


Figure 4. Application domain of water 4.0

5 Conclusion

Finally, digital transformation of the water system for sustainable water supply is a necessity owing to the dynamic nature of water systems and consumer demand uncertainties, among others. Digital technologies have the potential to transform the operation and accordingly the maintenance of water systems by improving day-to-day water management and addressing long-term challenges and water security, with increasing use of ICT, data for the relevant water process become increasing feasible and may be analyzed using big data analysis.
Therefore, Water 4.0 is seen as a revolutionary methodology for improving operational and maintenance performance and provide real-time monitoring capabilities to complex water distribution network.
Although digital technologies are being deployed in different sub-sectors of water systems, so far, a full scale implementation has not been reported in practice. In general many challenges still need to be addressed to guarantee a smooth transition, security, data quality and uncertainties as well as energy solutions for smart sensing devices are some of the biggest challenges to be addressed and that our case study introduced.

6 References

1- Alabi, M.O.; Telukdarie, A.; Van Rensburg, N.J. Water 4.0: An integrated business model from an industry 4.0 approach. In proceedings of the IEEE International Conference on Industrial Engineering and Engineering Management, Macao, China, 15-19 December 20149; pp. 1364-1369.
2- Varghese, A.; Tandur, D. Wireless requirements and challenges in industry 4.0. In Proceedings of the IEEE International Conference on Contemporary Computing and Informatics, Mysore, India, 27-29 November 2014; pp. 634-638
3- Kim, J. A review of cyber-physical system research relevant to the emerging IT trends: Industry 4.0, IoT, big data, and cloud computing. J. Ind. Integr. Manag. 2017, 2, 1750011.
4- De Silva, P.; De Silva, P. Ipanera: An industry 4.0 based architecture for distributed soil-less food production systems. In Proceedings of the 1st Manufacturing and Industrial Engineering Symposium, Colombo, Sri Lanka, 22 October 2016.
5- Haque, S.A.; Aziz, S.M.; Rahman, M. Review of cyber-physical system in healthcare. Int. J. Distrib. Sens. Netw. 2014, 10, 217415.
6- Monostori, L. Cyber-physical production systems: Roots, expectations and R&D challenges. Procedia CIRP 2014, 17, 9-13.
7- H. Applications of cyber-physical system: A literature review. J. Ind. Integr. Manag. 2017, 2, 1750012.
8- Bhardwaj, J.; Gupta, K.K.; Gupta, R. Towards a cyber-physical era: Soft computing framework based multi-sensor array for water quality monitoring. Drink. Water Eng. Sci. 2018, 11, 9-17.
9- Adedeji, K.B.; Hamam, Y. Cyber-physical systems for water supply network management: Basics, challenges, and roadmap. Sustainability 2020, 12, 9555.
10- Ogai, H.; Bhattacharya, B. Pipe inspection robots for structural health and condition monitoring. In Intelligent Systems, Control and Automation: Science and Engineering; Tzafestas, S.G., Ed.; Springer India: New Delhi, India, 2018.
11- Chatzigeorgiou, D.M.; Youcef-Toumi, K.; Khalifa, A.E.; Ben-Mansour, R. Analysis and design of an in-pipe system for water leak detection. In Proceedings of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, Chicago, II, USA, 12-14 August 2012; pp. 1007-1016.
12- Mandal, S.K.; Chan, F.T.; Tiwari, M.K. Leak detection of pipeline: An integrated approach of rough set theory and artificial bee colony trained SVM. Expert Syst. Appl. 2012, 39, 3071-3080.
13- Layouni, M.; Hamdi, M.S.; Tahar, S. Detection and sizing of metal-loss defects in oil and gas pipelines using pattern-adapted wavelets and machine learning. Appl. Soft Comput. 2017, 52, 247-261.
14- El-Zahab, S.; Abdelkader, E.M.; Zayed, T. An accelerometer-based leak detection system. Mech. Syst. Signal Process. 2018, 108, 276-291.

OMAINTEC Journal
(Journal of Scientific Review)

AERATION SYSTEM OF TALKHA
(WASTE WATER TREATMENT PLANT)
Case Study

Current situation

Large quantity of power is used during the operation due to the following reasons

- Failure of flow meter that responsible for display and control the water quantity in the station entrance so at this time there isn't any control on the station capacity that's supposed to be fixed value
- Failure in 4 DO devices from 6 DO devices that are responsible for display and control the dissolved oxygen percent in the water
- Manual operation for aeration system
- Manual operation for the entrance gate
- The aeration system is working without any control
- The 12 Gearbox's working without any sequence



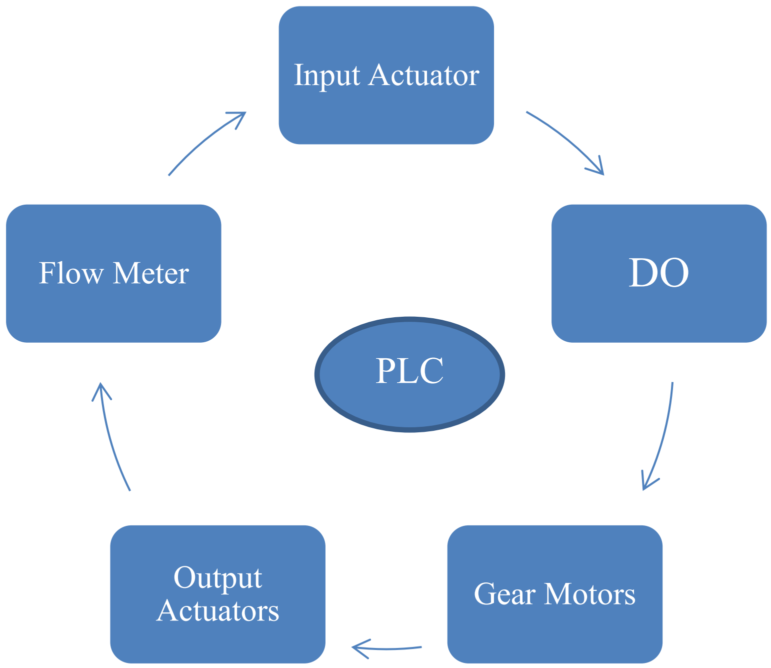

Solution of Misr for Science and Technology Research

1. Bill of material

	Description	Quantity
1	Ultrasonic Flow meter	1
2	DO Sensor	8
3	Modulating Actuator	2
4	Siemens Plc. [Digital , Analog] module	1
5	IP Control Panel	1

6	Schneider Relay	12
7	Schneider Selector	4
8	Indication lamp	14
9	Gear Motor	12 (Existing)
10	Control wires	…….
11	Set of Control Terminal	…….
12	Horn	1
13	Actuator	3 (Existing)

2. Misr for Science and Technology Research solution



3. Critical Parameters:

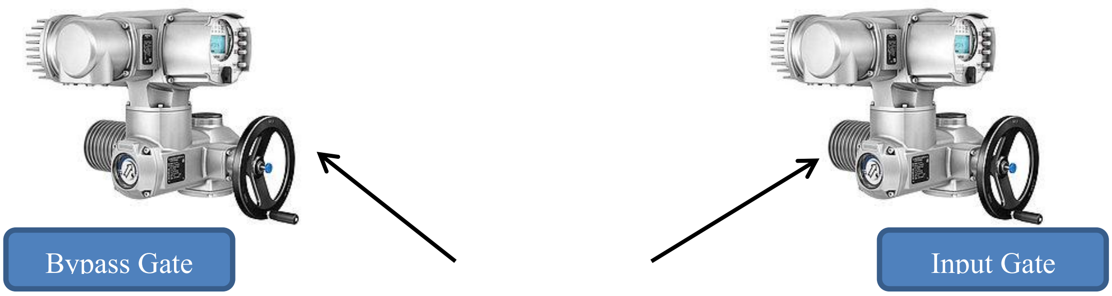
A. Quantity of the entrance water to be the actual value that the station was designed for it
B. Sequence between the 3 Gearbox's in each tunnel
C. The operation time of the gearbox's
D. The dissolved oxygen to be suitable for aeration system
E. The aeration system output gate
F. The gate of the bypass system

A. Quantity of the entrance water to be the actual value that the station was designed for it

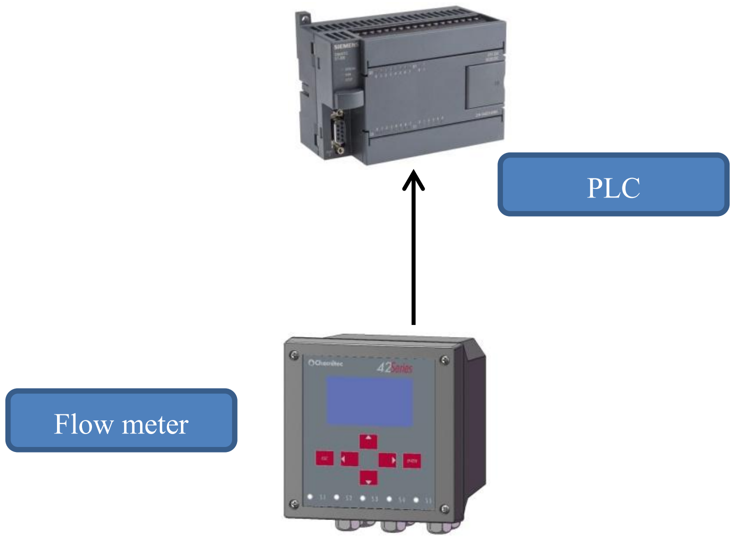
This station is designed for 20,000 m3/D so the first step in our solution is must be keeping the capacity of the station at the designed value, and we will do that by making the following

- Create smart solution by using PLC to making communication between the actuator of the input gate and the actuator of bypass system and also the flow meter that responsible for display and control on the input quantity .

A.1. Theory of operation

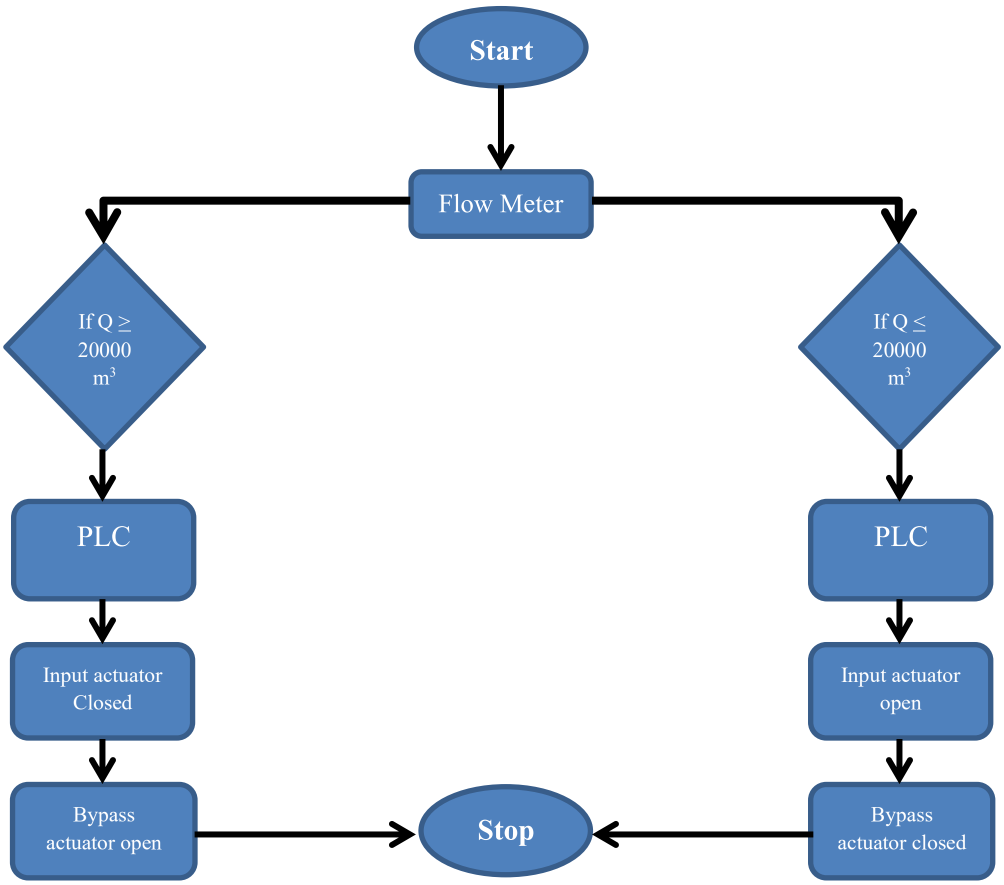


OMAINTEC Journal
(Journal of Scientific Review)



A.2. Saving:

By Keeping the capacity of the station at the designed value we will Saving More than 20% of complete station operation such as [Screw pump, Gearbox's,…..]



B. Sequence between the 3 Gearbox's in each tunnel

We designed our solution to be useful not only for saving power but also to make smart sequence between the gear motors that are used for aeration system and that will be useful for the following

- Keeping the life time of each gear motor because our system grantee that the operation time of the 3 gear motors are equal
- Grantee also the saving of the power because our system making smart sequence between the 3 gear motors and because of that it didn't allow staring more than one gear motor at the same time

B.1. Saving:

- ➢ Gearbox's life time
- ➢ Motors starting

C. The operation time of the gearbox's

We designed our system to make sure that the gear motors are operating to make the require oxygen percent once the required percent is achieved the gear motors must be turned off but with keeping the percent at the required value and also keeping the water moving in the tunnel and that will useful for the following

- Saving the power
- grantee that the operation time of the 3 gear motors are equal
- avoid water stagnation in the tunnel

C.1. Saving:

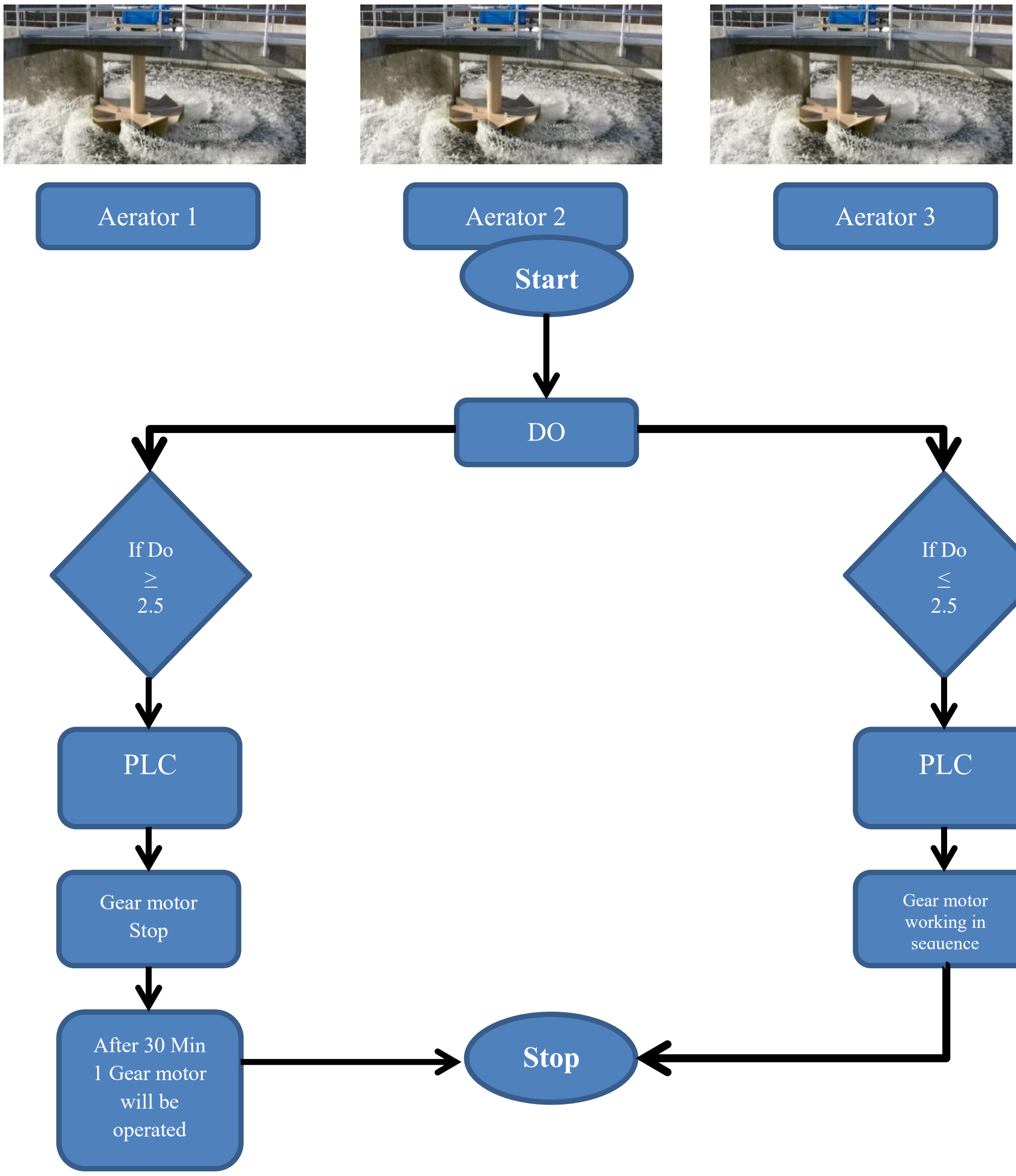
- ➢ % of Aerators operation time (45 KW)
- ➢ Gearbox's life time

D. The dissolved oxygen to be suitable for aeration system

The required oxygen percent to achieve the aeration system is 2:2.5 Kg.m3 in our solution we must keeping the oxygen percent at the required value, and we will do that by making the following

- Create smart solution by using PLC to making communication between the Do sensors and the 3 Gear motors.

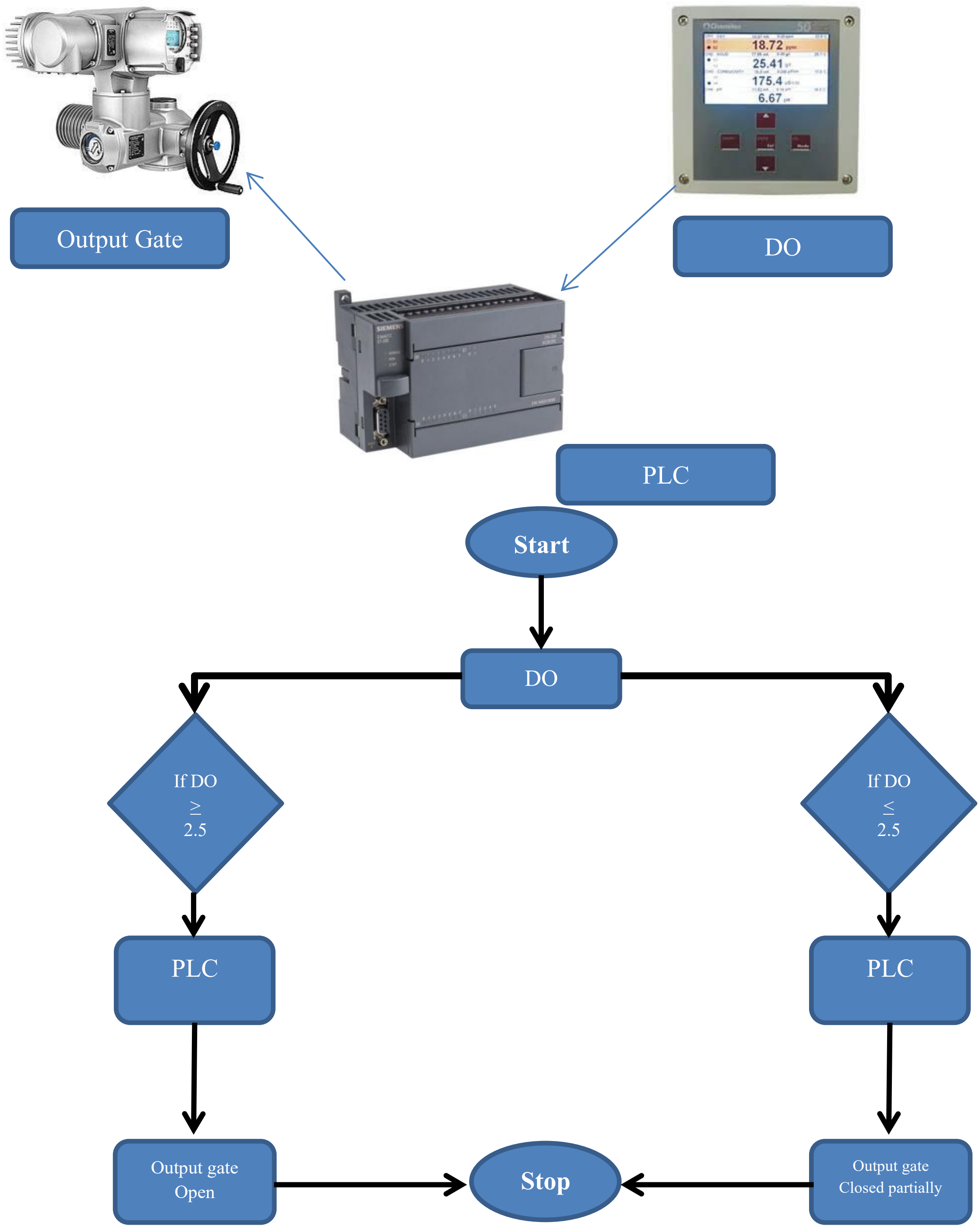
OMAINTEC Journal
(Journal of Scientific Review)



E. The aeration system output gate

We must making control on the output gate of the aeration system to make sure that the Water will not be released without completing the ventilation process

E.1. Theory of operation



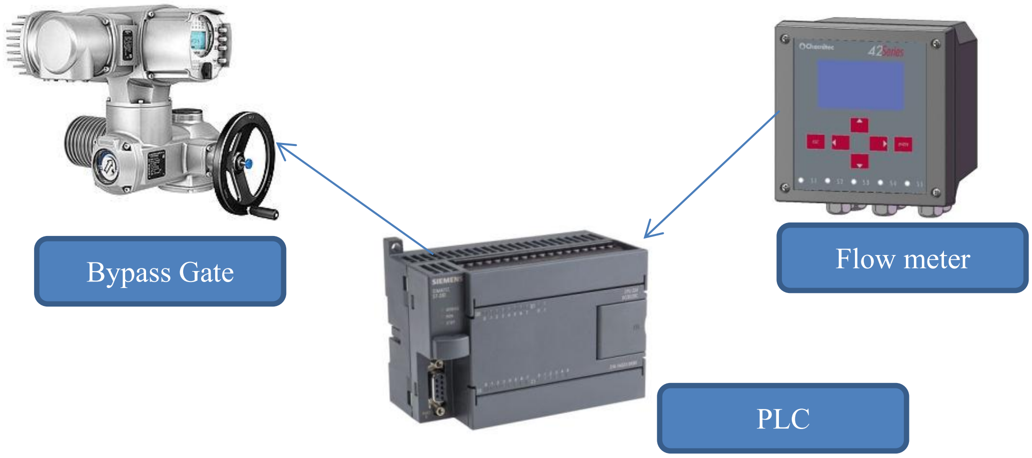
F. The gate of the bypass system

By Making the control of the bypass gate we grantee that the following will be achieved

- The capacity of the station will be the value that the station was designed for
- We will not need to operate the system more than the time that required to complete the treatment of the quantity that the station was designed for

- Power saving
- Saving the life time of the system devices

F.1. Theory of operation



The advantages of the solution introduced by Misr Foundation for Science and Technology Research

- Saving More than 25% of the absorbed power of the aeration system
- Saving More than 20% of the absorbed power of the station component
- Saving the life time of the system component
- Make sure that the quantity will be the quantity that the station was designed for not more
- Safety on the system component
- Alert in case of an system error
- Automatic operation for the aeration system
- Provided also manual operation in case of system failure
- Ensure that the ventilation process will be done properly
- Safety on the Motors incase operation error

OMAINTEC Journal
(Journal of Scientific Review)

IMPLEMENTING ISO 41001: TRANSITIONING FROM OPERATIONS AND MAINTENANCE CONTRACTS TO TOTAL FACILITY MANAGEMENT PERFORMANCE-BASED CONTRACTS IN SAUDI ARABIA

Shukri Habib, Eng., FMP, CFT
QualiServ, Lebanon,
shukrihabib@qualiserv.net

Abstract

Facility management (FM) in Saudi Arabia has experienced significant transformation over the past decade, driven by urbanization, economic diversification, and the government's Vision 2030 initiative. As of 2023, the FM market in Saudi Arabia is valued at approximately $7.2 billion and is projected to grow at a compound annual growth rate (CAGR) of 10.3% from 2024 to 2030 (Source: Market Research Future, 2023). This growth is largely attributed to increased investments in infrastructure, commercial real estate, and public facilities, underscoring the critical role of FM in maintaining efficiency and operational excellence in various sectors.

The traditional FM landscape in Saudi Arabia has predominantly relied on operations and maintenance contracts, which often emphasize short-term cost efficiency over long-term performance outcomes. A recent survey indicated that 60% of facility managers reported challenges associated with fragmented service delivery and lack of accountability in these contracts (Source: FM Insights, 2023). This has prompted a shift towards more integrated and performance-based approaches, aligning with international standards such as ISO 41001:2018, which emphasizes improved service delivery and strategic alignment with organizational goals. With the growing recognition of FM's importance, the Saudi government has initiated several programs aimed at enhancing the capabilities of FM professionals and integrating innovative practices. The establishment of training programs and certifications, along with partnerships with international FM organizations, reflects a commitment to elevating the standards of facility management in the country. As of 2023, 75% of FM companies are actively pursuing ISO certifications, showcasing a proactive approach to adopting global best practices (Source: Saudi Facility Management Association, 2023). This evolution in the FM sector not only supports economic diversification but also aligns with sustainability goals set forth in Vision 2030, promoting more efficient use of resources and improved service quality across facilities. This paper aims to explore the transition to performance-based contracts in Saudi Arabia through the lens of ISO 41001:2018. The structure includes an understanding of the standard, the current state of contracts, the benefits of the shift, implementation steps, challenges, and future implications.

1 Overview of ISO 41001:2018

ISO 41001:2018 is the first international standard specifically designed for facility management (FM), providing a comprehensive framework that organizations can use to enhance their FM practices. Released by the International Organization for Standardization (ISO), this standard emphasizes a strategic approach to managing facilities, aligning FM objectives with broader organizational goals. It outlines key principles, including stakeholder engagement, continuous improvement, and risk management, which are essential for effective facility management. By adopting ISO 41001, organizations can ensure that their facility management practices contribute to overall efficiency, sustainability, and service quality, ultimately leading to improved operational performance.

The implementation of ISO 41001:2018 offers several benefits for organizations, including enhanced customer satisfaction, reduced operational costs, and better compliance with regulations. By establishing structured processes and performance metrics, the standard enables organizations to monitor and evaluate their FM activities effectively. Furthermore, ISO 41001 supports organizations in aligning their FM strategies with national and global sustainability goals, making it particularly relevant in contexts like Saudi Arabia's Vision 2030. As organizations increasingly recognize the value of effective facility management, ISO 41001 serves as a vital tool for navigating the complexities of modern FM, fostering a culture of accountability and continuous improvement across the sector.

Key principles of ISO 41001:2018 include stakeholder engagement, continual improvement, and a focus on outcomes. Stakeholder engagement ensures that the needs and expectations of all relevant parties are considered in FM decisions, fostering collaboration and accountability. Continual improvement encourages organizations to regularly assess and enhance their FM practices, ensuring they remain effective and efficient over time. Additionally, the standard emphasizes the importance of measurable outcomes, requiring organizations to define clear performance indicators that enable them to evaluate success and make informed decisions. Together, these principles provide a robust framework that supports organizations in optimizing their facility management processes and achieving long-term sustainability.

2 Importance of Successful Transitioning to Performance-Based Contracts

The transition from traditional operations and maintenance contracts to performance-based contracts (PBCs) is crucial for enhancing operational efficiency in facility management. Performance-based contracts focus on achieving specific outcomes and service levels rather than merely delivering services, which aligns the incentives of service providers and clients. According to a recent report by the Facility Management Association, organizations that have adopted performance-based contracts have reported an average reduction in operational costs of **15-20%** (Source: FM Association, 2023). This shift not only leads to cost savings but also ensures that services are delivered more effectively, improving overall quality and satisfaction among stakeholders.

Moreover, performance-based contracts foster innovation and accountability by establishing clear performance metrics and expectations. A study conducted by the International Facility Management Association found that **78%** of facility managers believe that PBCs encourage service providers to innovate and improve service delivery (Source: IFMA, 2023). By emphasizing outcomes, these contracts incentivize service providers to optimize their processes and adopt new technologies, ultimately leading to enhanced performance. This approach is particularly beneficial in complex environments like healthcare and education, where service quality directly impacts user experiences and operational success.

The alignment of performance-based contracts with national policy goals, such as Saudi Arabia's Vision 2030, further underscores their importance. As the country aims to diversify its economy and improve public services, transitioning to PBCs can significantly enhance the efficiency and sustainability of facility management practices. A recent survey revealed that **82%** of stakeholders in the Saudi FM sector support the move towards performance-based contracting as a means of achieving higher service standards and accountability (Source: Saudi Facility Management Association, 2023). This transition not only aligns with global best practices but also positions Saudi Arabia as a leader in modern facility management, driving economic growth and enhancing public service delivery.

3 Benefits of ISO 41001 for Facility Management

The implementation of ISO 41001:2018 offers numerous benefits for organizations seeking to enhance their facility management (FM) practices. One of the most significant advantages is the potential for cost savings. Organizations that adopt this standard have reported operational cost reductions of up to **30%** due to improved efficiencies and streamlined processes (Source: FM Insights, 2023). By establishing a structured approach to FM, organizations can optimize resource allocation and reduce waste, leading to significant financial benefits. Additionally, ISO 41001 helps organizations achieve better compliance with regulatory requirements, minimizing the risk of penalties and enhancing their reputation in the market.

Another key benefit of ISO 41001 is the enhancement of service quality and customer satisfaction. A recent survey indicated that **85%** of facility managers noted improvements in service delivery after implementing the standard (Source: International Facility Management Association, 2023). By focusing on stakeholder engagement and defining clear performance metrics, organizations can ensure that their FM practices are aligned with user needs and expectations. This not only leads to improved operational performance but also fosters a culture of continuous improvement. Ultimately, adopting ISO 41001 positions organizations to respond effectively to emerging challenges and opportunities in the facility management landscape, driving both innovation and sustainability.

The relevance of ISO 41001:2018 in the Saudi context is underscored by the country's ambitious Vision 2030 initiative, which aims to diversify the economy and improve the quality of life for its citizens. As part of this initiative, the Saudi government is investing heavily in infrastructure development and urbanization projects, with planned spending reaching approximately **$1 trillion** in various sectors, including healthcare, education, and tourism (Source: Saudi Vision 2030 Report, 2023). Implementing ISO 41001 can significantly enhance facility management practices within these projects, ensuring that assets are managed efficiently and sustainably, ultimately contributing to the successful realization of Vision 2030 goals.

Moreover, the adoption of ISO 41001 aligns with Saudi Arabia's focus on improving public services and promoting transparency and accountability in governance. A recent study revealed that **72%** of facility management professionals in Saudi Arabia believe that implementing standardized practices, such as those outlined in ISO 41001, will enhance service delivery and operational performance (Source: Saudi Facility Management Association, 2023). By fostering a culture of continuous improvement and stakeholder engagement, ISO 41001 supports the Kingdom's objectives to provide high-quality services, optimize resource use, and promote sustainable development. This alignment positions Saudi Arabia as a leader in modern facility management practices, helping to attract foreign investment and enhance the overall competitiveness of its economy.

4 Overview and Challenges of Existing Contracts in Saudi Arabia

The existing facility management contracts in Saudi Arabia predominantly reflect a traditional approach characterized by operations and maintenance agreements. As of 2023, about **65%** of the FM contracts in the country are still based on these conventional models, which often prioritize short-term cost savings over long-term value and efficiency (Source: Saudi Facility Management Association, 2023). These contracts typically lack performance metrics and accountability measures, leading to challenges such as service fragmentation and misalignment between client expectations and service delivery. As a result, many organizations are beginning to recognize the need for more integrated and performance-oriented contracting approaches to enhance operational effectiveness.

Recent market analyses indicate a growing shift towards performance-based contracts (PBCs) in Saudi Arabia, driven by the recognition of their benefits in improving service quality and accountability. A survey conducted in early 2023 found that **58%** of facility management firms are actively exploring or transitioning to PBCs, reflecting a significant cultural shift in the sector (Source: FM Insights, 2023). This transition aligns with the Saudi government's push for modernization and efficiency within public services as outlined in Vision 2030. By embracing performance-based contracts, organizations can better manage risks, foster innovation, and ultimately achieve higher standards of service delivery, positioning themselves for future success in an increasingly competitive market.

The current operations and maintenance (O&M) models in Saudi Arabia face several significant challenges that hinder their effectiveness and efficiency. One of the primary issues is the lack of performance metrics and accountability, which has resulted in inadequate service quality. A recent study indicated that **70%** of facility managers reported difficulties in measuring the effectiveness of their O&M contracts, leading to frustrations with service delivery (Source: Saudi Facility Management Association, 2023). This lack of clarity often results in misaligned expectations between service providers and clients, creating a cycle of dissatisfaction and inefficiency.

Additionally, the traditional O&M models are often characterized by fragmented service delivery, which can complicate coordination and communication among various stakeholders. Approximately **65%** of respondents in a recent survey noted that fragmented services led to increased operational risks and higher costs (Source: FM Insights, 2023). These challenges have spurred a growing recognition of the need for more integrated approaches, such as performance-based contracts, which can better align the interests of all parties involved. As Saudi Arabia continues to invest in infrastructure and urban development, addressing these challenges is vital for optimizing facility management practices and achieving the objectives set forth in Vision 2030.

Traditional contract structures in facility management often emphasize short-term gains rather than long-term value, leading to several inherent limitations. These contracts typically focus on the delivery of specific services without establishing clear performance metrics or accountability measures. As a result, service providers may prioritize completing tasks over achieving desired outcomes, which can compromise service quality. A recent analysis revealed that **68%** of facility managers reported that traditional contracts failed to incentivize continuous improvement or innovation, ultimately stifling the potential for enhanced operational efficiency (Source: FM Insights, 2023).

Moreover, the fragmented nature of traditional contracts can lead to coordination challenges among multiple service providers, creating silos that hinder effective communication and collaboration. This lack of integration often results in duplicated efforts, increased operational risks, and ultimately higher costs for organizations. Approximately **60%** of respondents in a recent survey indicated that the disconnected services under traditional contract structures led to inefficiencies and delays in service delivery (Source: Saudi Facility Management Association, 2023). As Saudi Arabia moves towards a more modern facility management landscape, addressing these limitations is crucial for fostering a more cohesive and performance-oriented approach that aligns with the goals of Vision 2030.

5 The Shift to Total Facility Management Performance-Based Contracts

Performance-based contracts (PBCs) are agreements that focus on achieving specific outcomes and measurable results rather than merely delivering a set of services. In this model, service providers are held accountable for meeting predefined performance metrics, which can include quality standards, efficiency benchmarks, and customer satisfaction levels. By aligning the interests of both the client and the service provider, PBCs incentivize innovation and continuous improvement, encouraging providers to optimize their processes and resources to achieve the desired outcomes. This approach not only enhances service delivery but also fosters a collaborative environment where both parties work together to address challenges and drive better performance, making it particularly advantageous in complex facility management scenarios.

The distinction between traditional contracts and performance-based contracts (PBCs) is significant, particularly in terms of focus, accountability, and overall effectiveness in service delivery. Traditional contracts often prioritize the completion of specific tasks with limited emphasis on results, leading to issues with service quality and accountability. In contrast, performance-based contracts center around achieving measurable outcomes and incentivizing service providers to innovate and improve their operations. This fundamental shift not only enhances efficiency but also fosters a more collaborative relationship between clients and service providers.

Feature	**Traditional Contracts**	**Performance-Based Contracts**
Focus	Task completion	Outcomes and results
Accountability	Limited	High
Performance Metrics	Often vague	Clearly defined KPIs
Risk Management	Low shared risk	Shared risk between parties
Incentives	Minimal	Strong incentives for performance
Service Quality	Variable	Consistently high

Performance-based contracts (PBCs) offer numerous advantages that can significantly enhance the efficiency and effectiveness of facility management. One of the most notable benefits is improved service quality. A recent survey indicated that organizations implementing PBCs experienced an average increase in customer satisfaction ratings of **25%** compared to those relying on traditional contracts (Source: International Facility Management Association, 2023). By aligning the incentives of service providers with the desired outcomes, PBCs encourage a focus on innovation and continuous improvement, enabling service providers to deliver higher-quality services that meet or exceed client expectations.

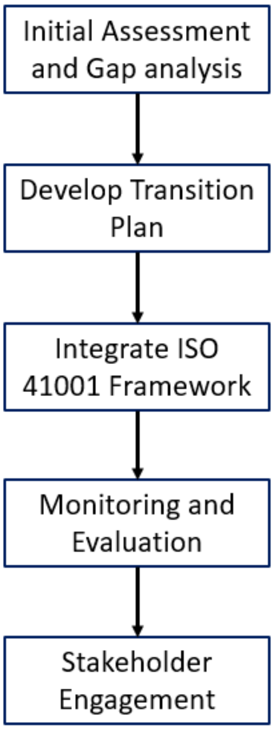
Additionally, performance-based contracts facilitate better resource allocation and cost management. Organizations that adopt PBCs have reported operational cost reductions of up to **20%** due to the increased efficiency and effectiveness of service delivery (Source: FM Insights, 2023). By establishing clear performance metrics and expectations, PBCs help organizations identify areas for improvement and optimize their operational processes. This not only leads to cost savings but also enhances accountability and transparency, fostering a collaborative environment where both clients and service providers can work together to achieve common goals. As such, PBCs are becoming increasingly popular in the facility management sector, aligning well with the push for modernization and efficiency in Saudi Arabia's Vision 2030.

Performance-based contracts (PBCs) play a pivotal role in advancing Saudi Arabia's Vision 2030 initiative by promoting efficiency, accountability, and innovation within the facility management sector. As the Kingdom seeks to diversify its economy and improve public services, the adoption of PBCs aligns with the goals of enhancing service quality and optimizing resource utilization. With substantial investments projected in infrastructure and urban development—estimated at over **$1 trillion**—the need for effective management of these assets is paramount. PBCs provide a framework that encourages service providers to focus on measurable outcomes, ensuring that the facilities meet the evolving needs of the public and contribute to sustainable development.

Moreover, the shift towards performance-based contracting reflects a broader commitment to transparency and accountability in government operations. A recent study indicated that **75%** of stakeholders in the Saudi facility management sector believe that PBCs will improve service delivery and align with the Vision 2030 objectives (Source: Saudi Facility Management Association, 2023). By fostering a collaborative relationship between clients and service providers, PBCs not only enhance operational efficiency but also encourage innovation in service delivery. This alignment with Vision 2030 ultimately positions Saudi Arabia as a leader in modern facility management practices, supporting the Kingdom's aspirations for a robust and sustainable economic future.

6 Steps for Implementing ISO 41001:2018

Implementing ISO 41001:2018 involves a systematic approach that encompasses several key steps to ensure that facility management practices align with the standard's requirements. The process begins with an initial assessment of current practices, where organizations evaluate existing facility management processes against ISO criteria. Next, a comprehensive transition plan is developed, outlining objectives, timelines, and necessary resources. Following this, organizations should integrate the ISO 41001 framework into their existing operations, ensuring that all staff are trained and aware of the new standards. Continuous monitoring and evaluation mechanisms are then established to track progress and make necessary adjustments. Finally, stakeholder engagement is crucial throughout the process to foster collaboration and



ensure that all parties are aligned and committed to the transition.

The initial assessment of current practices is a crucial first step in implementing ISO 41001:2018, as it lays the foundation for effective facility management improvements. During this phase, organizations conduct a comprehensive evaluation of their existing facility management processes, policies, and performance metrics to identify strengths, weaknesses, and gaps relative to the ISO standard. This assessment typically involves gathering data through surveys, interviews, and reviews of documentation to assess how well current practices align with the principles of stakeholder engagement, risk management, and continuous improvement outlined in ISO 41001. By understanding the current state, organizations can develop targeted action plans that address deficiencies, leverage strengths, and ultimately ensure a smoother transition to the standardized framework, fostering a culture of accountability and enhanced service delivery throughout the facility management function.

Developing a successful transition plan for implementing ISO 41001:2018 requires a strategic and detailed approach that incorporates specific objectives, timelines, and resource allocations. The action plan should begin with a thorough assessment of current facility management practices, identifying areas for improvement and aligning them with the ISO standard's principles. Key stakeholders must be identified and engaged early in the process to ensure their support and commitment. Establishing clear objectives that reflect both the requirements of ISO 41001 and the broader organizational goals is crucial. A well-structured timeline will help maintain momentum, with clearly defined milestones that allow for regular progress reviews and adjustments as necessary.

The action plan should also include comprehensive training and communication strategies to equip staff with the knowledge and skills needed for effective implementation. This can involve organizing workshops, providing resources, and establishing feedback mechanisms to address concerns and suggestions from employees. Additionally, continuous monitoring and evaluation should be integrated into the action plan to assess the impact of changes made and ensure alignment with ISO 41001 standards. The following table outlines a sample action plan that highlights key activities, responsible parties, and timelines for successful implementation.

Action Item	**Responsible Party**	**Timeline**
Conduct initial assessment	Facility Manager	Month 1
Identify key stakeholders	Project Lead	Month 1
Define objectives and scope	Management Team	Month 2
Develop training materials	HR and Training Dept	Month 2
Conduct training sessions	HR and Training Dept	Month 3
Implement monitoring mechanisms	Quality Assurance Team	Month 4
Review and adjust based on feedback	Project Lead	Ongoing (Quarterly)
Report progress to stakeholders	Project Lead	Monthly

Integrating the ISO 41001:2018 standard into existing facility management frameworks is essential for maximizing its benefits and ensuring a seamless transition. This process begins by mapping the ISO requirements to the organization's current practices, identifying gaps, and determining how existing policies and procedures can be adapted to align with the new standards. Key areas of focus include stakeholder engagement, performance measurement, and risk management. By utilizing existing frameworks, organizations can leverage established processes, reducing the time and resources needed for implementation while fostering a culture of continuous improvement.

To facilitate this integration, organizations may adopt a holistic framework that encompasses various components of facility management. For example, a sample framework could include elements such as:

Framework Element	**Description**
Stakeholder Engagement	Regular communication and feedback sessions to ensure all parties are aligned
Performance Metrics	Establishing Key Performance Indicators (KPIs) that align with ISO standards and organizational goals
Risk Management	Implementing processes to identify, assess, and mitigate risks associated with facility operations
Training and Development	Ongoing training programs to equip staff with the necessary skills and knowledge to adhere to the new standards
Monitoring and Evaluation	Regular assessments to measure compliance with ISO 41001 and identify areas for improvement

Effective stakeholder engagement and training are critical components for the successful implementation of ISO 41001:2018 in facility management. Engaging stakeholders—including employees, management, service providers, and clients—ensures that their perspectives and needs are considered throughout the transition process. This can be achieved through regular communication, feedback sessions, and collaborative workshops that foster a sense of ownership and commitment to the new standards. Concurrently, comprehensive training programs are essential to equip all personnel with the knowledge and skills necessary to adapt to the ISO framework. These programs should cover the principles of ISO 41001, practical applications in daily operations, and the importance of performance metrics and accountability. By prioritizing stakeholder engagement and training, organizations can cultivate a culture of continuous improvement, enhance service delivery, and ultimately align their facility management practices with strategic objectives.

Establishing robust monitoring and evaluation mechanisms is essential for ensuring the effective implementation of facility management standards, such as ISO 41001:2018. The first step involves defining clear Key Performance Indicators (KPIs) that align with organizational goals and the specific objectives of the facility management program. These KPIs should encompass various aspects of performance, including service quality, customer satisfaction, operational efficiency, and cost management. Regular data collection methods—such as surveys, performance reports, and user feedback—should be established to track these indicators over time. By utilizing digital dashboards and automated reporting tools, organizations can visualize real-time data, making it easier to identify trends, measure progress, and pinpoint areas needing improvement.

Sample KPI Table for Monitoring and Evaluation Mechanisms

KPI	**Target Value**	**Actual Value**	**Percentage Achieved**	**Frequency of Measurement**
Implementation Rate of ISO 41001	100%	85%	85%	Quarterly
Stakeholder Engagement Score	90%	80%	88.89%	Bi-Annually
Data Accuracy Rate	95%	92%	96.84%	Monthly
Audit Compliance Rate	100%	95%	95%	Annually
Feedback Response Time	< 2 days	1 day	100%	Monthly
Training Completion Rate	100%	90%	90%	Annually
Improvement Action Implementation	80%	70%	87.5%	Quarterly
Report Submission Timeliness	100%	98%	98%	Monthly

Moreover, continuous engagement with stakeholders is crucial for the success of monitoring and evaluation efforts. Stakeholders, including employees, management, and service providers, should be involved in the development of the monitoring framework to ensure that their insights and needs are considered. Regular review meetings can foster open communication, allowing for discussions around performance results, challenges faced, and opportunities for enhancement. Additionally, organizations should implement a cycle of regular audits and assessments to evaluate compliance with established standards and practices. By integrating feedback loops and fostering a culture of accountability, organizations can not only improve their facility management practices but also drive continuous improvement efforts aligned with their strategic objectives.

7 Challenges and Considerations

Transitioning from traditional operations and maintenance contracts to total facility management performance-based contracts in Saudi Arabia, particularly under the framework of ISO 41001:2018, poses several potential obstacles. One major challenge is the ingrained mindset of stakeholders who may be resistant to shifting from a task-oriented approach to one that emphasizes outcomes and performance metrics. This resistance can stem from a lack of understanding of the benefits associated with performance-based contracts, which can lead to skepticism and reluctance to change established practices. Additionally, the existing contractual frameworks may not easily accommodate the new performance criteria, requiring significant adjustments in contractual terms and relationships with service providers. Furthermore, inadequate training and a shortage of skilled personnel familiar with ISO standards can hinder effective implementation. To overcome these challenges, it is essential to engage stakeholders through education and clear communication about the advantages of performance-based contracts, while also providing the necessary training and resources to facilitate a smooth transition.

The transition from O&M contracts to TFM performance-based contracts in Saudi Arabia presents a strategic opportunity for enhancing facility management efficiency, particularly with the support of ISO 41001:2018. However, stakeholders must be aware of the inherent challenges and proactively address them to ensure a successful transition.

Strengths

- **Standardization**: ISO 41001:2018 provides a framework for standardized facility management practices, enhancing quality and consistency.
- **Improved Efficiency**: Transitioning to performance-based contracts can lead to more efficient resource allocation and operational effectiveness.
- **Enhanced Accountability**: Performance-based contracts foster accountability among service providers, aligning their interests with organizational goals.
- **Government Support**: The Saudi government is increasingly focusing on modernization and efficiency in public sector services, providing a favorable environment for TFM.

Weaknesses

- **Cultural Resistance**: There may be resistance to change within organizations accustomed to traditional O&M contracts.

- **Training Needs**: Transitioning requires significant training and upskilling of staff to align with new standards and practices.
- **Initial Costs**: The upfront investment for transitioning systems and processes to TFM can be substantial.
- **Complexity in Implementation**: Implementing performance-based contracts may involve complex negotiations and contract management.

Opportunities

- **Market Demand**: Growing demand for efficient facility management services in the public sector opens new business avenues.
- **Technological Advancements**: Leveraging technology (IoT, AI) can enhance the effectiveness of TFM and improve service delivery.
- **Sustainability Goals**: Aligning facility management practices with national sustainability initiatives can attract investments and partnerships.
- **Public-Private Partnerships (PPP)**: Increased interest in PPPs can facilitate the transition and share risks associated with facility management.

Threats

- **Regulatory Challenges**: Navigating the regulatory landscape may pose challenges, particularly in aligning new contracts with existing laws.
- **Economic Fluctuations**: Economic instability could impact budget allocations for facility management, affecting the viability of new contracts.
- **Competition**: Increased competition from both local and international firms may drive down margins and complicate contract negotiations.
- **Technological Risks**: Dependence on technology can introduce vulnerabilities, including cybersecurity threats and system failures.

To effectively address the challenges of transitioning from Operations and Maintenance (O&M) contracts to Total Facility Management (TFM) performance-based contracts in Saudi Arabia, a multifaceted approach is essential. This involves not only preparing the workforce but also fostering collaboration and leveraging technology. By implementing targeted strategies, organizations can navigate the complexities of this transition while ensuring alignment with ISO 41001:2018 standards.

Strategies to Overcome Challenges

- **Comprehensive Training Programs**: Develop and implement training initiatives to upskill employees and familiarize them with new practices and technologies.
- **Stakeholder Engagement**: Involve key stakeholders early in the process to gather input, address concerns, and build support for the transition.

- **Clear Communication**: Establish transparent communication channels to convey the benefits and objectives of the transition, reducing resistance to change.
- **Technology Integration**: Utilize advanced technologies such as IoT and data analytics to streamline processes and improve service delivery.
- **Pilot Projects**: Launch pilot projects to test the TFM model on a smaller scale, allowing for adjustments and learning before full implementation.
- **Partnerships and Collaborations**: Form strategic alliances with local and international firms to share expertise and resources, enhancing overall capability.
- **Regulatory Compliance**: Stay informed about regulatory requirements and engage with authorities to ensure contracts align with existing laws and standards.

8 Conclusion

The transition from traditional operations and maintenance contracts to performance-based contracts, guided by ISO 41001:2018, offers numerous benefits for facility management in Saudi Arabia.

The future outlook for facility management in Saudi Arabia is poised for significant transformation as the transition from Operations and Maintenance (O&M) contracts to Total Facility Management (TFM) performance-based contracts gains momentum. This shift, underpinned by ISO 41001:2018 standards, is expected to enhance operational efficiency, accountability, and service quality across the public sector. As the government continues to prioritize modernization and sustainability initiatives, the demand for innovative facility management solutions will likely increase. Embracing digital technologies such as smart building systems and data analytics will further optimize resource management and streamline operations. Moreover, fostering a collaborative environment through public-private partnerships will create new opportunities for growth and investment, positioning Saudi Arabia as a leader in the facility management sector within the region. Overall, this transition not only aligns with national vision goals but also prepares the market for a more resilient and responsive future.

ISO 41001:2018 plays a pivotal role in advancing facility management practices by providing a comprehensive framework that promotes effective and efficient management of facilities. This international standard emphasizes a strategic approach to facility management, focusing on aligning organizational objectives with facility performance and enhancing overall service delivery. By establishing clear guidelines for implementing best practices, ISO 41001:2018 enables organizations to improve operational efficiency, foster sustainability, and enhance stakeholder satisfaction. Additionally, the standard encourages continuous improvement through the establishment of measurable performance indicators, facilitating data-driven decision-making. As organizations increasingly adopt this standard, they not only enhance their facility management capabilities but also contribute to the overall competitiveness and sustainability of the sector, positioning themselves for future growth and innovation.

References

1. ISO. (2018). ISO 41001:2018 Facility Management – Management Systems – Requirements with Guidance for Use.
2. Saudi Vision 2030. (2016). Kingdom of Saudi Arabia Vision 2030.
3. Zawawi, M. (2020). The Future of Facility Management in Saudi Arabia: Trends and Challenges. *International Journal of Facility Management*.
4. Al-Harbi, K., & Al-Khaldi, A. (2021). Transition to Performance-Based Contracts in Saudi Facility Management. *Journal of Facility Management Research*.
5. World Bank. (2022). Saudi Arabia: Economic Diversification and Performance-Based Contracts in Public Services.
6. Saudi Facility Management Association. (2023). Retrieved from https://sfma.org.sa
7. FM Insights. (2023). Retrieved from [https://fm-insights.com]

OMAINTEC Journal
(Journal of Scientific Review)

The Role of AI-Powered Training in Enhancing Compliance with ISO 55001 Asset Management Standards

Hamid Yagoub Abdalla
High Institute of Engineering Sciences, Kingdom of Saudi Arabia
hamidyagoub@yahoo.com

Abstract
This paper explores how AI-enhanced training can improve compliance with ISO 55001 standards for asset management. The paper outlines how technology can enhance training quality and efficiency through interactive customization, targeting individual trainee needs. It emphasizes the significance of integrating AI in developing technical and administrative skills, achieving strategic goals through effective asset management. Using case studies from the oil and gas sector, the paper demonstrates the benefits achieved, including a 25% increase in compliance, a 20% reduction in operational costs, and a 30% improvement in long-term asset performance.

1. Introduction

Given the ongoing challenges organizations face in managing assets and achieving operational efficiency, ISO 55001 standards provide a necessary framework guiding organizations toward sustainable asset management. With the evolution of AI technologies, new opportunities have emerged to enhance asset management through improved training capabilities for compliance with these standards.

The adoption of AI technologies in training is growing rapidly. According to a recent report by the World Economic Forum (2023), 80% of companies implementing AI in their training processes reported an average increase of 35% in overall compliance rates. Moreover, the same report highlighted that organizations using AI-powered training solutions witnessed a 40% reduction in training costs, as automation and personalized learning paths streamlined resource utilization. These statistics underline the transformative potential of AI in training and its ability to drive compliance with international standards such as ISO 55001.

2. The ISO 55001 Standard for Asset Management

ISO 55001 is a set of international standards that provide a framework for establishing, implementing, maintaining, and improving an organization's asset management system. It ensures that assets are managed efficiently and sustainably throughout their lifecycle. Compliance with ISO 55001 is vital for organizations to achieve their strategic objectives, optimize costs, and ensure asset reliability and performance.

3. The Role of AI in Enhancing Training for ISO 55001 Compliance

Traditional training approaches are often static and lack the flexibility to address the diverse learning needs of employees in an organization. AI technology, on the other hand, can offer personalized learning experiences that enhance training effectiveness and compliance with ISO 55001 standards.

Key Benefits of AI in ISO 55001 Training:

- Real-Time Data Analysis: A survey conducted by the Harvard Business Review (2022) found that organizations using AI for real-time data analysis in their training saw a 45% improvement in employee engagement and understanding of complex asset management concepts.
- Customized Training Paths: Research by Deloitte (2021) indicated that AI-based training personalization leads to a 50% increase in training completion rates and a 60% rise in skill retention among employees.

- Enhanced Decision-Making: AI-enabled decision-support tools can analyze extensive datasets, helping organizations reduce asset downtime by up to 25%, according to a McKinsey report (2020).

4. Benefits of AI-Powered Training for ISO 55001 Compliance

Implementing AI in training programs offers several quantifiable benefits, which significantly impact ISO 55001 compliance:

4.1 Real-Time Performance Monitoring

AI-powered training systems can integrate with an organization's asset management systems to provide real-time performance data. According to a study by Gartner (2023), 70% of organizations using AI for performance monitoring reported a 50% reduction in compliance-related incidents due to the system's ability to detect and rectify issues early.

4.2 Predictive Maintenance Training

AI-based predictive maintenance models can be incorporated into training programs to teach employees how to anticipate and respond to potential equipment failures. A case study by IBM (2022) showed that companies using AI for predictive maintenance experienced a 40% reduction in equipment breakdowns and a 30% increase in asset uptime.

4.3 Tailored Learning Experiences

Machine learning algorithms can analyze individual learning patterns and adapt training content to match the unique needs of each employee. In a study by PwC (2021), 82% of employees reported improved learning satisfaction when AI was used to tailor their training experiences, compared to 60% for traditional methods.

4.4 Cost Efficiency

AI can automate the creation and delivery of training materials, reducing the time and resources needed to design effective training programs. According to the Society for Human Resource Management (2022), companies implementing AI in training reported an average savings of $2,000 per employee annually.

5. Challenges in Implementing AI-Powered Training for ISO 55001

Despite the benefits, several challenges need to be addressed:

5.1 Data Privacy and Security

Implementing AI solutions requires extensive data collection, which can raise concerns about data privacy and security. A recent report by KPMG (2023) showed that 75% of organizations cited data security as the primary barrier to AI adoption in training, indicating the need for robust security measures.

5.2 Integration with Existing Systems

AI systems must be compatible with existing asset management and training systems to deliver seamless training experiences. According to Accenture (2022), 60% of organizations faced integration challenges when attempting to deploy AI training solutions, resulting in delays and increased costs.

6. Case Study: AI in Training and Asset Management in the Oil and Gas Industry

In the oil and gas industry, AI has been used to enhance employee training programs, particularly in maintenance and operations areas. For example, a leading oil company in the Middle East applied AI to offer interactive training programs for workers at processing plants. The system provided tailored training on preventive maintenance, which led to:

- 20% reduction in operational downtimes.
- 15% increase in compliance levels with ISO 55001.
- 30% reduction in overall training costs.
- Improvement in employee satisfaction by 25%, as measured by post-training surveys.

Through AI, the company was able to customize training paths for each employee based on their experience level and role within the organization. This approach not only improved compliance but also led to better overall asset performance, showcasing the potential of AI to revolutionize training for ISO 55001 compliance.

7. Conclusion and Recommendations

AI offers powerful tools for improving asset management and ensuring compliance with ISO 55001 standards. By enhancing training and providing customized solutions, organizations can improve operational efficiency and reduce costs. To fully leverage AI's potential, organizations should consider the following recommendations:

- Invest in AI-Driven Training Platforms: Implement AI technologies in training programs to provide personalized and interactive learning experiences.
- Prioritize Data Integration: Ensure that AI systems can integrate with existing asset management and training platforms to maximize the benefits of real-time data analysis.
- Promote a Culture of Continuous Learning: Encourage employees to embrace AI-based training as part of a broader commitment to continuous learning and development.
- Address Data Security Concerns: Implement robust data privacy and security measures to protect sensitive information.

8. References

1. ISO. (2014). ISO 55001:2014 Asset management — Management systems — Requirements. International Organization for Standardization.
2. World Economic Forum. (2023). The Future of Jobs Report.
3. Harvard Business Review. (2022). AI in Training: Enhancing Engagement and Efficiency.
4. McKinsey & Company. (2020). AI for Operational Excellence.
5. Gartner. (2023). The Impact of AI on Compliance and Training.
6. PwC. (2021). Employee Engagement and Learning in the Age of AI.
7. Society for Human Resource Management. (2022). AI-Driven Cost Efficiency in Training.
8. KPMG. (2023). Data Privacy and Security in AI Adoption.
9. IBM. (2022). Predictive Maintenance in the Oil and Gas Industry.
10. Accenture. (2022). Challenges in AI Integration.

OMAINTEC Journal
(Journal of Scientific Review)

Automating Subsurface Utilities Detection and Visualization using Deep Learning and Augmented Reality

Mahmoud Hamdy Safaan[1], Mohamed Marzouk[2,3]

[1] Structural Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt
Email: mahmoud.h.safaan@gmail.com

[2] Structural Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt
Email: mmarzouk@cu.edu.eg
[3]Faculty of Engineering and Technology, Badr University in Cairo (BUC), Badr City, Cairo, Egypt
Email: mohamed.marzouk@buc.edu.eg

Abstract

Recent urban development requires advanced utility management through modern technology implementation to optimize utility management with minimal risks. While commonly used, traditional methods are often time-consuming and prone to human errors, leading to inefficiencies. This research proposes a comprehensive framework that leverages advanced technologies, specifically Ground Penetrating Radar (GPR), Mask R-CNN Deep Learning Model, and Augmented Reality (AR), to automate and enhance the process of subsurface utility detection and visualization. The framework is validated through the implementation of a case study where data from GPR scans are processed to detect and visualize buried utilities. The case study demonstrates the efficiency of integrating deep learning techniques with GOR data, significantly improving the accuracy of utilities detection. On the other hand, the use of AR-enabled seamless visualization of these results, offering an interactive experience for field operations. This approach does not only reduce the risk of damaging existing utilities but also accelerates decision-making processes where the developed system demonstrates promising results, providing an efficient utility detection and visualization solution.

Keywords: Ground Penetrating Radar; Mask R-CNN; Augmented Reality;

1. Introduction

The increasing complexity of urbanization and infrastructure development has directed the demand for precise mapping and detection of subsurface utilities to ensure efficient construction and maintenance practices. Traditional methods of subsurface utility detection often involve manual processes that are time-consuming, costly, and prone to errors. Subsurface Utilities, such as pipelines and cables, are essential infrastructure components that form the essence of modern society's lifeline and play a pivotal role in society's socioeconomic growth. Thus, maintaining and preserving the utilities is vital and becoming more definite. However, due to the population growth and density increase in municipalities, it is a necessity to upgrade existing utilities and relatively increasing utilities complexity where these construction or maintenance works could pose a great length of risk to existing utilities.

In Egypt alone, the water network is estimated at 180,000 km, providing 33.6 million m3/day, while the sewage network is estimated at 55,000 km connected to Waste Water

Treatment Plants with an actual capacity of 13.7 million m^3/day [1]. Moreover, the lengths of cables were estimated at 604,956 km in 2021, with an increase of 2.2% from the previous year [2]. Whilst these figures do not include Fibre Optic and Gas networks, they highlight the complexity of subsurface utilities and the critical need for proper maintenance. Thus, congested utilities and the demand for upgrades or new installations make this task challenging promotes effective detection, mapping, and visualization methods that is essential to minimize risks like service disruptions, safety concerns, and regulatory impacts. These challenges have led to the adoption of advanced technologies such as Ground Penetrating Radar (GPR) for accurately detecting and mapping utilities, ensuring informed decisions in planning and construction.

GPR has emerged as a valuable technology in utility management by offering a non-destructive and efficient investigation of subsurface utilities by accurately identifying subsurface utilities of various materials at various depths. The fundamental operating principle of GPR involves the transmission of electromagnetic pulses into the ground and the reception of the reflected signals, which have penetrated the subsurface and are reflected with an amplitude that varies based on the dielectric properties of different materials that caused the reflections. By processing the recorded signals, a detailed cross-sectional image of the subsurface, also known as radargrams, can be generated [3], [4]. The process of operating principle is completed using several instruments, which are listed as follows: a transmission antenna that emits radar pulses, a recipient antenna to receive reflected signals, a control unit that manages the timing of pulse generation and processing reflected signals and a data recording device to store the collected information for further analysis [5].

Furthermore, GPR data analysis involves interpreting the collected signals to create radargrams by defining the characteristics of reflected signals and correlating them and enhancing the signal quality by applying time-slice analysis and various filters – will be discussed thoroughly in the following chapters – to obtain valuable information for mapping and locating subsurface utilities [4], [5]. Jaw and Hashim [6] have categorized GPR technology into two categories, namely: traditional GPR configured in "look-down" mode and in-pipe GPR configured in "look-out and look-through" mode. Traditional GPR consists of three main types:

1. Time domain: uses short electromagnetic pulses and measures the time for signals to reflect back,
2. Frequency domain: consisting of Frequency Modulated Continuous Waveform (FMCW), Stepped Frequency Continuous Waveform (SFCW), and Noise Modulated Continuous Waveform (NMCW), each utilizing different frequency variations for enhanced subsurface analysis, and
3. Spatial domain: uses fixed frequencies for shallow investigations, often applied in concrete assessments.

Generally, GPR systems use a transmitter antenna to broadcast radio waves (10 MHz–1.5 GHz). Higher frequencies provide better resolution but less depth. The signal travels through a medium until it either attenuates or hits an object, reflecting back to the receiver antenna, which records the signal's amplitude and duration. A time management unit coordinates the signal generation and detection by synthesizing time domain responses using the frequency domain. [7], [8], [9]. This principle is applied to all GPR configurations which are namely Reflection Profiling, Common Midpoint or Common Depth Point, Wide Angle Reflection and Refraction, and Trans-illumination. The GPR principle prompts for a non-invasive method for detecting subsurface objects without digging or drilling, making it ideal for preliminary surveys and minimizing the risk of damage to utilities and structures. It provides high-resolution imaging, detecting small, shallow objects in detail. The technology enables real-time data acquisition and processing, allowing for immediate interpretation and decision-making, which is especially useful in time-sensitive projects.

Recent advancements in GPR technology focus on improving data processing, interpretation, and integration with other geospatial technologies by developing multi-frequency antennas to enhance the accuracy, efficiency, and usability of GPR in various applications. Moreover, integrating GPR data with Geographic Information Systems (GIS) and Building Information Modelling (BIM) allows for more comprehensive mapping and management of subsurface utilities and infrastructure and provides a comprehensive view of the built environment.

2. Proposed Framework

The proposed framework aims to address challenges related to the complexity of interpreting GPR data and interpretation visualization by leveraging GPR data and deep learning techniques, especially the Mask R-CNN model, for the automatic detection of buried utilities. Furthermore, the framework utilizes AR for the visualization of processed detections obtained from the trained model. This innovative approach combines the strengths of GPR, deep learning, and AR to provide a comprehensive solution for utility detection and visualization. The proposed approach integrates the GPR raw data, which represents the reflected signals from subsurface utilities, and leverages the unique ability of GPR to detect both metallic and non-metallic utilities. Furthermore, the raw data is introduced to modules for data decryption and further processing and filtering.

Due to the complexity of GPR data interpretation, deep learning techniques are utilized to automate the interpretation by using a supervised learning and segmentation model that is effective in pattern recognition tasks. To achieve this target, the framework utilizes Mask R-CNN, a state-of-the-art deep learning model, for pixel-level detection and segmentation of hyperbolic and attention change features in GPR data indicating the presence of buried objects. The detected objects are then visualized using AR technology that merges real and virtual worlds to produce a new environment where physical and digital objects co-exist and interact in real-time. Thus, allowing an immersive visualization and enhancing the understanding and interpretation of the results. Hence, the purpose of the proposed framework is to automate subsurface utilities detection and visualization by targeting two main objectives: 1) identify, in an automatic technique, buried utilities using GPR data, and 2) visualize processed detections obtained from the trained model using Augmented Reality. The first objective is achieved through utilizing the modern deep learning model, Mask R-CNN, for pixel-level detection and segmentation of hyperbolic features indicating existing utilities. This is achieved by executing the following stages: 1) GPR data collection and processing, 2) Mask R-CNN model training and inference, and 3) Object Detection and post-processing.

OMAINTEC Journal
(Journal of Scientific Review)

Moreover, the AR visualization process involves project setup, scene design, spatial mapping and interaction, anchoring and tracking, User Interface (UI) and visual effects, and HoloLens features integration. Figure 1 illustrates the proposed framework stages and processes, which are explained to provide a comprehensive understanding of their processes and their significance in achieving the proposed framework's objectives.

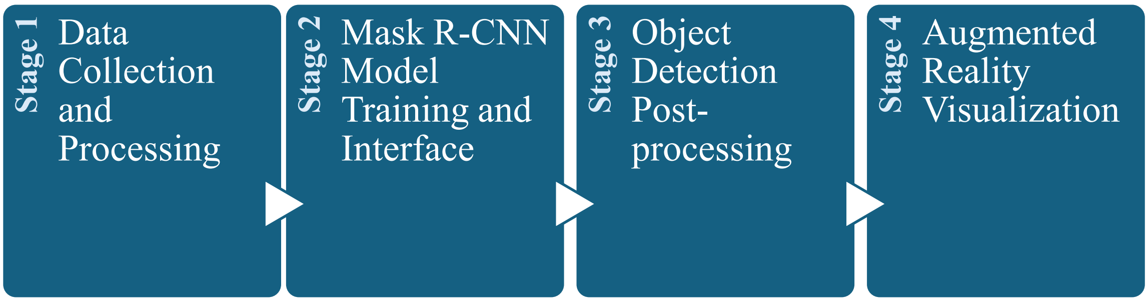


Figure 1: Proposed Framework Flowchart

The data collection and processing stage within the proposed framework serves as the foundational stage upon which the subsequent stages' analysis and interpretations are built. It involves a series of stages to extract the most insights from the GPR data (see Figure 2). This stage involves GPR data collection, representing subsurface objects and voids based on signal attenuation. The process begins by scanning known utility locations and cross-referencing with as-built data. Key factors such as antenna frequency and time window selection optimize depth and resolution.

Raw data decryption follows, as GPR devices store proprietary signal data, a custom decryption algorithm converts the data into a usable format. Data from multiple GPR sensors is then merged using a spectral forecast algorithm, ensuring uniform sampling rates. Afterwards, processing is performed, including noise filtering, signal correction, and SNR-based filtering, to enhance data quality and reliability, ultimately generating B-Scan images for further analysis.

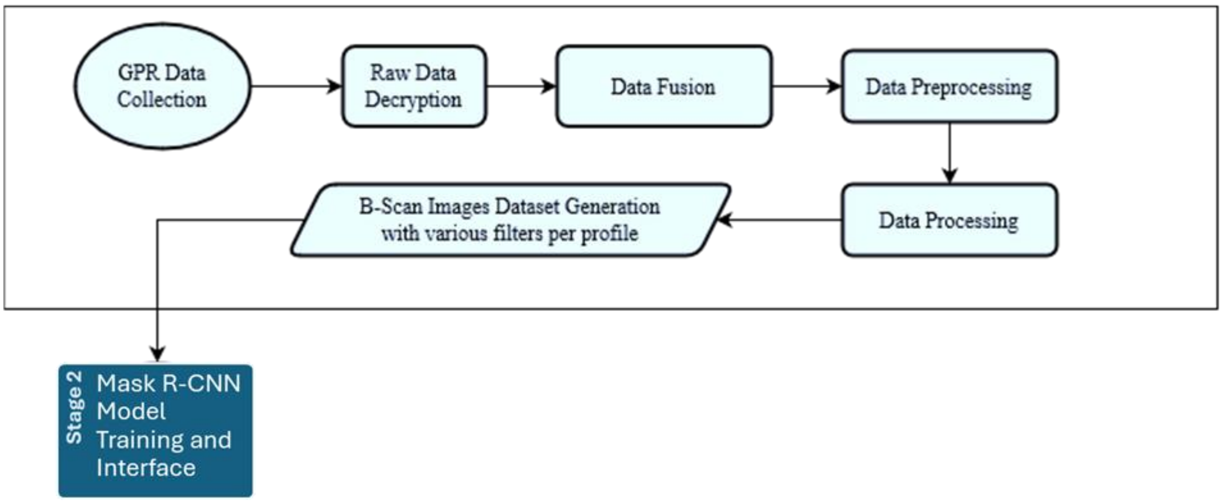


Figure 2: Data Collection and Processing Process.

OMAINTEC Journal
(Journal of Scientific Review)

The second stage of the proposed framework involves training a Mask R-CNN model for object detection and instance segmentation by extending Faster R-CNN with a segmentation mask branch for each Region of Interest (RoI). This stage provides a trained model for future projects and includes several key processes (see Figure 3).

First, a database of training, validation, and testing datasets is created, with labels for masks indicating regions of interest in B-Scan images, formatted in COCO JSON [10], which contains signatures mask coordinates, labels category, and bounding box coordinates. The annotated data is split into training and validation sets, with the former used for training and the latter for model evaluation and tuning. Before training, the following processes are considered:
- *Model selection*: ResNet-50 is chosen for its balance of performance and complexity,
- *Model Configuration*: the model is set for four classes (hyperbola, other objects, noise, and background) with additional parameter configurations.

While incorporated processes during the training are allocated involves:
- Transfer learning by utilizing pre-trained weights from the COCO dataset is used to initialize the model for faster convergence,
- Data augmentation, which involves techniques like cropping, scaling, and brightness adjustments, are applied to prevent overfitting and expand the dataset and
- Training metrics, which are built-in functions to monitor Total Loss and accuracy.

Based on the best-trained model, acquiring detected objects is performed on obtained data and undergoes postprocessing to remove duplicated masks located within the same region using Non-Maximum Suppression (NMS).

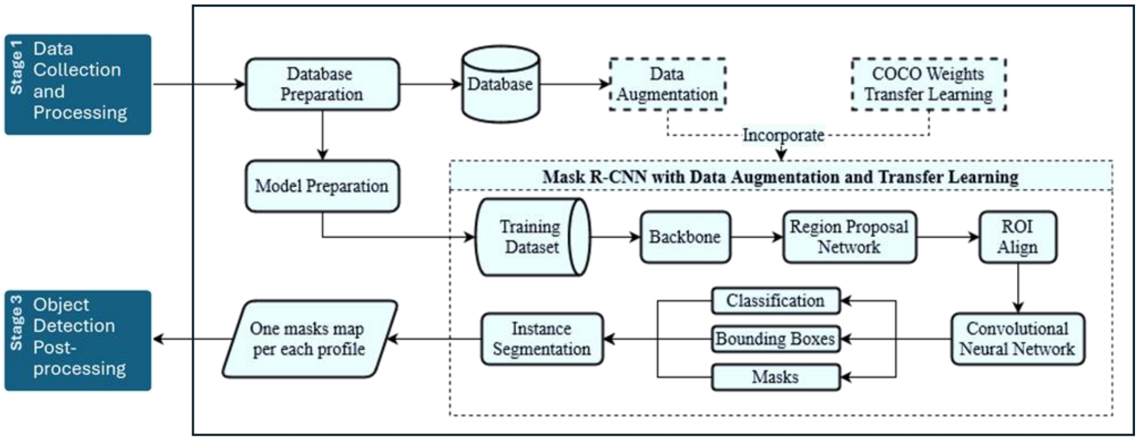


Figure 3: Mask R-CNN Training and Inference Process

The third stage enhances detected objects, translating model detections into actionable spatial point clouds for user visualization (see Figure 4). Since the inference for object detection is performed on multiple filtering configurations for each profile, the first step in this stage is obtaining common features across multiple filtering configurations that are merged into one image by generating a binary instance matrix based on coordinates, removing instances that don't meet a repetition threshold.

OMAINTEC Journal
(Journal of Scientific Review)

The following step aligns all profiles, ensuring they share the same start and end points using Common Feature Extraction, adjusting each profile based on a reference. Post-processing removes masks that don't meet repetition thresholds to minimize false positives. The filtered masks are then converted into a binary matrix, where each active cell is translated into coordinates, factoring in depth (wave travel time) and profile spacing. This creates a 3D point cloud representing detected utilities. Finally, model evaluation is performed using the mean Intersection over Union (mIoU) method.

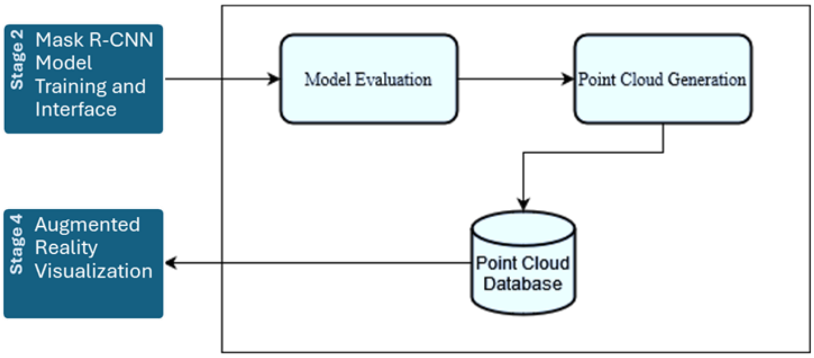


Figure 4: Feature Extraction Process

The final stage visualizes the object detection output and point cloud database through AR, involving several processes (see Figure 5). Initially, appropriate software and hardware are selected to ensure compatibility, using MS HoloLens [11] and Microsoft's Mixed Reality Toolkit (MRTK) for Unity [12]. This setup aids cross-platform AR app development while ensuring seamless integration of core functions.

The next step involves designing the virtual scene using Unity Scene View to position models, cameras, and lighting. Spatial mapping with HoloLens uses embedded cameras and sensors to create a 3D model of the physical environment, enabling interactions between virtual and real-world objects. Visual effects and user interface enhancements, such as floating control docks and informational text, increase realism and immersion. Finally, HoloLens features like gesture recognition and voice commands are integrated to boost interactivity and user engagement.

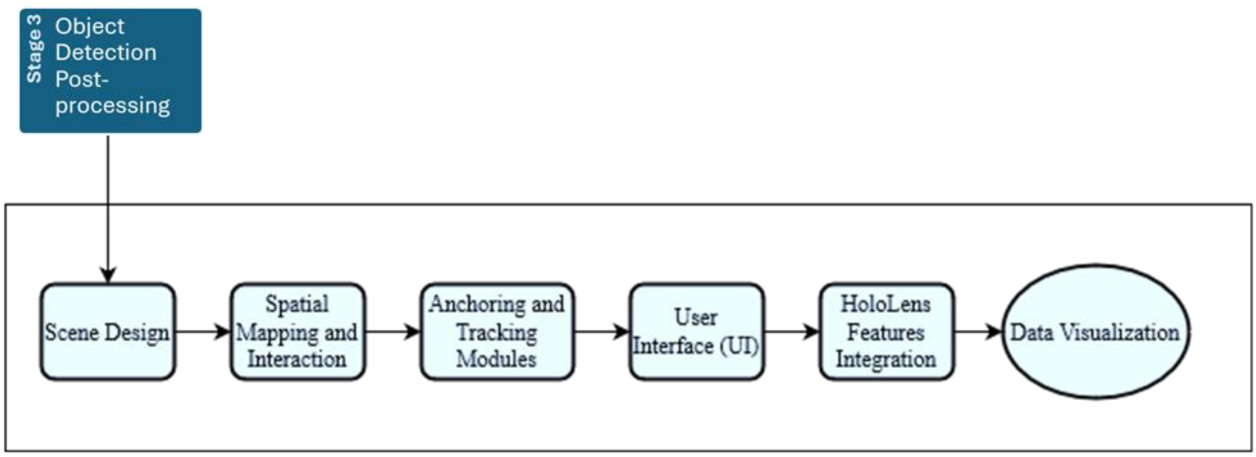


Figure 5: Augmented Reality Visualization Process

3. Case Study

The proposed framework is applied in a real-life case study to demonstrate its practicality and effectiveness in Mostakbal City, New Cairo, Egypt (see Figure 6). The city is planned over 5,200 acres across three phases. The focus is on the first phase (1,490 acres), where most utility construction was completed. The implementation follows the model development stages: 1) Data collection and processing, 2) Mask R-CNN model training and inference, 3) Object detection and post-processing, and 4) AR implementation. Each stage employs appropriate tools and software. The second and third phases cover 1,607 and 1,875 acres, respectively, serving residential areas and regional service centres.

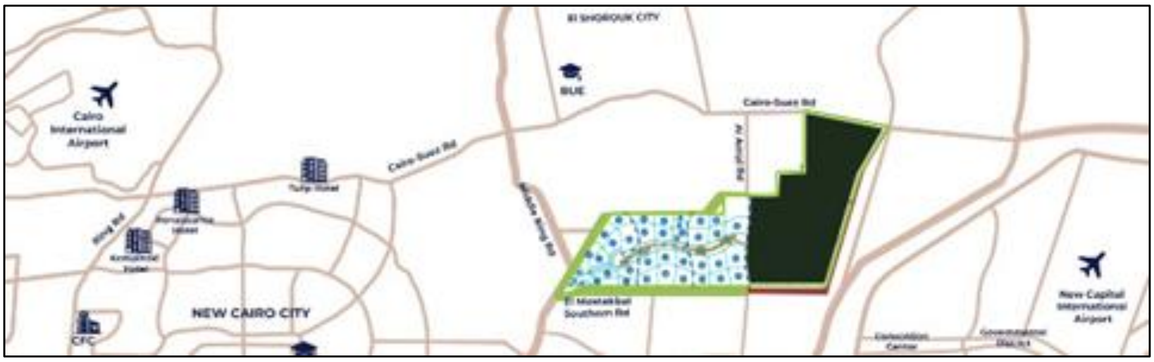


Figure 6: Mostakbal City Location

3.1. Data Collection and Processing

The data collection process for the model implementation involved the use of an IDS RIS MF Hi-MOD GPR system with two antennas. The first one is 400MHz to provide high penetration depth while the second one is 2,000MHz to provide high resolution for shallow depths. These selections were based on the as-built utilities located at the scanned areas, which are set as a reference for data annotation which showed that utilities such as water main and irrigation main are within a depth of 2.50-meter, gas lines within 2.0 meters, and electric duct banks within 1.20 meter. At the same time, some other sub-main utilities are located within 1 meter. The GPR system scans various sites within phase one of Mostakbal City for two purposes: 1) to obtain training and validation data for Mask R-CNN model training and 2) to acquire unseen data for measuring the framework's performance and complete implementation, including AR visualization. A total of 114 profiles are scanned and divided into two sets. The first set comprises 54 profiles, averaging 30 meters, in areas with congested utilities for training and validation. The second set consists of 60 profiles, averaging 20 meters, featuring two duct banks for performance measurement and full framework application. Figure 7 provides a schematic of buried utilities at the case study site.

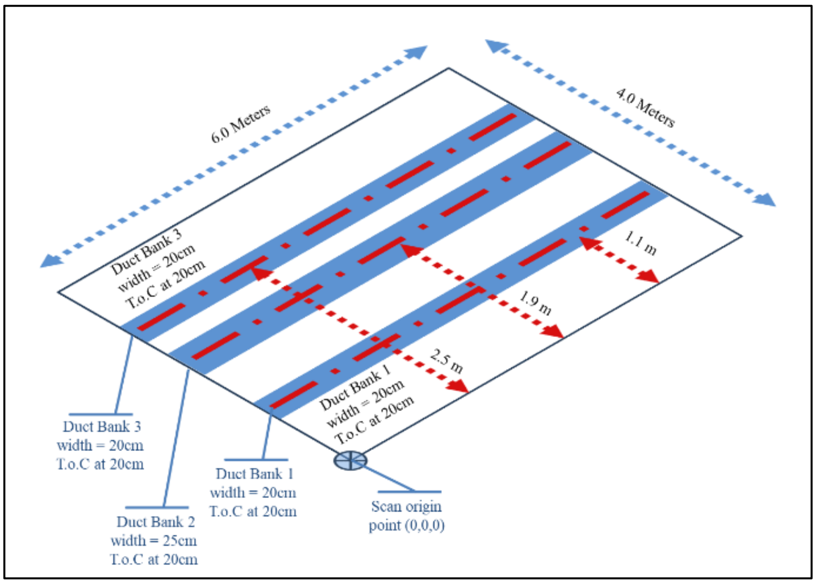


Figure 7: Schematic Representation of Buried Utilities at Case Study Location

Raw Data Decryption process involves converting raw GPR data into a format suitable for processing and interpretation. Each GPR hardware vendor provides proprietary software for data decryption, but this limits third-party processing. By reverse-engineering the IDS RIS format stored in *.DT files, data decryption becomes possible. The process starts by reading the file's header to determine scan parameters, then extracting data from the data section using a HEX editor to understand its format and address ranges (see Figure 8).

	Addres	Data Bytes	Hexadecimal converted to ASCII
Header Sample Snippet	00000800	00 00 00 00 00 00 00 00 43 00 00 00 30 35 2F 32	........C...05/2
	00000810	30 2F 32 33 20 20 31 31 3A 34 32 3A 34 33 00 00	0/23 11:42:43..
Raw Data Snippet	00003C30	20 20 20 20 20 20 20 20 20 20 20 20 52 00 00 00	R...
	00003C40	7B FE 8F FE BA FC D8 FB C5 FB BE FB C3 FB BF FB	{▪Å▪║ⁿ╪√┼√╛√├√┐√
	00003C50	BE FB BE FB BF FB BF FB C0 FB C1 FB C0 FB C1 FB	╛√╛√┐√┐√└√┴√└√┴√

Figure 8: Snippet Sample of The Header and Raw Data Sections

The data fusion process combines multiple data sources to produce more consistent and comprehensive information than a single source. It starts with signal resampling, which is crucial for integrating GPR data from sensors with differing frequencies. Resampling standardizes the temporal domain, enabling dataset integration and comparison by adjusting signals to a common frequency using Python's Scipy library's "`signal.resample`" function. The resampled dataset is organized into a structured format with trace count, time window, positions, and frequency characteristics, enhancing data accuracy and reducing redundancy.

After obtaining and decrypting the scan data, data processing enhances the signal-to-noise ratio and minimizes distortions for efficient interpretation. The preprocessing begins by applying noise filters to remove unwanted signals, including system noise between antennas, wave interference, material reflections, and external EM interference. Wavelet transform and A-Scan analysis use:

- *Low Amplitude Filtering*: Utilizes "`low_pass_filter`" to eliminate signals outside specific amplitude thresholds.

- *Dewow Filtering*: Suppresses low-frequency noise and removes long-term drifts caused by external factors.

3.2. Mask R-CNN Model Training and Inference

The second stage of the framework involves utilizing deep learning to interpret GPR data automatically. The processes involved in the deep learning integration stage start with data and deep learning model preparation and training the model while incorporating data augmentation and transfer learning and using the trained mode to provide object detection through inference and post-processing of the output detected objects. The processes of Mask R-CNN training and inference, along with their inputs and outputs, are listed in Table 1.

Process	Input	Output
Mask R-CNN Data Preparation	B-Scan images of fused datasets with different filtering configurations for each profile.	Training and Validation database.
Model Preparation and Training	Training and Validation Database.	Trained Mask R-CNN Model.
Inference and post-processing	Testing dataset.	Processed segmented instances detection.
Features Extraction	Detected objects of all profiles' filtering configurations.	Binary instance array for each profile.
Profiles Alignment	B-scan of each profile	Shifted B-scans with aligned profiles.
Point Cloud Generation	Shifted B-scans with aligned profiles and thier features.	Point cloud with pixel reduction.

Table 1: Mask R-CNN Model Training and Inference Processes Input and Output List

3.2.1. Data Preparation

The data preparation process includes dataset processing, data annotation, and database generation. Although dataset processing is redundant for this model, it's useful for external datasets using B-scans with padding or titles, as data augmentation could impact training. Data annotation is done using Makesense.ai, a free, open-source web app that supports multiple label types like bounding boxes, lines, and polygons. Annotations can be exported in formats like VGG JSON or CSV. Once data annotation is complete, model preparation begins by selecting and configuring the appropriate model. Mask R-CNN is chosen for its configurability and pixel-level object detection capabilities, and ResNET-50 is chosen as its base architecture for efficiency and performance. The result is a trained model ready for analysis to identify the best-performing configuration. The training process spans 100 epochs, starting with initial transfer learning using a COCO-trained model. Additional transfer learning occurs after epochs 60 and 80, accounting for the spikes in the learning curve shown in Figure 9.

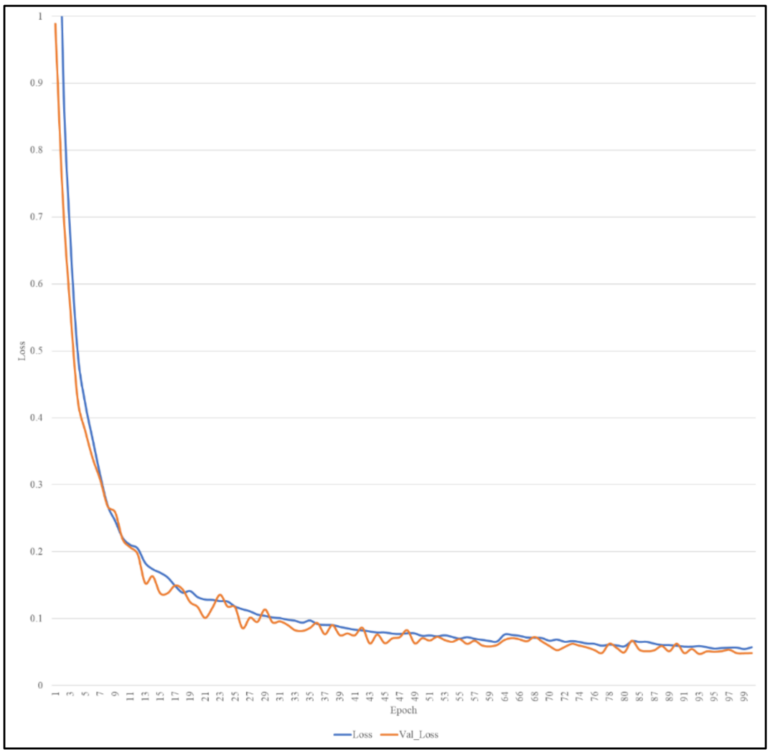


Figure 9: Model Training Loss and Validation Loss

3.2.2. Inference and Detections Post-processing

During training, each epoch includes a training and validation loss function. Epoch run time is calculated from the processor time difference between start and end. These metrics assess model performance, with lower loss values indicating better performance. Plotting these metrics visualizes convergence and helps identify the lowest validation loss without overfitting (see Figure 10). The first three epochs of each transfer learning stage are removed to manage spikes. The assessment utilized Equations (1) and (2) to show that model 93 is the best-trained model.

$$Combined\ Score = \frac{Loss + Val\_Loss}{2} \tag{1}$$

$$Efficiency\ Metric = (1 - w) * Combined\ Score + w * \frac{1}{Epoch\ Time} \tag{2}$$

Model 93 detects utility locations using a function that applies trained weights, generating masks on radargram images through:

1. Reading radargram images.
2. Running the object detection function for mask instances.
3. Exporting detected masks as arrays for post-processing.

Accordingly, the post-processing involves three steps:

1. *Mask Refinement*: Retain masks meeting thresholds across configurations, generating a binary instance array. Masks not meeting thresholds are removed, producing one binary instance array per profile (Figure 11).

2. *Profile Alignment*: Align profiles to common start and end points by setting a datum profile, extracting features, determining reference points, and applying shifts. Metallic tapes in data collection marked profile boundaries for alignment.
3. *Pixel Reduction and Point Cloud Generation*: Reduce pixels to enhance AR model performance and generate a point cloud.

Table 2 illustrates the process utilized to perform post-processing on obtained masks while Table 3 illustrates the point cloud generation process.

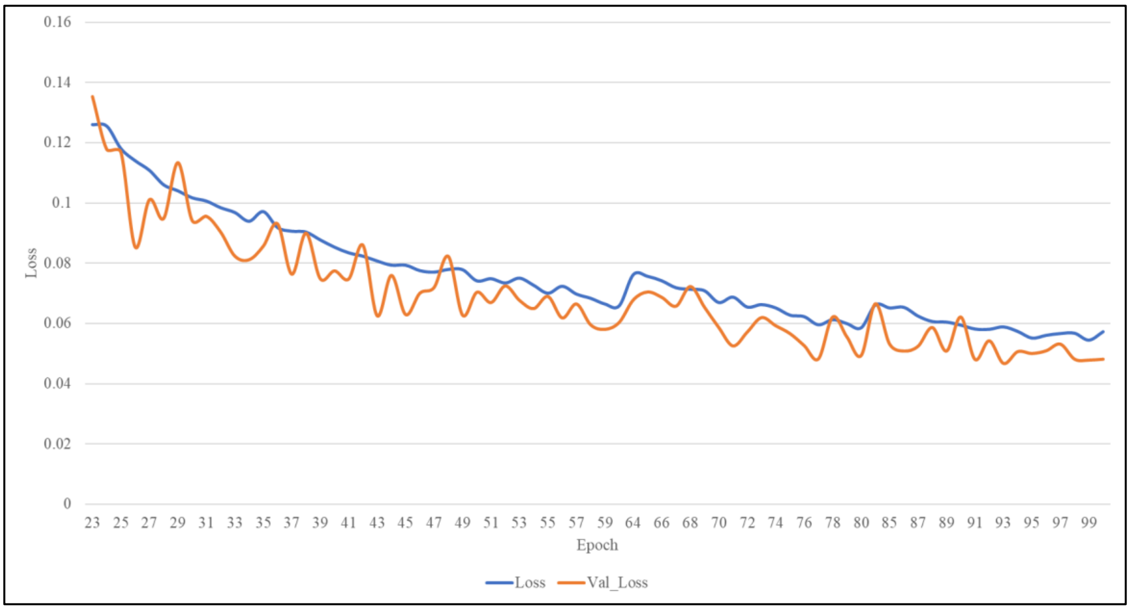


Figure 10: Model Preparation and Training Process

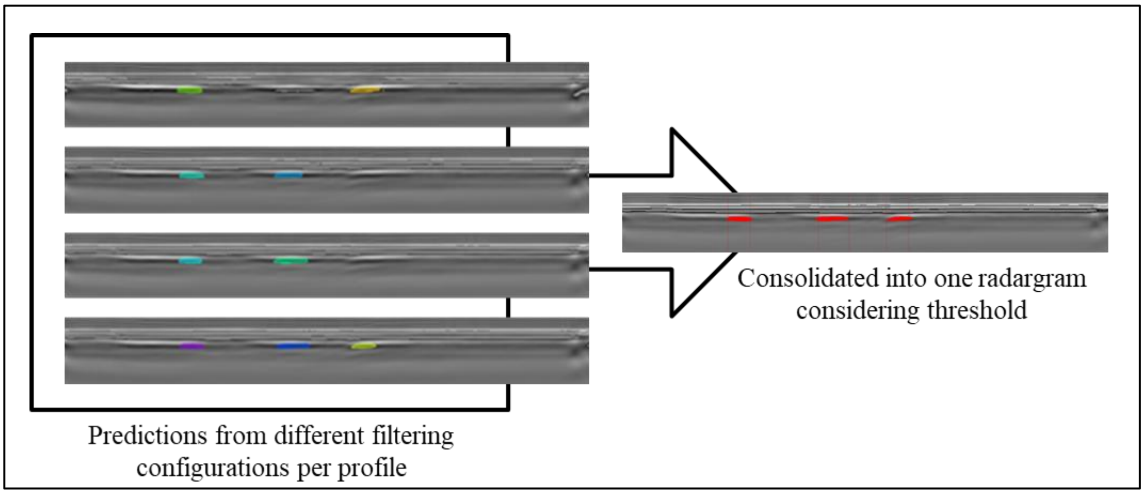


Figure 11: Feature Extraction and Retention of Valid Masks

OMAINTEC Journal
(Journal of Scientific Review)

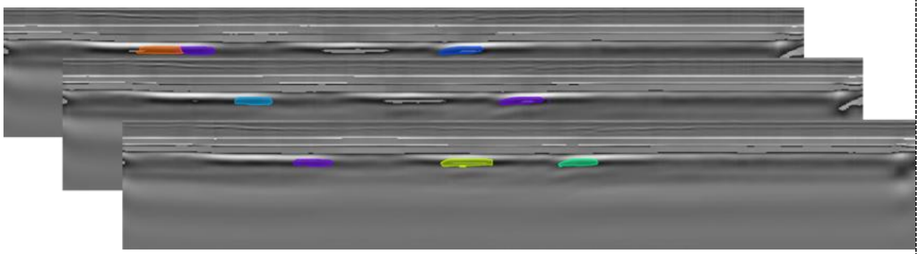
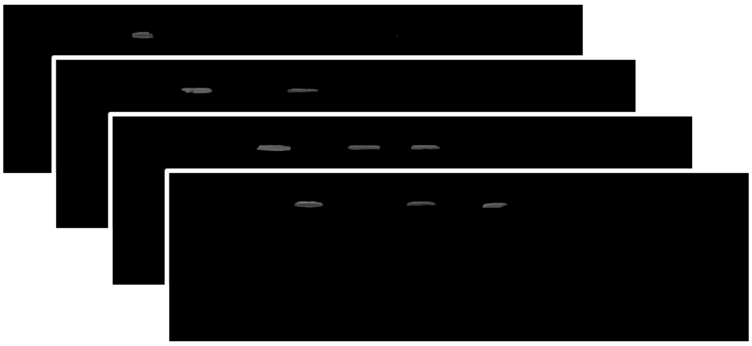
Input	Detected objects obtained for each configuration for each profile  Sample of detected objects of a profile's configurations.
Process	1- Cross-reference each profile for proper alignment. 2- Check mask occurrence and keep masks that meet the threshold. 3- Get a binary array of masks for each profile.
Output	Binary mask filtering only regions of interest.  Sample of filtered binary masks.

Table 2: Inference Post-processing Process

Input	Filtered binary mask for each profile.
Process	1- Perform pixel reduction. 2- Convert each pixel location into a point in a 3D space.
Output	Point cloud of the processed detected objects' masks. 

Table 3: Point Cloud Generation Process

OMAINTEC Journal
(Journal of Scientific Review)

3.3. Augmented Reality Visualization

The stage includes the use of several tools and preparation that are crucial for the development of the application, the development requires the installation of a number of software packages (e.g., *Adobe Illustrator, Visual Studio, Unity Hub,* etc.) to configure the project for AR by setting MR project, scene, and UWP Capability settings, creating a Main Camera with attached scripts for user interaction (see Figure 12). Subsequently, the next step involves creating objects that match the application's wireframe (see Figure 13). These objects serve as the application's front-end, with scripts providing back-end functionality, which involves designing and applying VuMarks as materials to game objects (see Figure 14). This results in objects and user interface shown in Figure 15. The final stage involves building and deploying the AR application to the HoloLens, as depicted in Figure 16.

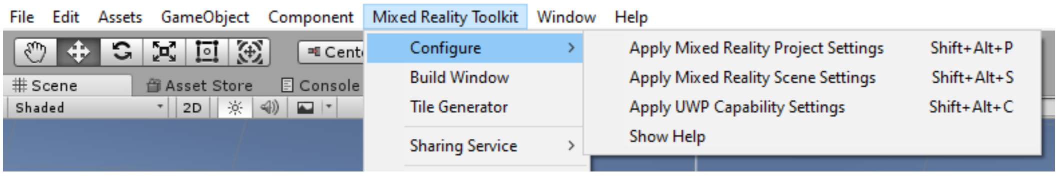


Figure 12: Project Configuration

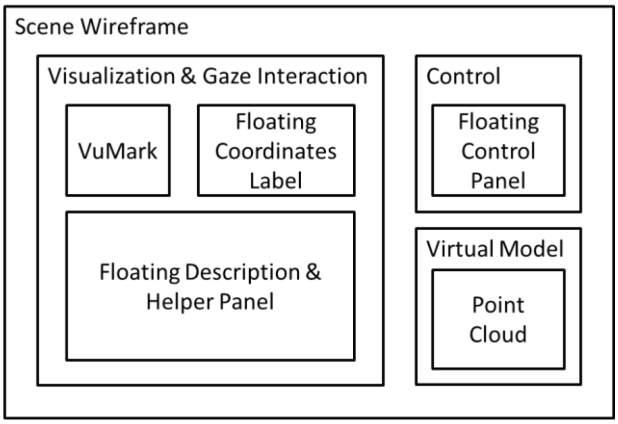


Figure 13: Planning Scene Using Wireframe

Figure 14: VuMark Employed in The Research

OMAINTEC Journal
(Journal of Scientific Review)

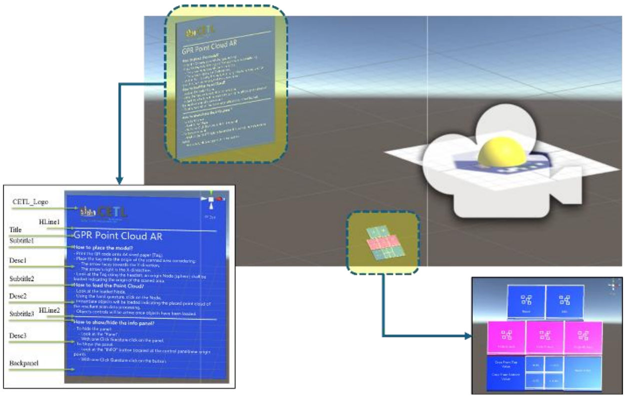
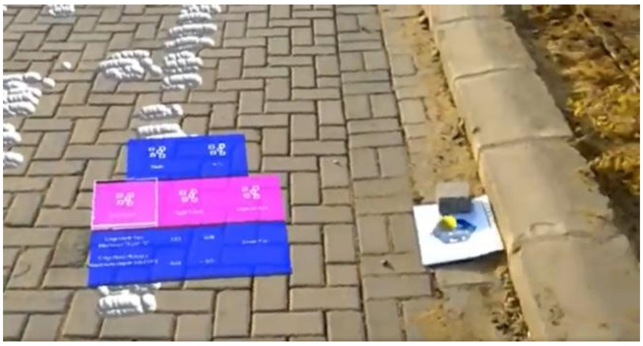


Figure 15: AR Application Scene Components

a) Initiation of The Application

b) Initiating Loading of Point Cloud



c) Application UI After Loading Point Cloud

d) Visualizing Point Cloud Coordinates Data

Figure 16: Building and Deploying the AR Application to the HoloLens

4. Conclusion

This research proposed a novel framework that integrates deep learning techniques and augmented reality to automate the interpretation of GPR data to detect and visualize subsurface utilities in urban environments. The framework addresses the increasing complexity of infrastructure development and the demand for precise mapping and detection of subsurface utilities, minimizing interruption of services and maintaining high service quality to mitigate socioeconomic impacts. The framework is shaped to address the purpose of the research, to reduce manual intervention by automating the process of subsurface utility detection accurately and in the most efficient way, elevating the current practices to meet modern technologies. The framework addresses the traditional methods of visualization of the subsurface utilities by integrating augmented reality to enhance the visualization and provide users with a more intuitive and immersive understanding of the results. Thus, it explores the potential of combining advanced technologies to revolutionize the current methods of subsurface utilities detection and mapping, which improve decision-making processes while ensuring the safety and efficiency of subsurface utilities management.

References

[1] E. Water and R. Agency, "Annual Report N° 14 Egyptian Water Regulatory Agency (EWRA)," 2022.

[2] Egypt Electricity Holding Company (EEHC), "Annual Report Year 2020/2021," 2021. [Online]. Available: http://www.moee.gov.eg/test_new. Accessed 1 Feb 2022

[3] W. Wai-Lok Lai, X. Dérobert, and P. Annan, "A review of Ground Penetrating Radar application in civil engineering: A 30-year journey from Locating and Testing to Imaging and Diagnosis," NDT E Int., vol. 96, pp. 58–78, 2018, doi: 10.1016/j.ndteint.2017.04.002.

[4] P. Zhang, X. Guo, N. Muhammat, and X. Wang, "Research on probing and predicting the diameter of an underground pipeline by GPR during an operation period," Tunn. Undergr. Sp. Technol., vol. 58, pp. 99–108, 2016, doi: 10.1016/j.tust.2016.04.005.

[5] H. Li, C. Chou, L. Fan, B. Li, D. Wang, and D. Song, "Toward Automatic Subsurface Pipeline Mapping by Fusing a Ground-Penetrating Radar and a Camera," IEEE Trans. Autom. Sci. Eng., vol. 17, no. 2, pp. 722–734, 2020, doi: 10.1109/TASE.2019.2941848.

[6] S. W. Jaw and M. Hashim, "Locational accuracy of underground utility mapping using ground penetrating radar," Tunn. Undergr. Sp. Technol., vol. 35, pp. 20–29, 2013, doi: 10.1016/j.tust.2012.11.007.

[7] S. Kuo, "Investigation of Ground Penetrating Radar for Detection of Leaking Pipelines Under Roadway Pavements and Deveopment of Fiber-Wrapping Repair Technique," University of Central Florida, 2004.

[8] H. R. Burger, A. F. Sheehan, and C. H. JONES, Introduction to applied geophysics : exploring shallow subsurface. W. W. Norton & Company, Inc., 2006.

[9] B. Maruddani and E. Sandi, "The development of ground penetrating radar (GPR) data processing," Int. J. Mach. Learn. Comput., vol. 9, no. 6, pp. 768–773, 2019, doi: 10.18178/ijmlc.2019.9.6.871.

[10] K. He, G. Gkioxari, P. Dollár, and R. Girshick, “Mask R-CNN,” in IEEE Transactions on Pattern Analysis and Machine Intelligence, 2017, pp. 2961–2969. doi: 10.1109/TPAMI.2018.2844175.

[11] Microsoft, “About HoloLens 2.” Accessed: Mar. 30, 2024. [Online]. Available: https://learn.microsoft.com/en-us/hololens/hololens2-hardware

[12] S. Ong and V. K. Siddaraju, Beginning windows mixed reality programming: For HoloLens and mixed reality headsets, Second Edi. 2021. doi: 10.1007/978-1-4842-7104-9.

[13] P. A. Gagniuc et al., “Spectral forecast: A general purpose prediction model as an alternative to classical neural networks,” Chaos An Interdiscip. J. Nonlinear Sci., vol. 30, no. 3, 2020, doi: 10.1063/1.5120818.

OMAINTEC Journal
(Journal of Scientific Review)