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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:

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Asset Management

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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

FROM EVIDENCE-BASED MEDICINE TO EVIDENCE-BASED MAINTENANCE: A MUCH-NEEDED PARADIGM SHIFT FOR MIDDLE EAST COUNTRIES

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Abstract

The practice of "critical appraisal" in medicine started in 1981 and was later named as "evidence-based medicine" (EBM) ranked seventh among the 15 most important milestones that shaped modern medicine in a poll by the British Medical Journal in 2007 [1]. Drawing from the principles of EBM, this paper describes a new approach for the maintenance of medical equipment: Evidence-Based Maintenance. Both EBM's have much deeper roots, i.e., the scientific method that started in the Renaissance (16th century) and first revolutionized physics and then chemistry and, later, biology. Evidence-Based Maintenance is based on the same principle as Evidence-Based Medicine, i.e., use clinical outcomes to evaluate and improve the care of patients. The only difference is that the "patient" is the medical equipment in the latter [2].

Keywords: Evidence-Based, Maintenance, Medical Equipment.

1 Introduction

In addition to ensuring safety, the main aim of the classical approach to medical equipment maintenance within the healthcare delivery organization (HDO) is to reduce maintenance costs and minimize capital investment (CapEx). This calls for the clinical engineering (CE) professionals to maintain equipment as recommended by the manufacturer as mandated by Joint Commission International (JCI) and manage the equipment lifecycle within the HDO.

However, CapEx is only ~20% of total cost of ownership (TCO), while the maintenance cost is only ~1% of total hospital operating expense (OpEx). Thus, CE professionals need to look beyond equipment safety and reliability in order to contribute more effectively to the care of patients not only within the HDO but also in the entire continuum of care, including ambulatory sites, clinics, and homecare.

Before explaining the EBM methodology, it is worthwhile to understand how CE professionals have been maintaining medical equipment for the last few decades and why there is a need to adopt a new approach.

2 Classical Approaches to Medical Equipment Maintenance

2.1 Risk-Based Criteria (the Fennigkoh & Smith model)

This approach assigns an Equipment Management (EM) number for every piece of equipment to determine the maintenance strategy as shown in Table 1 [3].

$$EM = \text{Function} + \text{Physical Risk} + \text{Maintenance Requirements} \qquad (1)$$

If $EM \geq 12$ include into PM inventory and the frequency depends on value of EM

If $EM < 12$ exclude from PM inventory and repair upon failure.

Where PM is the abbreviation for preventive maintenance (later recharacterized as scheduled maintenance).

While initially useful to stop performing PM on every piece of equipment with the same frequency and tasks, the Risk-Based Criteria actually only considers risk severity, without contemplating risk probability as recommended by the ISO 14971 standard, which defines risk as a combination of probability & severity [of harm]. A visualization of failure probability is provided in figure 1, which shows that while multiple layers of defense are usually deployed, each one has some gaps and holes that can allow failures to go through. The failures related to human actions are called "active failures," while those related to organizational processes are called "latent conditions."

CRITERA	CATEGORY	SUBGROUP	NUMERICAL VALUE
Function	Therapeutic	Life Support	10
		Surgical and intensive care	9
		Physical Therapy	8
	Diagnostic	Surgical and intensive care	7
		Additional Physiological monitoring and diagnostic	6
	Analytical	Analytical Laboratory	5
		Laboratory accessories	4
		Computer and related	3
	Miscellaneous	Patient related	2
Physical Risk		Patient death	5
		Patient or operator injury	4
		Inappropriate therapy	3
		No significant risks	2
Maintenance Requirements		Extensive	5
		Average	3
		Minimal	1

Table 1: Risk-Based Criteria for determination of maintenance strategy

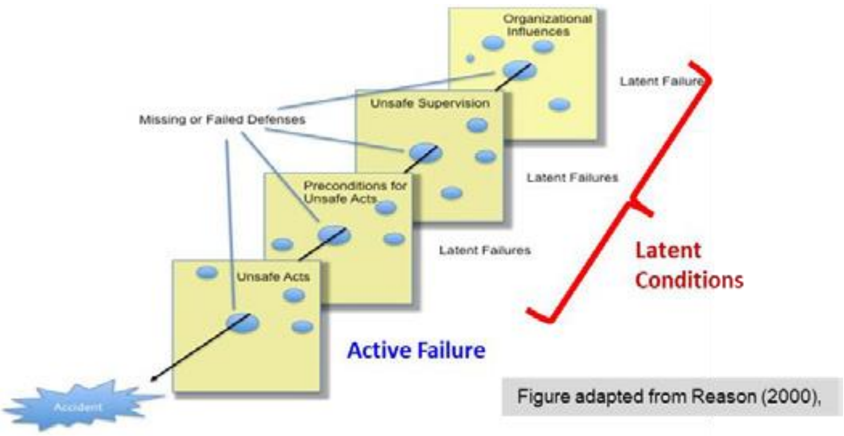

Figure 1: The Swiss-cheese model of risk

2.2 Reliability-Centered Maintenance (RCM)

RCM is defined as "a process used to determine what must be done to ensure that any physical asset continues to do what its users want it do to in its present operating context" [4]. This approach improves asset performance and is able to contain and even reduce the cost of maintenance. It has three basic elements: Planning, Implementation, and Evaluation.

- Planning
  - Asset selection
  - Characterization of function & failure patterns
  - Failure mode and effect analysis (FMEA)
  - Decision process
  - Develop performance measures
  - Define maintenance schedules & work instructions
  - Staff training
- Implementation
  - Implement adopted strategies
  - Maintenance data collection
- Evaluation
  - Evaluate maintenance performance
  - Use evaluation results to revise & update strategies

RCM uses a decision process to determine the best maintenance strategy according to an analysis of the failure modes and effects as shown in figure 2.

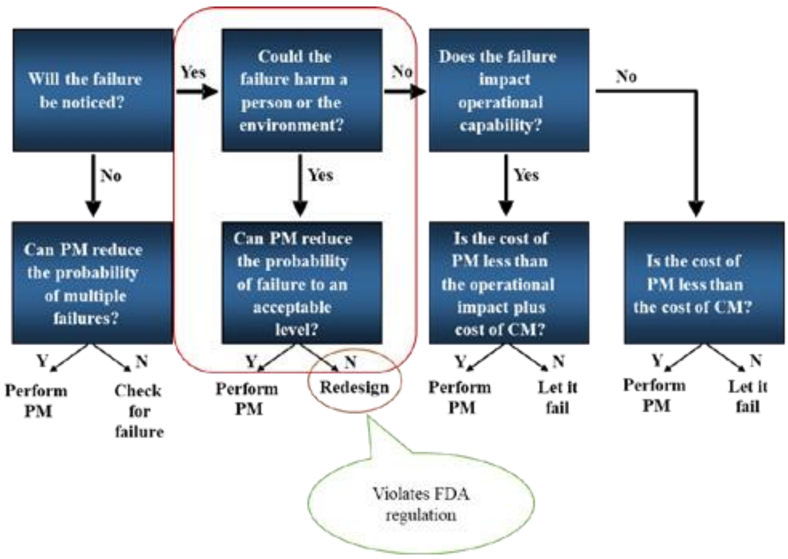

Figure 2: RCM Decision Process (Adapted from [4])

While RCM has been very successful in many industries, e.g., aviation, manufacturing, and electricity generation and distribution, it has significant challenges for application to medical equipment due to:

a) Failure mode and effect analysis (FMEA) is often not possible because the manufacturers do not share the software embedded into the medical equipment.
b) When PM cannot reduce probability of failure, RCM recommends redesigning the device. However, this is almost always in violation of regulations of national medical device authority, e.g., the Food and Drug Administration (FDA) in the USA.
c) Without manufacturers' assistance, it is difficult to define maintenance schedules & work instructions.

3 Evidence-Based Maintenance – EBM

EBM is a continual improvement process that analyzes the effectiveness of maintenance resources, structure and processes deployed in comparison to outcomes achieved previously or elsewhere and makes necessary adjustments to maintenance planning and implementation [2].

The EBM methodology is based on the analyses of maintenance data collected, not only from an individual hospital, but also hundreds of others whenever those are available. The aim is to improve capital planning, increase utilization, reduce unnecessary maintenance, delay premature replacement, enhance safety, and protect against cyberattacks and thus increase productivity and revenue.

3.1 Maintenance Strategy Selection (Planning)

Medical equipment maintenance is composed of two type of maintenance activities:

(1) Scheduled Maintenance (SM), which is composed of
   a. Preventive Maintenance (PM): replacement of parts with predictable deterioration (e.g., O2 cell or rubber gaskets), and
   b. Safety & Performance Inspection (SPI): detection of hidden and potential failures.

(2) Corrective Maintenance (CM), which aims at restoring the equipment to its original safety and performance specifications.

SM should be planned as a function of the technology used its construction (e.g., mechanical, pneumatic, and/or chemical) and not as a function of the mission criticality or the risk of the device to individual patients. This is because more frequent or elaborate maintenance cannot increase safety or reliability, unless there are failures that can be prevented by PM or detected by SPI. As most CE professionals know by their experience, maintenance needs have changed significantly with technology evolution. For example, changing from CRT tubes to LED panels in patient monitors and from X-ray films to digital X-ray detectors have dictated completely the proper maintenance methods for those types of medical equipment.

In industrialized countries CM of the equipment is done as needed if the cost of repair is below a certain percentage of replacement cost (e.g., 25%); otherwise, it will be replaced. However, this may not be easy now with budget problems or in other countries. Examples of such equipment are patient monitors based on solid-state electronics and pulse oximeters.

The references used for the determination of SM frequency and activities are the manufacturer's service manual (if available), the published recommendations by professional organizations, the past experience of individual hospitals, and the shared experience among hospitals.

3.2 **Evaluation of the Maintenance Strategy EB**

In EB Medicine, a drug or medical procedure must be evaluated for its safety and effectiveness before it can be marketed. In EB Maintenance, we also need to evaluate the maintenance strategy for its safety and effectiveness. To measure effectiveness, we use reliability because the availability of the equipment for use whenever needed tells us how effective the maintenance strategy was adopted.

In other words, a maintenance strategy should be evaluated for its reduction of equipment malfunctions that can negatively affect patients and clinical users (safety) and for the equipment availability when needed (reliability = effectiveness). These two dimensions are like the two sides of the same coin. It is useless to have a safe equipment that is not reliable or to have a reliable piece of equipment that is not safe.

Like EB Medicine, EB Maintenance tries to find ways to address the root causes of the failures (diseases in medicine) and uses the outcomes to determine which maintenance strategy works best. Root Cause Analysis (RCA) of failures is needed to know why a piece of equipment failed and then, determine what can and needs to be done to prevent it. Full RCA is time consuming but is necessary when a patient injury occurred. On the other hand, a simplified RCA can be used for routine assessment of equipment failures. Thus, a limited set of failure causes, called Failure Cause Codes (FCCs), have been developed and deployed. The FCCs are show on Table 2.

Using the FCCs, one can evaluate the maintenance strategy adopted (i.e., maintenance activities and respective frequencies) for safety and reliability as described below [2].

3.2.1 Safety Evaluation Using EBM

First, record all patient incidents (including "near misses") involving medical equipment failures. Next, perform a root-cause analysis (RCA) and assign the appropriate FCC. Then focus on incidents related to these FCCs: service induced failure (SIF), hidden failure (HF), potential failure (PF) and preventable and predictive failure PPF, as these causes are related to maintenance. Finally, determine whether these failure causes are related to individual actions or maintenance strategy, i.e.:

a) "unsafe acts" (or "active failures") committed by individual staff (employed by hospital, original equipment manufacturer (OEM), or third party), e.g., lapses or slips.
b) "latent conditions" created by the organization due to oversight or deliberate violation of regulations, codes or standards.

How the results of safety evaluation are used to improve maintenance is described later in section 3.3.

Code	Failure Cause Description	SM/CM
NPF	No problem found (or the reported problem was not duplicated).	both
UPF	Unpreventable failure, typically caused by normal wear and tear but is unpredictable.	CM
ACC	Accessory failure, excluding batteries, typically caused by normal wear and tear.	both
BATT	Battery failure, i.e., battery(ies) failed <u>before</u> the scheduled replacement time. Does not include scheduled replacement of batteries.	both
NET	Failure in or caused by network, while the equipment itself is working without problems. Applicable only to networked equipment.	both
USE	Failures induced by use, e.g., abuse, abnormal wear & tear, accident, or environment issues.	CM
EF	Evident failure, i.e., a problem that can be detected, but was not reported by the user, without running any special tests or using specialized tester.	SM
SIF	Service-induced failure, i.e., caused by CM or SM that was not properly completed or a part that was replaced and failed prematurely ("infant mortality").	CM
HF	Hidden failure, i.e., a problem that could not be detected by the user under normal circumstances, unless running a special test or using specialized tester.	SM
PF	Potential failure, i.e., failure is either about to occur or in the process of occurring but has not yet caused equipment to stop working or problems to patients or users.	SM
PPF	Preventable and predictable failure, typically caused by wear and tear that can be predicted or detected.	CM

Table 2: Failure Cause Codes (FCCs). The rightmost column shows in which types of maintenance activity (SM or CM) the FCC can be used.

3.2.2 Reliability Evaluation Using EBM

First, collect all the service records with the following FCCs: service induced failure (SIF), hidden failure (HF), potential failure (PF) and preventable & predictable failure (PPF) found. Within each of these 4 FCCs, determine the number of equipment groups (i.e., same brand and model, and similar ages, utilization location and intensity, and users). Next, look for the equipment groups with unusually high number of FCCs, especially PPFs.

For these equipment groups, determine the underlying cause like "unsafe acts" (or "active failures") committed by individual staff (employed by hospital, OEM, or third party), e.g., lapses or slips (individual) and "latent conditions" created by the organization due to oversight or deliberate violation of regulations, codes, or standards. If >50% of the FCCs are due to "latent conditions," then determine whether it is caused by the adoption of a specific maintenance strategy. If so, revise it.

3.3 Use of EBM Evaluations

Results of the safety and reliability evaluations should be used to revise and refine SM and CM strategies, i.e., to determine appropriate corrective and preventive actions that will not only correct but also prevent similar failures in the future in the maintenance of those equipment groups but also in others, if needed.

For "unsafe acts" (or "active failures") committed by individual staff use one or more of the following actions: training, revision of work instructions, and disciplinary actions.

For "latent conditions" created by the organization use one or more of the following actions: revision of SM/CM strategies (procedures, frequencies, work instructions, etc.), and supervision of in-house and external service staff

4 Discussion & Conclusions

4.1 EBM Limitations

While EBM tries to imitate the methods of EB Medicine, there are some fundamental differences:

- Equipment is designed by people and, thus, is less complex and better understood than human beings
- Equipment does not suffer from psychosomatic effects, so double-blind approach is not needed
- Cannot blindfold CE professionals when performing service

In essence, it is not possible to conduct "double-blind randomized clinical trials" (RCT) like drug testing. EBM is more analogous to "cohort studies" in which the outcomes of two groups of patients are compared, one having received a certain therapy while the other did not.

4.2 Lessons Learned

Data analysis show SIF is very rare [5]. Most maintenance errors are caused by active failures (human) instead of latent conditions (maintenance strategy). Thus, there is no reason to follow OEM maintenance recommendations, as these are typically overburdensome due to their desire to protect themselves against lawsuits. True PM is becoming obsolete with technology advance and will not provide job security. Artificial Intelligence (AI) and Machine Learning (ML) will soon allow predictive maintenance and, thus, reducing significantly CMs. Finally, relying solely on MTBF is misleading as many failures are not predictable or preventable. Should focus only on MTBF related to failures caused by maintenance activities.

4.3 How can EBM improve equipment maintenance?

Why should CE professionals perform SM if it does not reduce failure or increase safety? For example, routine electrical safety tests (ESTs) have been abolished in the USA. Therefore, there is no reason to spend limited resources (time, material, money, etc.) on unnecessary maintenance activities. Instead, CE departments should reallocate its limited resources to:

- Help plan and select better equipment before purchase
- Help users to understand and use better the equipment
- Help users to understand and take better care of the equipment
- Help to determine when equipment needs to be replaced
- Help to investigate patient incidents related to medical equipment
- Address recalls promptly to reduce risks to patients and users
- Address cybersecurity issues presented by equipment

The results of adopting EBM in the USA have been replicated in Italy [6]. Other countries are also starting to adopt it although their results have not yet been published.

For over 30 years, the Fennigkoh & Smith model was adopted for maintenance of medical equipment at the American University of Beirut Medical Center (AUBMC). During this period of time, a failure coding system more elaborate than the EBM method described above was used. Although the data thus obtained helped to improve the maintenance strategy, it was more labor intensive and did not allow evaluation of safety and reliability as easily as the EBM method describe above.

The main challenges lying ahead in getting the full benefit of this system in our MENA region are:

a) Willingness to adopt this method and share information across different institutions.
b) Marketing the advantages of applying this method within each institution to the several key stakeholders.
c) Convincing JCI and national accreditation bodies of the advantages of this approach instead of using the OEM recommendations and electrical safety checks.

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CERTIFICATION OR MATURITY MENTORING AUDIT - DRIVING THE ASSET MANAGEMENT JOURNEY.

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Abstract: For many organisations around the globe, ISO 55001 certification has been a strategic component of their Asset Management journey. However, not all organisations consider formal third party certification to be necessary, feasible or in fact desirable for that journey. Other ways of achieving the growth required in asset management capability are available, and for many organisations, may be a more productive journey than ISO Certification alone. This paper will describe the why and how of an Asset Management maturity assessment that drove the improving performance of a support organisation for maritime assets. The role and content of a "mentoring audit" of the Asset Management maturity of the organisation will be described along with the outcomes and lessons learned during the two year journey. Comparisons of the results achieved will be made with another similar program using frameworks drawn from national and international "not for profit bodies".

Keywords: Asset Management, 55001, Certification, Maturity, Audits

1 INTRODUCTION

ISO Certification is understood by many as demonstration of an organisation's management system capacity to achieve a particular set of outcomes. These outcomes are often enunciated in the form of principles such as those that underpin Asset Management. These principles become the basis of a formal management system against which organisations may test themselves. This test is like an athlete in a high jump that is concerned only that the qualifying bar was cleared, not with how much the bar was cleared by.

Without a structured management system an organisation cannot claim an asset management capability. Without a sufficiently mature management system for asset management, the organisation cannot claim a match between the management system capability and the managed asset related risks that is necessary to achieve the organisation's objectives. In this context, formal certification to the ISO 55001 standard for a management system for asset management is not a guarantee of required management capability. Certification only establishes a single "go/no go" threshold for the listed requirements in the standard.

The Maritime System Program Office (MSPO) involved does not have asset management accountability for the physical assets serviced. Operations belongs to the Royal Australian Navy. Navy outsources the sustainment function to Capability Acquisition and Sustainment Group who, for a variety of reasons, outsource their core management function to an industry service provider (ISP). Two key goals from the scope of work for the ISP were:

- (1.2.3) *The Contractor is required to deliver and manage the Services using an asset management approach based on and consistent with ISO 55001:2014 Asset Management*.
- (1.2.4c) *The Objectives.............. are to implement a structured asset management framework to maximise the value of the Commonwealth's assets and in doing so minimise the Total Cost of Ownership;*

As the program progressed, evidence from assessment of Project plans and related independent audits, indicated that the required Asset Management objectives and expectations were not being achieved. A number of critical Asset Management – Management System Plans (AMSyPs) such as the Enterprise Management Plan had not been approved. While asset management maturity in the organisation was anecdotally considered low, some formal means to assess the level of maturity was required to determine how low that maturity was in the Management System for Asset Management (AMS). An asset management maturity audit of some form was needed.

2 THE PROPOSITION

A brief to undertake an Asset Management Audit of the ISP was accepted on 3 March 2019. Three alternate approaches to assessing the level of performance of an MSPO in establishing an asset management system framework were:

- An audit process based on the Maintenance Engineering Society of Australia (MESA) original excellence award in maintenance and asset management between 1996 and 2014, which was based on the Australian Business

Quality Awards Process. Development would be quick and there is a successful provenance of providing a reasonable coverage of asset management capability.

- An AM maturity assessment using the Asset Management Council maturity tool. This approach uses a large question set (158) to test an organisation's maturity in asset management. Significant written effort and knowledge of asset management is also required to describe the organisation's current capability. Many workshops would be required and key staff would need to be made available.
- An independent gap analysis conducted by a certifying agency such as SAI Global or Bureau Veritas. Such a formal analysis, often quite basic, is meant to be a gap closure activity followed by a full ISO Certification effort. In the context of MSPO many independent and mandatory certification activity was already underway thus challenging both the value and available resourcing for yet another independent formal audit.

The brief's recommendation to adopt Approach 1 above was accepted, with the following key points agreed. The audit would:

- adapt the now obsolete MESA assessment tool from the 1990s which would be upgraded to assess the ISO 55000/1 essentials.
- be conducted by existing internal staff with guidance from the MSPO Asset Management Specialist;
- establish a baseline for the current state of AM maturity;
- gain an understanding of the potential gaps in the ISP asset management capability to allow for future AM capability development programs;
- assess the shape and size of options to close, over the next three years, the identified AM capability gaps; and
- provide a means of assessing the effectiveness of the AM capability defined in a suite of Asset Management System Plans being the plans for the Management System (AMSyPs).

3 DEVELOPING AN AUDIT TOOL

As attainment of ISO 55001 Certification was not a stated objective for the MSPO, the priority was process development. A process audit tool was developed using the following list of sources:

- ISO 55001:2014 Management system for asset management;
- Australian Quality Awards and Bainbridge Awards assessment criteria;
- MESA Excellence Awards process 1996 to 2014;
- AM Council Asset Management System Model 2015;
- AM Council Capability Delivery Model 2005.

The views of what maturity in Asset Management might look like for an organisation in delivering a process gradually evolved to reflect a combination of the following attributes:

- Is there a defined **process** to satisfy the posed questions?
- Has that process been **implemented** and at what level?
- Are **measures** of achievement collected that allow measurement of process success? and
- Is this information used to **continuously improve** those processes?

The developed audit process comprised:

- 101 questions - see example set at Table 1,
- across 20 Topic areas such as "Context Setting" – See example at Table 2 and full Topic listing at Figure 1,
- with each question being assessed against four criteria – See example at Table 3, and
- marked on a scale 0 to 9 in 5 pairs (i.e. 0-1, 2-3, 4-5, 6-7, 8-9) – See example at Table 3.

The audit tool was used for both the initial audit and the complete follow on Mentoring Audit. The largest difference between the audits was in the extended involvement of both MSPO Governance and ISP over a 15 month period after the initial audit.

The initial audit required speed and a broad understanding of our current position. To achieve this requirement the following approach was adopted:

- The Auditor was to be certified at CFAM level with AM Council and a Certified Asset Management Auditor (CAMA) with the World Partners in Asset Management.

- Only half of the 101 questions were posed in the interviews – questions were not asked if the general consensus was that a score of zero was most likely.
- Only 3 of the 4 assessment criteria would be valued as "Improvement" was generally not possible due to the lack of documented processes to formally improve or measurements and results to provide data for improvement action.
- Only 15 of 19 Topic areas were assessed as 4 Topic areas were still at the stage of developing initial processes. These 4 Topics were assessed some 6 months later to provide a complete baseline.
- Interviews were conducted one on one by the Auditor with the responsible Lead Manager on the basis that results would not be circulated outside the MSPO. An Observer from the MSPO Commonwealth Governance team was present to assure probity.
- All statements were assumed as honestly given (and no OQE was requested or assessed).
- All interviews were documented and passed to the Interviewees for a fact check.
- Lists of Issues and Opportunities for improvement were noted.
- A final score for each audit Topic was allocated by the Interviewer in conjunction with the Observer.
- The Auditor produced a report on the outcome for the first15 Topics and a second combined report for all Topics.

Topic 1	**Context Setting (7 Questions)**
a	Does the organisation have a defined list of stakeholders?
b	Is there an assessment of their importance?
c	Has an associated stakeholder engagement regime been defined?
d	Is there a list of internal and external issues determined from the stakeholder engagement process?
e	Has the asset management portfolio of assets been identified?
f	Is that asset scope clearly identified in a document under quality management control?
g	Is the scope aligned with the SAMP and AM Policy?

Table 1 Example Question Set

Topic 01	Context Setting	**Topic 07**	Decision Making
Topic 04	Asset Management Objectives	**Topic 11**	Resourcing
Topic 05	Culture and Leadership	**Topic 13**	Outsourcing

Table 2 – Example Tranche Topic Set

Score	**Process**	**Implementation**	**Results**	**Improvement**
0 -1	Practices & processes do not apply ISO 55000/1 intent or meet a moderate amount of the Process Model	The process is not documented. There is little or no evidence of any *systematic* achievement of purpose.	Ad hoc and/or poor results achieved. Goals are not identified.	No improvements have been recorded. Improvement goals are not identified.
2-3	Description here	Description here	Description here	Description here
4-5	Description here	Description here	Description here	Description here
6-7	Description here	Description here	Description here	Description here
8-9	Description here	Description here	Description here	Description here

Page 3

Table 3 – Example Audit Assessment Criteria Set and Scoring Levels

A key characteristic of the scoring matrix with its 5 levels, is the non-linearity of the scores. That exact level of exponential growth between scoring blocks e.g. "0-1" and "1-2" has yet to be determined. Rule of thumb would indicate that each block is twice as hard to achieve change to the next block i.e. from "0-1" to "1-2" versus "1-2" to "3-4". Thus going from a score of 1 to a score of 6 is 4 times as difficult as from a score of 1 to a score of 3. This non linearity, which creates an increasing cost of compliance as the assessment score rises, requires careful consideration of the value to be achieved by increasing levels of maturity.

4 MATURITY SCORES FROM THE INITIAL 2019 AUDIT

The audit using the process described at Section 3 had some urgency. Accordingly, individual interviews of 9 Team Leads and the Head Manager were conducted between 24 April 2019 and 9 May 2019. The results were documented and circulated for fact checking by each interviewee. All interview outcomes were documented and signed off by the interviewee. The final report of 71 pages, was submitted on 19 July.

The initial Asset Management Maturity Audit of the ISP in 2019, indicated the lack of an Asset Management (management) System (AMS) as required by the contract. The performance produced low scores for virtually all Topics assessed as shown at Figure 1. The impact of the MSPO governance function's asset management responsibilities on a number of the initial scores was noted in the report and it was observed that the Asset Management outcome is a team effort not just the effort of one party.

As shown at Figure 2 achieving ISO certification would likely require at least an average score of about 4.5 out of a maximum of 9 i.e. a mix of scores between 4 and 5 as a minimum across all criteria . Clearly certification would not be possible with the scores at Figure 1 where the average for each Topic was between 0.5 and 3.5. Additionally, as noted in over a decade of AM Council Excellence Awards Audits using similar criteria, the Criteria scores for immature organisations generally degrade across the quality management Plan, Do, Check and Act cycle. This is also clearly evident from the marks at Figure 2 as the audit progresses from assessing "Process" then "Implementation" then "Results". As noted "Improvement" was not measured.

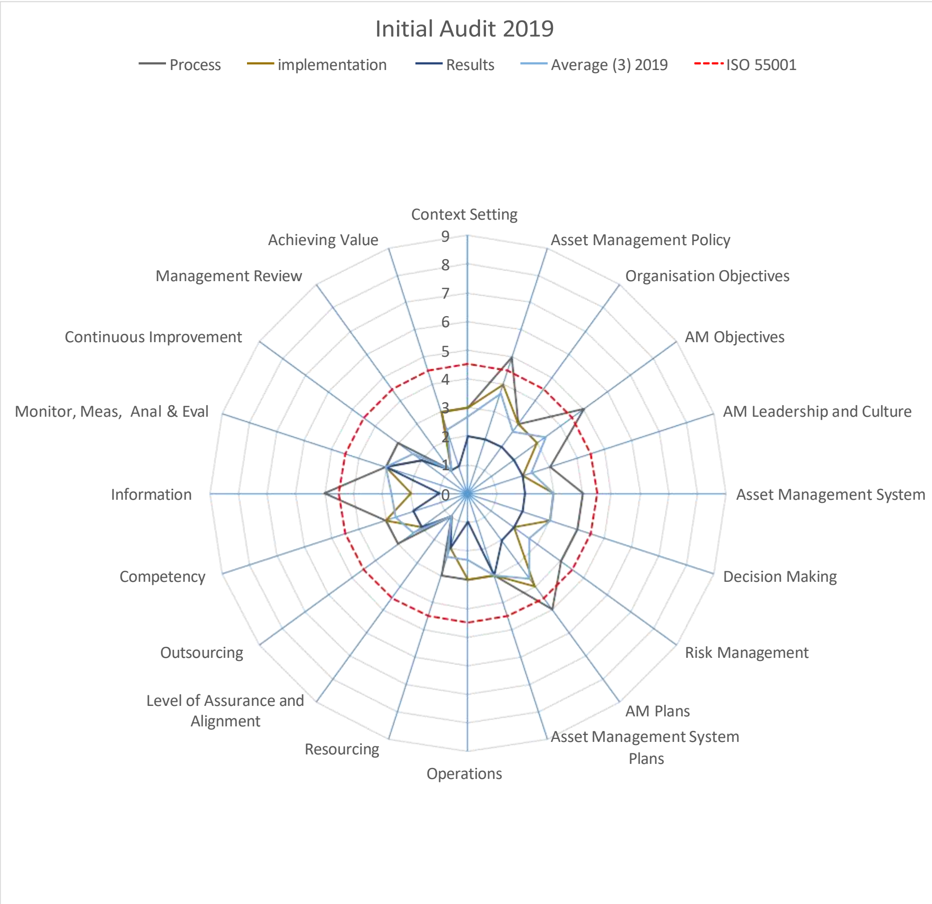

Figure 1: Radar Plot for Initial AM Maturity Audit Scores by Topic

5 INITIAL AUDIT OUTCOME

Using Figure 1 as the performance source and noting that the scores for each Topic go from 0 to a possible 9, the current Asset Management performance was clearly quite immature. As noted, a score of about 4.5 for all Criteria in all Topics would be indicative of a capacity to achieve a formal ISO certification if desired. The outcome did not satisfy the contract requirements to establish an Asset Management Framework and supporting system that achieved the intent of ISO 55001. Something now needed to be done, and fast.

Based on the assessment outcomes, the MSPO leadership (including the ISP) accepted a program of follow up actions focused on rapidly improving their asset management maturity by:

- conducting a progressive “Mentoring Audit” with MSPO Asset Management Specialist in the role of Mentor, which is intended to encourage the understanding and adoption of a management system for asset management in line with the principles of ISO 55000 and the requirements of the ISO management system 55001;
- extending the coverage of the audit to the MSPO governance function as well the ISP in a joint interview process’
- encouraging engagement by including the first Tranche of the audit (Six selected Topics) in the contract Milestone payment for the next reporting period (a minimum average score of 3 across all criteria was to be achieved), funded from past unclaimed Asset Management milestone payments; and
- designing a low human resource impact audit program with progressive delivery that would grow capability without adversely effecting MSPO output imperatives.

6 THE MENTORING AUDIT 2020/21

The full Asset Management System maturity assessment comprising three Tranches was constrained to the MSPO which was only accountable for producing plans for the materiel system and contracting those plans out for delivery by other Service Providers. Thus, the “Materiel System” comprising maritime physical assets operated by others outside the MSPO, could not be included in the scope of the assessment. Only those aspects, which relate to the management system being the people, processes and information necessary to satisfy agreements with stakeholders for the development and delivery of the technical and management plans were included. Some of these stakeholder agreements are enforceable contracts such as those with the ISP and any outsourced arrangements from the ISP to others. Other internal providers had agreed Memorandums of Understanding or Agreements that are not enforceable at law..

The initial maturity audit outcomes recommended a number of process changes to create a “Mentoring Audit” (MA) approach that was focussed on progressive continuous improvement rather than achieving a particular threshold maturity score. The MA concept was new being a combination of an audit with the key mentoring characteristics of:

- **Preparation:** This required the Lead Auditor to meet with the two assessed parties to set expectations for the completion of a pre-audit template. The template captures succinct responses to the questions to be asked and progress with opportunities identified in the Initial Audit.
- **Negotiation:** During the Topic Audit session with both Governance and ISP parties present and physically together, discuss each of their roles when answering the listed question. Discussion is to include processes applied, measures made, results achieved and improvements identified and progressed. Objective quality evidence is provided and opportunities for improvement sought.
- **Enable Growth:** Opportunities are listed for all Topics. This produces a large number of potential improvements which must be filtered for duplication, grouping, priority, and development of project portfolios.
- **Provide Closure:** Recognise what has been achieved. Create a vision of what comes next in the AM journey to a desired maturity.

The improved MA process (incorporating recommendations for improvements to the Initial audit progress) was as follows:

- The audit comprises three separate tranches of 6 to 7 Topics about 6 months apart. The 20 Topics (including a 9a and 9b) are depicted in the radar plot at Figure 3.
- The lead responsible person for the ISP and for MSPO Governance would respond jointly in the same room at the same time to each question;
- Both lead persons responding to the Topic pre-audit are to provide a written response to the question set of about one page maximum for each question. This is to prepare all parties for the audit response and provide time for the participants to prepare their evidence and any need for additional elaborating questions;
- The pre-audit response template is the basis of the conduct of the audit, with additional questions asked as necessary and the provision of evidence to support claims of conformance during the audit;
- The Tranche audits are conducted in two groups of three Topics, each at weekly intervals, with each group separated by a two week gap as shown at Figure 3. This intent may and did vary based on the availability of key

persons and MSPO events;

- The Audit lead shall create a draft report for each topic audit. The draft is verified by the assisting auditors and fact checked by both CoA and ISP participants; and
- The completed individual reports shall be aggregated into a single Tranche report.

To encourage engagement, the first Tranche was linked to an existing AM milestone contractual payment by requiring each of the 6 Topics to achieve an average score of 3 or greater. The remaining Tranches audits were not subject to milestone payments. However, the conduct of Tranche 1 had successfully set the scene for the following Tranches with improved understanding of AM processes and the benefits. Financial reward closely linked to a measurable and achievable outcome achieved focus on the task at hand and the indicated the value assigned to AM maturity by the asset owners/operators and the responsible MSPO Governance function

The program described at Figure 2 was completed in the period allocated with the first audit interview conducted on the 26 June 2020 being Context Setting and the last audit interview conducted on the 14 April and the Final Draft Report submitted on the 3 June 2021.

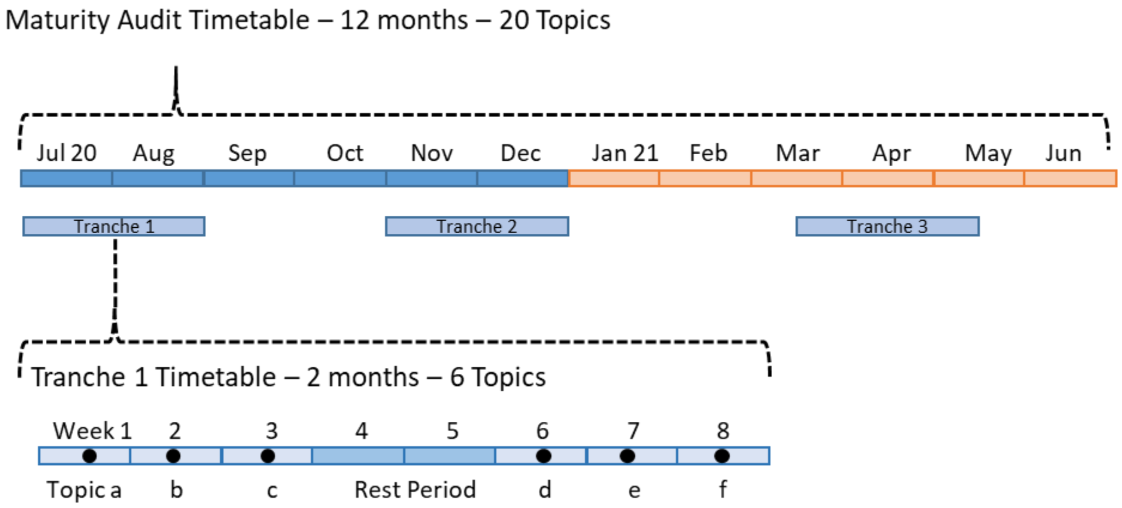

Figure 2: 2020/21 Asset Management Maturity Audit

7 MENTORING AUDIT OUTCOMES

The scores achieved for each Topic and each criteria during the three audits are shown diagrammatically in the radar plot at Figure 3. The average score applies to only the first three Criteria to allow a valid comparison between the 2019 Initial Audit and the 2020/2021 full audit. The reduction in scores as criteria transition from Process defined to Implemented to Measured to Improved are readily evident. Also evident is the modest score of arguably two of the most important Topics after setting Objectives being Decision Making and Risk Management. Without the robust connective tissue between Organisational Objectives and Asset Management Plans an effective asset management capability will never be achieved.

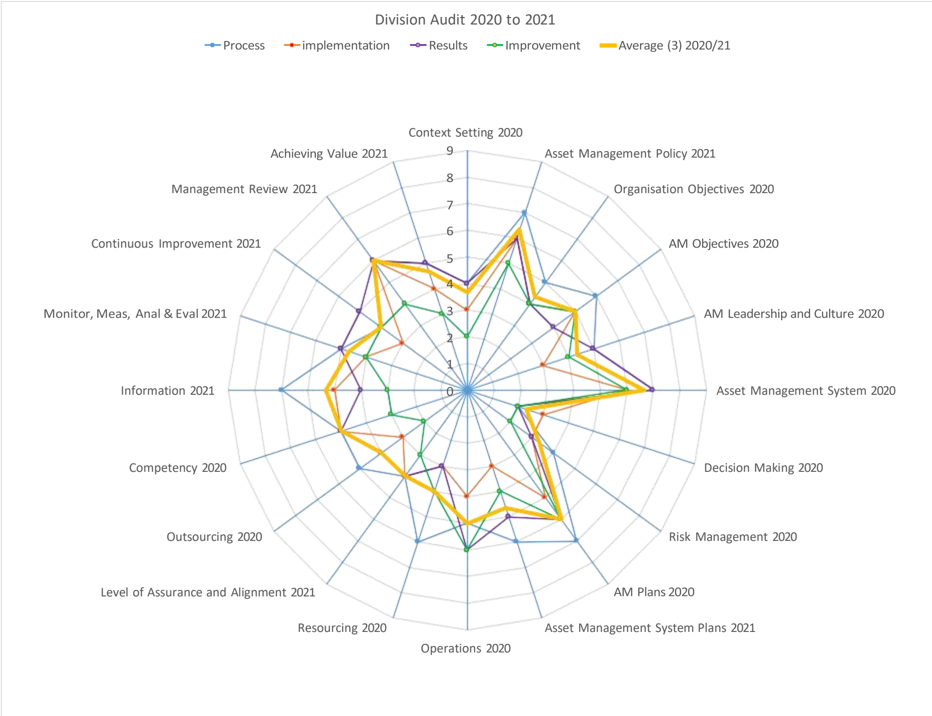

Figure 3: Topic Scores for each Criteria and the Topic Average.

The initial 2019 audit identified 84 opportunities. The Mentoring Audit produced another 226 opportunities across three Tranches. Many of these opportunities were duplicates effecting multiple Topics. One specific example was the large number of quality management issues effecting multiple Topics as identified in Tranche 1. A summary of the opportunities by Tranche is provided at Table 4 noting that the numbers shown include some duplicates. This table is slightly misleading as Tranche 1 created a set of noted opportunities (100+) that would overwhelm the system both in numbers and our ability to aggregate into a portfolio of projects of repeated in Tranches 2 and 3. Some self-regulation during the subsequent Tranche audits kept the opportunities in Tranches 2 and 3 to manageable bounds.

Initial Maturity Audit (Issues and Opport)	84
Tranche 1 Opportunities	101
Tranche 2 Opportunities	73
Tranche 3 Opportunities	52
Tranche Total	226
Grand Total	**310**

Table 4: Identified Opportunities for Improvement by Tranche

Based on the Topic scores and the overall improvements achieved by each Tranche listed at Table 5, the following interpretations for the differences are advanced:

- The complete set of 101 questions focusses more on the asset management system and its process maturity.
- Improvement actions grew organically in MSPO with no formal project plan or overarching resource allocation to resolve the identified opportunities from the initial program (a form of gap identification).
- The MSPO rate of change from the initial 2019 scores to results achieved in Tranche 1 to 3 show the rate accelerating after Tranche 1 then decelerating after Tranche 2 as shown in the following Table 5. This reflects the increased time available for Tranche 2 improvements from the initial audit increasing and the difficulty of achieving improvement as the audit scores increase from 0 to 8.

Tranche 1 - % Improvement from Initial Audit	45.8%
Tranche 2 - % Improvement from Initial Audit	78.4%
Tranche 3 - % Improvement from Initial Audit	87.0%

Table 5: Percentage Improvement of Topic Scores from Initial Audit

Tranche 1 audit was 12 months after the 2019 audit with Tranche 2 being 18 months after and Tranche 3 some 22 months after the initial audit. As Table 5 demonstrates this essentially organic growth, without the assistance of outside resources, was changing the business. As time progressed "getting better got better". A deeper understanding of what Asset Management truly meant was percolating across the MSPO, not from high cost workshops, training or targeted programs of change, but from leadership:

- Taking accountability for audit delivery;
- Involvement with staff in developing pre-audit response documents; and
- Fact checking the reports and lists of opportunities identified.

Doing the audit and the hard work of management commitment to improvement including the involvement of a large number of personnel engaging with the MSPO Asset Management SME while completing the pre-audit questionnaires / reviewing prior opportunities creates change, it wasn't just about being told to 'do better'. It's the journey that matters, not just the end score.

8 COMPARATIVE CASE STUDY

Audits must deliver value for money beyond just the comfort given. While this value may be difficult to measure directly, a comparative assessment of results achieved by another like sized organization over a similar time period from a similar start point can provide some insight into the advances made during the entire "end to end" process. Fortunately, just such a case study was published recently by the Asset Management Council. In 2018, Southern Rural Water (SRW) commenced a two year maturity journey following an initial maturity assessment. The need to improve asset management maturity was driven by the requirements of the Victorian Government Asset Management Assurance Framework (AMAF) mandated by Victorian Treasury to enforce compliance with a number of financial Acts of Parliament.

The SRW audit process applied public domain questions sets such as those from the Institute of Asset Management or the Global Form on Maintenance and Asset Management which have much in common with MSPO audit process. The asset base is less expensive at A$1.3 Billion but the widespread nature of a network of irrigation pipes, ditches, weirs and SCADA for flow measurement plus seven major dams requiring compliance to ANCOLD (Australian National Committee on Large Dams) safety and risk management guidelines, creates a complex mix of requirements.

In comparing resource efforts of internal staff the direct involvement in the maturity assessments were:

- Southern Rural Water (SRW) – 16 half day workshops;
- MSPO – 20 by one to two hour question and answer audit sessions and 20 pre-audit template completed by Team Leaders.

Figure 4 below shows a comparison of the two improvement outcomes on a similar radar plot where Green represents the starting point and Orange represents the end point. MSPO is on the Left Hand side and SRW on the Right Hand side.

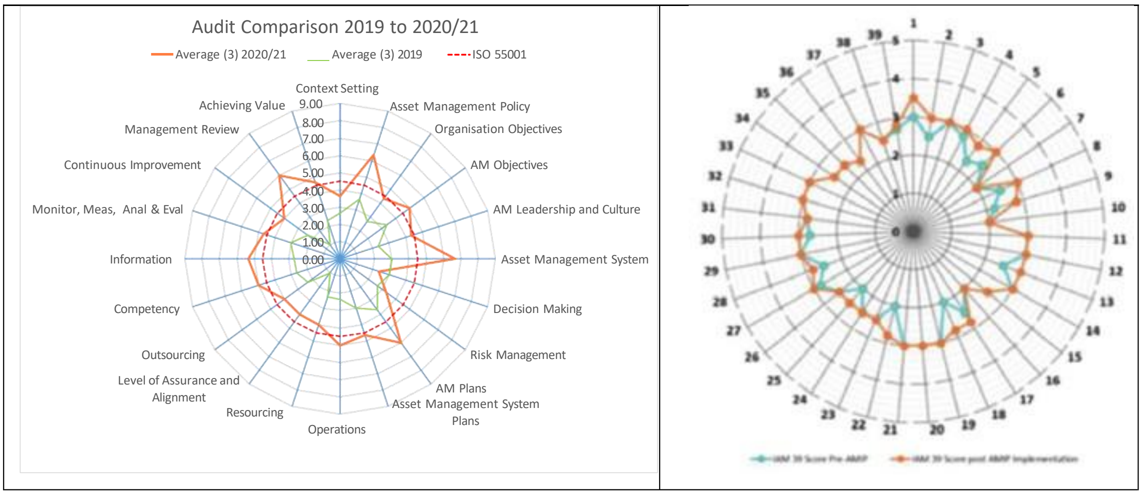

Figure 4: Comparative Radar Plot of 2 Year AM Maturity Improvement Programs – MSPO and SRW

The 39 assessment points for Southern Rural Water reflect their origins in the Institute of Asset Management and the Global Forum on Maintenance and Asset Management (GFMAM) Asset Management Landscape including Subject Areas. Some of the 39 points are not specifically required in an Asset Management System by the ISO standard such as "Shutdowns and Outage Strategy" or "Reliability Engineering" or are subsets that may not be required by all industries. The Subject Areas are described in the GFMAM document The Asset Management Landscape Second Edition.

In comparing the two organisations' outcomes, the following statistics on the two-year improvement effort at Table 6 are noted. In both MSPO and SRW, the ISO certification points are similar with a scoring midpoint being a 4.5 for MSPO and at 2.5 for SRW. Key observation for SRW is that for 59% of the assessment points had no change in score.

Score Improvement	Southern Rural Water Topics (39)	DDGSPO Topics (20)
Less than 0	0	5%
0	59%	0
0 to 50%	15%	15%
50% to 100%	21%	50%
100% plus	5%	30%

Table 6 Comparative Improvements in Maturity Score

Based on these scores and the overall improvements achieved by each Tranche shown at Table 6, the following interpretations for the differences are advanced:

- The MSPO set of 20 topics and associated questions better focusses on the asset management system and its process maturity.
- Improvement actions grew organically in MSPO with no formal project plan or resource allocation to resolve the 100 identified opportunities from the initial program (a form of gap identification)
- The MSPO rate of improvement from the Initial Audit scores to results in Tranche 1 to 3, show the rate of change decelerating after Tranche 2 as shown in Table 5. This reflects the increasing difficulty of improvement as the maturity scores increase.

9 OBSERVATIONS

Five core observations were noted when summing up the results of the MSPO Asset Management maturity assessment program:

- Many advances in maturity were achieved over the two years. However, they are from a low base and likely unsustainable beyond current scores of 5 to 6 out of 9 using existing ad hoc approaches to change.
- As observedin the slowing of improvement as scores rise and as advised in the initial audit, the marking is not linear in effort but exponential in nature. Moving beyond an average score of 4 to 5 will become increasingly difficult and clear priorities and targets will become necessary to allocate resources appropriately.
- Step advances in performance can be best achieved by an in-house capability that is well led technically and culturally.
- The Mentoring Audit was a drawn out process with much effort and time spent preparing responses. It should only need to be done once to establish a baseline that is broadly compliant with ISO 55001. Notwithstanding, a defined measure of required AM maturity will be required in the future to asses status and inform continuous improvement efforts.
- The MSPO is close to a level that would achieve an Independent ISO 55001 certification for its scope. Certification to the ISO though is not considered good enough for the criticality of the operations supported nor the requirements of their stakeholders. The challenge that MSPO's scope does not include the operations of the physical assets being supported would also need to be addressed.

This result would not have been achieved during the short burst of formal Certification. The large numbers of opportunities (200+) discovered, if identified in a formal audit, would have overwhelmed the participants and challenged growth. The mentoring approach created an audit that was the AM Journey itself not just a measure.

10 ACKNOWLEDGEMENTS

The authors wish to thank the many people involved in this effort and its clear success. Without their efforts this progress would not have been achieved. Thanks specifically go to the Leadership Team that made it happen and especially the impact of CAPT Grant McLennan, Director and Mr Neil Comer, ISP Program Manager whose relationship building efforts drove the leadership and culture score up by 86% in the 12 months between the initial and mentoring audits.

11 ABBREVIATIONS

AM	Asset Management
AM Council	Asset Management Council
DCPAS	US Civilian Personnel Advisory Services
GFMAM	Global Forum on Maintenance and Asset Management
IAM	Institute of Asset Management
ISO	International Standards Organisation
ISP	Industry Service Provider
MA	Mentoring Audit
MESA	Maintenance Engineering Society of Australia (predecessor to AM Council)
MSPO	Maritime System Program Office
RAN	Royal Australian Navy

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MIRCE SCIENCE: MAINTENANCE IS THE MANAGEMENT OF FAILURES AND PROVISION OF WORK

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Abstract: The main objective of this paper is to introduce the global maintenance management and engineering community to the body of knowledge contained in MIRCE Science for the innovative approach to maintenance, which is perceived as the management of failures and provision of work. Thus, maintenance manages the consequences of the complex interactions between failure events and maintenance actions are taken that drive the behavior of functional systems, which can be quantified by the MIRCE Functionability Equation. Hence, in the future maintenance managers will be able to perform quantitative trade-offs between feasible failure management options to determine one that would yield the greatest benefit measured through the expected work. To illustrate the advantages of applying MIRCE Science to the maintenance management process a numerical example is provided, where several feasible maintenance options are considered and quantified.
Keywords: MIRCE Science, MIRCE Functionability Equation, quantitative maintenance management

1. Introduction

The philosophy of MIRCE Science is based on the premise that the purpose of the existence of any functional system[1] is to do work. The work is done when the expected measurable function is performed through time. The best way to achieve that is to increase the revenue-generating work done while reducing the resources consumed for it. One way towards that target is to improve the reliability of consisting parts by using appropriate engineering and production methods. Another way is to reduce maintenance time by applying appropriate condition monitoring and data management technologies proposed by maintenance 4.0. Although there are an infinite number of combinations between the number of improvements in reliability and reduction in maintenance time, it is necessary to recognize that the work done by a functional system is driven by their combined impact. Their impact on the amount of work done by a functional system could be quantified through the following two approaches:

- Measuring the work done during the operation process
- Predicting the work during the planning process.

Measuring the work done is a rather straightforward process where the operational hours are counted together with the resources consumed[2]. However, collecting data regarding the past performance of functional systems does not have any impact on the past revenue, reputation, loyalty, and other measures of a functional system's effectiveness.

Predicting future performances, at the planning stage, gives an opportunity for any changes necessary to create functional systems with desirable performance to be made, within the

[1] Functionable system is operationally defined functional system. [2]
[2] Boeing 747, registration number N747PA, which belonged to Pan Am airways, have delivered the work of 80,000 flying hours and received 806,000 maintenance man-hours, during the 22 years of in-service life. [2]

given budget. In return, it will generate the expected return on their investment (e.g. profit, reputation, loyalty, public benefit, and similar). However, to achieve that, it is necessary to have a mathematical model[3] that would facilitate that, as mathematics is the only body of knowledge that enables quantitative predictions to be made in all natural sciences, from quantum mechanics (the motions of subatomic particles) to astrophysics (the motion of spacecraft).

Although reliability engineering and maintenance engineering are well-recognized disciplines in their own rights, best to the author's knowledge there is no body of knowledge for predicting their combined impact on the work done and resources consumed, in a quantitative and comparative manner.

The main objective of this paper is to introduce reliability and maintenance engineers to MIRCE Science, a body of knowledge that enables quantitative prediction of the complex interactions between reliability and maintenance options on the work done and resources required [2]. Hence, by making use of the MIRCE Functionability Equation it is possible to perform a quantitative trade-off between feasible reliability and maintenance options to select the compromising solution that would yield the greatest effectiveness, measured through the work done or expected profit.

2. Brief overview of MIRCE Science

According to MIRCE Science, at any instant of calendar time, a given functional system could be in one of the following two macro states Knezevic [2]:

- Positive Functionality State (PFS), a generic name for a state in which a functional system is able to deliver the expected measurable function(s),

- Negative Functionality State (NFS), a generic name for a state in which a functional system is unable to deliver the expected measurable function(s), resulting from any reason whatsoever.

In MIRCE Science work done by a functional system is uniquely defined by the trajectory generated by its motion through MIRCE Space[4]. That motion is driven by functionality actions, which are classified as:

- Positive Functionality Action (PFA) is a generic name for any natural process or human activity that compels a system to move to a PFS. Typical examples are servicing, lubrication, visual inspection, repair, replacement, final repair, examination, partial restoration, inspection, storage, modification, transportation, sparing, cannibalization, refurbishment, health monitoring, restoration, packaging, diagnostics, and similar

- Negative Functionability Action (NFA), is a generic name for any natural process or human activity that compels a system to move to an NFS. Typical examples are thermal aging, actinic degradation, acid reaction, bird strike, warping, abrasive wear, suncups formation on the blue ice runway, fatigue, pitting, thermal buckling, photo-

[3] Newton, Maxwell, Lagrange, Boltzmann and other well know and applied equations used as the mathematical models for the predictions of the physical behaviour of natural world.
[4] MIRCE Space is a conceptual 3-dimensional space containing infinite set of possible discrete functionability states that a functionable system could be found in, at any instant of the calendar time, and corresponding probabilities. [2]

oxidation, production errors, strong wind, maintenance error, hail damage, lightning strike, COVID-19, quality problems, hard landing, sandstorm and so forth.

The time evolution of a functional system through MIRCE Space is physically manifested through the occurrences of functionality events, which are classified as:

- Positive Functionality Event (PFE), a generic name for any physically observable occurrence in the calendar time that signifies the transition of a functional system from an NFS to a PFS.
- Negative Functionality Event (NFE), a generic name for any physically observable occurrence in the calendar time that signifies the transition of a functional system from a PFS to an NFS.

Consequently, the concept of time evolution in MIRCE Science is conceptualized as the motion of a functional system through functionality states, resulting from any functionality actions whatsoever and the actions required to generate any functionality motion.

3. Mathematical Principles of MIRCE Science

The ability to "normalize" all competing options of a functional system enables comparisons to be made between them and finally select the best one, in accordance with a given criterion. Hence, MIRCE Science is a body of knowledge that enables quantitative assessment of the impact of the multidimensional interactions between:

- consisting of components (mechanical, electrical, electronics, and so forth)
- system architecture (active and passive redundancies)
- natural environment (temperature, wind, humidity, fog, and many others
- human rules regarding:
  - operation process (levels of stress, frequencies of use, and similar)
  - maintenance policies: preventive, condition-based, opportunistic, etc.
  - support strategies: in-house support, and outsourcing, combined.

According to the MIRCE Science Philosophia[5] positive work is done when a functional system is delivering a functionality performance, which means that it must be in a PFS. According to Knezevic [2] the expected positive work to be done by a functional system during a given interval of calendar time *T*, $PFW_S(T)$, measured in calendar hours, Hr, can be calculated by making use of the following equation:

$$PFW_S(T) = \int_0^T y_S(t)dt \qquad [Hr] \qquad (1)$$

where: $y_S(t)$ is MIRCE Functionability Equation [3] that quantifies the probability of the event *{system is being in a PFS at the instant of calendar time t}*, thus:

$$y_S(t) = P\left\{PFS_s\,(t)\right\} = \sum_{i=1}^{\infty} y_S^i(t) = \sum_{i=1}^{\infty} \left\lfloor \left\lceil O_s^{i-1}(t) - F_s^i(t) \right\rceil \right\rfloor,\ t \geq 0 \qquad (2)$$

[5] In Greek, *philosophia* "love of knowledge, pursuit of wisdom; systematic investigation," from *philo-* "loving" + *sophia* "knowledge, wisdom

where: $O_s^{i-1}(t) = P(TPE_s^{i-1} \le t)$ and $F_s^i(t) = P(TNE_s^i \le t)$. It is necessary to point out that $O_{s,0}(0) = 1$, in accordance to the 1st axiom of MIRCE Science, Knezevic [2].

The infinite sum of positive and negative functions represents a mathematical scheme that in MIRCE Science defines the sequential occurrences of the functionality events in the direction of the calendar time, for each feasible variation of the functional system considered. In the language of mathematics, these are systems of convolution integrals. Thus, the sequential positive functionality function, $O_s^i(t)$, which defines the probability that the life of a functional system, will take place before or at the instant of calendar time *t*, is defined by the following convolution integrals [2]:

$$\begin{aligned} O_s^i(t) &= P(TPE_s^i \le t) = P(TNE_s^i + TPE_{s,i} \le t) \\ &= P(TNE_s^i \le x \cap TPE_{s,i} \le t-x) = P(TNE_s^i \le x) \times P(TPE_{s,i} \le t-x) \\ &= \int_0^t F_s^i(x) o_{s,i}(t-x)dx = \int_0^t F_s^i(x) dO_{s,i}(t-x), \quad i = 1,2,.,\infty, \ t \ge 0 \end{aligned} \tag{3}$$

In order for the i^{th} sequential positive functionability event, PFE^i, to take place before, or at the instant of calendar time *t*, it is necessary that the previous functionality event, which in this case is NFE^i, takes place sometime before time *t*, denoted by *x* in the above expression. Then, the sequential PFE_i has to take place during the remaining interval of calendar time, which in this case is denoted with *t-x*.

The process of defining the negative sequential distribution Function, which defines the probability that the i^{th} sequential NFE_S of a functional system will take place before or at an instant of calendar time *t*, follows the same mathematical principle. Thus, the sequential negative functionality functions are fully defined in the following way:

$$\begin{aligned} F_s^i(t) &= P(TNE_s^i \le t) = P(TPE_s^{i-1} + TNE_{s,i} \le t) \\ &= P(TPE_s^{i-1} \le x \cap TNE_{s,i} \le t-x) = P(TPE_s^{i-1} \le x) \times P(TNE_{s,i} \le t-x) \\ &= \int_0^t O_s^{i-1}(x) f_{s,i}(t-x)dx = \int_0^t O_s^{i-1}(x) dF_{s,i}(t-x), \quad i = 1,2,.,\infty, \ t \ge 0 \end{aligned} \tag{4}$$

This multidimensional set of convolution integrals defines the motion of a functionable system through MIRCE Space, depicting and passing through each sequential functionality state in the direction of calendar time, generating a trajectory unique to each functional system, [5]. Thus, the same set of generic equations, when applied to different operational and maintenance policies generate different trajectories of the motion through MIRCE Space, which means different functionality performance, namely different work done and different resources consumed. Hence, Knezevic [2] has created a generic platform on which each feasible plan for the operation and maintenance policies and strategies would generate its own future “trajectory” for a system under consideration.

4. Maintenance management options: An illustrative Example

To illustrate the applicability of MIRCE Science to the reliability engineering design process the quantitative assessment of the combined impact of reliability and maintenance on the performance of a functional system, a hypothetical example will be used.

The simplest possible functional system consists of one component that exists in two functional states, namely PFS and NFS. Even further, a single positive or negative action causes the occurrences of positive and negative events at which the functional system changes its functional states.

It is necessary to stress that this example is chosen, not because the real functional systems consist of a single component, but because it is extremely useful for the understanding of the mathematical scheme that defines the motion of a functional system through MIRCE Space. This knowledge, in turn, quantifies its expected functionality performance, namely the expected work done, and corresponding resources consumed.

To demonstrate the applicability of the MIRCE Science mathematical scheme to the quantitative assessment of the combined impact of reliability engineering and maintenance management decisions on the performance of a functional system the following three options for the future system are addressed:

Option 1: Basic engineering design: The functional system under consideration is expected to experience an occurrence of an NFE during a continuous operation with the expected value of $E[TNE_{S,}]$ =1080 Hr. What is the amount of positive work expected to be delivered during a calendar year of continuous operation, without performing any maintenance action?

Option 2: Adding Maintenance actions: What would be the additional work done if the system is designed in a way that maintenance actions could be performed after occurrences of failures? Assume that the design-in-maintenance action that returns a functional system to PFS has the expected value of $E[TPE_{S,}]$=168 Hr.

Assuming that options 1 and 2 are not satisfied system engineering requirements, an additional amount of money has been allocated to the project. Contributing engineering departments have been asked to make the proposal for the increase of the expected work done, for a given extra budget. The following two proposals were made:

- **Option 3**: The Reliability Engineering department submitted a proposal in which they were stating that by investing the additional funds allocated into new technology in the manufacturing process it is possible to extend the basic design expected life of component A by 50%.

- **Option 4**: The Maintenance Engineering department submitted a proposal in which they were stating that by investing the additional funds allocated into new testing and diagnostic equipment it is possible to reduce the duration of a maintenance task defined for component A in option 2 by 50%.

Which option should be adopted and why?

Best to the author's knowledge today there is no maintenance management body of knowledge that is able to provide a quantitative justifiable answer to the above questions. In the remaining part of the paper, it will be shown how to apply MIRCE Science equations to provide the quantitative answer to the question posed, to maximize the return on investment like profit, reputation, loyalty, public benefit, and so forth.

5. MIRCE Science based solution for analysis of maintenance management options

Option 1:

Based on the information available the only possible conclusion regarding the probability distribution of the TNE of component A is that it is fully defined by the exponential distribution, which is uniquely defined by the expected value, which in this case is equal to scale parameter A_N= E[$TNE_{S,}$]=1080 Hr. The expected positive functionality work from this design option could be determined by obtaining the numerical solution to Eq. 1.

A generic expression for an exponentially distributed cumulative distribution function of a random variable TNE_i is $F_{S,i}(t) = P(NFE_{S,i} \le t) = 1 - \mathrm{e}[-(t / A_N)], \quad i = 1,\infty$. Based on the data available, the probability of the first negative functionability event of a system, taking place before of at a given instant of time t is:

$$F_S^1(t) = P(TPE_{S,0} + NFE_{S,1} \le t) = \int_0^t O_{S,0}(x) dF_{S,1}(t-x) = F_{S,1}(t) = 1 - \mathrm{e}[-(t/1080)], \quad 0 \le t \le \infty$$

In this specific case, where it is decided not to take any action after the occurrence of the first negative functionability event, the MIRCE Functionability Equation is defined as:

$$y(t) = \sum_{i=1} \left[O_S^{i-1}(t) - F_S^{i}(t) \right] = O_S^{0}(t) - F_S^{1}(t) = 1 - F_S^1(t) = \mathrm{e}\left[-\left(t/1080\right) \right].$$

Finally, by making use of Eq. 1 it is possible to derive the expression for the expected work done, as follows:

$$PFW(T) = \int_o^T \left[\mathrm{e}(-t/A_N) \right] dt = A_N \left[1 - \mathrm{e}^{-\left(\frac{T}{A_N}\right)} \right]$$

For the planned continuous operation of the functional system during a calendar year, T=24x365= 8760 Hr. Hence, the amount of expected positive functionality work to be done by the design option considered is:

$$PFW(8760) = 1080 \times \left[\left(1 - \mathrm{e}\left(-(8760/1080) \right) \right) \right] = 1079.68 \text{ Hr}$$

In summary, a functional system defined with the available data is expected to deliver 1079.68 hours of work during the available 8760 calendar hours.

Option 2:

Following the logic used in the analysis of option 1, in this particular example, the exponential theoretical distribution with the expected value of E[$TPE_{S,}$]= A_P= *168* Hr, is used to describe the motion of a system through PFS. Thus, according to the data available, the cumulative distribution function for the time of occurrence of i_{th} positive functionality event is defined as**:** Thus, the MIRCE Functionability Equation (Eq. 2) becomes fully defined by the set of convolution integrals which are of the form of the Gamma probability distribution, as the convoluting functions are defined by the identical exponentially distributed random variables, $TNE_{S,i}$ and $TPE_{S,i}$ in the following way:

$$O_s^i(t) = P(TPE_s^i \le t) = \int_0^t \left[\frac{(1/A_P)(t/A_P)^{i-1}\, e^{(-t/A_P)}}{(i-1)!} \right] dt, \quad i = 1, 2, \infty, \; t \ge 0$$

$$F_s^i(t) = P(TNE_s^i \le t) = \int_0^t \left[\frac{(1/A_N)(t/A_N)^{i-1}\, e^{(-t/A_N)}}{(i-1)!} \right] dt, \quad i = 1, 2, \infty, \; t \ge 0$$

Dubi [1] has proven that a generic expression for the MIRCE Functionability Equation (Eq. 2) for equally exponentially distributed time to negative and positive functionability events, as defined above, is equal to:

$$y_S(t) = \left[\frac{A_N}{A_P + A_N} + \frac{A_P}{A_P + A_N} e^{-\left(\frac{A_P + A_N}{A_P A_N}\right)t} \right] \tag{5}$$

The amount of the expected positive work to be done by the system defined by option 2 could be calculated by substituting the function *y(t)* into Eq. 1, thus:

$$\begin{aligned} PFW(T) &= \int_o^T y(t)dt = \int_o^T \left[\frac{A_N}{A_P + A_N} + \frac{A_P}{A_P + A_N} e^{-\left(\frac{A_P + A_N}{A_P A_N}\right)t} \right] dt \\ &= -\frac{A_N A_P}{A_P + A_N} \left[-\frac{T}{A_P} - \frac{A_P}{A_P + A_N} \left(1 - e^{-\left(\frac{A_P + A_N}{A_P A_N}\right)T} \right) \right] \end{aligned} \tag{6}$$

After substituting the values for the parameters in the above expression the expected positive functionality work will be 7600.34 Hr.

Thus, by designing a system in a way that it is possible to return it in PFS after the occurrence of NFE by performing specific maintenance activities, the expected work done by a system will increase by 6520.66 Hr, in respect to the expected work done by option 1.

Option 3: By implementing proposed changes in design, originated by the reliability engineering team, the expected time to the occurrence of NFE, will increase from 1080 Hr to 1620 Hr, while maintaining the same probability distribution for $TPE_{S,i}$, thus:

$$\begin{aligned} PFW(8760) &= -\frac{A_N A_P}{A_P + A_N} \left[-\frac{T}{A_P} - \frac{A_P}{A_P + A_N} \left(1 - e^{-\left(\frac{A_N + A_P}{A_P \times A_N}\right)T} \right) \right] \\ &= -\frac{1620 \times 168}{1620 + 168} \left[-\frac{8760}{168} - \frac{168}{1620 + 168} \left(1 - e^{-\left(\frac{1620+168}{1620 \times 168}\right)8760} \right) \right] = 7951.21\ Hr \end{aligned}$$

Option 4: As a result of improved testing and diagnostics equipment, proposed by the maintenance engineering department the expected time in NFS will be reduced to A_P=84 Hr, while maintaining the same probability distribution for $TNE_{S,i}$, hence:

$$PFW(8760) = -\frac{A_N A_P}{A_P + A_N}\left[-\frac{T}{A_P} - \frac{A_P}{A_P + A_N}\left(1 - e^{-\left(\frac{A_N + A_P}{A_P \times A_N}\right)T}\right)\right]$$

$$= -\frac{1080 \times 84}{1080 + 84}\left[-\frac{8760}{84} - \frac{84}{1080 + 84}\left(1 - e^{-\left(1080 \times 84\right)8760}\right)\right] = 8133.46\ Hr$$

Based on the predicted expected work done by the system under consideration, by applying the MIRCE Science equations the final solution to be recommended for the adoption for the future system is option 4. This feasible maintenance solution provides additional work of 351 Hr in respect to option 3 (improved reliability) and 533 Hr in respect to option 2, as illustrated by Figure 1.

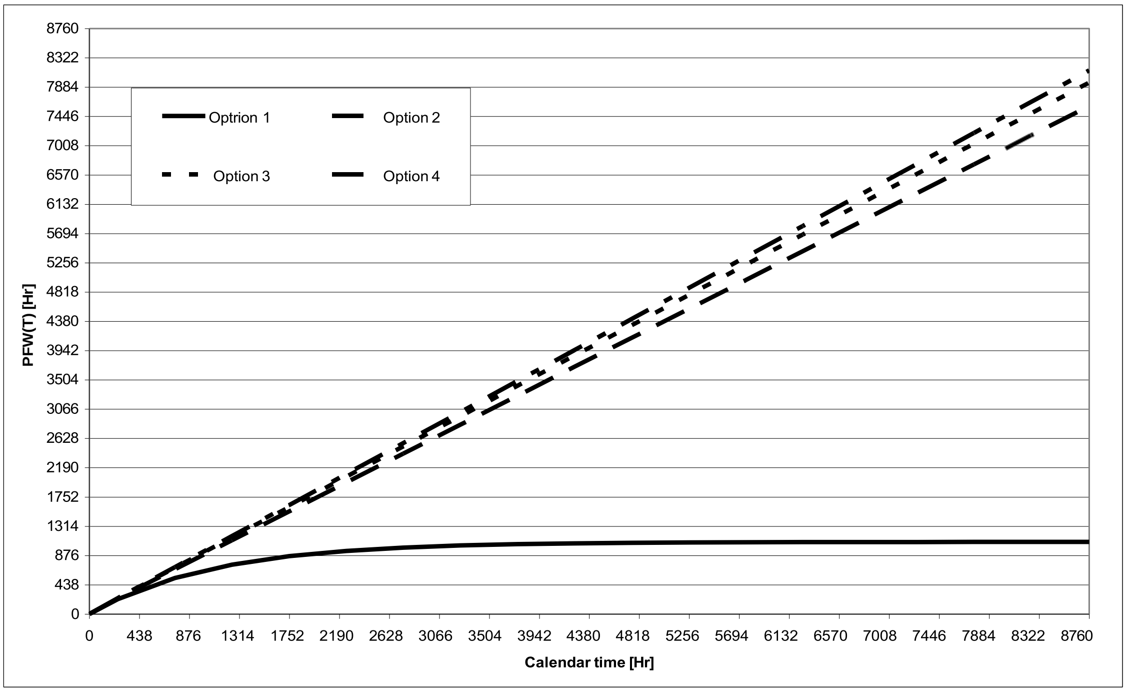

Figure 1: Expected work done by all four feasible maintenance management options

The impact of all feasible solutions presented above on: revenue, cost and profit could be easily computed by making use of the MIRCE Profitability Equation presented in [4].

6. MIRCE Science based physical analysis of maintenance management options

The mathematical analysis of the four feasible design options, considered above, has shown that is expected that option 4 will provide the highest amount of work done during the year of operation, with the same monetary value of resources invested in design as the other three. This conclusion was made by quantitatively evaluating the MIRCE Functionability Equation for each design option using the available input data.

From a mathematical point of view, the obtained results are correct as none of the mathematical equations violate any mathematical laws. However, as these are engineering design options, it is the duty of design engineers and reliability analysts to select the input data into mathematical predictions. This is primarily related to the selection of mathematical models that define physical mechanisms that generate the motion of functionable systems through functionability states, as the MIRCE Functionability Equation is presented in a generic form, suitable for any application. However, the specific probability functions have to be selected by the designers of specific systems.

In the above example, exponential probability distributions are selected for random variables, TNE_i and TPE, purely for ease of the calculation of corresponding convolution integrals (Eq. 3 and 4).

From a reliability point of view, the mathematical assumption made had the following physical consequences, thus component A cannot:

- experience any manufacturing, transportation, and installation actions that would generate an NFE,
- experience any time or usage-related degradation mechanisms, like corrosion, fatigue, thermal deformation, creep, wear, and similar,
- experience any maintenance or storage-induced action that would generate an NFE
- be exposed to seasonal, operational, or geographical variability.

From a maintenance point of view, the mathematical assumption made had the following physical consequences; no maintenance action applied to the system can have fix duration of time required for its successful completion, like:

- 24 hours for the paint to dry
- 12 hours for a physical/chemical analysis used as a part of the troubleshooting process,
- 7 days contractual provisioning of spare parts

The above statements of reliability and maintenance are a physical reality known and experienced by engineers, managers, technicians, and others involved with the operation process of functional systems. Based on the above analysis of the observable physical reality excluded by mathematical assumptions of exponentially distributed times of the evolution of functionality of a system through MIRCE Space, [5], presented in the numerical example used in this paper, the following two points must be made:

1. Equations 1 and 2 are generic expressions applicable to any functional system, operating in any natural environment, and exposed to any human-imposed rules. In order to be utilized during the design process it is necessary that reliability and maintenance professionals are involved to identify mathematical laws that adequately described the physical reality of their systems and then seek a method for evaluation of convolution integrals defined by Eq. 3 and 4.

2. Equations 5 and 6 provide accurate predictions of the expected work to be done during the in-service lives of functional systems given that operational and maintenance limitations, some of which are listed above, and many others, are not applicable to their systems, otherwise the predictions would be incorrect.

7. A few words more about the use of MIRCE Functionability Equation

The numerical example used in this paper is related to a system that consists of a single component, where both positive and negative functionality actions are mathematically represented by corresponding exponential probability distributions, for a very simple reason. This combination is the only case for which an explicit closed mathematical solution exists.

In view of the fact that realistic systems involve more than a single component with more than one functionality event generating mechanisms the possibility of finding an analytical solution for multidimensional convolution integrals defined by Eq. 3 and 4 is seldom possible due to the inability of mathematics to deal with a large number of convolution functions and their interactions. These types of problems are not specifically related to MIRCE Science, they are common to all scientific disciplines of this nature, as it is a known mathematical fact that integral equations do not have analytical solutions. [1]

The most suitable way forward for any real functional system, of any complexity of operational reality, is to apply the Monte Carlo method as the only viable approach with which solutions for the MIRCE Functionability Equation and thereby for the system performance may be obtained. It is applicable to systems with multiple interacting components, aging mechanisms, and any operation, maintenance, and support rules. Thus, the Monte Carlo method provides the performance function of a system for any given scenario and with any form of resources, but it is beyond the scope of this paper.

8. Conclusions

The main objective of this paper is to introduce the global maintenance management and engineering community to the body of knowledge contained in MIRCE Science for the innovative approach to maintenance, which is perceived as the management of failures and provision of work. Thus, maintenance manages the consequences of the complex interactions between failure events and maintenance actions are taken that drive the behaviour of functional systems, which can be quantified by the MIRCE Functionability Equation. Hence, in the future maintenance managers will be able to perform quantitative trade-offs between feasible failure management options to determine one that would yield the greatest benefit measured through the expected profit. To illustrate the advantages of applying MIRCE Science to the maintenance management process a numerical example is provided, where several feasible maintenance options are considered and quantified.

To illustrate the advantages of applying MIRCE Science to the reliability engineering decision-making process a numerical example is provided, where the trade-off between reliability improvements by increasing the expected time to failure by 50% or decreasing maintenance time by 50%, is addressed.

The challenges related to the applicability of MIRCE Science to the future maintenance management process, mainly driven by the mathematical inability to analytically deal with multidimensional convolution integrals, are highlighted in the paper and the use of the Monte Carlo method is recommended.

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A NOVEL FRAMEWORK FOR IMPROVED MAINTENANCE ENGINEERING DECISION MAKING BY THE FUSION OF PROBABILISTIC TECHNIQUES FOR HUMAN AND HARDWARE AVAILABILITY ASSESSMENT

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Abstract

Human errors are significant contributors to the overall risk in the industry. In fact, 80% of marine failures and shipping accidents are caused by human errors. Human errors, additionally, are often a root or significant cause of a system failure which could lead to tremendous undesirable consequences such as fatalities and financial losses. Currently, most industries use the latest technologies in order to maximise the availability and reliability of their equipment and minimise human interventions. However, the human role is still vital in different phases of a plant life cycle, especially during maintenance. Traditional Reliability, Availability and Maintainability (RAM) methodology, a well-known methodology for optimising maintenance strategies in an organisation, does not incorporate human reliability analysis. Therefore, this research aims to develop a novel framework for improved maintenance engineering decision-making, which can be achieved by fusing probabilistic human and hardware availability assessment techniques. The proposed framework has a systematic process that helps analysts, engineers, and decision-makers consider and manage risk effectively in a complex system. A publicly available case study in an offshore oil and gas platform is selected as an example for demonstration purposes. The values of human error probabilities (HEPs) for maintenance activities are calculated by using the Human Error Assessment and Reduction Technique (HEART). These maintenance activities' reliability values are improved by using a novel Human-based Decision-Making Grid (H-DMG). This framework, including H-DMG, can improve a system's availability, reduce downtime cost, and reduce human errors.

Keywords: Reliability Availability and Maintainability; Human Reliability Assessment; Decision-Making Grid.

1 Introduction

There has been a significant change over the past eight decades in maintenance engineering practices. This change has affected maintenance engineering's concepts, techniques, and technology. In addition, organisations have become more aware of the significant impact of maintenance engineering on businesses. Historically, Maintenance engineering is divided into three generations [1]. Simple corrective maintenance, i.e. 'operate and fix' when fails, was considered as the first generation. Preventive maintenance, which was considered as the second generation, is developed during the Second World War. Preventive maintenance aims to increase equipment reliability, extend an asset utilisation, and reduce maintenance cost. Later, when equipment has become more complex, maintenance techniques and technology such as Failure Mode Effect and Criticality Analysis (FMECA), Reliability-centred Maintenance (RCM), condition-based maintenance (CBM) were developed. This was the beginning of the third generation. Recently, a fourth industrial revolution has begun. Industry 4.0, which was first mentioned in Germany 2011 [2], can be defined 'the integration of complex physical machinery and devices with networked sensors and software, used to predict, control and plan for better business and societal outcomes' [3]. Another defines Industry 4.0 is 'the technological integration of cyber-physical systems (CPS) in the production process' [4]. This revolution has many associated terms which could include cyber-physical systems (CPS), Internet of Things (IoT), Industrial Internet of Things (IIoT), big data, smart manufacturing, etc. Industry 4.0 could change traditional maintenance practices by digitising and automating production systems and introducing a new connectivity method in the whole supply chain [2].

Although these technologies have advanced modern maintenance practices in the industry, human errors in maintenance activities are still inadequately assessed. In fact, human and organisational factors (HOF) have a significant impact on asset value. Still, some organisations neglect considering or reviewing human errors that could cause a system's failure [5]. As a result, this research aims to address this problem.

1.1 Research purpose

Human errors are considered a major contributor to the risk in the industry. In fact, over 37% of the US railways accidents are caused by human errors [6]. Also, 80% of offshore oil and gas failures are caused by human errors [7, 8]. Further, 80% of these failures can occur during maintenance activities [9]. This has led to catastrophic consequences that urge the need to study, understand, analyse, and evaluate human errors to help designers and engineers eliminate or reduce risk. Traditionally, a reliability, availability, and maintainability (RAM) analysis does not consider human reliability assessment (HRA). This could be due to the lack of data in a particular industry [10]. Although some methodologies could consider human factors within a design process [11] collecting and assessing the necessary data can be challenging [12]. Further, although there are several optimisation techniques for maintenance strategies such Decision-Making Grid (DMG) [13 - 17], these DMGs do not provide actions or measures to reduce human errors in maintenance activities. Therefore, new techniques and models are required to tackle this gap, and this research aims to address this problem.

This research aims to develop a novel framework for improved maintenance engineering decision-making, which can be achieved by fusing probabilistic human and hardware availability assessment techniques. This framework can help analysts and decision-makers to identify, manage and reduce potential risk in a complex system effectively.

This paper is structured as follows. Section 1 introduces the problem statement and objective of this study. Section 2 reviews briefly common HRA methods, human error classification, and some of the decision – making grid. Section 3 illustrates the development of the framework. Section 4 illustrates the application of the developed framework. Section 5 concludes this study.

2 Literature Review

2.1 Availability

There is a significant demand in many industries to produce and operate to the level of free defects or free failures. In addition, today's demand expects to functionally operate safely and without causing any hazards that could lead to catastrophic consequences. In order to achieve the previous targets, there is a need to study and assess equipment reliability as well as human reliability. Reliability engineering is a vast discipline of system engineering, and it is becoming more involved with the emergence of Industry 4.0. The main objective of reliability engineering is to identify, assess, and prevent the likelihood of failures by applying engineering knowledge and techniques. Reliability of a piece of equipment can be defined as the successful probability of this equipment to perform a task, under operational conditions, without failures, during a specific time [18]. It is important to mention that failures can be identified when there is a total loss of production or a complete shutdown. However, a partial loss in production or a delayed train, for example, can be considered a failure in some high-reliability organization [19]. Generally, the availability of a piece of equipment can be affected by several factors: the reliability of that piece of equipment, maintainability, supportability, maintenance strategies, and accessibility, as shown in **Figure 1** [20]. So, in order to estimate the actual availability of a system, there is a need to calculate the theoretical availability, first, which is affected by the reliability, maintainability and supportability of that system. Once the theoretical availability of a system has been calculated, both maintenance strategies and accessibility factors, which include human factors, can be considered to estimate the actual availability of a system.

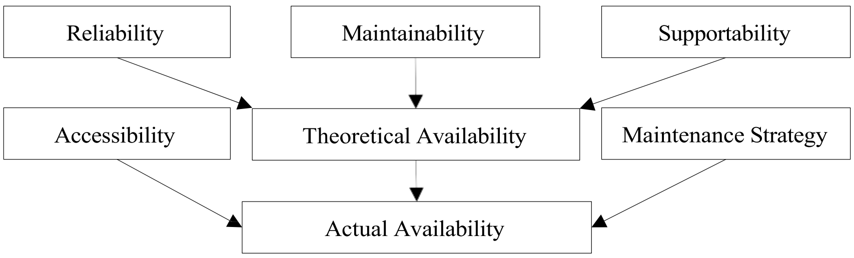

Figure 1 Factors affecting actual availability [13]

2.2 Human Reliability Assessment

There are many areas where human reliability assessment (HRA) can be used. First, in the design phase of a system when humans are involved, their behaviours can affect the overall system. Second, during the licencing discussion, a system can meet safety or legislation requirements. Third, HRA can be used during the modification of a system [21]. Finally, HRA can be considered as a robust assessment in any plant life cycle stage [22]. Although most industries are moving toward fully automated production or process, still there is a need for a human element to interact with equipment specifically during a maintenance task. Traditionally, the influence of a human being on system reliability is omitted from a quantitative perspective. This has motivated many researchers to study and develop several methods that assess human reliability in a Man-Machine System (MMS). **Figure 2** illustrates the interaction between a human being and a technical component (e.g., a pump or a compressor) and how can some factors influence the reliability of both.

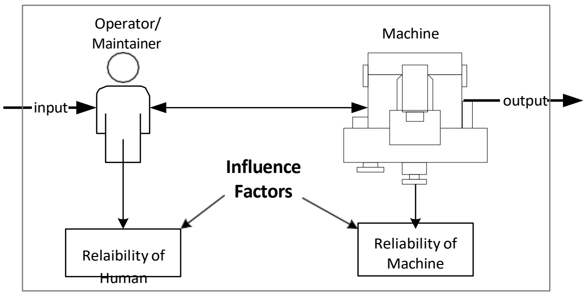

Figure 2 Human and technical reliability in MMS [23]

Human reliability assessment (HRA) can be considered as a subsection in the field of reliability engineering although the founders of the most utilised human reliability assessment methods are psychologists. A human reliability assessment can be defined as ‘a systematic identification and evaluation of the possible errors that may be made by technicians, maintenance personnel, and other personnel in the system’ [24]. An HRA activity's objective is to maximise the workforce's performance, which will improve the overall effectiveness of an organisation and minimise the impact of potential risks. Therefore, reliable human performance is when individuals perform a task, make a decision, or respond to action according to their organisations' expectations [25]. In literature, researchers classify HRA methods into two generations. The HRA first generation is developed based on the study of human error probability and does not consider the cause of behaviour [26]. Some of these methods are: Technique for Human Error Rate Prediction (THERP) [27], Accident Sequence Evaluation Program (ASEP) [28], Human Error Assessment and Reduction Technique (HEART) [29], and Simplified Plant Analysis Risk Human Reliability Assessment (SPAR-H) [30]. These methods break a task into component parts to calculate human error probabilities (HEPs) and later consider potential impact of modifying factors such as pressure and stress [23]. The second-generation methods consider the context as a factor affecting human performance failure and later evaluate the relationship between the context and HEPs [8]. Some of these methods are: A Technique for Human Event Analysis (ATHEANA) [31], and Cognitive Reliability and Error Analysis Method (CREAM) [32]. These methods consider cognitive behaviour of the human. The activities of the human are assumed as performed for specific purpose. Some researchers have added a third generation in HRA methods, which considers dynamic simulation system with a virtual representation of human to determine challenging human performance situations [26].

2.2.1 HRA process

There are seven main steps to perform a complete human reliability assessment study, illustrated in **Figure 3**. The first step is formulating a scenario which could be performing a maintenance task in a separator. The second step is to collect the required data for the formulated scenario. The third step is to analyse the task. The Hierarchal Task Analysis (HTA), which is a top-down approach, breaks a task into sub-tasks and multiple levels in order to achieve the desired goal (i.e. top-level task) [33].

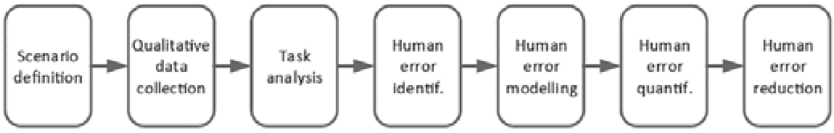

Figure 3 A generic human reliability analysis process

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It should be noted that critical tasks should be identified during this step. A critical task is a task that if it is not performed adequately, and according to a standard procedure, it could lead to highly undesirable consequences [25]. The fourth step is to identify the human errors. The fifth step is to model the identified human errors by using, for example, FTA, Event Tree, etc. This sixth step is to quantify human errors. Some of the published methods only quantify human errors and fail to provide a reduction technique [34]. The last step, and most importantly, is to perform a human error reduction activity. The human error probability (HEP), which is estimated by Equation – 1, can be defined as the number of errors (z) which are caused by human over the total number of potential errors (n) during tasks [35].

$$HHHHHH = \frac{NNNNNNNNNNNN\ \ oooo\ \ NNNNNNooNNee}{NNNNNNNNNNNN\ \ oooo\ \ ooooooooNNooNNooooooooNNee\ \ ooooNN\ \ NNNNNNooNN} \quad \textbf{(Equation – 1)}$$

2.2.2 Human error classification & causes

The previous sections have mentioned the term *Human Errors* several times. Therefore, there is a need to define it and understand its classifications. Thus, human error can be defined as “an action that goes beyond the acceptable limits, those being defined by the system” [27]. There are three main classifications for human error in literature including a) the Skill – Rule – Knowledge classification [36], b) commission and omission errors [27], c) error and violation classification [37]. Also, there is a need to understand what the possible causes behind them are. Initially, unlike equipment, a human being's behaviour is hard to predict. Similarly, human errors could occur during any phase of the system lifecycle. There are three main aspects where human errors are linked to [32]. First, individual aspects are linked to the ability, psychological and physical characteristics of a person. Some of these aspects cannot be changed; however, some could be improved by learning and training. Second, technological aspects are linked to the interaction between a human and a machine. Last, organisational aspects are linked to an organisation's culture, and these aspects have a significant impact on both previous aspects [21]. It should be noted that the performance of individuals, organisations, hardware, and software can be affected by environmental factors as well. These environmental factors are classified into external, internal, and sociological factors. External factors could include wind, temperature, rain, and time of day. Internal factors can include lighting, ventilation, and noise. Sociological factors could include values, beliefs and moral.

2.2.3 Human error in maintenance

The impact of human errors in maintenance are reviewed [38]. This review aims to increase the awareness of maintenance practitioners on the impact of human errors in maintenance and develop mitigation actions. Generally, the study suggests six classifications of human error which could include operating errors, assembly errors, design errors, inspection errors, installation errors, and maintenance errors. Often, maintenance error could occur due to inadequate repair or preventive actions. This paper can be a useful reference for researchers who are concerned about human error in maintenance. Similarly, 78 publications on human factors in maintenance are reviewed in order to identify critical human error influencing factors [16]. The study finds that equipment reliability and human error are a primary concern in the industry. This study reports that fatigue, lack of experience, and inadequate communication are the most critical human influencing factors related to maintenance. The study concludes that some future directions could include predicting human error in maintenance and how they can affect the reliability of a system. Another study suggests that human errors can affect the availability and performance of equipment and products' quality [39]. A piece of research is conducted to identify critical human error influencing factors in maintenance activities within a petroleum facility [40]. They conduct a structured interview with 38 maintenance technicians. The study finds that the most critical human error influencing factors, which could lead to maintenance failures, are flawed assumptions, poor design and maintenance practices and poor communication. Although maintenance technicians answer the survey, it would be beneficial if they could have access to supervisors or top management. In addition, this study is limited to a single facility, and it would be beneficial if more organisations are included.

2.3 Decision-Making Grid

The first decision-making grid (DMG), which can be seen in **Figure 4**, was developed by Labib in 1996 [13]. Later, this DMG has become a good decision-making technique to improve maintenance practice and reduce downtime. A DMG's objective is to provide a systematic and consistent methodology to select an appropriate maintenance strategy for a given piece of equipment to reduce both downtime and failure frequency [41]. These maintenance strategies are operate-to-failure (OTF), condition-based maintenance (CBM), total productive maintenance (TPM), skill level upgrade (SLU), and design out maintenance or machine (DOM). Simply, the objective of the DMG is moving problematic machines into the top-left corner. a detailed explanation of how to use these maintenance strategies are explained in [42]. Although the DMG considers upgrading 'operators' skills to perform some maintenance tasks, it does not consider some improvement measures to reduce human errors in maintenance. Therefore, this research aims to address this problem.

		Downtime		
		Low 0 – 10 Hrs	**Medium 11 – 20 Hrs**	**High > 20 Hrs**
Frequency	**Low 0 – 5 failures**	OTF	TPM	CBM
	Medium 6 – 10 failures	TPM	TPM	TPM
	High > 10 failures	SLU	TPM	DOM (A)

Figure 4 Original DMG

3 Method Development

This research develops a framework by fusing probabilistic techniques for human and hardware availability assessment, as shown in **Figure 5**. This framework's novelty can be seen in the integration process of probabilistic techniques and providing a human-based decision-making grid (H-DMG), which can help reduce human error probability (HEP) in a given maintenance task.

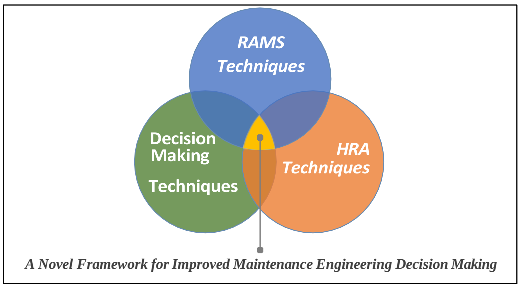

Figure 5 A Venn diagram for the developed framework

3.1 Developing a Human-based Decision-Making Grid (H-DMG)

The overall objective of this H-DMG is to reduce the probability of human error (HEP) and minimise the associated active repair time (Ha-MTTR). This can be achieved by implementing the human error control measures (HECMs) identified in the literature review. The H-DMG can be divided into three zones***: Critical, Critical – Moderate, and Moderate - Low***. First, the critical zone requires at least three HECMs, as shown in **Figure 6**. These HECMs are: i) improve supervision, ii) reduce task complexity, and iii) improve or design out procedure. These measures are incredibly vital to reduce the probability of human error for a given task and minimise the duration of an asset's active repair time. Second, the critical to moderate zone requires at least two HECMs. For example, suppose the human error probability for a given maintenance task is high, and the associated active repair time is moderate. In that case, the required HECMs are i) improve man-machine interface and ii) control time pressure. Finally, the moderate to low zone requires at least one HECM. For instance, if the HEP for a given task is moderate and the Ha-MTTR is low, the required HECM can be improve training and enhance competence.

This H-DMG is tested in a simulated case study in the following section. Since this research will use the HEART method, described in [29].

		Ha-MTTR		
		Low 0 – 8 hours	Moderate 9 – 24 hours	High >24 Hours
HEP	Low 0.001 – 0.01	Improve team communication and documentation	Improve supervision	Reduce task complexity & Improve supervision
	Moderate 0.01 – 0.1	Improve training and enhance competence	Improve team communication and documentation & Improve training and enhance competence	Improve supervision & Reduce task complexity
	High 0.1 – 1	Improve training and enhance competence & Improve /Design out procedure	Improve Man-Machine interface & Control time pressure	Improve supervision, Reduce task complexity & Improve /Design out procedure

Figure 6 The developed H-DMG

3.2 Developing a Framework for Improved Maintenance Engineering Decision-Making

This section introduces and explains the developed framework for improved maintenance engineering decision-making. The framework, which is illustrated in **Figure 7**consists of four main phases: a) asset selection and data gathering, b) system modelling and simulation, c) criticality analysis, and d) sensitivity analysis and risk reduction.

Phase one: Asset selection and data gathering

The first phase consists of scope definition, asset(s) selection, data gathering, and conducting a feasibility study. First, scope definition can include the analysis objectives, the available time, teams' roles and responsibilities, and the business requirements. Second, asset selection can include identifying the boundaries of selected assets and stating any critical analysis assumptions. Third, data gathering includes historical failure rates, failure modes, repair times, spare parts, maintenance crew and logistics. These data can be retrieved from a computerised maintenance management system (CMMS) if possible. Alternatively, if these data are not available in the CMMS of an organization, they can be extracted from original equipment manufacturer (OEM) catalogues. Last, there is a need to check the feasibility of an intended study. Analysts should ensure that all the previous steps are completed before proceeding to the next phase. This is a critical step in this framework because if, for example, the scope is insufficiently defined, the output of the analysis will probably be inadequate, and inaccurate decisions might be taken. If the study is feasible, it is possible now to proceed to the next phase.

Phase two: System modelling and simulation

The second phase consists of system modelling and simulation. Initially, System modelling can be constructed by using reliability block diagram (RBD). The required data for this subprocess is the mean time to failure (MTTF) and main time to repair (MTTR) for the selected assets. Simultaneously, an HRA can be conducted for the maintenance procedures of the selected assets. The HRA's objective in this phase is to generate a HEP value for each activity of a maintenance procedure and then incorporate this value into the simulation process. The system simulation, where the mean availability of a system can be estimated, can consider both the reliability of an asset and the reliability of a maintenance procedure for that asset. This step can be carried out by a well-recognised approach such as Monte Carlo simulation.

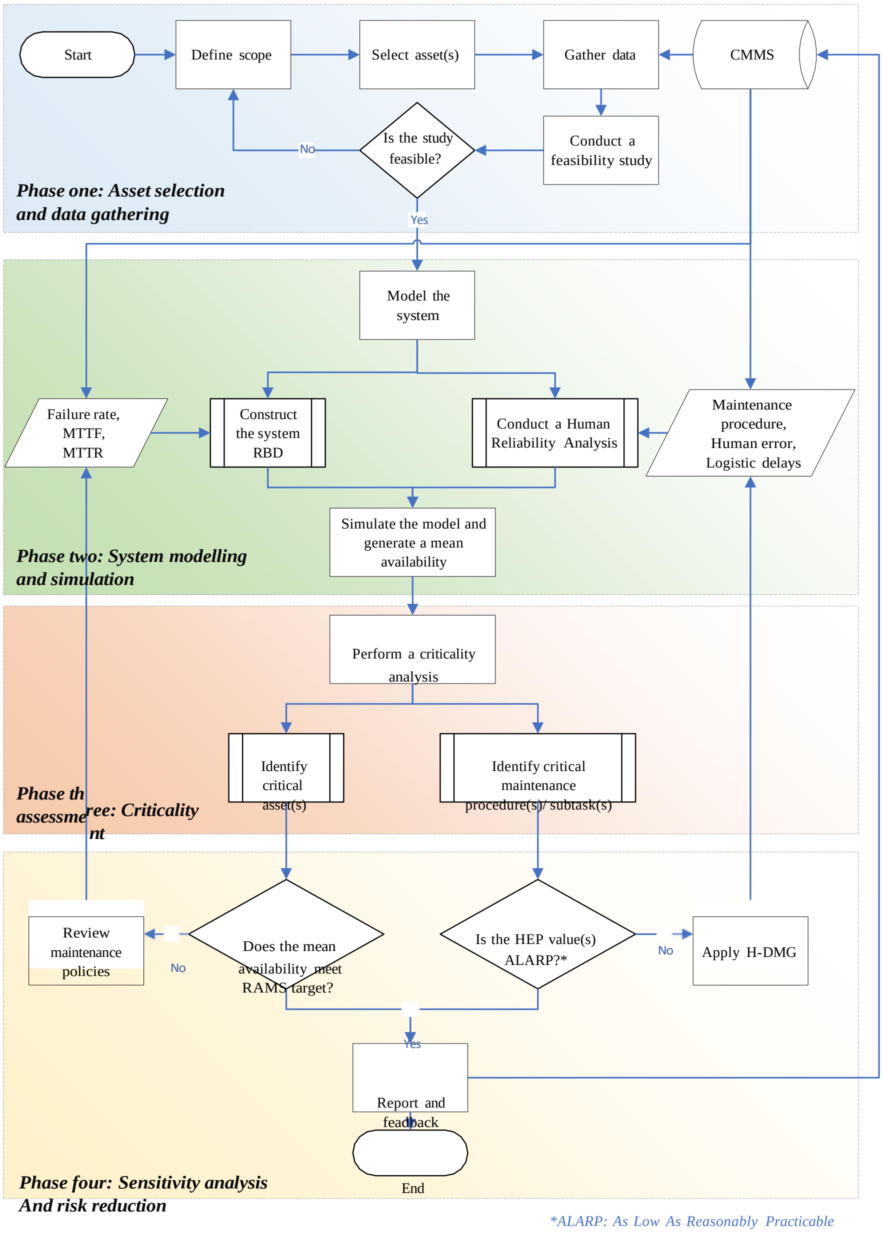

Figure 7 The Developed Framework for Improved Maintenance Engineering Decision-Making

Phase three: Criticality analysis

Once a system has been simulated, and the mean availability is estimated, criticality analysis should be conducted. During this phase, analysts can identify critical asset(s), component(s) or failure mode(s) that significantly impact the unavailability of the system. Similarly, maintenance procedure(s) or subtask(s) that could cause a total loss of production or undesirable events can be identified.

Phase four: Sensitivity analysis and risk reduction

The last phase is sensitivity analysis and risk reduction, where improvements and actions are needed to reduce failures and increase system availability. First, analysts can check if the conducted study's output meets the stated objectives and the RAMS target. If the output of the study does not meet the RAMS target, maintenance policies can be revised, and certain decisions for improvement regarding equipment redundancy, for example, can be taken. At the same time, if the HEP value(s) for a given maintenance procedure is not as low as reasonably practicable (ALARP), analysts can apply the novel H-DMG in order to reduce the probability of errors. A good practice when conducting this framework is creating different scenarios and assumptions to determine which one has a cost-effective and safe impact on the availability of a system. Lastly, conducting this framework can be complex and has a significant amount of information. Therefore, analysts can document the output of this framework, and it is important to state the recommended improvements and actions adequately.

4 Application of the framework: A case study

This research considers a typical offshore oil and gas production facility as a case study. Generally, there are five stages in which oil and gas can be processed [43]. The first stage is the exploration of oil and gas, including prospecting, seismic and drilling activities. These activities are carried out before the development of an oil and gas field. The second stage, which is known as the upstream, is the production of oil and gas. Production facilities in this stage can be located onshore or offshore. The third stage, known as midstream, consists of transporting oil and gas via pipelines, chips, or tanker vehicles. Midstream can include the storage of crude oil and gas. The fourth stage, which is known as downstream, is refining oil and condensate into marketable products. The last stage is processing and producing petrochemical products such as plastic and fertilizer.

4.1 Case study scope, boundaries, assumptions, and limitations

This section defines the scope, boundaries and assets selection for an offshore oil and gas production facility. This is the first phase when applying the novel framework for improved maintenance engineering decision-making.

Scope and boundaries

A typical offshore oil and gas production system consists of power and heat generation system, process plant, produced water and seawater treatment system, and subsea systems. This case study considers the process plant systems only. The process plant can include production manifolds, a separation train, export pump(s), recompression train, gas treatment train(s), and fuel gas system. This production facility can be considered a medium-size offshore platform, seen in **Figure 8**. It has one separation train, one gas recompression train, and one gas treatment train. The produced oil rate can be 40,000 BPD after the separation process. Part of the processed gas is used to power the platform, and the rest is injected to the well. At this stage, the processed gas is not exported.

Case study boundaries

- This case study considers the process plant of an offshore topside platform.
- This case study considers corrective maintenance tasks.
- This case study excludes inspection tasks, preventive maintenance tasks and major shutdowns.
- This case study does not consider the power and heat generation systems, process sensors, fire and gas detectors, pipelines, valves, and logic controls.
- Each equipment unit has a predefined system boundary which can be seen in Appendix C.1.
- The reliability data are extracted from the publicly available Offshore Reliability Data OREDA [44].

Assumptions and limitations

It is imperative to identify relevant assumptions and limitations of a production system when conducting a RAMS Analysis. The RAMS analysis's quality can be significantly affected by these assumptions. For example, optimistic assessments and results can be driven by unrealistic or inadequate assumptions. Also, the accuracy of a RAMS assessment depends on the quality of the reliability data in order to reflect a realistic operational scenario. Therefore, the RAMS assumptions should be measurable, unambiguous, and easy to understand. A list of assumptions and limitations considered when conducting this analysis are listed below.

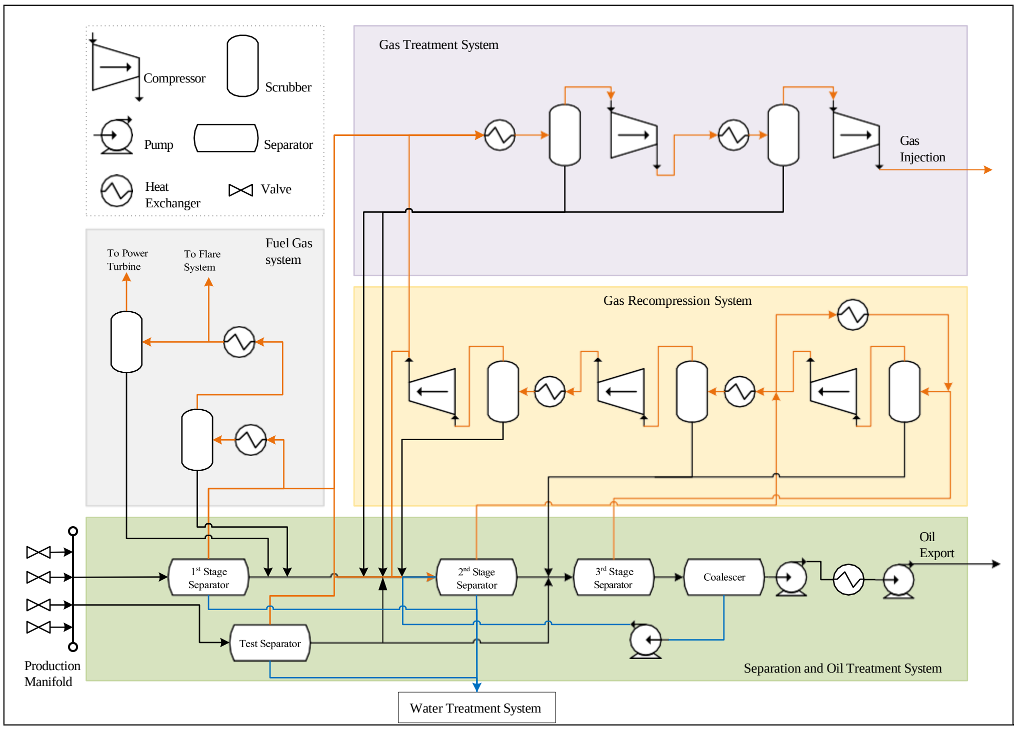

Figure Error! No text of specified style in document. A typical offshore oil and gas process plant [45]

- This case study assumes that considered failure modes are critical. This means that if a failure mode occurs, an equipment unit will shut down and cause a total loss of production.
- This case study assumes that failure rates are constant, i.e. the failure rates are exponentially distributed. This means that the simulation is conducting during the useful life phase of an equipment unit.
- This case study assumes that all failures are independent. This means that if a failure occurs in one system, it does not trigger another failure.
- This case study assumes that all equipment units are not deteriorating, which means that a repaired component is as good as new after repair.
- The simulation time of this case study is limited to 10 years. This is mainly because new investment decisions for offshore oil and gas platforms can be taken every 5-10 years [22].
- The number of simulations is limited to 1,000 runs. This is mainly because the desired results can be presented as the average results over these multiple runs.
- This case study assumes that a maintenance crew is available on-site in order to avoid backlog and delays.
- This study assumes that there are some logistic delays for each failure mode.
- This case study assumes that the downtime cost is £20,000 per hour.

System overview and objectives

This simulation aims to determine the mean availability of the process plant, uptime, total downtime, MTBF, MTTR, expected number of failures, failure downtime, number of corrective maintenance tasks, corrective maintenance downtime, and system downtime cost. This simulation's mean availability target is 95%.

4.2 Modelling, simulating, and improving the selected case study

The second phase is system modelling and simulation. There are four scenarios which will be modelled and simulated. The first scenario is modelling and simulating the selected process plant based on equipment critical modes only. It should be noted that human reliability assessment is not considered in the first scenario. The second scenario is modelling and simulating the selected process plant based on critical failure modes and HEPs. The objective of modelling and simulating these two scenarios is to demonstrate the effect of human errors on a system availability. The third scenario is improving the selected process plant by reducing the HEPs in order to demonstrate how a system can be improved by using the developed H-DMG. The last scenario is improving the selected process plant by reducing the HEPs and implementing a system redundancy in order to demonstrate how a system availability can be improved. In general, when modelling an offshore oil and gas process plant, the RBD is presented in a series configuration [22]. This means that if a piece of equipment fails, the overall production system will be stopped.

Scenario One: *Modelling and simulating the process plant based on equipment critical failure modes level*

As introduced above, the first scenario is modelling and simulating the selected process plant based on equipment critical modes only. and the simulation results can be seen in **Table 1**. It can be noticed that the mean availability of the process plant is 95.50% over a period of 10 years. In addition, the total downtime during these ten years is 3,547 hours, and the number of failures is 108 failures. Based on the simulation, the estimated total downtime cost is almost £71 million. It should be mentioned that this is not an adequate assessment of a system availability because it did not consider HEPs.

Table 1 Simulation results for the first scenario

System Overview	
Mean Availability	95.50%
Expected Number of Failures:	108
Corrective Maintenance Downtime (Hr):	3,547
System Downtime Cost:	£71m

Scenario Two: *Modelling and simulating the system based on equipment critical failure modes and human error probabilities*

As mentioned above, the second scenario is modelling and simulating the selected process plant based on critical failure modes and HEPs. The objective of this scenario is to demonstrate the effect of human errors on a system's availability. Also, the HEART method is used to estimate the values of HEPs for a hypothetical maintenance task for repairing the export pump. This maintenance task includes 35 activities, which is based on [46] and [7]. This maintenance task includes pump's isolation, connecting and reinstating activities. It should be noted that the generic HEP is 0.001, and the Assess Proportion of Affect (APOA) for all activities is assumed to be 1. The reliability values of these activities are shown in **Figure 9-11**.

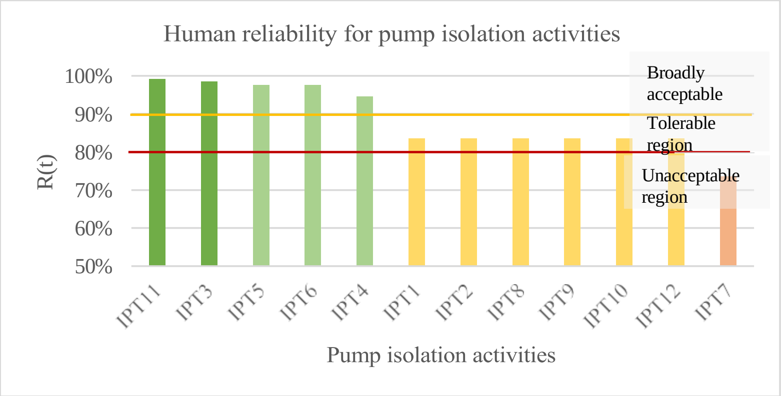

Figure 9 The estimated reliability for the pump isolation activities

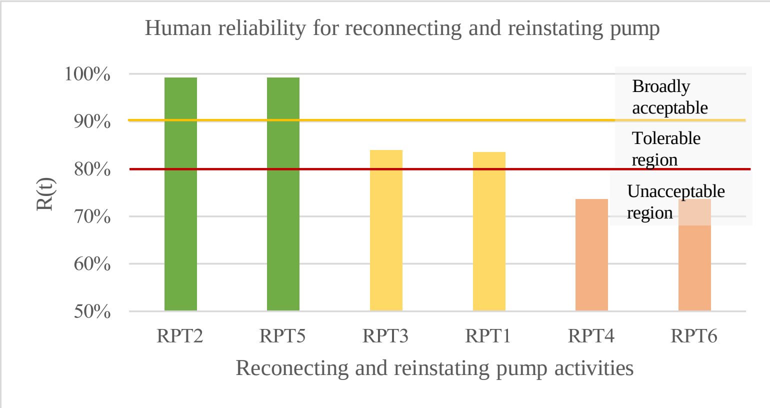

Figure 10 The estimated reliability for the pump reconnecting activities

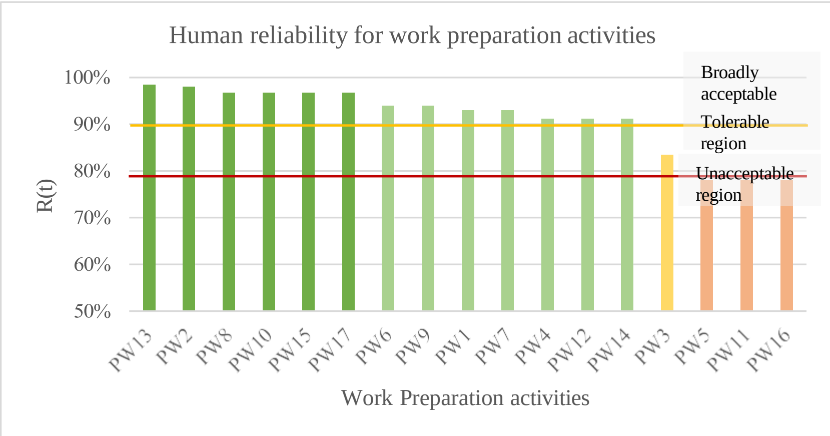

Figure11 The estimated reliability for work preparation activities

The simulation results can be seen in **Table 2**, and it can be noticed that the mean availability of the process plant is reduced to 91.30% over a period of 10 years. Additionally, the total downtime during these ten years is almost doubled to 6,852 hours, and the number of failures is 110 failures. Although the number of failures has increased by two failures only, these two failures could have a significant and adverse impact on the platform. In fact, it can be noticed that the estimated total downtime cost has been increased to almost £137 million. This scenario can be considered as a real representation of a system's availability. Further, the simulation results do not meet the targets of this study.

Table 2: Simulation results for the second scenario

System Overview	
Mean Availability (All Events):	91.30%
Expected Number of Failures:	110
CM Downtime (Hr):	6,852
System Downtime Cost:	£137m

Improvement One: *an improved offshore oil and gas topside systems by reducing HEPs*

Since the previous scenario did not meet the target of this study, there is a need to improve the system by, identifying critical assets and maintenance procedures, and then providing some recommendations using the H-DMG. The most critical maintenance activities that have a significant impact on the process plant unavailability are:

- Perform pressure test & isolation valves
- Test pressure
- Opening valves, filling pump, and testing for leaks
- Perform a risk assessment of activity
- Perform and document initial gas test
- Workforce supervisor (WFS) hold toolbox meeting

These activities are influenced by several error producing conditions (EPCs) defined by [29]. For example, "*Ambiguity in the required performance standards*" **EPC 11** has influenced 33 out of the 35 activities. Therefore, in order to reduce the HEP values and increase the process plant availability, these EPCs should be reduced or eliminated. Since the HEP values are not ALARP, these HEP values will be reduced by using the H-DMG. For example, the maintenance activity (IPT7), "*Perform pressure test & isolation valves*", is located in the ***critical zone***. In order to reduce the HEP value of this activity, there is a need to improve the supervision of this task, reduce the task complexity, and improve the procedure.

The simulation results can be seen in **Table 3**, It can be noticed that the mean availability of the improved process plant is increased to 93.1% over a period of 10 years. Additionally, the total downtime during these ten years is reduced to 5,440 hours, and the number of failures is reduced to 105 failures. This can be considered as a good improvement of the recommended HECMs are followed. In fact, it can be noticed that the estimated total downtime cost has been reduced to almost £109 million. A total of £28 million can be saved if human errors can be reduced. Further, in order to meet the target of this study, some further technical improvements are required.

Table 3 Simulation results for the first improvement

System Overview	
Mean Availability (All Events):	93.1%
Expected Number of Failures:	105
CM Downtime (Hr):	5,440
System Total Cost:	£109m

Improvement Two: *Improved offshore oil and gas topside systems by reducing HEP and implementing system redundancy*

Although the previous scenario improved the process plant's availability, this study's targets are still not met. Therefore, there is a need to improve the system by identifying critical assets that have a significant impact on the process plant unavailability. According to the simulation results, a single compressor is responsible for 11% of the process plant unavailability. This is followed by the export pumps which are responsible for 9.02% of the process plant unavailability. Several maintenance strategies and decisions can be taken based on an organisation's available resources, budgets, and investments to improve the system. For demonstration purposes, an active redundant gas compression train is added, and active redundant export pumps are added.

The simulation results can be seen in **Table 4**. It can be noticed that the mean availability of the improved process plant is increased to 95.4% over a period of 10 years. Additionally, the total downtime during these ten years is significantly reduced to 3,635 hours, and the number of failures is reduced to 70 failures. Further, it can be noticed that the estimated total downtime cost has been reduced to almost £73 million. A total of £63.3 million can be saved if both human errors can be reduced, active redundant systems are included.

Table 4 Simulation results for the second improvement

System Overview	
Mean Availability (All Events):	95.4%
Expected Number of Failures:	70
Corrective Maintenance Downtime (Hr):	3,635
System Total Cost:	£73m

4.3 Validation of the framework

Based on the previous assumptions and assessments, this research has simulated four different scenarios for an offshore oil and gas process plant. In order to validate the developed framework, comparative analyses were carried out to evaluate the proceed plant. It is a standard practice in industry to perform a RAM study by using simulation methods for a piece of equipment during the design or operation phase. The simulation's results of this study can be benchmarked against a publicly available similar study and then validated by subject-matter experts.

5 Discussion

The RAMS analysis objectives are: providing a prediction of a system's behaviour to meet design specifications; assessing the life-cycle costs of a system; and identifying critical systems or components that can cause undesirable consequences. Based on the finding of the literature review and some informal interviews with senior reliability engineers in industry, human errors in maintenance are not considered during a RAM analysis [22]. This issue has been considered as one of the motivations to conduct this research. Although a RAM study can have several advantages, analysts might face some limitations when conducting a RAM study [19]:

- There is a degree of uncertainty when estimating reliability values
- Reliability models depend heavily on historical data
- A tremendous amount of data points is required to form a statistical distribution
- When predicting future events, there is a need to assume that operating conditions of simulated systems are similar to the current situation
- Often, failure and repair rates are assumed to be constant. This is not always the case
- A RAM study might require a tremendous amount of resource
- There is a possibility to underestimate or overestimate failure and repair rates which can affect the predicted availability of a system

In addition, when applying a human reliability assessment, analysts might face some limitations, such as [10]:

- Reliable information and data might be lacking
- PSFs can be insufficiently selected.
- Cognitive behaviours are inadequately estimated.
- There is a great focusing on human errors, not the causes.
- Experimental data is not sufficient for validation and modelling.

It can be noticed that the top five HECMs are: improve supervision, improve team communication and documentation, improve training and enhance competence, reduce task complexity, and improve /design out procedure. This outcome was consistent with the findings of the literature review. In fact, organisations should invest in implementing these improvement measures in order to reduce the probability of human errors in maintenance activities. Therefore, the H-DMG can be used as a map to improve maintenance activities by selecting the appropriate HECMs based on the magnitude of HEP and Ha-MTTR.

Initially, the developed framework was theoretically validated by using a simulation case study. This case study has used publicly available data to simulate an offshore oil and gas process plant. The output of this simulation has proven that the developed framework can reduce human error probabilities in maintenance activities and improve the availability of a system.

The results of this simulation can be benchmarked against a publicly available similar study [47]. Also, the framework was validated by subject-matter experts in the field of human factor and reliability engineering. The first two human factor specialists are HRA authors and have an experience of 25 years in a high-risk industry. The other four experts are senior engineers and managers in the field of reliability engineering. This validation process was conducted by using several interviews where the research was fully presented to them. They have had a chance to ask questions for further clarification if needed. Then, the experts completed a feedback form, which can be used as a means of validation.

5 Conclusion

Human errors can be significant contributors to the overall risk in the industry. Human errors, in fact, are often a root or significant cause of a system failure which could lead to tremendous undesirable consequences. Although most industries use the latest technologies in order to maximise the availability and reliability of their equipment and minimise human interventions, the human role is still vital in different phases of a plant life cycle, especially during maintenance activities. Traditional RAM methodology did not incorporate human reliability analysis. Therefore, this research developed a novel framework for improved maintenance engineering decision-making, which was achieved by fusing probabilistic human and hardware availability assessment techniques. Initially, the proposed framework has a systematic process that can reduce HEPs in maintenance activities and improve the availability of a system. A publicly available case study in an offshore oil and gas platform was selected as an example for demonstration and validation purposes. The output of this case study has proven that the developed framework can reduce HEP by 35% and reduce the downtime cost by 45%. Also, the framework was validated by subject-matter experts in the field of human factor and reliability engineering. These experts have found that the developed framework can be easily applied and has great potential applications in the industry. Finally, it was not possible to apply and validate the developed framework on a field case study due to time constraints; however, this research recommended utilising this framework on a full-scale case study for further validation and enhancement.

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OVERSAMPLING AND PATTERN RECOGNITION TECHNIQUES TO ENABLE REMAINING USEFUL LIFE ESTIMATION

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Abstract
Remaining Useful Life (RUL) estimation is a crucial factor of Predictive Maintenance. Through the predictive maintenance the maintenance departments of the industry field are able to increase the efficiency of the maintenance process, planning well in advance all its aspects. This research work proposes a data-driven RUL estimation approach based on the Long Short-Term Memory (LSTM) algorithm, which is a type of Recurrent Neural Network. LSTM is a supervised method that requires a sizeable amount of run-to-failure historical data, which, in most real industrial environments are hard to obtain as the end-of-life or failure incidents of the critical equipment are rare. To alleviate this issue, we propose a data over-sampling approach to artificially increase the number of run-to-failure-data. In order to enable the RUL estimation approach to output results in the form of remaining Product Cycles (PCs), we also propose an automated PC detection technique based on a motif detection algorithm. For the evaluation of the approach a real industrial scenario is used.

1 Introduction

The Remaining Useful Life (RUL) analysis can provide valuable information regarding the deterioration rate of assets, as the former is defined as the length from the current time to the end of the useful life. Accurate RUL estimation plays a critical role in the improvement of the quality of the produced products and in the Zero-Defect Manufacturing process in general. Providing accurate estimations of the remaining working hours of a machine or the remaining number of items that the machine can produce (i.e., remaining product cycles), enables the production and maintenance engineers to be well prepared, scheduling in advance the production plan, or obtaining the required parts for maintenance, in order to minimize the downtime of the machine.

RUL estimation can be approached with different techniques, that rely on two main families, the model-based and the data-based techniques. Model-based techniques rely on statistics, like distribution fitting, in order to map the distribution of the actual data to a known distribution and provide the probability of a failure based on a survival function, as it is depicted in the example below (Figure 1).

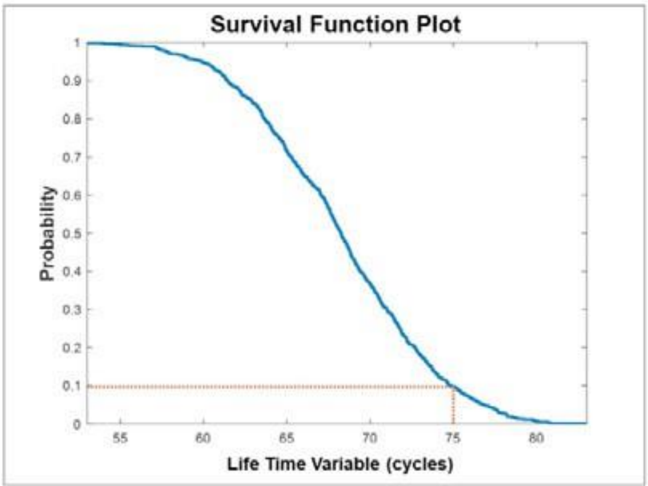

Figure 1: Survival function plot indicating at the end of 75 cycles, the probability of a battery's continuing to operate is 0.1, or 10%[1].

The example of the figure presents the remaining useful life of a battery, showing its deterioration of its life time.

[1] source: https://www.mathworks.com/content/dam/mathworks/ebook/estimating-remaining-useful-life-ebook.pdf

Data-driven techniques like similarity models, Figure 2**,** capture degradation profiles (blue) based on run-to-failure data. The distribution of the asterisks (or endpoints) of the nearest blue curves gives a RUL of 65 cycles for the current data (red).

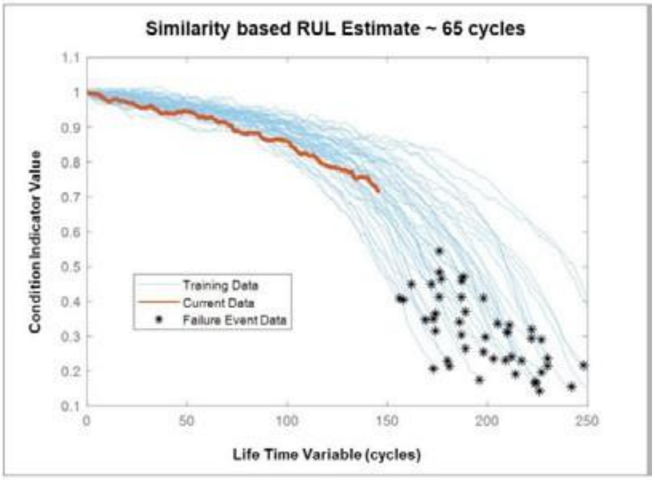

Figure 2: Similarity models capture degradation profiles (blue) based on run-to-failure data. The distribution of the stars (or endpoints) of the nearest blue curves gives a RUL of 65 cycles for the current data (red). Source: mathworks[2]

More advanced data-driven techniques like the one of this work, propose the use of Neural Networks (NNs) algorithms trained with run-to-failure data in order to estimate the current RUL, either in remaining working hours or product cycles. Properly trained data-driven techniques can outperform the model-based ones, as they are adjusted to specific use cases and do not rely on fixed distributions. However, this type of analysis requires a large amount of run-to-failure data for the training of the network, that in real industrial scenarios are difficult to obtain. To address this issue, the present work proposes an over-sampling technique to increase the number of run-to-failure data generating artificial data based on the real ones.

For the scenario showcased in the experimental evaluation section, the output of RUL estimation is required to be in terms of Product Cycles (PCs), indicating the remaining number of items that the machine can produce until the occurrence of a failure. To be able to output the RUL estimation into PCs, the model needs to be trained in a dataset that is split into PCs. However, the number of PCs at a given time point needs to be extracted for the data itself as it is not provided explicitly. To achieve this task, a pattern recognition mechanism is proposed based on motif detection, which is able not only to compute the number of PCs in each time point, but also to identify the exact point where a PC is started and finished.

To summarize, the contribution of this work is threefold:

- It presents an oversampling technique to increase the number of run-to-failure-data.
- It proposes a pattern recognition mechanism to count and identify the PCs.
- And finally, it applies and evaluates a RUL estimation approach based on NNs.

The remaining of the paper is organized as follows. Section 2 presents an overview of related works from the literature on the fields of RUL estimation and data generation. Sections 3 to 5 present the theoretical background of the techniques that are utilized to implement the proposed solution. Section 6 showcases the integration of the RUL estimation approach into a Predictive Maintenance Platform, while Sections 7 and 8 present the experimental evaluation and conclude the work, respectively.

2 Related Work

The literature is rich of studies concerning both the RUL estimation and the artificial data generation fields. Plethora of works utilize the LSTM algorithm[3], as in the current work, for the RUL estimation due to its performance. Some papers utilize simple LSTM architectures for RUL estimation, such as [4], [5] and [6], where they achieve performance of 85% or score higher than the Support-Vector Machine model accordingly. Specifically in [6], the authors propose the use of a

[2] https://www.mathworks.com/content/dam/mathworks/ebook/estimating-remaining-useful-life-ebook.pdf

[3] Hochreiter, Sepp, and Jürgen Schmidhuber. "LSTM can solve hard long time lag problems." In Advances in neural information processing systems, pp. 473-479. 1997.

custom feature extraction technique in combination to the LSTM algorithm to enhance its results. Combinations with the LSTM algorithm are popular in the literature. In a variety of papers, the LSTM is combined with other ML techniques for optimization purposes. To mention a few, the authors in [7] utilize a Restricted Boltzmann Machine (RBM) with an LSTM to estimate the RUL and Genetic Algorithms for the model's parametrization. Their focus rests on the case of partially (under 40%) labelled data. In [8] they develop a deep level LSTM and Convolutional model, which is compared with the model of [9] and is considered satisfactory. The authors of [10] combine a Convolutional and LSTM neural network via a Directed Acyclic Graph to estimate the RUL. [11] proposes Bidirectional LSTMs combined with Linear Regression, while the authors of [12] utilize a Bidirectional Handshaking LSTM with Asymmetric Squared Error as the cost function. Last but not least, [13] uses an LSTM for RUL estimations combined with a mechanism of detecting the cause of error. In our case we propose a simple LSTM model that considers internal motifs (i.e. Product Cycles (PCs)) for optimized results

A common challenge in real applications of RUL estimation, is the lack of a significant amount of properly labelled and suitable data. This can be explained to the transient state of the industry. which is still in the process of familiarizing with the Machine Learning (ML) technologies and their requirements. Thus, it is not uncommon to observe a lack of substantial data or imbalanced datasets that have a great impact on the performance of the supervised ML techniques. For this reason, multiple works focus on the generation of artificial data with various techniques such as Generative Adversarial Networks (GAN) [14]–[16] and DTW, [2] and [17]. [15] utilizes a new variant GAN-based framework called auxiliary classifier GAN (ACGAN) to learn from mechanical sensor signals and generate realistic one-dimensional raw data, while [14] utilizes a Conditional GAN (CGAN) to learn and simulate data. In [16] the authors aim to synthesize ECG signals to prevent the re-identification of individuals, while addressing GAN's problem of lack of suitable evaluation measures with the introducing of two evaluation metrics specific to their case. Despite their results, GAN networks are also known for training issues such as vanishing gradients, failures to converge and model collapse[4]. To avoid these issues, we based our data generation mechanism on [2], where the authors utilize DTW's warping path and a teacher sample for artificial data generation. However, our approach deviates from theirs by utilizing classic DTW and no standard teacher but alternating samples as base samples. Finally, the authors of [17] utilize DTW's path as a way to combine two different samples.

3 RUL estimation using Neural Networks

For the RUL estimation, a supervised ML technique is utilized and more specifically a type of Recurrent Neural Networks (RNN) called Long Short-Term Memory neural networks [5].

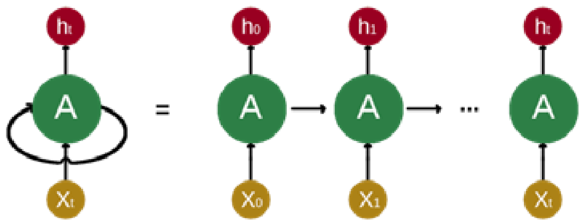

Figure 3: Decomposition of a node in an RNN.

A RNN allows the persistence of information using inner loops. As it is depicted in Figure 3 the output of a node of a RNN in time tt is re-fed on the same node along with the input in time$tt + 1$. This creates a sequence of recurrent feedings. LSTMs, unlike the traditional RNNs, can efficiently handle the problem of long-term dependencies, which means that for a given timeseries, the problem of recognizing a dependency between points that are far in time, or simply the problem of being able to remember old values along with the new ones. To achieve that, LSTMs maintain a cell state for each neuron and a set of three gates that control the cell state: forget, input, output.

To estimate the RUL of a part of a machine using LSTMs, run-to-failure data are required for the training of the network. Then for each point of time, its preceding n-1 points are considered, creating a sequence of total n-points. n can be quite large since LSTMs can do well at big sequences. These sequences are the training data of the network. Its sequence is mapped to a specific Label (prediction target) which is expressed in the appropriate units (i.e., product cycles, or time units) left till the failure from the last point of the sequence.

The full process for the RUL estimation is presented in Figure 4.

[4] https://developers.google.com/machine-learning/gan/gan_structure

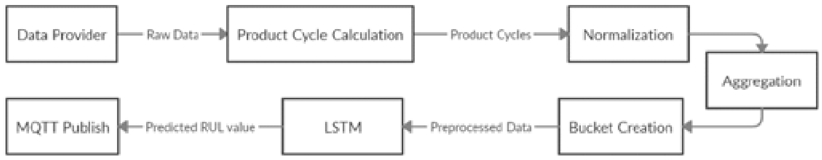

Figure 4: RUL estimation process

The initial step is the data fetching, which is achieved through an implemented service called Data Provider, which communicates with the servers in the shopfloor and fetches the latest sensor measurements to the RUL estimation tool. The data are then forwarded to the component responsible for PC detection that transforms the raw signal to a PC oriented structure. The structured data are pipelined to a transformation process, which includes Normalization, Aggregation and Bucket Creation tasks before being directed to the trained LSTM model for RUL estimation. The result of the tool is circulated back to the plant through a publish in a MQTT broker.

4 Oversampling run-to-failure data

One of the main requirements of RUL estimation with supervised ML techniques, such as the LSTM algorithm, is the need for a significant amount of data of both normal and faulty behaviour. However, in real industrial environments the required amount of run-to-failure data is not always possible to be obtained since it is an unwanted state that the industries strive to avoid. For this reason, an alternative method for obtaining and increasing the existing amount of data is proposed. More specifically, an artificial data generation technique is implemented that exploits historical run-to-failure data to generate new data with similar characteristics. For the generation of data, the Dynamic Time Warping (DTW) metric [1] is used. The developed technique receives samples of existing faulty data and computes iteratively a user-defined number of similar run-to-failure sequences.

Given two sequences, DTW is used to determine a global distance between them, by matching non-linearly timeseries elements in the time dimension to match features and remove time distortions. To achieve that DTW calculates the minimal path on an element-wise cost matrix using dynamic programming. This minimal path is referred to as the warping path and it provides a mapping of one series to the time steps of another.

The warping path, according to [2], can then be used to produce a warped version of the initial timeseries. This method is called Guided Warping technique and it utilizes the dynamic alignment function of DTW to warp the elements of a reference pattern to the elements of a teacher pattern. The result is a generated pattern that contains features of the input sample at the time steps of the teacher sample.

In our use case, we utilize two distinctive fault instances, and we alternate them as the teacher (base sample). As it is presented in more detail in the next subsection, the information regarding the start and the end of a PC is not provided explicitly, hence it needs to be extracted from the values of a specific measurement that the production engineers had indicated. That means that the artificially generated data need to retain as close as possible the *shape* of the PCs in order to allow our algorithmic solution to identify the PCs in both the original and the generated data.

The following two figures present a PC from the original data (Figure 5), which is a recurrent motif that signifies that a new product is being processed in the machine and a PC from the generated data (Figure 6), which although it does not maintain the exact *shape* it maintains some characteristics especially at the beginning and the end of the PC, which allow the PC detection algorithm to work properly.

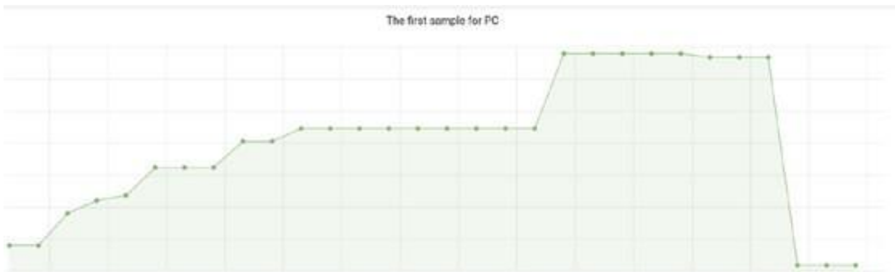

Figure 5: The original data Product Cycle. This motif reappears throughout the dataset and depicts the processing of a new product.

Figure 6: A Product Cycle as observed in a newly generated dataset.

In the figures above we have removed the axes with the magnitute and the time respectively, along with the description of the ploted measurement for confidentiality purposes.

5 Product cycles detection

In order to estimate the RUL in terms of remaining PCs, it is important to implement a reliable mechanism for PC identification. In the original dataset, we have used a condition-based mechanism to identify the PCs in the raw signal, however the generated data present slight alternations both from the original data and the different generated sequences, so use of the condition-based approach is not possible.

For this reason, we have implemented a more reliable PC detection technique, which is based on a similarity search algorithm. The Mueen's Algorithm for Similarity Search (MASS)[6] algorithm [3], calculates the Distance Profile (DP) of a query with a timeseries in an efficient way. A DP is a vector of the Euclidean distances between a given query and each subsequence in a timeseries. The sub-sequences are obtained by sliding a window of length m or the length of the query. The MASS algorithm computes the DP with a complexity of O(nlogn) by exploiting the fast Fourier Transform (FFT) algorithm to calculate the dot products between the query and all sub-sequences of the time series as, depicted on Figure 7.

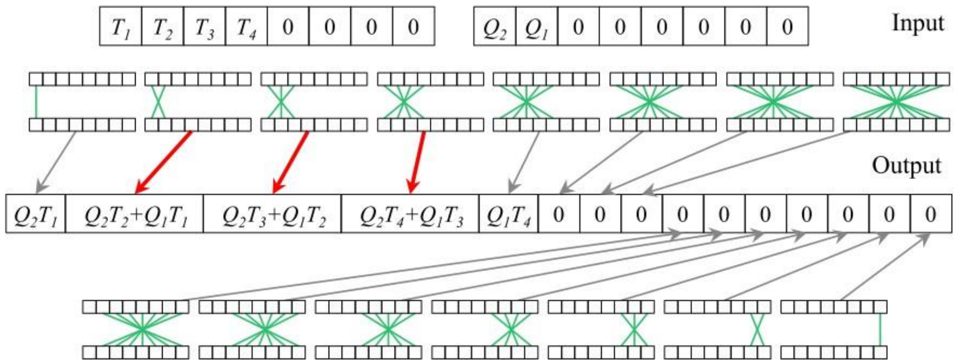

Figure 7: An example of convolution operation for the sliding product and consequently the Distance Profile calculation.

6 https://www.cs.unm.edu/~mueen/FastestSimilaritySearch.html

In our implementation, we calculate the DP of a historical sample of a single PC with the fully generated dataset, locating the start of a potential match and thus the beginning of a new PC. In the example of Figure 8 we provide the first motif as the representative sample and detect the following ones that are depicted with the red line.

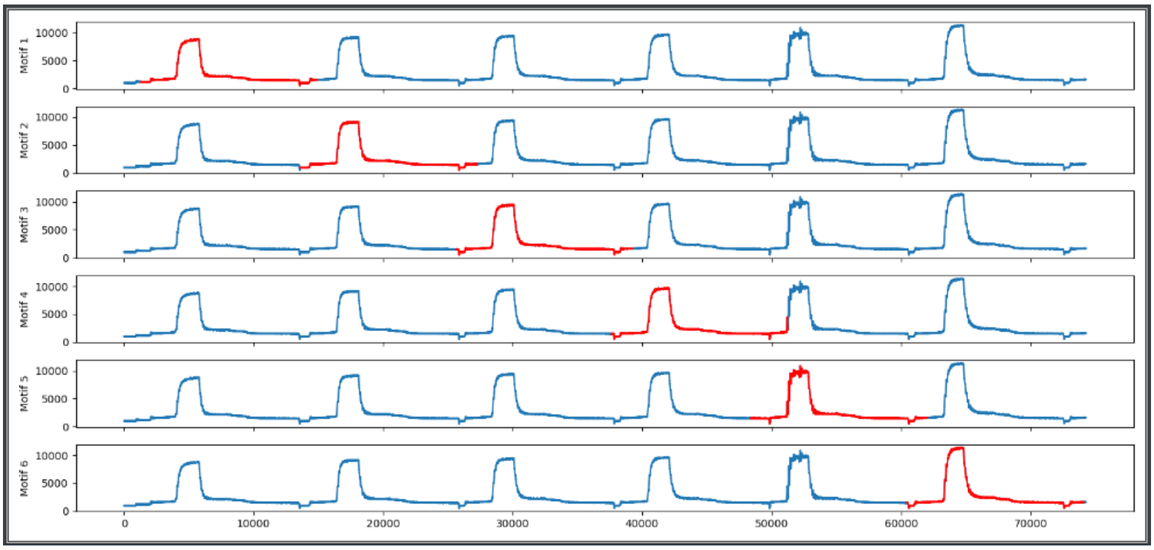

Figure 8: A MASS based PC detection example that utilizes the first motif as a historical profile and detects the upcoming ones. The detected motifs are depicted with the red lines.

In this paper we utilized the PC depicted on Figure 9 as the representative sample. The PCs are detected with a distance threshold that can be defined by the user. This distance threshold controls the amount of the detected PCs based on their similarity level. The higher the distance threshold the more PCs are detected due to lower similarity constraint. For example, setting the distance threshold to 4, as depicted in the upper plot of Figure 10, detects more PCs (red dots) than the other two cases (i.e., middle and bottom plots) with distance thresholds 3.5 (blue dots) and 3 (orange dots), respectively.

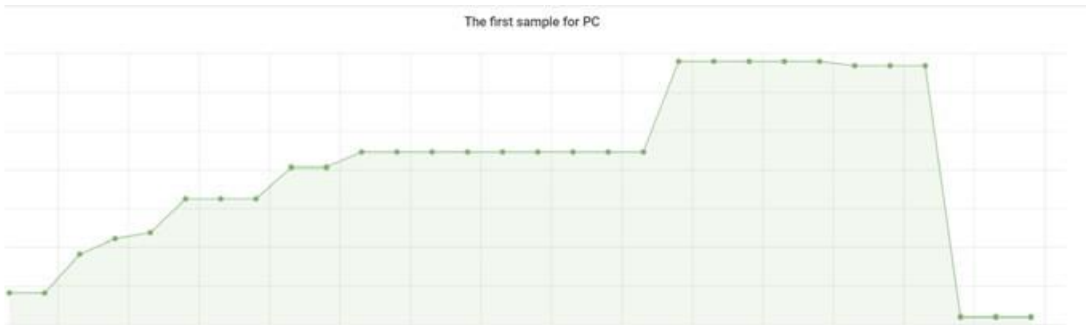

Figure 9: The PC that we utilized as a historical sample for PC detection.

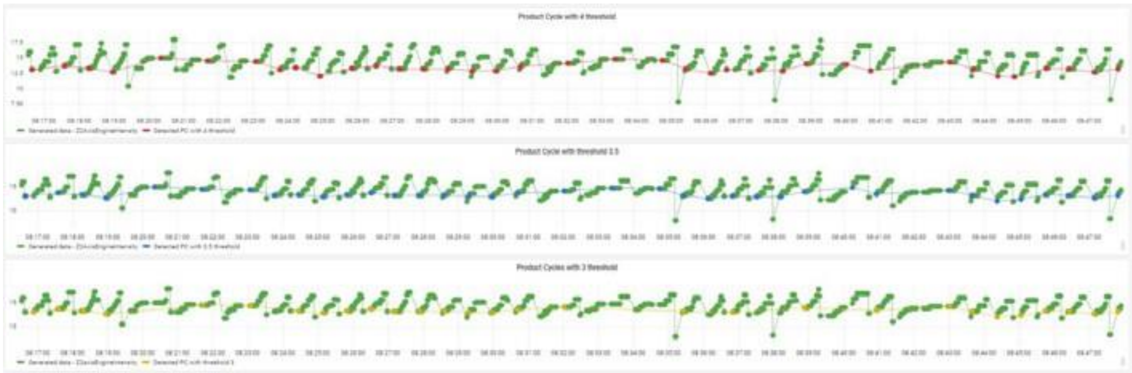

Figure 10: The detected PCs for different distance threshold. The red dots depict PCs with a distance threshold of 4, the blue dots PCs of distance threshold 3.5 and the yellow PCs with distance threshold of 3.

6 Integration to predictive maintenance platform

The proposed algorithms are encapsulated to a predictive maintenance platform, which allows the maintenance engineering to configure and instantiate the RUL estimation process and monitor its results through a visualization dashboard. The platform implementation is based on a micro-services architecture. The user interface is implemented on the angular framework and the micro-services can operate either through the web interface or through the provided API endpoints.

The platform offers forms for parametrization of the various micro-services, a Task' status page, a KPI's page as well as integrated visualization dashboards to enable easy data and results monitoring. The following figures, Figure 11 and Figure 12**,** depict two pages that fetch data and initialize a RUL estimation model accordingly.

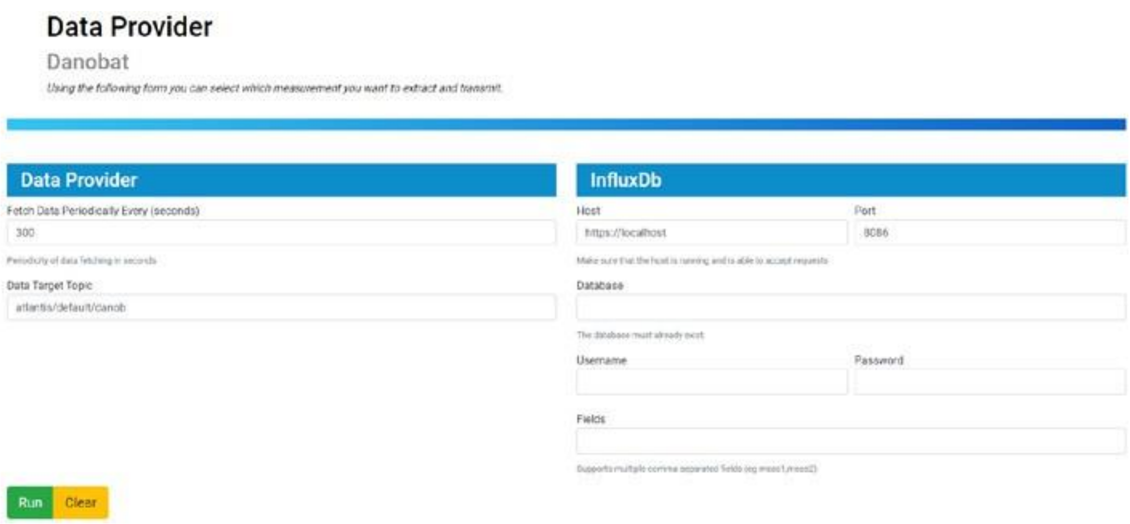

Figure 11 Smart maintenance platform form for data fetching configuration.

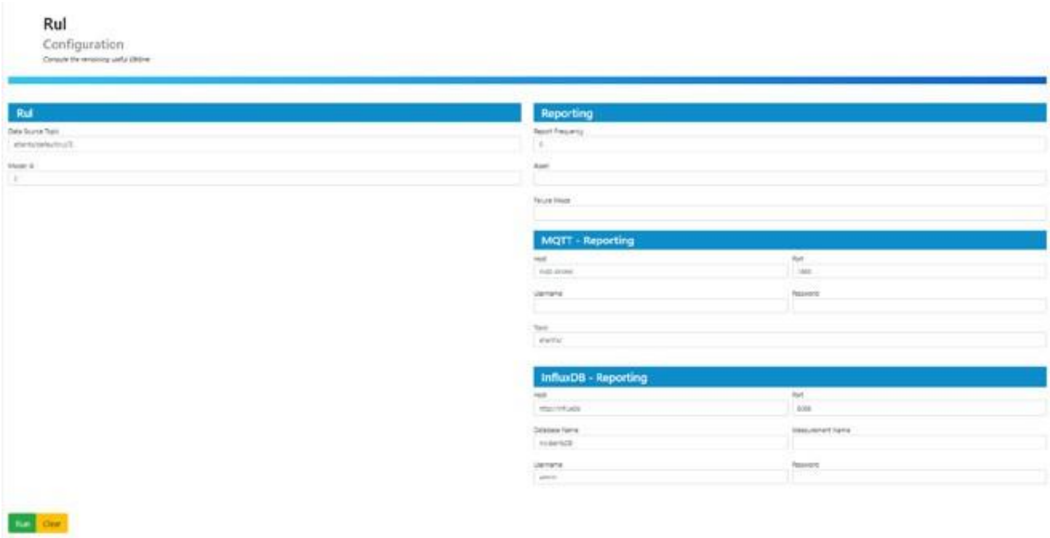

Figure 12 Smart maintenance platform form RUL estimation process configuration

7 Experimental Evaluation

7.1 Training - Testing Dataset formation

Our experimentation focuses on the RUL estimation of a specific component of a grinding machine from a big grinding and lather machines manufacturer. The goal is to provide accurate RUL estimation to this critical part of the machine, to achieve Zero-Defect Manufacturing and to satisfy customer quality requirements by systematizing quality control. The selected part, which is presented in Figure 13, is a grinding wheel with high productivity and constant working conditions, which has a higher probability of failure than the other components, hence its close monitoring is crucial. Deviations or variability in the working conditions of the machine, might be an indication of high deterioration of the machine condition, that could affect the grinding process and cause geometry or quality defects, which in turn, cause the need for extensive rework and increase of the produced scrap.

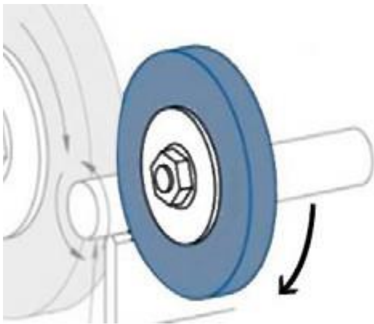

Figure 13: Grinding wheel used for the RUL estimation analysis.

The provided dataset spans across 11 months of constant production, where there are only two occurrences of failure into the specific component, thus the dataset is highly unbalanced with an influx of normal behaviour data and only scarce appearances of faulty behaviour data.

To compensate this behaviour, we applied our data generation technique to oversample the run-to-failure data. For this purpose, we utilized two sets of 12-hour data close to each reported failure and generated similar datasets that mimic the behavior of the grinding machine when it is close to the reported failures. Through this process we have created 5 added run-to-failure datasets.

Next, followed the detection of the PCs using the implemented technique based on the MASS algorithm, setting a distance threshold to 3 in order to detect as similar PCs as possible. The distance threshold was set after an iterative experimentation process with different parametrizations. After some steps of pre-processing that transform the generated data to compatible formats, the training and testing sets were ready to be forwarded to the RUL estimation tool with the LSTM algorithm for evaluation.

The architecture of the utilized NN is a double layered LSTM model, where the first layer contains 100 units followed by 20% dropout rate and a second layer of 50 units and 20% dropout rate. The last network layer is a dense output layer of a single unit. The model uses a linear activation function, the mean squared error metric for the loss function and the mean absolute error metric for the LSTM's performance.

Once trained the model is loaded in a TensorFlow server (TFX). A TFX is a Google-production-scale machine learning platform, based on TensorFlow. It provides a configuration framework and shared libraries to integrate common components, needed to define, launch, and monitor a machine learning system.

7.2 Experimental Results

The presented experimental results of this section are derived through a cross-validation process, where the 5 run-to-failure datasets are split into 4 datasets for training and 1 for testing, producing all the 5 different combinations.

Table 1: Mean Absolute Error results derived through the cross-validation process.

	1st iter.	2nd iter.	3rd iter.	4th iter.	5th iter.	Average	Std.
MAE	59.92	67.8	42.76	81.67	82.91	**67**	14.8

As it is depicted in the Table the average Mean Absolute Error (MAE) is 67. Since the estimation is between 1 and 300 Product Cycles that means that our estimation is off by +-22%. However, as we observe in Figure 14 and Figure 15 as the machine approaches the end of life the estimation becomes more accurate.

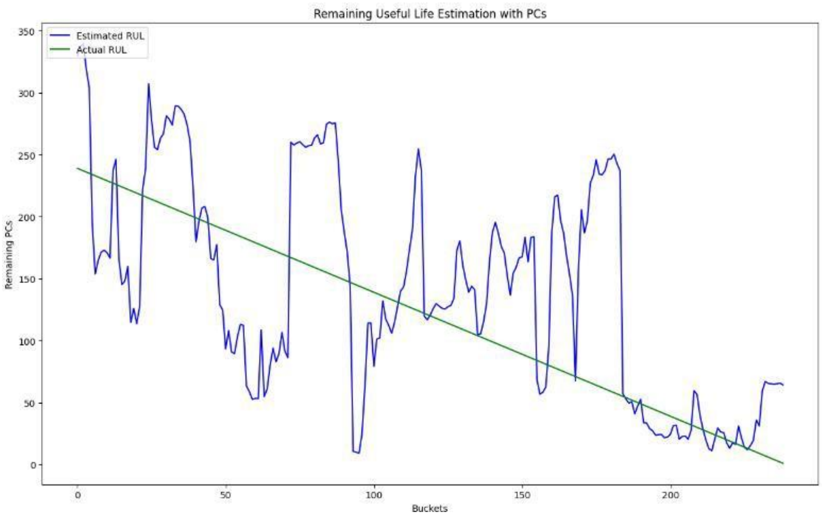

Figure 14 : RUL estimation result achieved on the 1st iteration of the cross-validation process. The green line indicates the actual value while the blue the estimated one.

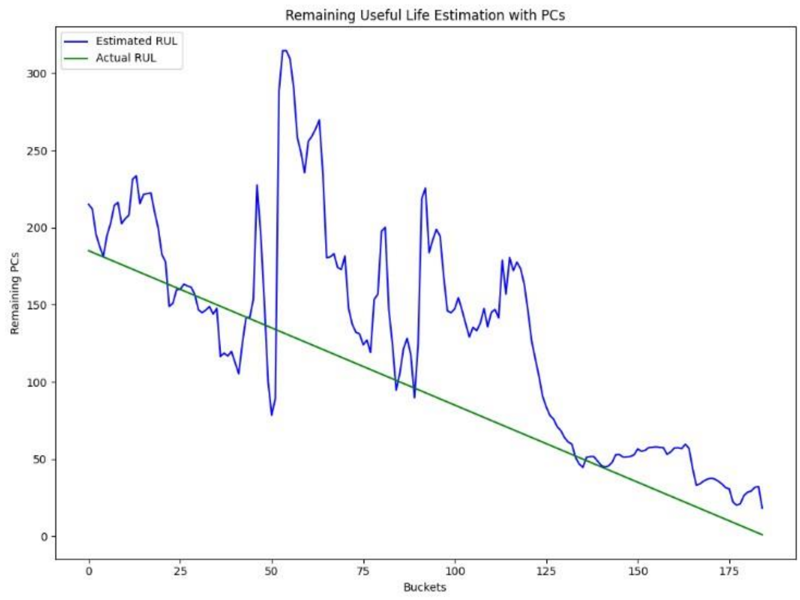

Figure 15 : RUL estimation result achieved on the 3rd iteration of the cross-validation process. The green line indicates the actual value while the blue the estimated one.

8 Conclusions

RUL estimation assists the maintenance departments to increase the efficiency of the planned maintenance process decreasing the downtime of the machines, by planning all the aspects of the maintenance well in advance. This work proposes a RUL estimation technique based on the LSTM algorithm, in combination with a data generation approach in order to over-sample the run-to-failure data, needed for the accurate training of the model. In order to provide results in the form of remaining PCs, an automated approach of PC detection is implemented based on the MASS algorithm.

The presented algorithmic solution was encapsulated into a predictive maintenance platform, offering a user-friendly graphical interface to the maintenance engineers in order to instantiate and monitor the RUL estimation process.

For the evaluation of the proposed approach, data from a real industrial environment are used and more specifically from a grinding machine. The results obtained from a 5-fold cross validation process, indicate that the model is able to learn the RUL based on the provided artificially generated data, especially when the machine approaches its end of life.

As a future work, as the production continues, the occurrence of more failure incidents will assist the generation of more accurate artificial data and RUL estimation models.

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Maintenance of Solar Energy Systems Using Autonomous Unmanned Air Vehicle with the Novel i-Sweeping Technology

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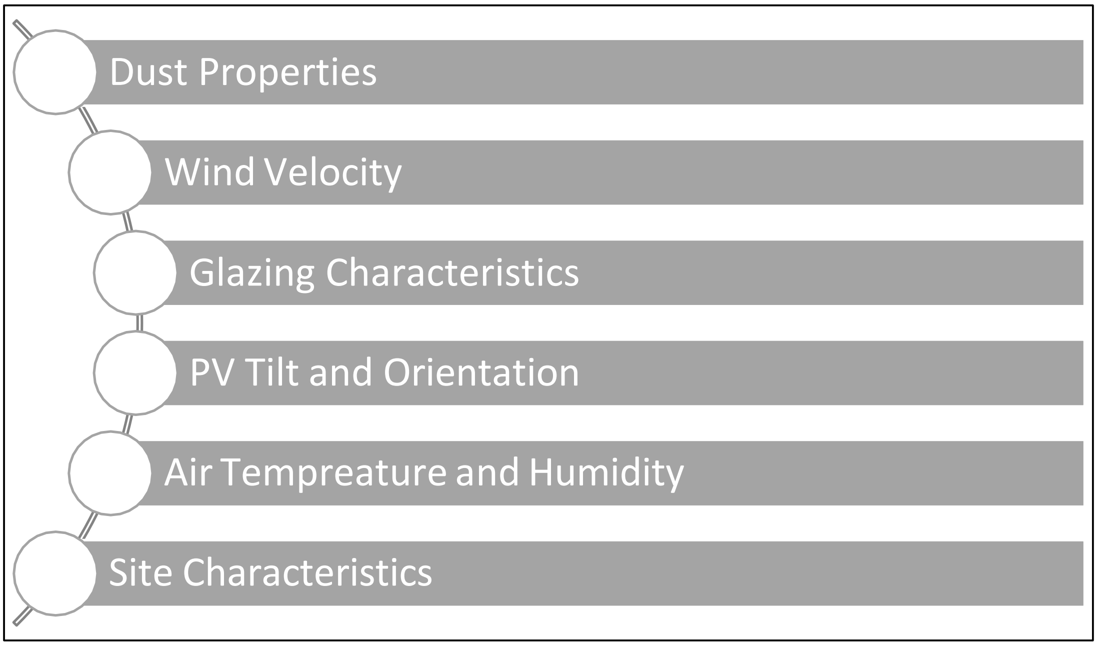
Abstract

Dust and hot spots are the most challenging topics facing the maintenance of solar systems including photovoltaic flat panels, concentrated solar power systems, and concentrated photovoltaic systems. This challenge raises especially for the companies providing aftersales services and the contractors providing maintenance guarantees. The cost of such type of maintenance in solar energy contacts is an important number added to the value of energy production. In dusty regions, like Saudi Arabia, this topic is mainly in the solar energy market and categorized in the same importance and priority with high-temperature challenges. The current paper discusses a novel technology owned by the German company Ressol Energy. The discussed technique uses the attraction force between ions to collect the dust on the surface of photovoltaic (PV) solar panels as well as the mirrors attached to the concentrated solar power (CSP) and concentrated photovoltaic (CPV) energy systems. The results show the improvement of energy production.

Keywords: solar, UAV, IoT, digitalization, cleaning, photovoltaic, concentrated photovoltaic, CPV, CSP

Introduction

A photovoltaic panel generates electricity from solar radiation. Photovoltaic panels consist of semiconductors, with the help of solar radiation it is converted into direct current. As this technology is pollution-free, renewable, and safe, it has achieved rapid growth in the recent past. Mega solar power plants have already been installed in different countries such as Australia, Middle East, the USA, Europe, and China He et al. [1]. Huge solar power plants are installed in deserts where the sun's rays are brightest at lower altitudes. On-site problems that are usually overlooked are bird droppings, dust deposition, and water spots, which reduce the efficiency of solar panels drastically. Also, there is a 10-25% reduction in efficiency due to losses in wiring, unit contamination, and inverter [3]. It was analyzed that dust accumulation mainly depends on the slope, direction, type of coating, surface roughness, etc. The factors affecting dust stability are shown in Figure 1. It is reported that the energy loss is large in the fixed horizontal panels, which is about 8-22%, then compared to the inclined panels (45 °C), here the losses are only about 1-8%. Also, other external factors such as humidity, temperature, wind speed, and regional characteristics such as traffic, air pollution, and vegetation play important roles in dust deposition. Moreover, the biological, electrical, and chemical properties of the dust, as well as the shape, size, and weight of the dust particles affect the accumulation of dust on the surface of the panels [4]. A large number of studies have been conducted on the process of dust deposition on PV modules. It is observed that the density of dust accumulation mainly depends on the angle at which the PV module is installed [5]. The penetration of sunlight through the glass cover of the PV module was hindered by dust deposition, which greatly affected the arrival of sunlight to the solar cell [6]. Energy loss due to pollution may vary based



on the physical and chemical properties of dust particles, and it may also vary depending on geographical locations [7]. The process of cleaning the solar cells will produce slurry residue due to sticky dust, cleaning fluids, etc. [8]. With the help of a wind cleaning process, Jiang et al. [9], concluded that the wind speed ranged from 0.82 m/s to 2219.8 m/s and that the ratio of shear speed to wind speed ranged between 0.04 -0.06. They calculated particle diameters ranging from 0.1 m to 100 m. Hussein et al. [10] did a comparative study of seven different types of dust samples on photovoltaic panels under the three different radiation levels such as 650, 750, and 850 W/m2. They note that the smaller particles block the more sunlight.

Figure 1: Factors influencing dust settlements [3]

Saidan and others. [11] I recommend that the scheduled cleaning of the solar panels is very important, otherwise, the impact size of dust will be too high. Margaret K. S. and others. [12] Discuss the robot cleaning system where the robot's control system consists of an Arduino microcontroller. Gayer and others. [13] He experimented to find out the effect of Mars dust particles on photovoltaic cells at varying wind speeds (23 to 116 m/s). The superb hyperbolic shell Polydimethylsiloxane (PDMS)-coated PV solar panels will reduce the efficiency degradation of solar panels by airborne dust [14]. Figure 2 [15] shows different dust removal methods for solar collectors. The dry-cleaning method removes dust particles from the surface, but the wet cleaning method has been observed to be more effective [16].

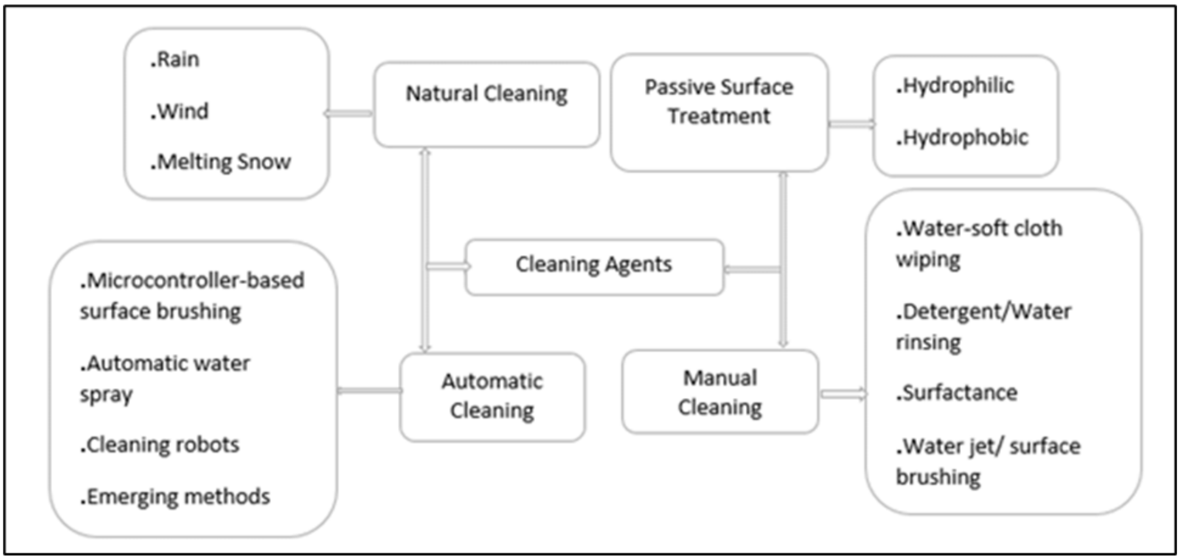


Figure 2: Different cleaning methods for removing dust from solar collectors [15]

Dust buildup on solar panels affects performance. As a result, it was observed that the performance of the PV panel decreased by up to 85% [17]. Compared with flat-panel PV, the 360° automatic cleaning and solar tracking system generate 30% more energy [18]. Both anionic and cationic surfactants are used to remove dust from solar panels. For the precipitated sand particles, the anionic surfactant is the most effective compared to the cationic surfactant [19]. Spraying water on photovoltaic cells increases the efficiency of the photovoltaic system [20]. Gheitasi et al. [21] He made an experimental setup consisting of a wireless sensor network to collect data on dirt levels from each solar panel. Then the robots clean the dirty plate system with the help of the collected data. Electric blinds can be used with standing waves to remove particles from the surface [22]. Carlson et al. [23] Studied inorganic hyperbolic coatings for self-cleaning surfaces. Chen et al. [24] Invented multifunctional coating with different properties from anti-reflective, ultra-hydrophobic, etc. to solar PV sheet glass cover uses TiO_2 / SiO_2 compound to reduce dirt accumulation [25]. PV panel tilt angle affects the density of dust deposition. dust deposition density ranges from 15.84 to 4.48 g/m2 [26]. Kao et al discuss the possibilities of anti-freeze coated surfaces that are ultra-waterproof and change surface texture. Jagila et al. [28] With their empirical analysis they calculated an average annual PV efficiency of 8.7% under outdoor conditions in Athens, Greece. To resolve cloud cover over photovoltaic panels Gandoman et al. [29] Suggest a model that has the advantage of supporting cloud cover throughout all seasons. Ganesh et al [30] highlight the peeling effect on self-cleaning surfaces. Due to the regional weather in Brighton in the UK, the effect of dust deposition on the solar PV module was found to be smaller. But the performance was greatly affected by the local problem of bird droppings [31], which would lead to lower efficiency. The performance of nanoscale solar cells decreased with an increase in air mass. They are about 94.18%, 81.86%, and 37.47% for direct, global, and diffuse solar radiation, respectively [32]. John and others. [33] Demonstrated anti-reflective and highly hydrophobic photovoltaic cells with large energy conversion efficiency using highly hydrophobic nanogram glass.

Methodology

As mentioned, and discussed in the introduction above, there are many technologies used to clean solar panels. On another hand, several factors can influence the accumulation of dust on the solar panels. The same situation can be applied to the CSP and CPV mirrors and lenses.

The research and development team of Ressol Energy Global was focused in its research on finding a cost-effective method to remove the dust efficiently. The concept of the current design was built on the physical phenomenon of ions' attraction force. Figure 3 shows the process, in which the dust particles coagulate to the positive ions to form heavier particles.

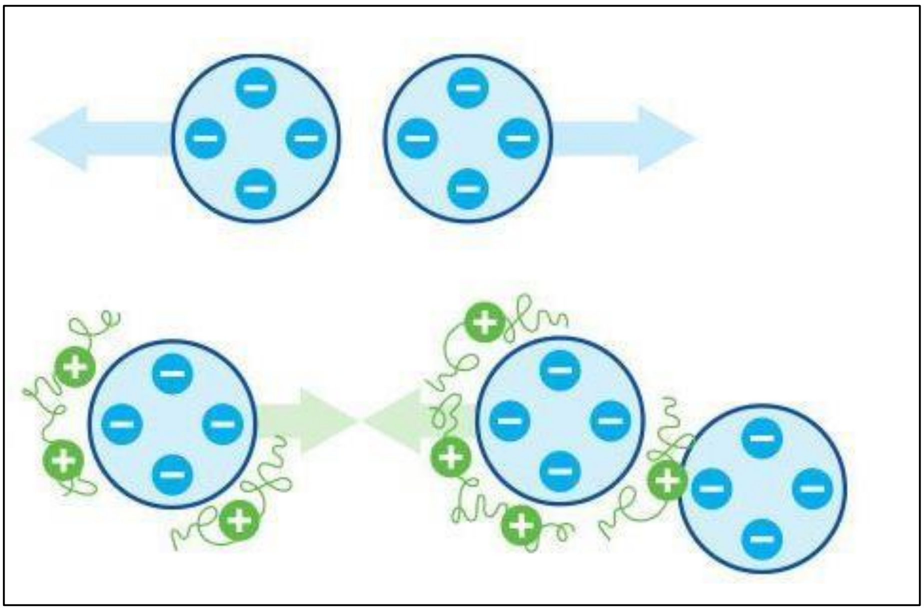


Figure 3: dust collecting process

The heavily positive ion content of the fluid solution made by Ressol Energy can force the dust accumulated on the solar panel to be swept into heavier flocs. The positive ions fluid is to be spayed by a big drone using the draft force produced by the rotors. Figure 4 shows the used drone. The injectors could be seen clearly under the propellers, where the double injectors are used.

The drone used in the experiment was produced in cooperation with the drones' company ***DJI.*** The drone can fly 3.8 km without recharging to cover a long range of solar panels at once. Furthermore, it can fly autonomously or remotely controlled. The high technical specification of the drone ensures a highly efficient cleaning process.

In further steps of the cleaning process, the flocs resulted from the physical reaction described above move downward. The motion of flocs is a result of gravity, surface properties, and tilt angle.

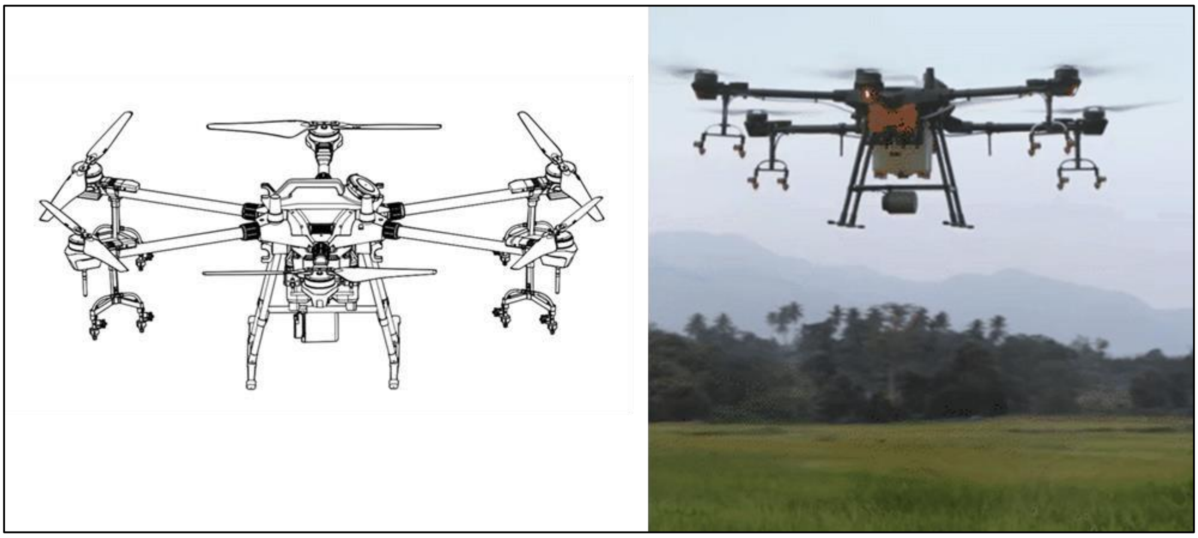


Figure 4: the drone used in the spraying process

The experiment was done to measure the effectiveness of the mentioned cleaning method is simple. A flat solar panel was subjected to natural dust covering in aggressive dusty weather conditions in North Africa. The energy production was decreased by 43% compared to the cleaned panel in the same position and under the same solar conditions. The drone flew over the panel at its rated speed and sprayed the fluid at a height of 30 cm of panel upper tip. The following figure 5 shows a side view of the experiment setup. In the following section, the results are shown.

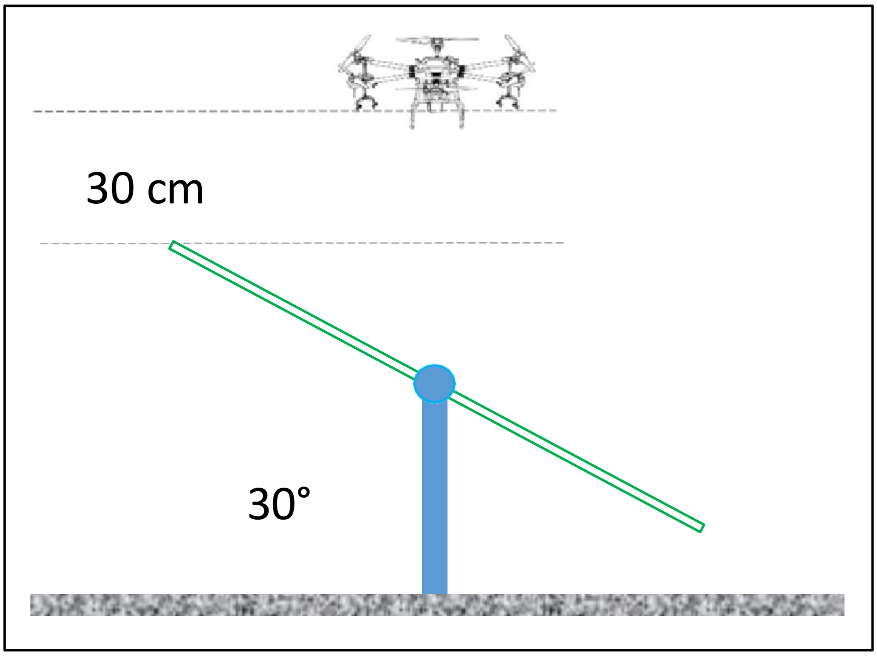


Figure 5: a side view of the experiment setup

Results

The mentioned experiment was done several times to ensure the correctness of the gathered data. The power production was improved by 52% compared to the power produced before the cleaning process takes place.

Conclusions

The present paper discussed a novel concept of cleaning technology developed by the research team of the German company Ressol Energy. The research was done in north Africa where the factors affecting the dust accumulation on solar panels are significant. The experiment was done in a repeating process to ensure the precision and accurateness of the readings.

The discussed technology shows an improvement in the production of energy compared to the uncleaned situation by 52%.

Since the product is already offered on market by Ressol Energy Global, the company took this research and development activity as further development over the old version of the technology. That opens doors for further research will be done shortly to bring this technology to the top of performance and to provide a significant research contribution.

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IMPACT ON PRODUCTIVITY BY WORKER FOR MAINTENANCE SITES OF UNIVERSITY HOUSING PROJECTS IN SAUDI ARABIA

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Abstract

Currently, the benefits of adopting and using building information Modeling (BIM) methodologies are still an issue that researchers have not fully explored in the design and construction phase. The cost associated with maintaining a structure is significantly huge, especially when a precise mechanism and methodology of care do not exist. On many occasions, the cost of maintenance is never taken into consideration during the design phase. Therefore, the research evaluates workers' efficiency to reduce the time to complete maintenance requests and work for more outstanding quality- at King Faisal University housing projects in Saudi Arabia. The study will use building information modeling BIM and studying the areas of weakness in the Extend program. There will be a need to access frequently used information hubs such as material, equipment, supplier, and maintenance history information. Therefore, to facilitate the operations and maintenance, each statement will be embedded in the BIM model to help convey prompt feedback. The studying anticipates that adding two experts shall increase efficiency in identifying the problem, guiding workers, and making a digital program to follow up on requests. It is also expected to increase worker productivity and reduce the time to solve University Staff housing maintenance problems.

Keywords: The Efficiency Of Workers , Building Information Modeling , simulation,

1. Introduction

The Kingdom of Saudi Arabia comprises one of the most robust construction sectors in the Middle East region. The rapidly growing construction industry results from increased domestic and public needs. The revenues generated from the oil industry benefited the construction industry. It was projected that the Saudi Arabian construction industry is expected to experience an accelerated growth rate for the next 10–15 years. An increase in the lifecycle of an installation calls for an increase in the build's age. It is achieved by building maintenance such as painting, plumbing, repairs, and sanitation.

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According to Addai (2017), facilities' maintenance and management are the practical and organized maintenance system of established activities to handle problems associated with the building's upkeep. However, building maintenance is not the industry's priority (CAT, 2020). Ensure that a building continues fulfilling its objectives while also appealing from its exterior is essential for maintaining the facility is a proposal by Sylva & Kulatunga (2018),

2. Literature review

Taraniuk, Kobyzskyi & Thomson (2018) give a varied translation of various categories of maintaining and managing the building. Irrespective of this, each of them explains that the process with multiple operations like planning, plans for implementation, control, support, decision-making, and many more is essential for carrying out successful procedures. To create more efficient onsite labor workflows, construction firms must use a standard data-backed formula streamlining a necessary impact of the workflow they can consult across all projects (CAT, 2020). The term manages and supervises an activity based on the owner's objectives, strategy, and economic principles (Lucas 2016). When analyzing various scientific-related articles from varied periods, Bhaskar (2016) noted that it is easy to identify development trends and the functions linked with a process. Management needs to review modulation techniques quicker and more efficiently, allowing individual elements to be constructed onsite.

Building maintenance is work to keep, restore, or improve each building section. It consists of maintaining the building performance fabrics, services, and surroundings to accommodate the building's standards and sustenance of utility and value. The second purpose is to ensure that facilities are fit for utilization. The third purpose is to provide the fulfillment of the requirements based on the statutory needs. Another goal is to ensure the maintenance of the necessary work to preserve the assets' physical value, while the fifth purpose is to provide the supervision of the building's quality.

Building maintenance and management usually share a relationship with innovative strategy and future sustainability (Lucas, 2016). Various work methodologies are incorporated when it comes to the performance of building maintenance and its management. According to Lucas (2016), two things are involved: managing the assets and building maintenance management. Cost evaluation of all aspects and the allocation of budget to attain their respective activities' success. Construction industry productivity rates rise when companies do not have to manage everything onsite; they must consider which construction components can be put together beforehand, fabricated in outsourced factories, and then transported to the build (CAT, 2020). Interior maintenance is keeping the internal sections of the building secure, pleasant, and usable. Factors like surfaces plus the finishing, windows, and doors, fixing of equipment, fire safety must be considered. Bhaskar (2016) identified preventive maintenance and stressed its vital roles. Hence, the best practices associated with preventative maintenance suggested are quite broad. Consequently, the second case is building the capabilities for ranking the maintenance projects and evaluating their respective costs (Bozorgi, Gao, Eastman & Self, 2018). An essential part of this framework is equipment management administration, which closely monitors the data generated from machine-installed software; it frees site supervisors to focus on the business and the overall operation (CAT, 2020).

2.1. Building Management Systems and Economics

Renovation and maintenance can be evaluated scientifically. The technique of arriving at decisions needs to be done to guarantee the house's normal functioning for its longevity. The idea behind the best housing maintenance cycle is characterized by its maintainability and defines repair and renewal state. They suggested a system of management regarding the safety of the building then highlighted in the paper. Therefore, the system entails several aspects: regulating the industry of government, laws linked with the building's management, and departmental leadership. Others include the technical specifications for regular evaluation of facilities, technical design standards, construction and maintenance of information systems on the building, measures linked with the emergency, and internet or intranet. It is also essential to include outstanding education on the building's safety, technical decision making, coupled with managing the facility. Lastly, project management software helps managers sequentially design, prepare and do onsite tasks, schedule daily tasks, and activities into appropriate project phases (CAT, 2020).

In their research in this field, it was established that often the planned preventive maintenance had high failure rates because of the poor management of information(Bozorgi, Gao, Eastman & Self (2018) and Pishdad-Bozorgi, Gao, Eastman & Self (2018). Management controls like budgeting, programming, costing, and reporting are challenges in implementing the contract's selection, procurement, and varied aspects of service contracts and agreements. Housing maintenance and paying attention to buildings repairs have recently employed three-dimensional modeling. Information management for building maintenance depends on action planning considered and the finalized work. The 3D model associated with the database connected with care creates a virtual environment that can be manipulated by parties with interest in consultation, creation, transformation, and evaluation of data to obtain results and arrive at decisions. 3D use is considered the main breakthrough towards the closure of the gap between the client's needs and what is seen by the designer as those constituting the client's needs.

Lastly, the use of BIM is one of the most significant breakthroughs in the construction sector. The tool can reduce rework by bringing high to a very high value to the project. Consequently, Architects have recommended the software because it improves productivity, as seen in their technology investment return. BIM significantly reduces conflicts in performing a task and when a change of design is necessary (Fadeyi, 2017). Besides, BIM provides preprogrammed portrayals of how a construction project should look across its entire lifecycle and provides a resource to check and follow a project's given schedule (CAT, 2020).

2.2. Building Re-engineering and work scheduling

Universities and other public facilities have been shared increased maintenance costs to improve the lives of buildings. Process re-engineering is an excellent strategy for cutting operational costs. Therefore, BIM use in University's building maintenance is likely to bring out the quality result. In our case study, BIM shall be employed for this purpose. Lucas (2016) states, "the private sector was efficient and effective in their service delivery because they applied re-engineering processes in building management." Work orders mainly drive maintenance operations. A logical work order reduces maintenance costs. As such, BIM use focuses on increasing maintenance operations efficiency.

3. Methodology

Staff Housing-288 Villas, located at King Faisal University-Hofuf in Saudi Arabia, is the research area. It followed the following overall scope- inputs, processes, and outputs, as shown below:

Inputs

- The use of some statistics from the MAXIMO program for maintenance operations during two years at the university
- Data to be collected by using both structured and semi-structured form of the interview guide to get primary data.
- Use secondary data that shall be obtained from published articles like websites, newspapers, journals, and books.
- Case study on Staff Housing-288 Villas located at King Faisal University-Hofuf, at the moment is under construction and maintenance.

Processes

- Use of BIM simulation to sort the data by (extend) program
- Data analysis can establish any weaknesses, identify improvement opportunities, and analyze all available assumptions attached to employee inefficiency.
- Use of simulations for the optimization of resources.

Output

- Maximum performance of the whole maintenance period due to efficient work order process and increased productivity among workers.
- Optimal utilization of resources, maximize asset administration.
- Completed maintenance projects and leverage construction technologies for more efficient fleet management.

3.1. Input

I plan to achieve my goal by using the following two inputs: previous works and a case study at University-Hofuf in Saudi Arabia. The techniques on how other studies are used will also be taken into consideration. The primary data used in the investigation shall have its collection done by using a structured and semi-structured form of the interview guide (Terrell, 2012). The permission to conduct this project will also be sought from the University's vice-chancellor.

3.2. Process

For the maintenance process to occur, there will be the need to award contracts to a contractor. The BIM software will also be procured. The right staff will be put in place to run the software to supervise the project through simulations to enhance monitoring, managing, and controlling resources. The use of BIM shall be essential in reducing the project's complexity that directly affects time, performance, and cost. BIM adoption challenges include; low availability of skilled staff, the high price of BIM implementation, and construction managers must determine if necessary to complete a project efficiently. If implemented, BIM software creates 3D visuals that provide clarity on the product to various stakeholders, thus providing them sufficient visibility of the practical challenges (Dashore, 2020).

3.3. Output

Upon analyzing the results we get from the studies, we will compare what we will obtain after applying BIM software and the old maintenance methods. In this manner, we shall establish the optimal scheduling that gives the best yield. BIM guarantees a better certainty of the end product over traditional CAD technology and helps the user check on a project's progress across all construction project operations (Dashore, 2020). Figures 2.4 and 2.5 below shows typical logical work order process flow that may be adopted by the university management:

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4. Data Collection

The primary data used in the study had its collection done by the use of a semi-structured form of the interview guide. The structured questions were preferred to save time, costs, and for the sake of ensuring easy analysis because the questions were in their immediate nature. On the other hand, according to Knowles & Cole (2008), unstructured questions assisted in encouraging the respondents to give detailed and felt feedback without hiding any content of information. Again, there was the supplementing of the primary data with the secondary ones obtained from published articles like websites, newspapers, journals, and books. The respondents that were of the target during the study were four senior site contractors involved in the re-engineering and maintenance work at Staff Housing-288 Villas in King Faisal University-Hofuf in Saudi Arabia. The research first asked for permission from King Faisal University-Hofuf's Vice-Chancellor before embarking on the process of collecting data. This is done by writing an introductory letter to King Faisal University-Hofuf University,

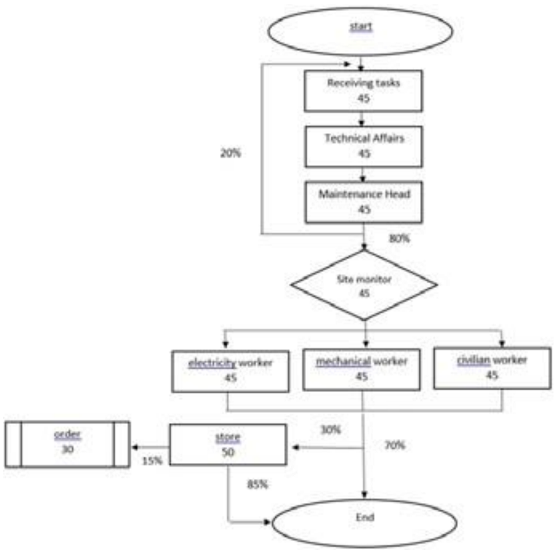

Figure 2.4: A typical logical work order process flow

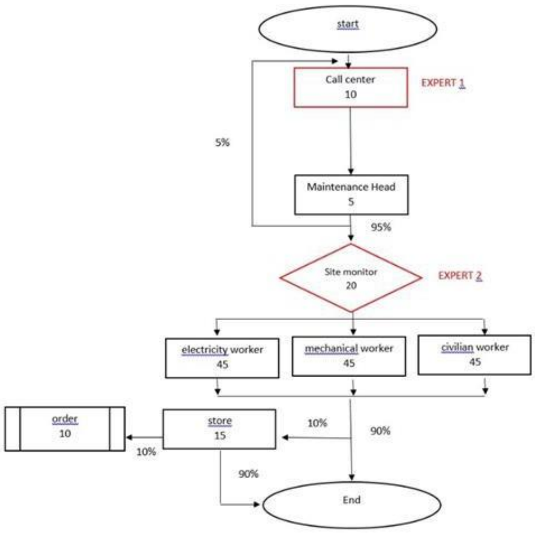

Figure 2.5: A typical logical work order process flow As Propose to add 2 Expert

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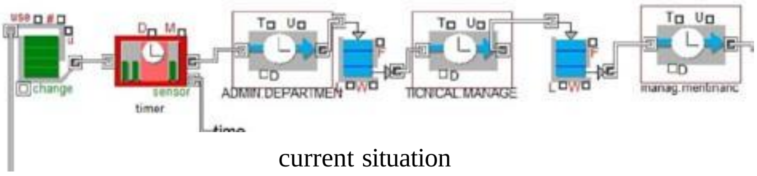
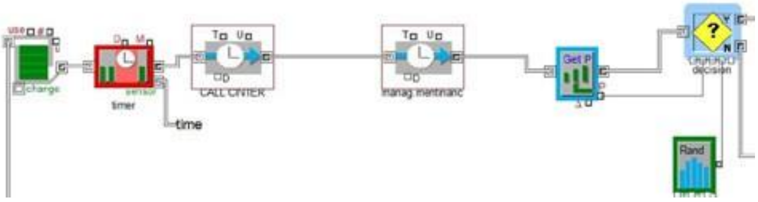


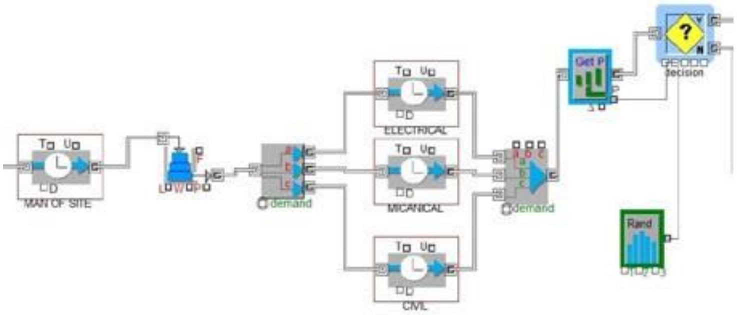
current situation



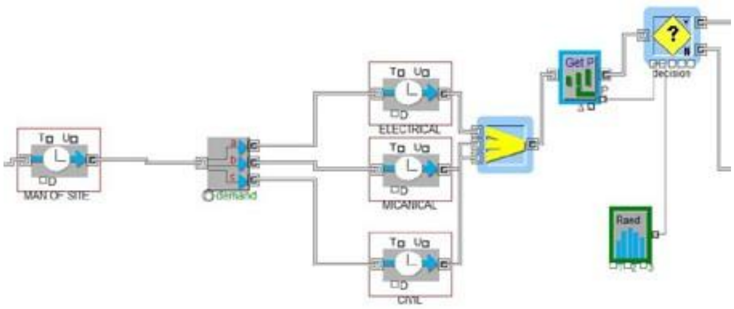
proposed situation

In the current situation / the process of receiving transactions is done through administrative communications (incoming and outgoing section) and this section is working on studying transferring the transaction to the Technical Affairs Department, which in turn is studying the transaction and transferring it to the maintenance department.

In the proposed situation / the process of receiving transactions is done through an expert in maintenance, a contact is received and a work order begins and all the details needed by the maintenance department are identified, which determines the location of the problem,



current situation



proposed situation

In the current situation / the problem is examined by sending a team of workers through which the problem is studied and then a description of the problem is written and then the problem is transferred to the supervisor to provide spare parts and then the maintenance process is completed and work is finished.

In the proposed situation / the transaction examination process is carried out through an expert 2, where the work order is read according to the description of the problem and then go to the site to determine the spare parts and determine the method of repair and also the competent department to finish it according to the technical principles

1. Findings

NO	current situation	Mission time by MINUTES	UTILIZATION	proposed situation	Mission time BY MINUTES	UTILIZATION	NOTE
1	Receiving tasks (Administrative Communications)	45	0.86	Receiving tasks BY call center (EXPERT 1)	10	1	
The paper system is used through the outgoing and incoming department, which is not technical in an administrative employee. Administrative matters are used only to transfer transactions. Simultaneously, a communication base, an expert person, and a model have been set up to receive maintenance requests via a unified number, which conveys the problem, identifying all requests, preparing orders, and describing problems, and 100 have been exploited. % According to the results in the program							
2	Task Transfer (Technical Affairs)	45	0.86	NO NEED - JUST REPORT	0	0	
The paperwork is transferred here to the Director of the Technical Affairs Department, which increases the workload on him and takes 86% of his time to study the issue and then sends it to the concerned department, while this procedure was canceled in the proposed situation and only a report was sent to him for follow-up and knowledge, which increases his production efficiency in Other business							
3	Maintenance Head	45	0.86	Maintenance Head	5	0.49	
Through the current system, the transaction is transferred to the head of the maintenance department to start the study, determine the problem and its location, and study the transaction. In contrast, in the proposed situation, the transactions are sent by the expert on them with all the data to study the possibility of their implementation and refer them to the competition area. This gave more generous access to transactions. More, the occupancy rate is now only 49%. There is time to end administrative work or receive additional requests that increase productivity.							
4	Decision 1	80% ok and 20% back		Decision 1	95% ok and 5% back		

We note here that the current situation was the percentage of inquiries up to 20%, while after the organization and the presence of an expert person, the data is completed, leaving only private or legal inquiries for the possibility of working according to the concluded contract, as the inquiries do not exceed 5%							
5	Site Monitor	45	0.21	Site Monitor (EXPERT 2)	20	0.98	
Here, the task of the site supervisor, who was only working to send the team of technicians from all disciplines and study the site each according to its specialty and determine the problem, was transferred to an expert person with experience to be examined when needed, then determine the materials and the person responsible for the repair process, along with providing him with the method of repair. Through simulation, the percentage of expert employment was 98%, unlike the previous one, which was only 21%, which contributed to the speed of completion and accuracy of work and complementary follow-up.							
6	electricity worker	45	0.96	electricity worker	20	0.41	
In the previous case, the employee's utilization rate in the task was 96%. At the same time, after re-engineering operations for maintenance orders, greater accuracy occurred. The worker's occupancy rate was 41%, which gives the worker a more remarkable ability to complete a more significant number of transactions.							
7	Mechanical worker	45	0.96	Mechanical worker	20	0.41	
In the previous case, the employee's utilization rate in the task was 96%. At the same time, after re-engineering operations for maintenance orders, greater accuracy occurred. The worker's occupancy rate was 41%, which gives the worker a more remarkable ability to complete a more significant number of transactions.							
8	Civilian worker	45	0.96	Civilian worker	20	0.41	
In the previous case, the employee's utilization rate in the task was 96%. At the same time, after re-engineering operations for maintenance orders, greater accuracy occurred. The worker's occupancy rate was 41%, which gives the worker a more remarkable ability to complete a more significant number of transactions.							
9	Decision 2	70% ok and 30% back		Decision 2	90% ok and 10% back		

In the current situation, the need for materials is known by the workers. However, after studying the situation, the spare parts are determined by expert 2, who is familiar with the method of solution and the materials needed to finish the work.							
10	Store	50	0.35	Store	15	0.05	
In the current situation, a paper form is made, and it is done by the method of administrative procedures for approvals to exchange spare parts, but through the proposal submitted, all operations are done electronically, which works to determine the existing spare parts that require making a purchase order with a final inventory							
11	Order	30	0.04	Order	10	0.018	
In the current situation, the purchase requisition processes are carried out via an advance and require paper procedures and approvals of the authorized holders. In the proposed situation, approvals are made electronically and do not require effort to find out the problem. There is a technical report by experts to describe the problem with the availability of materials in the warehouse or request additional materials. According to the technical opinion of it							
	Average time to complete the work	621.55 MINUTES / ORDER		Average time to complete the work	272 MINUTES / ORDER		
We note that the time to complete the process in the past is about 621 minutes, either through the process of re-engineering operations and adding experts two and improving the distribution of tasks with the same previous technical and administrative staff contributed significantly to reducing the time to finish work to 272, which means about 60% so that now a more significant number is accomplished Of transactions in addition to the presence of technical reports to contribute to future reforms while preserving a copy of the preventive maintenance operations and also for the technical body responsible for maintenance work.							

2. Discussion and conclusions

Tracking of the maintenance operations may be quite hectic. To manage operational costs associated with maintenance, BIM could help enhance work order practices' efficiency and accuracy. However, it is prudent to note that it will only be effective if operated by the right people with knowledge of using it, just like any other software. No matter how useful BIM can be, university management is likely to face accessibility problems.

- Diagnostic expert: the webmaster manager must see the problem and identify when there is a lack of clarity in locating the problem and visiting the problem location. The diagnostic expert must also make a corrective decision and treatment by identifying the type of workers, mechanisms, tools, and the time of repair for the problem to determine the pain when they need to make several decisions depending on the problem's type and size. The investigation of upkeep activities and the development of exchanges made accessible by straightforward arrangements come noteworthy outcomes as it decreased the administration conveyance by just two changes by 60% comparable to tending to the advancement of work productivity on the site, and it likewise straightforwardly adds to enormous arrangements through fundamental changes and handy arrangements that add to offering Faster support, more prominent quality and lower cost, by utilizing crafted by an electronic framework to get issues and furthermore to characterize the issue all the more decisively and to dispense more work materials and the term of work and the quantity of laborers, which has become the work under the oversight and those with industry resources and the guidelines of an accomplished manager, notwithstanding similar staff and similar Mechanisms and techniques for arrangement just an association has been made to move the exchange precisely and rapidly to the concerned division and the capable specialist to make the administration simpler. We recommend that an incorporated connection be made between offices, chiefs, stockrooms, and buys about crafted by a framework that offers more to offer the assistance with full fulfillment to the recipients and incredible reserve funds.

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SMART WATER DESALINATION: DIGITAL TRANSFORMATION APPLICATION

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Abstract

Industries across the world are realizing the benefits of Industry 4.0 and digital transformation. The University of South Carolina (UofSC) has been using digital transformation to transform processes in multiple industries and has defined a clear roadmap for implementing digital transformation that has been validated by use cases. UofSC has partnered with The British University in Egypt (BUE) to develop a framework for applying digital transformation to advance the water desalination industry. This collaboration utilizes BUE's experience in design and manufacturing of physical systems such as a high-pressure pump and UofSC's experience in applying digital transformation to industries and developing digital twins of systems.

Keywords: Digital Transformation, Water Desalination, Industry 4.0

1 Introduction

Fresh water shortage is threatening development and prosperity in many Middle Eastern countries, as well as several areas in the United States. Sea water and ground water reverse osmosis desalination is fast becoming a dominant technology for facing water shortage threats by cost effective production of fresh water for multiple purposes. Water desalination applications extend not just for desalinating drinking water, but also impacts various types of industries. With the rapid growth in the pharmaceutical industry, desalinated water is used for drug testing and diluting certain solutions, and in the oil and gas industry, fresh and low salinity water supplies are essential for enhanced oil recovery (EOR) applications. Offshore and onshore petroleum platforms in remote areas require gallons of freshwater every day, while shipping to these platforms is costly and inefficient. Furthermore, low salinity water injection is required to maintain reservoir pressure and stabilize the production rate. Consequently, on-site water desalination technology can benefit the oil and gas industry as it is efficient and less expensive.

This paper will present a methodology for applying digital transformation and the impacts it can have on the water desalination industry. The next two sections of the paper present an introduction to digital transformation, industry 4.0, and the water desalination industry. Following is the methodology developed by UofSC for digital transformation and a water desalination use case focusing on a single component, a high-pressure pump, will highlight the challenges and outcomes of digital transformation. Future work could include the expansion of this use case to additional components, subystems and systems.

2 Digital Transformation and Industry 4.0

Digital transformation is more than just a singular tool, it is an entire process that takes advantage of new technologies and techniques such as artificial intelligence and augmented reality while also utilizing and optimizing the human factor in a workflow. It is a shift in the way people think about technical challenges that combines systemic problem-solving, cost-reduction, product creation, and decentralization to approach the problems of the future with new methods, new mindsets, and a finely tuned drive to do better. Implementing digital transformation will lead to a decrease in cost, a decrease in time spent, and an increase in overall quality. An effective digital transformation implementation is not only about using state-of-the-art technologies but also includes the training and education of all users.

The following technologies are key to the successful implementation of an industry 4.0 or digital transformation program.

- **Cyber Physical Systems:** Integrated computational and physical capabilities
- **Internet of Things:** Network of physical components that are digitally connected and can sense, monitor, and interact
- **Digital Twin:** Developed in conjunction with its physical twin and remains its virtual counterpart through the whole product lifespan

- **Virtual Reality/Augmented Reality:** Can be used to mimic and simulate real-life scenarios that are either expensive or challenging to conduct
- **Cloud Computing:** Model for enabling on-demand network access to a shared pool of configurable computing resources
- **Simulations:** Computer-based technologies focused on explicit and specific modeling tasks

In addition, there are 5 key challenges when implementing industry 4.0 and digital transformation technologies. These challenges include:

- **Integration:** Data is key to an Industry 4.0 or Digital Transformation program. It is necessary to incorporate data from multiple sources to support preliminary connectivity. There is also no one size fits all approach to implementing an Industry 4.0 program.
- **Control:** Industry 4.0 requires the connection of every sensor, actuator, PLC and other elements. It is important to ensure that there is a secure and reliable method for transferring data in place and to allow for analysis in real time. This also requires reliable internet and wireless connections to facilitate these transfers.
- **Communication:** How to create an appropriate model for secure communication and interaction between autonomous agents (with different operating systems) that are all connected through an IIOT network?
- **Legacy Systems:** A main difficulty with the integration of Industry 4.0 into legacy systems is the availability and or accessibility of data to obtain information. Consequently, the communication infrastructure must be altered and improved to a more transparent architecture.
- **Cyber Security:** In the age of Industry 4.0, where machines and “things” are connected to the network and each other, the scale and variety of cyber-attacks have grown exponentially. Data rights concerns when deciding on third-party vendors for hosting and operating company data.

2 Water Desalination

Drinking water is considered a gift from nature to many countries. As the world population grows and consequently the demand for freshwater for urban, agricultural, and industrial use increases, so do the challenges arising from the need to meet global market demand with innovative technologies. Fresh water shortage imposes considerable threats and challenges for the development plans in many Arab and Middle Eastern countries. During the coming decade, it is expected that about two thirds of Arab countries are expected to suffer from acute water scarcity [1, 4]. Sea Water Reverse Osmosis (SWRO) desalination is fast becoming an inevitable solution for facing water shortage threats by cost effective production of fresh water.

2.1 Desalination Plant

The main components of a reverse osmosis desalination plant are illustrated in Figure 1.

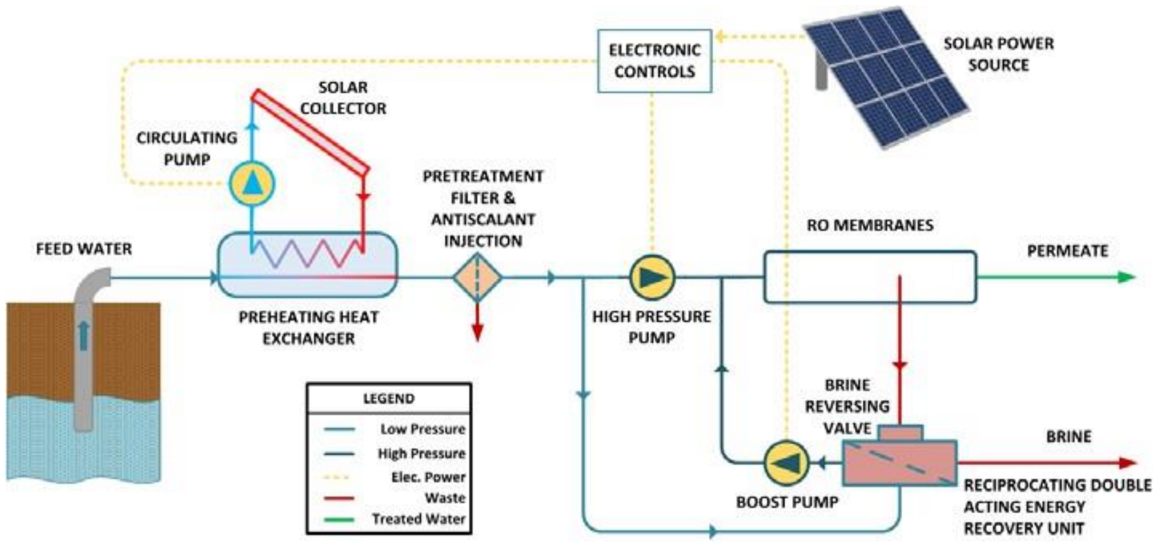


Figure 1. Key Components and Systems of a Water Desalination Plant

These components include:

- The energy source that is used to operate the desalination systems can either be conventional or renewable energy.
- The feed pump for the high-pressure pump should be a self-priming pump to protect from cavitation. It should also be in an accessible place below or above the waterline to allow for easier maintenance in the future.
- Pretreatment system is essential to pretreat the feed water from any suspended solids and make sure that microbial growth and salt precipitation is not taking place on the membranes surface. Pretreatment can include chemical feed followed by sand filtration, sedimentation, flocculation, and coagulation as conventional methods.
- High-pressure pump (HPP) is considered the heart and the essential mechanical element of the reverse osmosis water desalination system since the reverse osmosis (RO) is a pressure driven separation process as required feed pressure must go beyond the built osmotic pressure, increasing directly with water salinity. The HPP generates in the range of 600-1200 psi with seawater and around 150 psi for slightly brackish water that generated pressure supplies the water with the needed pressure to pass across the RO membranes and reject salt.
- Reverse osmosis membranes are a pressure driven separation process that is simple, economically competitive, and do not require phase change, which is particularly important for heat solutions sensitivity, such as pharmaceutical materials and food products. RO has become the primary desalination method in the United States and is capable of desalinating high saline feed water. There are two common RO membrane types for water desalination: Spiral wound and hollow fiber. The spiral wound membrane is widely used in desalination more than the hollow fiber membrane. The advantages of reverse osmosis are considerable:
    1. Capable to waters with any saline content, from groundwater to seawater.
    2. Relatively low operating costs compared to resin plants, especially in the presence of influential high salinity.
    3. The simplicity of operation is a process that does not require periodic regeneration as occurs in resin plants.
- Post-treatment at this level, water is getting to stabilize and getting to prepare for distribution. Disinfection and adjusting the alkalinity, hardness, and pH are necessary if combined with other water supply sources to meet up with the drinking water standards and prevent any corrosion effect in the distribution network.

2.2 High Pressure Pump

Pumps are mechanical devices that converts mechanical energy into hydraulic energy. They are divided into two main types the positive displacement pumps such as piston pumps with industry market share of 27% and rotodynamic pumps such as centrifugal pumps with industry market share of 73%. Typical pressures for SWRO desalination are in the range of 50 – 80 bar. High-pressure pumps (HPP) have a critical role in an SWRO desalination plant. The role of the HPP is to raise the pressure of the feed flow to allow for the permeation process through the RO membranes. Maintaining the HPP and working under healthy conditions keeps the desalination plant running smoothly, this is crital as fresh water is vital to maintain human lives. The use of the centrifugal pumps is 16% among all the rotodynamic pumps and their area of applications are continuously expanding [5]. With the continuous expansion of centrifugal pumps usage new problems will exist, proper pump selections are essential as it can avoid/prevent problems that may occur. improper pump selection leads to several operating problems such as cavitation, flow discontinuity, pump surge, etc.

Either single-stage or multi-stage centrifugal pumps prevail the desalination plants for feeding and pressurizing the feed stream. Common problems experienced by centrifugal pumps such as cavitation, water hammering, sludge, high-pressure pulsation, excessive power consumption, and other mechanical and hydraulic failures may be attributed to one or several probable causes. Low suction pressure and low flow rate problems can be attributed to either air leaks in inlet piping or a faulty mechanical seal [1]. Centrifugal pumps cavitation can also lead to the same problems. Excessive lateral or axial vibration and noise can also be attributed to either pump rotor misalignment, excessive axial thrust or cavitation and reduces the pump efficiency.

2.3 Fault Detection

Fault detection improves the system reliability, safety, energy, and cost-efficiency, extends the pump lifetime and performance, achieves the efficient maintenance strategy, and reduces occurring unpredicted events that can lead to system shutdown and breakdowns. Early fault detection and diagnosis are essential to ensure cost-effective and safer operation to avoid performance degradation, unpredicted maintenance events, product deterioration, minor and major damage to the physical system, damage to human health, or even loss of lives. This paper focuses on one type of fault which is the cavitation as a use case due to its frequent occurrence. Many papers have been done fault detection in the pumping system based on speed variation and vibration details using signal processing and statistical models or based on machine learning algorithms that identify the cavitation using speed and pressure historical data [6, 7].

Cavitation can be considered as a major cause for centrifugal pump failures. In the first phase of cavitation, vapor bubbles are formed around the pump's impeller in areas of relatively low pressure below the associated vapor pressure of the working fluid. While in the second phase of the cavitation, the collapse of these bubbles allows the triggering of intense shockwaves leading to high-speed fluid particles impact causing significant pitting and erosion of the internal pump parts [9]. Cavitation is a main source of centrifugal pumps health and performance degradation. Several researchers employed CFD analysis [1] to detect cavitation and evaluate its effect on the rotor and the pump's casing, which allowed the minimization of the experimental investigations.

Cavitation analysis is performed at different operating conditions including different pump speeds and flowrates. The detection of bubbles formation by CFD analysis is performed by allocating the zones where pressure is lower than the associated vapor pressure of water. Figure 2 presents a flow field visualization at the suction side of a centrifugal feeding pump impeller-diffuser arrangement where symptoms of vapor bubbles formation at the leading edges of vanes are shown [1].

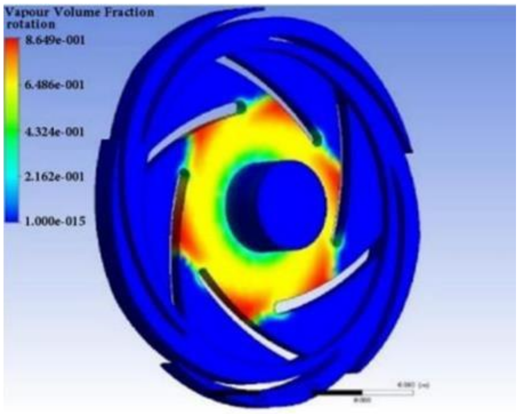


Figure 2. CFD Cavitation Zones Detection [1]

3 UofSC Digital Transformation Methodology

The University of South Carolina is continuing the development of an end-to-end methodology, shown in Figure 3, that leverages computer aided design and manufacturing, sensing systems, data and physics-based models, fault prediction and diagnosis and data visualization to create a virtual asset management toolbox.

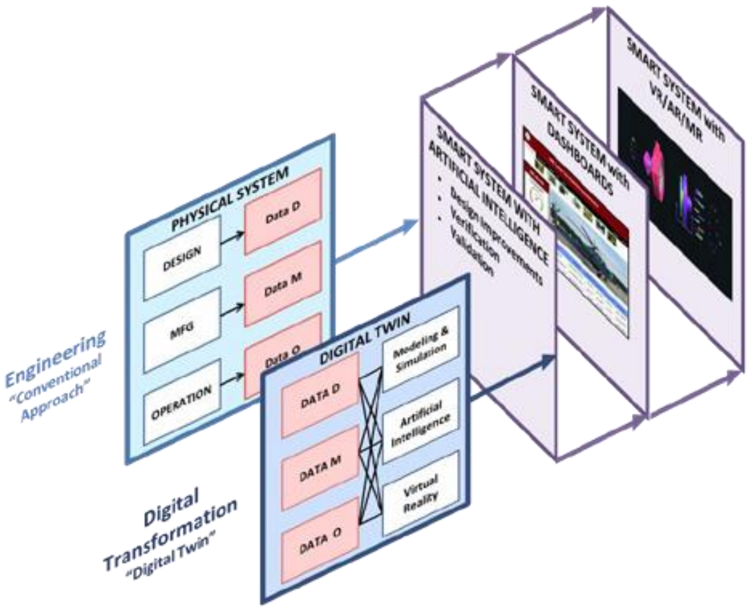


Figure 3. UofSC Developed Digital Transformation Methodology

Varying types of analysis can be performed to look at areas such as fault detection, prognostic/diagnostic algorithms, power usage metric, cost benefit analysis and fault analysis. This toolbox consists of cyber-physical systems to recreate a digital twin in any area of interest. This approach can be used to better maintain the integrity of processes and products at any stage of a component's life cycle.

There are three types of data associated with a physical system: design, manufacturing, and operational. The data is collected and analyzed at the different stages of a systems life cycle and can be used to make various improvements. The data collected from the physical system is then used to create the digital twin of the system. In this stage of digital transformation, how the data is collected is important to consider. The optimal type, location and number of sensors needed must be identified.

When used in parallel, a physical system and digital twin create a smart system. This smart system can be useful in many areas from design improvements, verification, validation, monitoring, and even improved productivity. This smart system is key to digital transformation and is built on the data collected and models developed. In addition, a smart system can have many ways of displaying data depending on the need.

3.1 Use Cases for Validation

The above methodology has been validated on use cases with application in multiple industries including:

- **Healthcare:** Digital transformation was used in the healthcare industry to address the need of monitoring premature infants. A framework for collecting infant data, conducting analysis in real-time, and presenting this information in easy-to-read dashboards was developed.
- **Automated Fiber Placement**: The application of digital transformation to the AFP machine was needed to enhance capabilities, refine processes, and create overall improvements. The developed use case demonstrates a framework for applying new technology to legacy equipment and addressed problems in the areas of data collection and modeling, training, and fault detection. Digital transformation elements included augmented and virtual reality, machine learning, and thermal modeling.
- **General Machinery (Apache Gearbox):** This use case showcased the flow of data from collection to analysis to presentation. The data collected includes sensor data such as vibration, temperature and torque, logistical data from maintenance records and manuals, and human knowledge from past experiences. This data is then analyzed with the intermediate gearbox model to create predictions and recommendations on the gearbox. The analysis is presented in the form of custom dashboards that are tailored to fit the needs of different users.

4 Application of Digital Transformation to Water Desalination

Digital transformation can be used to address the challenges faced with fault detection of components in the water desalination plant. For this use case, the focus will be on a single component of a single system – the high-pressure pump found in the reverse osmosis system. Elements of the digital transformation used will include digital twins, machine learning, and interactive dashboards.

4.1 Physics-based Digital Twin of High-Pressure Pump

Digital twin is the virtual representation for the physical systems. This virtual representation can be representing the physical system dynamics and the products [12]. The digital twin can achieve based on one digital model or combination of digital and mathematical models, such as computational fluid dynamics, finite element analysis, thermodynamics, kinematic, dynamic, and machine learning models. These models can be simulated or experimented with real-world data [14]. The digital twin is used to simulate and generate data under healthy environmental and harsh conditions and properties, shuffling these generated data with the real-world collected data to improve the digital twin accuracy. Using digital twin helps decision-makers better understand the system and improve and optimize the design, manufacture, health monitoring, and performance. Digital twins can also be used in predictive maintenance by generating sets of faulted data under different harsh conditions and integrating them with machine learning and real-time control algorithms to teach the physical system to detect and classify the faults in real-time and react accordingly to each type of failure. Augment digital twin model in the predictive maintenance area aims to predict and prevent future faults from occurs [1]. In our research paper, the machine learning model and saw-tooth model will be integrated together to detect cavitation and implement more unsupervised algorithms to the machine learning model to generates several faults data sets and classify the fault severity. For example, our use case in this paper is the cavitation fault the machine learning model will be able to classify what type of cavitation based on the location of bubbles implosion, the location of the cavity inception, and the difference in the frequency range. After integrating the HPP digital model together and achieve HPP digital twin move forward to the following water desalination system components such as the RO membranes to the next element. When each component has its own digital twin, start to connect all these digital twin models to achieve a smart water desalination plant; after that, it combines more than one plant to be monitored from one dashboard.

The following are the steps to build a digital twin:

- Understand the physics that governs the operation of the physical system (pump)
- Determine the input/output variables (that can be measured) and the design parameters that control the performance
- Build physics-based digital models to simulate the pump behavior under healthy environmental and harsh conditions and to detect and predict the future faults.
- Interconnect the physical system (pump) and its digital models

4.1.1 Models of Cavitation Pressure Pulses in Centrifugal Pumps

The paper presents two different fault detection digital models one using the saw-tooth model that can express the excitation of the centrifugal pump under cavitation with Fourier expansion and describe the periodic function with combination of sine and cosine waves instead of transfers the real-world data from time domain to frequency domain which made this model more cost and time effective. As the pressure pulses within the diffuser tongue region can be modeled as a sawtooth wave, each pressure pulse acts on the blade's projected area, resulting in a periodic exciting force on the rotating impeller. Each blade projected area has a zero value at both the beginning and the endpoints of the blade-diffuser interaction region. Therefore, it can also be approximated in terms of another saw-tooth wave. The saw-tooth digital model was successfully integrated and tested with the physical system, and it showed its accuracy, as shown in the section below. The second cavitation detection model is a machine learning model that integrated three machine learning algorithms-- the support vector machine, k-nearest neighbors, and logistic regression. The data analysis is based on millions of real-world historical data points that are processed from mounted sensors on the physical system, the data were mainly collected from six different parameters vibration sensors, dynamic and static pressure sensors, and flow rate sensors. Based on this machine learning model, potential cavitation faults are successfully classified and recognized, ensuring 99.5% prediction accuracy after preprocessing and training 80% of these data sets and testing the 20%.

Pressure pulsations developed due to cavitation in centrifugal pumps were investigated experimentally by several researchers [2, 3]. It was reported that interaction between impeller blades and the diffuser results in pressure pulsations dominated by the Blade Pass Frequency (BPF) times the number of diffuser tongues [2, 4]. These pressure pulsations are converted into periodic force pulsations affecting the rotor as well as the casing of the pump through the impeller projected area. Ref. [1] presented an illustration that describes how blade-diffuser tongues interaction causes sudden changes in pressure over each blade. This sudden change in pressure is repeated five times which matches the number of diffuser tongues.

Equation (1) and Equation (2) presents the saw-tooth function that expresses the pressure pulses.

$$PP(tt) = 2.PPPPPPPP.tt/(TTTT) \qquad [0 \le tt \le TTTT/2] \tag{1}$$

$$PP(tt) = PPPPPPPP - 2.PPPPPPPP((tt - TTTT/2)/(TTTT)) \qquad [TTTT/2 \le tt \le TTTT] \tag{2}$$

Where; $PPPPPPPP$ is the peak value of the pressure pulse and $TTTT$ is the period of the pressure pulse.

Equation (3) and Equation (4) presents the saw-tooth function that expresses the blade projected area.

$$AA(tt) = (2.AAAA.nn.NN).tt \qquad [0 \le tt \le 1/(2.nn.NN)] \tag{3}$$

$$AA(tt) = (2.AAAA.nn.NN).\left(\frac{1}{nn.NN} - tt\right) \qquad [1/(2.nn.NN) \le tt \le 1/(nn.NN)] \tag{4}$$

Where; $AAAA$ is maximum projected area of the blade. nn is the number of the diffuser tongues and NN is the rotational speed of the pump c.p.s. where the normalized saw-tooth pressure pulses as well as the blade projected area during one revolution (1/ NN = 0.02857 sec) respectively. Equations (1), (2), (3), and (4) are combined to determine the periodic force acting on each blade due to its interaction with the diffuser tongues during each revolution at the cavitation condition

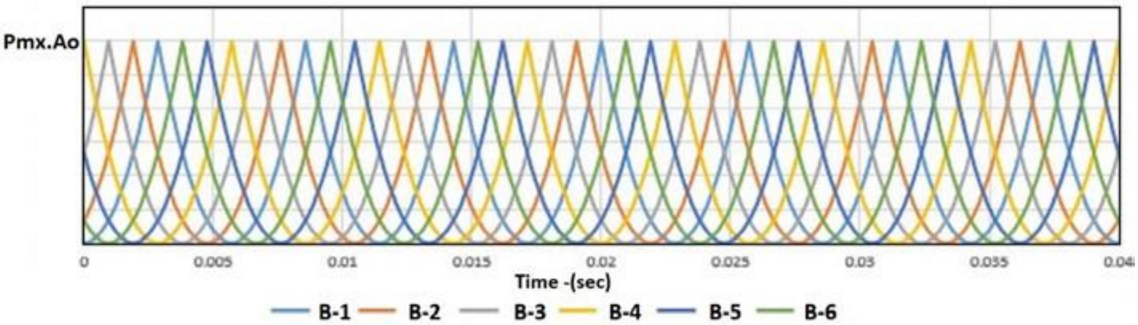


Figure 4. Normalized Forces on All Blades During One Revolution

Figure 4 depicts the normalized force pulsations on the six blades of the impeller, assuming that the first blade of the impeller is at a zero-degree angle and the six blades are equally spaced at $2\pi\pi/6$ rad (60-degree angle).

The summation of normalized forces on the six blades in time domain and frequency domain are shown in Figure 5 and Figure 6 respectively. The major frequency observed at 1050 Hz corresponds to the blade pass frequency (BPF) (6 x 35 Hz) times the number of diffuser tongues. It is worthwhile to note here that results of this pressure pulsation model agrees with experimental results obtained in [2, 4].

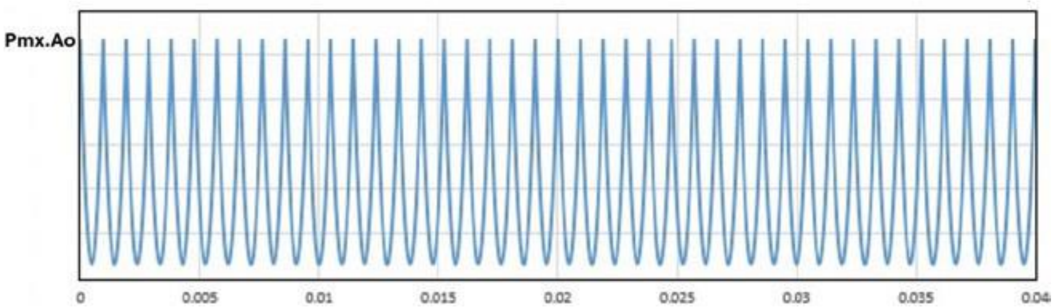


Figure 5. Time Domain of Net Pressure Forces on All Blades During One Revolution

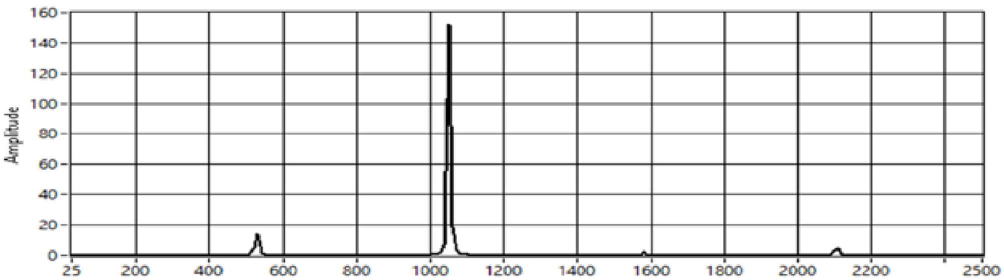


Figure 6. Frequency Domain of Net Pressure Forces on All Blades During One Revolution

4.1.2 Investigating the Vibration Response of Centrifugal Pumps Under Cavitation Condition

Models are derived to describe the vibration response of the rotor as well as the casing of feeding centrifugal pump under cavitation condition.
Equation (5) depicts the forced vibration of the rotor in matrix form.

$$mm.XX^{\circ\circ}(tt) + CC.XX^{\circ}(tt) + KK.XX(tt) = FFFF(tt), XX(oo), XX^{\circ}(oo) = 0 \quad (5)$$

Where; $XX(tt)$ is the state vector that expresses the rotor displacement in horizontal and vertical directions, CC is viscous damping matrix, KK is the stiffness matrix and $FFFF(tt)$ is the periodic exiting force vector that results from the cavitation condition. Table 1 presents the main specifications of the rotor under consideration [1]. Effectively the periodic exiting force acting on the rotor, results from the summation of all forces acting on each blade of the impeller. Accordingly, the horizontal component and the vertical component of the resultant force vector are given by Equations (6) and (7) respectively.

Part	Specification
Impeller	Mass=0.507 kg
Motor Rotor	Mass=2.264 kg
Motor fan	Mass=.04 kg
Rotor	Length=0.251 m

Table 1: Rotor Main Specifications

$$FFFFFF(tt) = FFFF(tt).ccoocc\,(wtt) \quad (6)$$

$$FFFFFF(tt) = FFFF(tt).ccssss\,(wtt) \quad (7)$$

Figure 7 and Figure 8 presents the normalized horizontal and vertical exiting force components on the six impeller blades in time domain and frequency domain respectively.

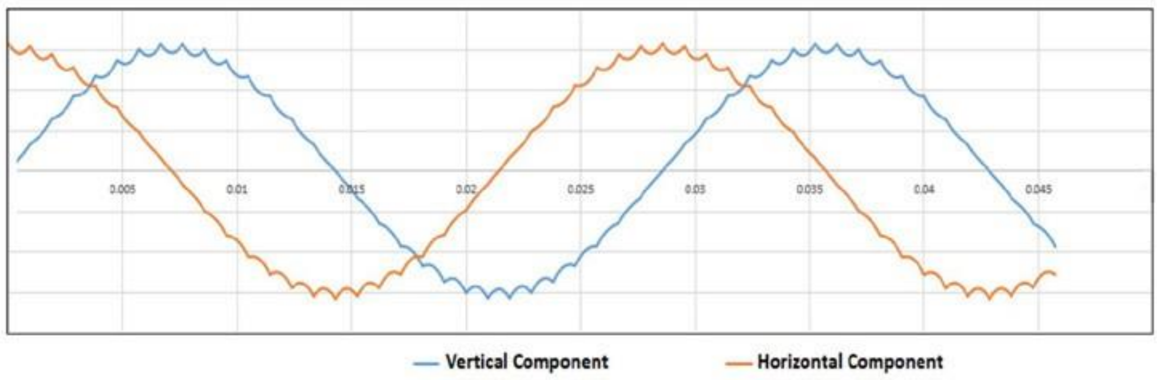


Figure 7. Normalized Exiting Force Components of Pump Rotor Under Cavitation Fault

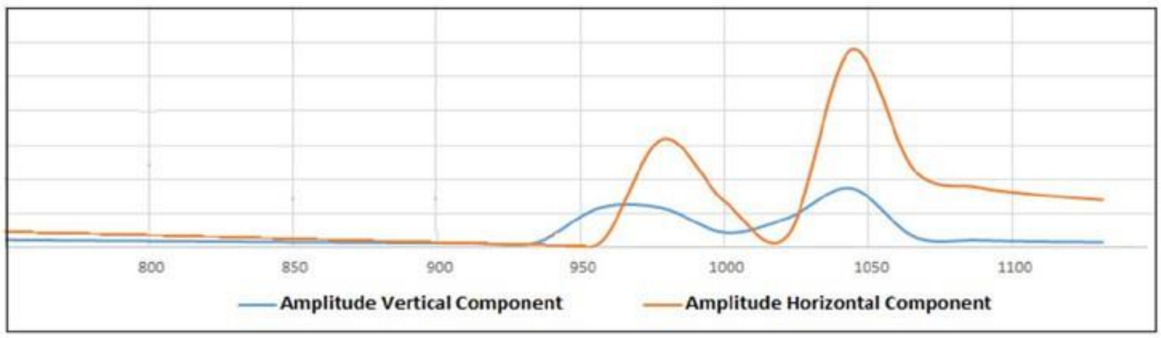


Figure 8. Normalized Exiting Force Components of Pump Rotor Under Cavitation Fault

Figure 9 depicts the rotor response to the periodic exiting vertical force component under cavitation condition.

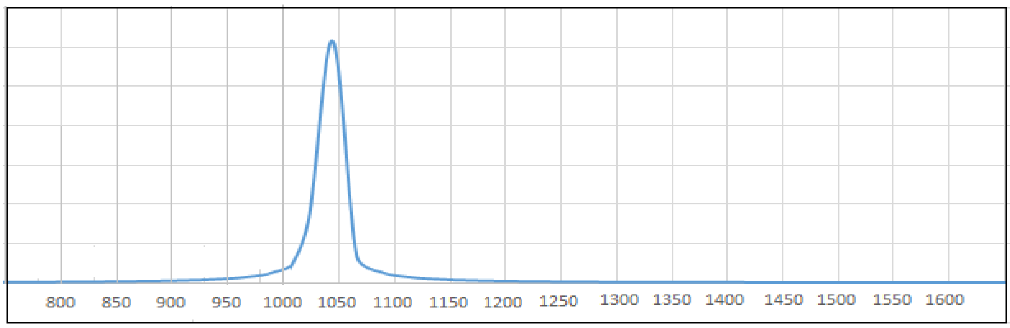


Figure 9. Pump Rotor Response to Periodic Pressure Force Vertical Component

The pump casing can be treated as a pressure vessel subject to periodic internal radial force resulting from the pressure waves of vapor bubbles collapse under the cavitation condition. In this case, the periodic internal force is determined by the pressure pulses times the casing internal surface area. The frequency of this periodic internal force corresponds to the number of impeller blades times the number of diffuser tongues times the synchronous frequency. Physically this frequency expresses the number of pressure pulses resulting from the total number of blade-diffuser tongues interactions per one revolution.

A simple state space model that describes the vibration of the pump casing is given by Equation (8).

$$M_M.\ddot{q}(t) + K_M.q(t) = F_M(t),\quad q(0) = 0\,,\ \dot{q}(0) = 0 \qquad (8)$$

Where, $MMMM$ is the mass of the casing, $KKMM$ is the stiffness of the casing and $qq(tt)$ is the displacement. $FFMM(tt)$ is the periodic internal exiting force that can be determined by multiplying the pressure pulses function of Equations (1) and (2) by the internal surface area of the casing. To investigate the vibration response of the casing, one approach is to integrate equation (8). In this case $FFMM(tt)$ is expressed in time domain using Fourier expansion where $FFMM(tt)$ is decomposed into the sum of harmonic functions whose frequencies are multiples of the exiting force frequency. Equation (9) depicts the Fourier expansion expression of $FFMM(tt)$.

$$FFMM(tt) = \frac{aa0}{2} + \sum_{ii=1}^{\infty} [aaaa.\cos(aawoott) + bbaa.\,ssssaa\,(aawoott)] \quad (9)$$

Where:

$$a0 = 2AAMM/TTTT[\int_0^{\frac{TTTT}{2}} 2.\,PPPPaaPP.\frac{tttttt}{TTTT} + \int_{\frac{TTTT}{2}}^{TTTT} PPPPaaPP - 2.\,PPPPaaPP.\left(\frac{tt-\frac{TTTT}{2}}{TTTT}\right) ddtt] \quad (10)$$

$$aaaa = AAMM/TTTT[\int_0^{\frac{TTTT}{2}} 2.\,PPPPaaPP.\cos(aawoott)\frac{tttttt}{TTTT} + \int_{\frac{TTTT}{2}}^{TTTT} PPPPaaPP - 2.\,PPPPaaPP.\cos(aawoott)\left(\frac{tt-\frac{TTTT}{2}}{TTTT}\right) ddtt \quad (11)$$

$$bbaa = 0 \qquad (FFMM(tt) \text{ is an even function}) \quad (12)$$

Figure 10 presents the time domain of the normalized steady state vibration response of pump casing. Figure 11 presents the frequency response of the pump casing subjected to the simulated periodic internal force due to cavitation.

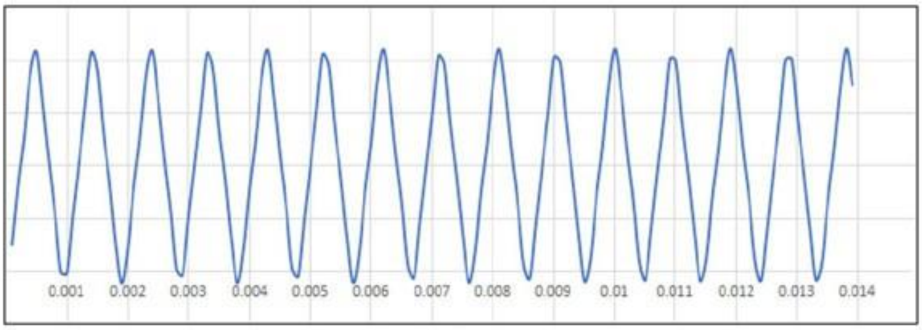


Figure 10. Normalized Steady State Vibration of Pump Casing

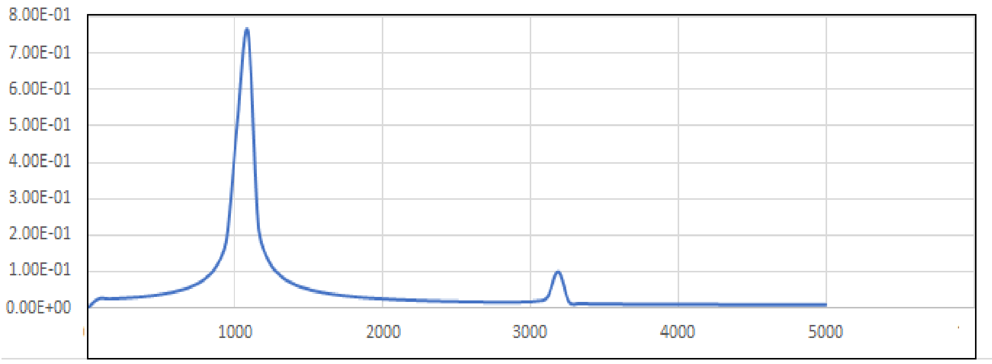


Figure 11. Vibration Response of Pump Casing

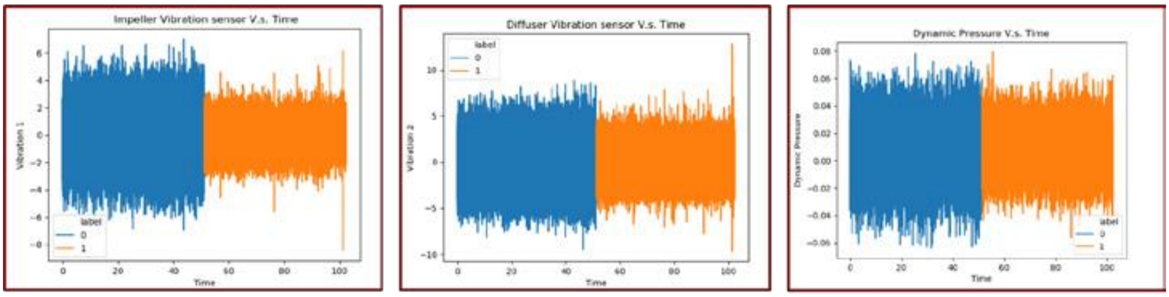
The main vibration frequency is 1050 Hz which corresponds to synchronous frequency times the number of blades times the number of diffuser tongues. This result indicates that the developed pump casing model governed by Equations (8) through (12) has detected the vibration of the casing due to the pressure pulses generated by the cavitation.

The centrifugal pump is a hydraulic turbomachinery that continuously transfers energy to the feed water in a desalination plant. The longevity of centrifugal pumps depends on proper maintenance and early faults detection. In this case study, cavitation in centrifugal pumps is considered. Mathematical models that express pressure pulses as well as the resulting exiting periodic forces were developed. Digital models describing the vibration response of pump rotor and casing under cavitation periodic excitation were tested for a typical small feeding centrifugal pump. Power Spectrum analysis was conducted to present the frequency response characteristics of pump rotor and casing. The dominant detected vibration frequency was 1050 HZ which corresponds to the synchronous frequency times the number of impeller blades times the number of diffusers tongues such results are in agreement with previously published work as well as actual vibration measurements.

4.1.2 Using Machine Learning models in fault detection

Regarding the trendy automatisms and working in an uncertain, evolutionary environment the current industrial plants and systems become more and more mechatronics complex [13]. The classification and detection of the mechanical system faults is an essential task for a reliable operation. As mentioned above cavitation is one of the most disadvantage problems that occurs frequently in the centrifugal pumps Fault detection using Machine learning algorithms attracted much attention this decade because it is a powerful, fast, computational method that can detect the centrifugal pumps faults efficiently [10, 11]. Fault detection using machine learning has been a promising technique of releasing the human labor contribution as it is recognizing the machines health state automatically [14]. The ML model is integrated three machine learning algorithms:

- SVM: is a supervised classification and regression learning algorithm that has strong linear, nonlinear and kernel generalization ability functions. The goal of the algorithm is to create a hyperplane boundary between the possible outputs to separate them into the correct categories. Any new data point can be easily put in the correct category using the hyperplane. SVM algorithm trains different real-world historical data and can efficiently detect cavitation with high accuracy and excellent performance.
- KNN: is a supervised classification learning algorithm and one of the simplest ML algorithms that help in fault detection. KNN algorithm assumes the similarity between the data and puts them into the most similar category to the available categories. KNN has been applied before for different fault detection mechanical use cases, and it showed high accuracy and good scalability.
- Logistic Regression: is a supervised regression analysis method in which the outcome is binary or dichotomous using predictor variables. Logistic regression is also considered a supervised learning classification algorithm used efficiently in predicting the probability of a dependent variable. The model showed a high accuracy to detect the cavitation as it has been used to build predictive models as a function of predictors and because of the data linearity.



(a) (b) (c)

Figure 12. (a) and (b) Collected vibration data before and after cavitation, (c) Collected dynamic pressure data before and after cavitation

Parts a and b of Figure 12 represents the vibration data that have been collected from two vibration sensors one is mounted to collect the pump's impeller vibration data and the second vibration sensor is mounted to collect the pump's diffuser vibration data. The blue plots represent the data before cavitation exist and takes 0 label, where the orange plots represent the data after cavitation and takes label of 1. The vibration amplitude before cavitation was greater than after cavitation and these real-world collected results can be explained by studying the pressure pulsation data that was collected by using dynamic pressure sensor and represented in part c of the above figure. Part c shows that the dynamic pressure amplitude before the cavitation was greater than after cavitation because of decreasing in the exciting force magnitude affecting the pump's rotor during the cavitation and this decreasing magnitude corresponds to the decrease in $\Delta PP = (PP_{2} - PP_{1})$ [1]. Due to the bubble's explosion at this point during cavitation PP_1 increase at this BPF frequency the spectral peak does not show any significant decrease from normal to cavitation condition [1].

Figure 13 shows three confusion matrices generated by three different ML algorithms the SVM, the KNN, and the Logistic regression. Confusion matrices represent the detailed algorithm performance in terms of true negatives (TN), true positives

(TP), false positives (FP), and false negatives (FN). In the presented use case, 104,963 TP data sets were predicted successfully as cavitated data sets. In contrast, three FN data sets were falsely predicted as healthy data before the cavitation generates. Where 104,652 TN data sets were truly predicted as healthy data sets successfully, while 97 FP data sets were falsely predicted as cavitated data, however, it was not cavitated data sets. This SVM algorithm accuracy is > 99.5% however, the occurrence of 97 falsely predicted as faulty data sets was not acceptable because that can yield to an unplanned/spontaneous decision like shutdown the pump several times, which cause unstable water production and industry disturbance. The KNN algorithm improved the predicted data by decreasing the number of FP data sets; the algorithm is more accurate and efficient than the SVM model as it is more cost and time-efficient in detecting the cavitation faults. However, while the KNN algorithm was working on decreasing the number of FP data sets to 36% of the SVM model, the number of FN data sets increased, which is not acceptable as it means more cavitation data sets will exist without predicting them. Applying the logistic regression algorithm to reduce the two types of errors, the FP and FN detected data sets. The logistic regression algorithm was the most time-efficient model, and it supported the most accurate fault detection result with f1 accuracy of 99.996% because of the data linearity.

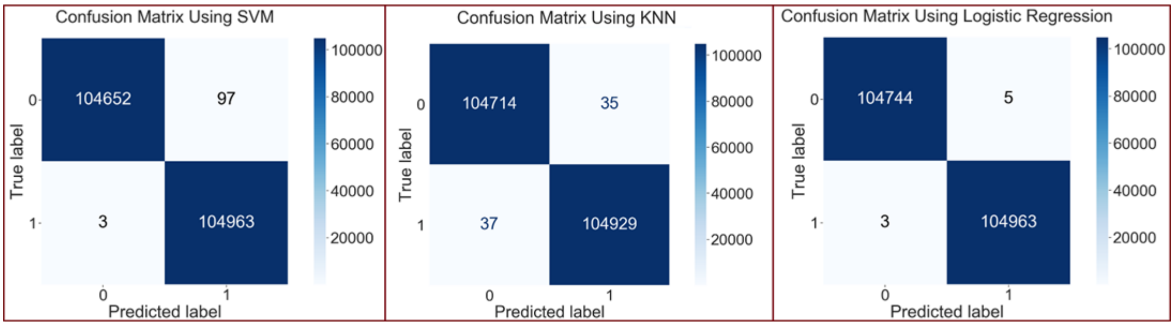


Figure 13: Confusion matrix using SVM, KNN & Logistic Regression

The machine learning models accuracy was calculated using the F1 score method. Different methods can calculate the accuracy of the three models; two methods are recommended for calculating the model accuracy and their equations are listed below. The accuracy method is more recommended when the machine learning models users are more attracted to the True Positives, and True Negatives detected points [15]. In contrast, the F1 score method is more recommended when False Negatives and False Positives are crucial. In most real-life classification problems, the F1 score method is applied because the imbalanced class distribution exists, and it is a better metric to evaluate the model [16]. The aim of using three different ML algorithms and comparing them with each other even with each model's high accuracy, which exceeds 99.5%, is to combining these three models' fault detection before making any decision that can affect the industry. For example, the SVM algorithm is one of the most robust classification algorithms that has been introduced and applied before on several fault detection problems on mechanical, hydraulic, and electrical components. However, SVM showed less efficiency than the KNN model, which was lower than the Logistic regression model in our cavitation detection case. SVM showed the existence of 97 false positives detected points and if the fault detection model depended on just one ML algorithm instead of the three ML models combined with the saw-tooth physical-based model, several false decisions would occur by the machine operators due to generated false alarms, which could affect the logistics, planning and disrupt the production systems by causing production delay.

$$AAAAAAAAAAAAAAAA = \frac{TTTT + TTTT}{TTTT + FFTT + TTTT + FFTT}$$

$$FF1 - mmmmAAmmAAAAmm = 2 * \frac{TTAAmmAAPPmmPPPPPP * RRmmAAAARRRR}{TTAAmmAAPPmmPPPPPP + RRmmAAAARRRR}$$

4.2 Monitoring

In the last decade identifying fault occurrence in time was a challenge not only in mechanical components but in several industrial components. These industrial components are subjected to different uncertain environmental conditions and damage caused by acoustic emissions, misbalance, misalignment, occasional shocks, poor power quality, supply imbalance, and vibrations, and the way it is handled, which can lead to unscheduled maintenance interventions which is difficult to perform and expensive [5, 8]. Nowadays with the development of the diagnostic abilities in the health monitoring area because of the enhancement of the sensor's technologies, data driven techniques, big data analytics, data preprocessing, machine learning, signal processing algorithms, smart control, artificial intelligence, and the development of the computational power. Health monitoring advancing the evaluating and monitoring of the industrial systems by improving the systems reliability and life cycle management and avoiding machines shutdown for more periodic maintenance and breakdown time.

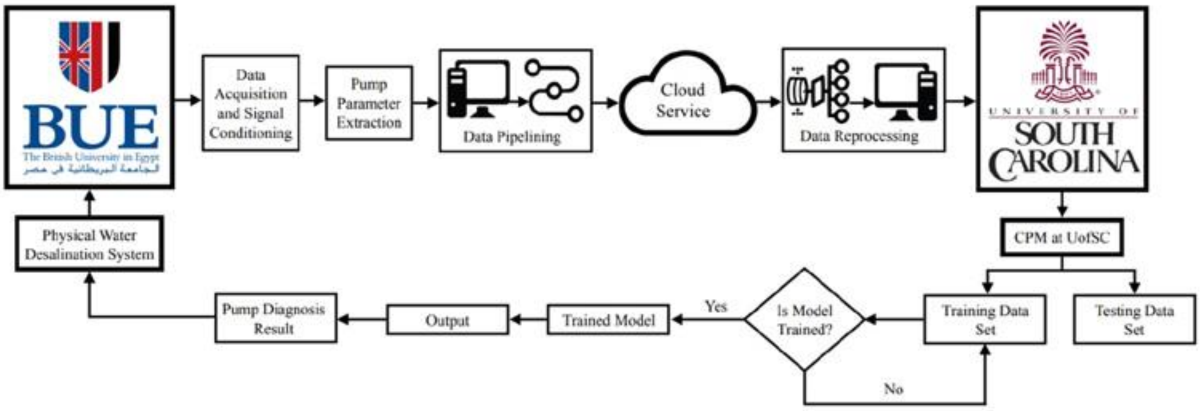


Figure 14. Implemented water desalination system status monitoring scheme for fault prediction

This approach is conducted by a joint team from the Center of Excellence in Predictive Maintenance (CPM) at the British University of Egypt (BUE) and the Center for Predictive Maintenance (CPM) at the University of South Carolina (USC), USA. The Egyptian team leads the part of designing and manufacturing and full integration of the small RO water desalination system equipped with onboard monitoring, data extraction and control system. Having the physical system in Egypt supported both teams with a solid understanding of the system's physical behavior and properties, by monitoring the system under healthy and generated harsh conditions, collecting real-world data by employing adequate sensors and a data acquisition system that sensing and extracting the pump parameters such as static and dynamic pressure, flow rate, salinity, and vibration data. The US team develops an Industry 4.0 framework, including a digital twin of the system that will allow for self-diagnosis and system decision making to ensure optimal performance. These features enable remote monitoring and control of the desalination plant. The digital twin (DT) health monitoring system (HMS) receives data from onboard sensor monitoring critical variables of the plant in Egypt, train and compare these extracted measurements to the plant's historical and theoretical models' output. This enables the system to optimize its performance to achieve prolonged life predictions and better efficiency. The current health of the system will be updated in real-time and will be shared with a remote decision-making authority. If there is an anomaly in the readings, corrective action will be initiated, and responsible personnel would be alerted to the new state of the system. The Internet of Things (IoT) enables this interconnected network of machines and people and will enable the existence of a reliable, remotely operated, automated, decentralized SWRO water treatment plant in the desert.

4.3 Dashboards

Dashboards allow for all processing, storage, and calculations to be conducted in one location. They also present the necessary information quickly and in an easy-to-understand format so that decisions are made with more knowledge and can yield better results. Once the fault detection models have been implemented, the analysis and results will need to be presented to allow users to quickly understand any problems and inform their decisions. Additional benefits of these dashboards are the ability to enhance training and facilitate knowledge transfer through simulating hands-on experience. A key part of these dashboards is that the information presented is customized and tailored to fit the needs of different users. Two sample views are shown in Figure 15. The left side shows a user the health status of the multiple water desalination plants they are overseeing, an executive might use this view to make decisions. The right side shows the health and status of a specific system and the fault detection analysis.

5 Conclusion

The use case in Section 4 was only applied to a single component, a high-pressure pump, but digital transformation can be applied in stages. The lessons learned, framework, data, and algorithms developed when focusing on a single component can be expanded to cover the system and later the entire plant. Figure 16 shows the steps of expanding from high pressure pump to smart plant.

- Step 1: Apply Digital Transformation to a single component of a system in the plant such as the high-pressure pump of the reverse osmosis system.
- Step 2: All algorithms, models and techniques developed in Step 1 will be expanded and applied to all the components of the reverse osmosis system.
- Step 3: All algorithms, models, and techniques developed in Step 2 will be expanded and applied to the remaining systems of the plant.
- Step 4: Expand the application of digital transformation to a network of smart plants allowing users to monitor both individual plants and the interactions between plants.

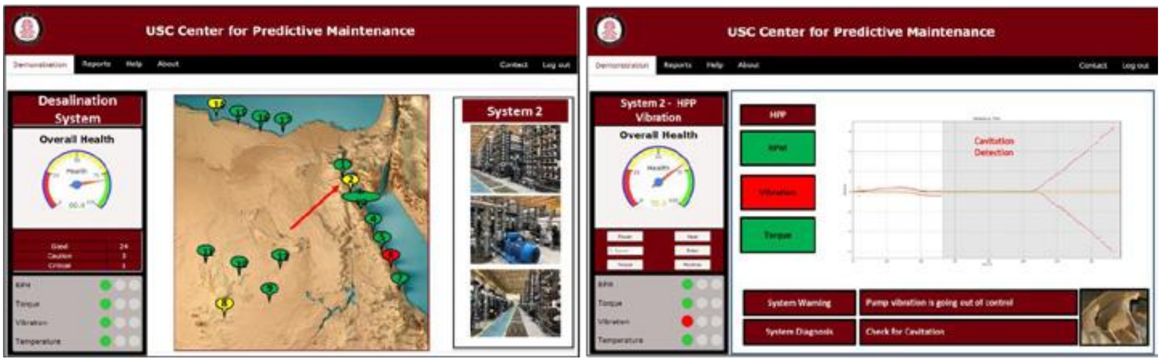


Figure 15. Dashboard Views

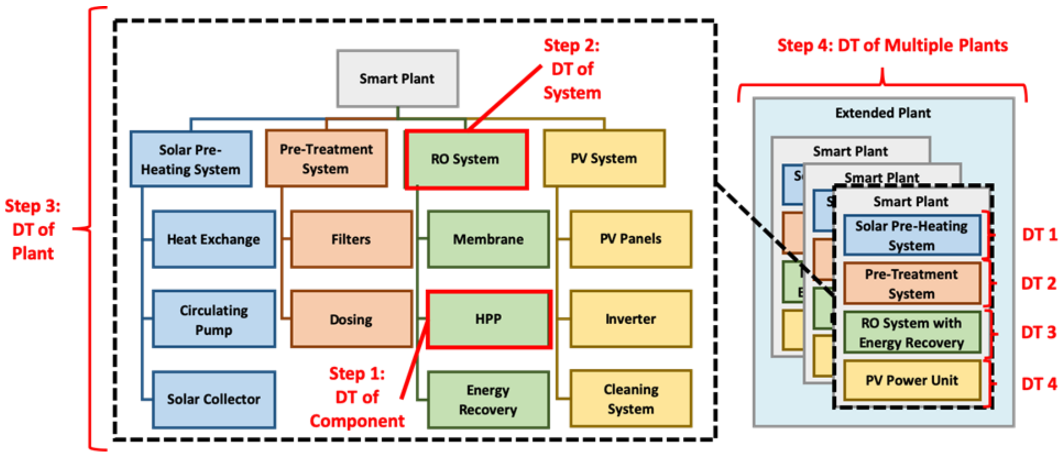


Figure 16. Incremental Application of Digital Transformation

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Operational Challenges Associated with Integration of One Solar & One Wind Plant in Weak part of SEC Grid : A Case Study for Northern Operating Area

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Abstract

The Northern Operating Area is the weakest part of the of the SEC system. It is connected to rest of the system through only one 380kV double circuit interconnection. The Kingdom of Saudi Arabia has set out a roadmap to rapidly diversify the domestic power supply. In this regard a strategic initiative under vision 2030 has been taken up to maximize the potential of renewable energy in Saudi Arabia. As a part of this initiative 300MW Sakaka PV power plant has already been commissioned whereas 400MW Doumat Al Jandal Wind Power Plant is expected to be commissioned next year. Unlike conventional generation whose output can be controlled, renewable generation especially Wind/PV introduces variability and uncertainty in to the grid. This requires increased flexibility in the system. In the existing power structures around the world this flexibility is usually managed through conventional power plants. Use of storage technologies can also provide additional flexibility but its use is still limited due to various reasons. Integration of Wind/PV into the power system brings new challenges for the power system operator. Two time scales of concern here are minutes to hours timescale and hours to several days timescale. First one directly impacts the regulating reserve and ramping requirements whereas later impacts the production cost by reducing the efficiency of generation unit commitment and dispatch. Increased penetration can also lead to possible grid blockage or power flow management issues. A specific combination of renewable generation and load demand may change the magnitude and direction of power flow in the transmission system and further power flow in the interconnected grid. Primary objective of this paper is to identify the operational challenges that may be faced with integration both power plants in this area with focuses on determining reserve requirements for system balancing using statistical approach and identifying the combination of renewable generation & load demand that may lead to power flow management issues.
Keywords : RES Penetration, Regulating Reserves, SEC Grid, Data Analysis, Statistical Analysis

I. Introduction

Some known challenges associated with Renewable integration on power system operation are transient stability, frequency and voltage control [1, 2]. Renewable energy especially wind and PV will introduce intermittency into the system operations. Limited predictability and increased uncertainty means that additional reserves will be required in the system to guarantee operational reliability [3,4]. With this increased variability conventional method of allocating spinning reserves equal to largest infeed or online generator are no more adequate. Extensive literature is available on various approaches to calculate spinning reserve with integration of renewable energy. One approach is to keep spinning reserve equal to the largest online generator or some portion of the standard deviation of net load or wind/PV forecast error or a combination of them [5 -9]. This approach has been used by Sweden in integrating wind power, reserve capacity margin on hydropower & thermal power is determined according to the forecast error of both wind power and loads [4]. Probabilistic method of reserve allocation is discussed in [10-13]. In this method Loss of Load Probability (LOLP) or Expected Energy Not Served (EENS) determines the spinning reserve requirement. This approach neglects the setting of reliability & rationality of such metrics. Ortega-Vazquez et al. [14] use a cost/benefit analysis to determine the optimal spinning reserve level for each time interval. These optimal spinning reserve levels are set as constraints in reserve constrained unit commitment. In [15], they add the uncertainty of wind power generation into the model. The Gaussian distribution of net demand forecast error is approximated by seven intervals. A capacity outage probability table (COPT) [16] is used to calculate the EENS of system. In [17], an artificial neural network model for wind generation forecast is presented and integrated in unit commitment. The probabilistic concept of confidence interval is used to account for the wind forecast uncertainty, but determining the optimal confidence level creates another difficult problem. stochastic optimization scheduling model considering wind power production as stochastic input is presented in [18], which makes use of a scenario tree tool to commit the scenario reduction and reschedules based on the most up-to-date forecast information.

Review of integration studies conducted in various parts of the world reveals that although type of operating reserves considered are similar but method to determine the quantum of reserves varies. Minnesota and New York Integration Studies [19, 20], Eastern Wind & Integration Study [21] and Hydro Qubec [22, 23] used statistical analysis, standard deviation of wind variability for regulating reserve calculations. Spain & Portugal used time-stepping Monte Carlo simulation for evaluating operation reserve strategies [24]. Netherland uses frequency domain peak to peak analysis [25]. Whereas Denmark uses Market based risk Model for this purpose [26].

Kingdom of Saudi Arabia has also setup an ambitious target of integrating 60GW of Renewable energy by 2030. As a part of this initiative 300MW Sakaka PV plant has already been commissioned whereas 400MW Doumat Al Jandal Wind Project is expected to be online next year. Both plants are located in the weakest part of the SEC grid. Each sub area within this area is only interconnected through a long 380kV Double circuit only. The objective of this paper is to identify the operational challenges with focus on regulating reserves & balancing requirements. Statistical analysis will be performed on generation production profile of wind/PV to determine expected regulation reserve. Similarly Load forecast of 2020 will be used to determine variability due to load. Renewable generation will be considered as negative load. Hourly regulating reserves based on net load variability will also be estimated using the same statistical approach.

II. Statistical Framework for Hourly Regulating Reserves Evaluation

The statistical analysis can be used to evaluate power system reserve since it deals with characterizing the nature of random variables. . It is a good way of describing large amounts of data in an abbreviated way and to define important characteristics and properties of a given set of data. There are two key variables here, one is the variability of the electrical load other is the renewable generation. Both are expected to have several time frames of variability such as annual, seasonal, daily, minute-to-minute and second-to-second changes. Load demand and the power produced by renewable plants and their synchronous combinations are random variables. The variation in load is driven largely by consumer behavior, it has a distinct daily, weekly and seasonal trend that can be observed on time series of system load. The scope of this analysis is to determine how much variability exists in a set of given data, such as load, wind/PV production and their combination during a period of time (day, week, month, etc.). Considering the RES power and load time series, hourly variation within each time step can be calculated by taking the difference or "deltas" between successive data points. Hourly variability of load and RES power with time series of variations can be calculated using the following equations

$$\Delta Load_i = Load_i - Load_{i-1}$$
$$\Delta RES_i = RES_i - RES_{i-1}$$

Where
ΔLoad is variability of load at hour i = 2,3,4…8760
ΔRES is variability of Renewable generation at hour i = 2,3,4…8760

The resultant time series will be concentrated around mean with residuals varying around the mean. From statistical theory; any sampling distributions based on large N can be approximated by the normal distribution even though the population distribution itself is definitely not normal. In probability theory, the normal distribution is a continuous probability distribution that is often used as a first approximation to describe real-valued random variables that tend to cluster around a single mean value

$$P(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\mu)^2/(2\sigma^2)}$$

Where
μ is the mean
σ is variance (also known as measure of the width of distribution

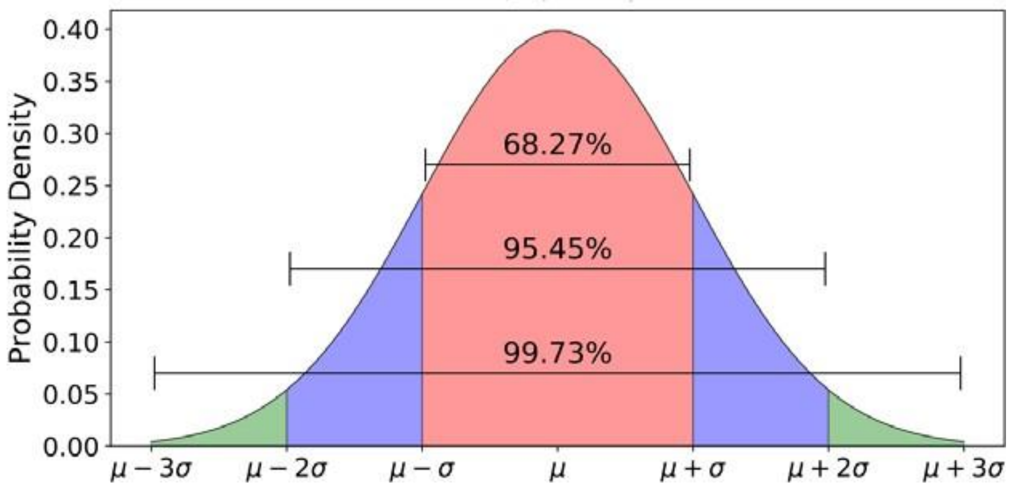

Figure-1 : Normal Distribution Curve

Figure 1 shows a normal distribution curve. About 2/3 of all cases fall within one standard deviation of the mean

$$P(\mu-\sigma \leq x \leq \mu+\sigma) = 0.6826$$

About 95% of cases lie within 2 standard deviations of the mean

$$P(\mu-2\mu \leq x \leq \mu+2\sigma) = 0.9544$$

About 99.74% of cases lie within 3 standard deviations of the mean

$$P(\mu-3\sigma \leq x \leq \mu+3\mu) = 0.9974$$

Here Standard Deviation will be used as metric to describe the variability of the time series.

III. Statistical Analysis of Hourly Regulation Requirements

The production variability of wind farms and PV plants has been carried out considering expected production profile of each plant. Hourly variability is calculated using hour by hour difference between the current production and the production in the previous hour. Approximating the distribution of the production variation as normal distribution, 99.7% of the samples is included in $\pm 3\sigma$. Here σ is evaluated for monthly samples and total population sample i.e. for the whole year. Statistics of the production variability monthly & annually for Wind farm, PV plant, Aggregate RES production (Sakaka + Doumat), Northeast area load demand, Northwest area load demand, Aggregate load demand (Northeast + Northwest) & Net Load is tabulated in table 1. The statistical value in which the typical hourly variations can be expected, is an appropriate driver for determining the regulating reserve of the system with RE plants. The hourly variation must be faced by the conventional plants operating on the system. It means that both NWA and NEA systems should be operated with an adequate amount of reserve on the regulating plants. In order to cope with the 99.7% of the expected hourly variation, the reserve of the entire NOA system must be at least ±340 MW. This reserve has to be allocated on plants with enough dynamic capacity of regulation: each plant must be capable to provide an adequate output power variation. The NOA is interconnected with the rest of SEC network. Also the interconnection could potentially provide the regulating service. In order to provide this kind of service, the interconnection must be of course operated with an adequate margin in respect to the security limitations (e.g. due to N-1 constraints).

Table-1 : Monthly & Annual Statistical Results for Hourly Variability

Month	Hourly Up/Down Regulation in MW						
	Sakaka PV	Doumat Wind	Total RES	NEA Load	NWA Load	Total Load	Net Load
Jan	104	233	256	116	97	181	331
Feb	105	239	257	118	92	191	345
Mar	106	232	252	110	91	185	338
Apr	106	266	283	103	81	165	339
May	108	260	276	119	105	193	328
Jun	102	235	241	139	110	221	322
Jul	96	231	239	140	97	216	314
Aug	105	259	273	142	91	214	357
Sep	107	242	259	121	101	204	332
Oct	111	269	292	102	94	172	353
Nov	102	230	252	126	87	194	338
Dec	92	242	258	153	106	246	376
Annual	104	245	262	125	96	200	340

There are two aspects of Table-1 which is of our interest. One is the hourly RES production variability and the other one is the hourly net load variability.

A. Analysis of RES Production

Statistics of the production variability of the wind farm and PV plant is summarized in Table-1. Table-2 summarizes the production variability related to their installed capacity. Similarly the statistics for the total variation in NOA (combining production of both Wind & PV) is also tabulated.

Table-2 : RES Production Variability related Installed Capacity

Duration	Hourly Variation as Percentage of Total production		
	Sakaka PV	Doumat Wind	Total RES
Jan	35%	58%	37%
Feb	35%	60%	37%
Mar	35%	58%	36%
Apr	35%	66%	40%
May	36%	65%	39%
Jun	34%	59%	34%
Jul	32%	58%	34%
Aug	35%	65%	39%
Sep	36%	61%	37%
Oct	37%	67%	42%
Nov	34%	58%	36%
Dec	31%	60%	37%
Annual	35%	61%	37%

Annual variation for Doumat Al Jandal wind farm is about ±61% of the installed capacity. The variation tends to increase in April, May, August & Oct, whereas for the rest of the year it varies in the range of 58% - 60%. Sakaka PV plant production variability on the other hand varies in the range of 34% - 36%. Maximum variability is observed in May, September & October and lowest variability of 31% is observed in December. Whereas Annual variability remains ±35%. Interesting point to note here is that although wind variability is much but when combined with PV production, variability tends to decrease drastically. Annual aggregate RES production variability is only ±37% compared to wind farm production variability of ±61%. This shows that wind and PV production tends to reinforce each other.

B. Analysis of Net Load

Since renewable generation wind/PV is considered non dispatchable in most of the utilities around the world, therefore it can be considered as negative load. Net load represents load minus RES production. Hourly trend of Net Value is the algebraic sum of synchronized trend of load, wind & PV production. Figure 2 shows the hourly net load deltas on a histogram as frequency distribution. The yearly $\sigma_{\text{Net Load}}$ of the load delta is 113 MW. Considering $3\sigma_{\text{Net Load}}$ coverage of the variability (and assuming that the load variation is normally distributed) is expected in 2020 that 99.7% of the Net Load deltas will be within ±339 MW/hr.

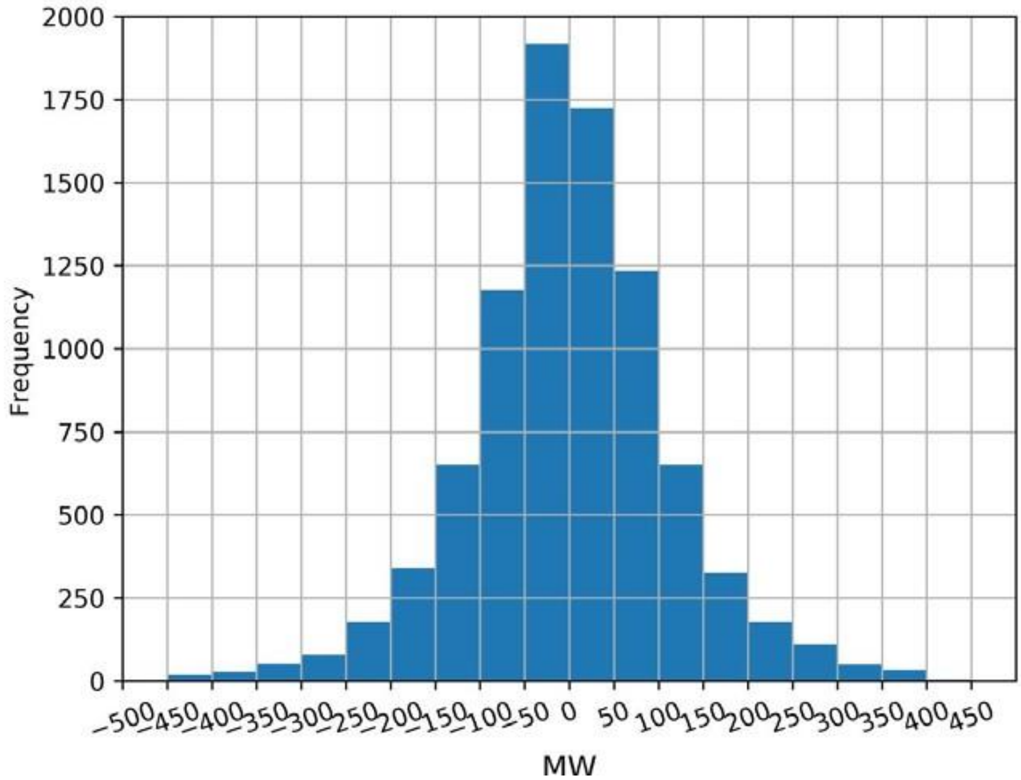

Figure-2 : Net Load Frequency Distribution of Hourly Differences

To understand the impact of RES generation on load demand and net load demand Figure 3 & 4 are shown. Figure 3 shows a typical load curve for a day with Peak load demand in NOA & figure 4 show a typical load curve for a day minimum net load.

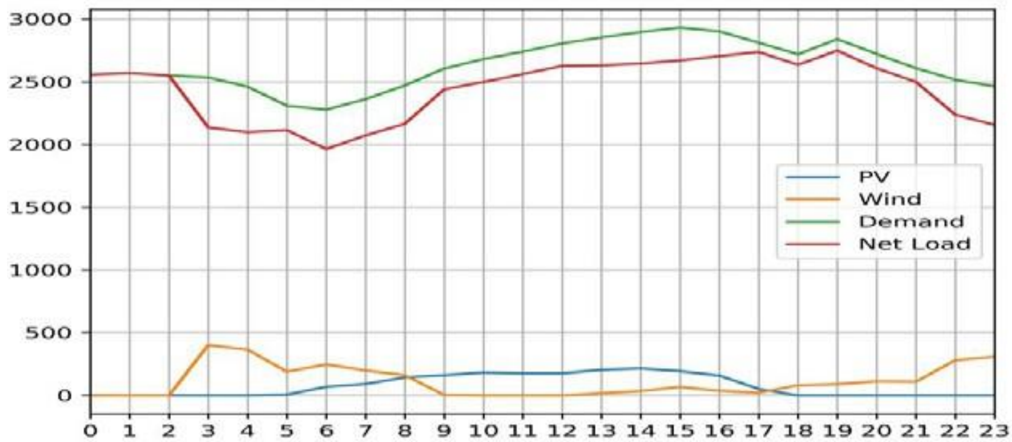

Figure-3 : Typical Day with Peak Load Demand in NOA

It can be seen in figure 3 that drop in drop in wind production is compensated by increase in PV production. Similarly during the evening when PV production is dropping wind production is picking up.

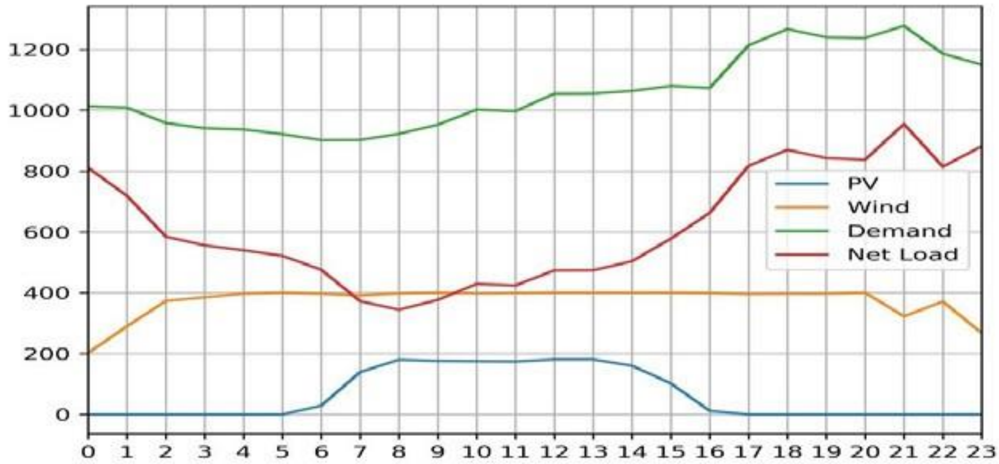

Figure-4 : Typical day with Minimum Net Load Demand in NOA

On the other hand figure 4 details one of the extreme scenario where maximum production is expected from RES during low demand period. Such scenarios will the most challenging one for power system operation and control with renewable integration. Maintaining Load-Generation balance with additional constraints such as restricted Net Transfer Capabilities and Minimum Must Run requirement will further complicate the problem.

IV. Evaluation of Load Generation Balancing

There is no standard practice regarding what share of wind/PV is considered low/high share [27]. This will depend on the power system characteristics. For instance in NOA while comparing the RES share (assuming maximum production of 700MW) with the peak load demand (2931MW), share is only 23.8%. However when load demand is plotted against expected RES production, RES shares at some instances can be as high as 60% as shown in figure 5. Generally shares of 20% - 25% are referred to as high shares. System operation becomes critical when operating at Res shares above 50%. There are considerable instances when in NOA RES share will be higher than 50%. Higher renewable energy share will have a direct impact on the optimal generation mix. One of the major aspect of RES integration is how this new power is added into the system. Whether it replace the existing generation fleet or optimized scenarios will be developed. Overall objective in SEC system is to develop optimized portfolios, however in NOA case it will be replacing existing convention generation in order to maintain Net Transfer limits. North Operating area is the weakest part of the SEC system. Each Area in NOA is only connected through 380kV double circuit transmission line. Net transfer capacity in this area are dictated by stability limits. Generation in this area is greater than total load demand of the area. Interconnection between NOA & COA provides a flexible way to maintain load generation balance in this area. However the capacity of this link is limited to 1000 MW only, owing to stability issues. Two gas based power plants one 500MW Plant in NWA & other 1280MW plant in NEA can easily cover load demand of this area along with the interconnection with COA.

However due to local stability issues several expensive plants have to be kept on bar as Must Run.

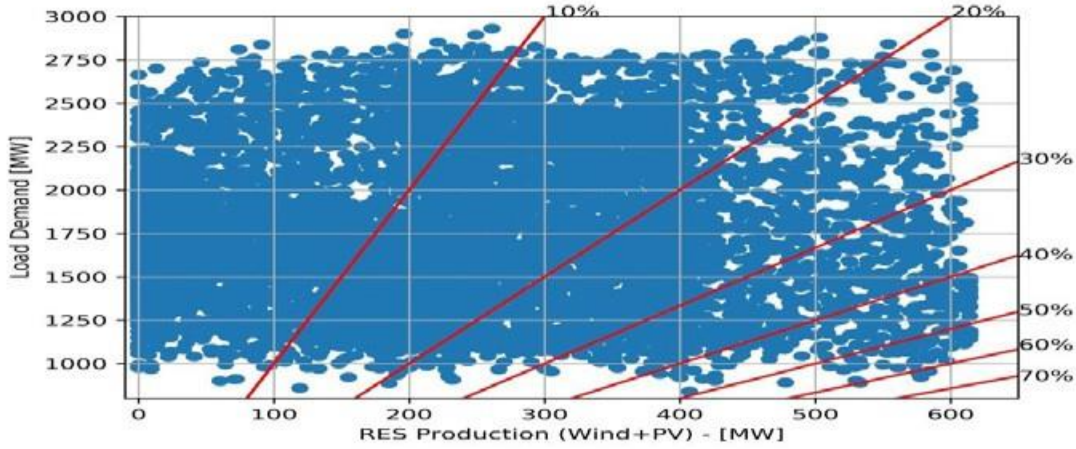

Figure-5 : RES Production Share as a function of NOA Load demand

Figure 6 shows duration of curtailment in number of hours. As expected curtailment has increased drastically with penetration of RES. Without RES integration maximum curtailment up to 500MW above stability limit was expected with a total duration of 2643 Hours. With RES integration maximum curtailment has increased up to 1050 MW above stability limit with a total duration of 4640 Hours. This corresponds to almost 6 months of curtailment. From the analysis it is clear that NOA lacks compressibility in terms of generation reduction. With the existing transmission infrastructure even integration of 700MW of RES can cause massive congestion issues on the interconnection with neighboring areas. Relieving of this congestion will either require curtailment of RES generation or reduction of cheap gas based plants. Reduction of conventional generation to accommodate RES has its own issues. This may lead to inertia reduction.

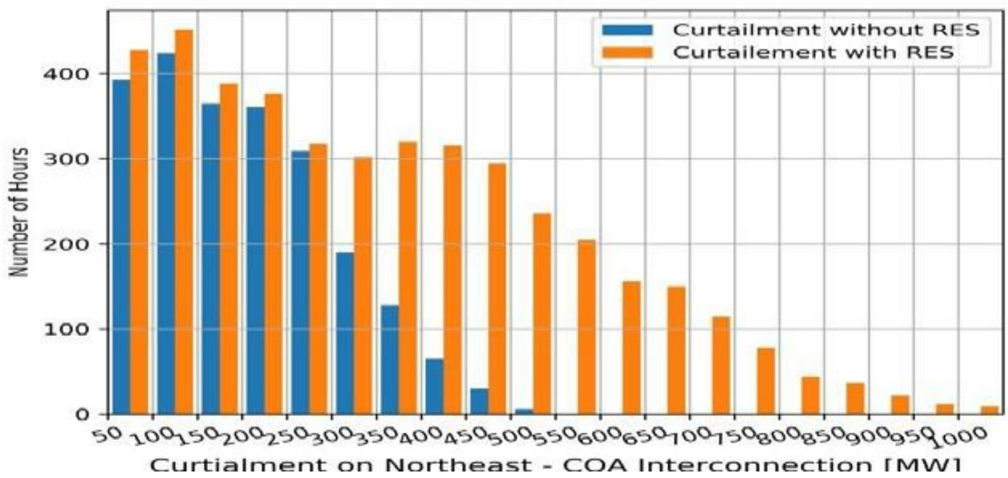

Figure-5 : Curtailment of Power in MW on NOA – COA Interconnection

V. Conclusion

RES integration will introduce variability into the power system operation. This is primarily due to the natural factors affecting RES production which are complex to predict. This will bring new challenges which requires flexibility in the power system. Flexibility can be described as the ability of the power system to respond to changes in different time scales. A case study of NOA with integration of one wind and one PV plant is demonstrated in this paper. With the help of statistical analysis requirement of hourly regulation reserves are analyzed. Hourly regulating reserves of ±340MW will be required to covered variability associated with RES generation. Similarly optimal generation mix is expected to change as well. Critical situations like high wind/PV and minimum loads will be the most challenging. Most of the RES penetration is expected to remain between 0-30%. However there are instance when this value can reach up to 60%. Integration of RES may lead to congestions of power on NOA – COA interconnection for up to 4640Hours in an operational year. This means that either cheap gas based generation has to be reduced or RES generation has to be curtailed.

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DEVELOPMENT OF AN UN-BIASED OPERATION CRITICAL KPI TO MEASURE PERFORMAN

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Abstract

Organizations measure or monitor KPIs and present this information at various operation stage for different levels of stakeholders and business managers. This becomes significantly complex and challenging when the requirement is to monitor multiple KPIs simultaneously. Higher level decisions are required to be made as to which KPIs are the most important and correctly represent the business unit activities. This leads to oversight, if multiple factors including priority and criticality of a certain KPI is not taken into consideration, and sometimes, the selected KPI can often reflect SME bias than the relevance with the business unit performance.

This article presents a risk-based approach in developing an un-biased composite KPI to measure and monitor performance. The emphasis is to derive a measurement index, which adequately reflects the performance indicators in accordance with their importance and criticality to operations

Keywords: Un-Biased, Operation Critical, Performance Measure

1. Introduction

The global leader, such as Saudi Aramco, is continuously striving to improve quality, increase efficiency and enhance reliability, by empowering business units to react quickly to rapidly changing market environment for gaining competitive edge. Business units, through operational excellence, are tooled to self-monitor their performances and gauge achievements through internal comparison and external benchmarking. For thriving to become “Best-in-Class”, operating, management and business units rely heavily on information (or data), which plays a pivotal role in promoting continuous improvement. Accurate performance measurement dependent on information, which is of good quality, comparable, and most importantly, relevant to operational criticality.

It is a widely acknowledged fact [1-6] that performance measure of a complex entity, cannot be a single point index. It is multidimensional, which requires the measurement of several key indicators with a number of varied scales to capture each element. When an activity performance is measured through a simple relationship, the measurement process is usually quite straightforward, and activity performance is monitored to determine the status and to act (or not). However, when any activity may have more than one associated metrices, it becomes complex to visualize and measure the success or failure.

In oil and gas industry, it is common to measure the performance of every single activity or using the expert opinion and analysis to monitor performance of key indicators. It is counterproductive, from an executive perspective, to monitor, visualize and discuss the performance of every activity periodically and also risky to measure & visualize only the selected indicators. The conundrum is that monitoring performance of every relevant indicator is impossible, whereas, leaving a few or including some can also lead to the dilemma of improper performance representation and risk of affecting the long-term business objectives.

This work attempts in proposing a methodology to develop a composite performance measurement index, which represents multiple activities and combine them by taking into consideration their interdependence, cross relationship and operational criticality [7,8]. The approach is to take the subject matter expert (SME) and key stakeholder influences out-of-the-equation in combining the individual activities to arrive at a composite index, which adequately represents the performance of a business unit, within a global organization.

The use of composite index to measure or monitor performance is not new. There are multiple global entities in business and financial sector (e.g. Dow Jones, S&P, TSX, etc …), as well as in health and related sciences use composite indexes very effectively to monitor and visualize performances on a routine basis [4,5,9]. The focus of this work is to derive a performance index which is easy to visualize and flexible to handle, with a relative ease to change and accommodate the market needs, business requirements and operational criticality. Furthermore, the development is approached as top down, where the holistic performance is visualized and if required, separate combining elements can be monitored and tweaked for improvement.

2. The Performance Visualization through KPIs

There are three distinct drivers, which encourage organizations for improving performance on a continuous basis – safety, environment and business or economic impact [7]. Measuring the performance of a business unit is becoming increasingly important because, unless we actually measure the performance, we cannot determine if improvements are being made [10-14]. Performance measurement contributes to improvement in a number of ways. It drives improvement through comparing the performance resulting in a desire to improve or maintain performance relative to others and reliability of services that they provide.

The key performance indicators (KPIs) are an invaluable tool that contribute immensely to the performance monitoring process. However, for KPIs to be effective, they need to have clear definition to ensure that the data collected is of high quality, i.e. consistent, reliable and most importantly relevant. Relevant KPIs measure what they are intended to measure and show a “right” performance picture and reliable KPIs will consistently produce the same result regardless of who performs the measurements. It is important to note that using performance indicators at a business unit level assists organization develop strategies, determine the gap between actual and targeted performance and estimate organization effectiveness and operational efficiency.

Business related and operation critical KPIs provide an objective way to see if the organization improvement strategy is working with a comparison that gauge the degree of performance change over time. They allow measurement of accomplishments with a common language for communication to help reduce intangible uncertainty. All this can be achieved, only if the KPIs are valid and configured by taking into consideration their criticality and relative importance. Hence, the famous saying, “If you can’t measure it, you can neither manage it nor improve it.”

3. Development of an Un-Biased & Operation Critical Composite KPI

Development of an operation critical composite KPI requires the understanding of several (or all activities) within a business unit. These activities (denoted as sub-KPIs), can have independent and/or combined effect on service and support to operation, their interdependency as well as the relative importance and criticality.

3.1 Sub-KPIs and their Interdependence

Consider an example of six activities (sub-KPIs). Figure 1 provides a schematic, with sub-KPIs (or activities) denoted as A-01, A-02, A-03, A-04 A-05 and A-06. The diagram (Figure 1) shows that how different activities can be interrelated and are interdependent, as follows:

- A-01 to A-05, all activities are somehow interrelated and dependent on others,
- A-06 is an independent activity, which is self-sufficient and didn’t depend on any other activity, and
- A-03 is the most connected activity, depending on the input or adequate functionality of four other activities (i.e. A-01, A-02, A-04 and A-05).

This illustration provides a snapshot of how important different activities are in relation to each other in an operating organization, hence emphasizes the fact that every activity cannot be considered equal when developing a composite KPI (**Note**: *the small numerals, under each activity in Figure 1, denote the respective interdependence of each activity).*

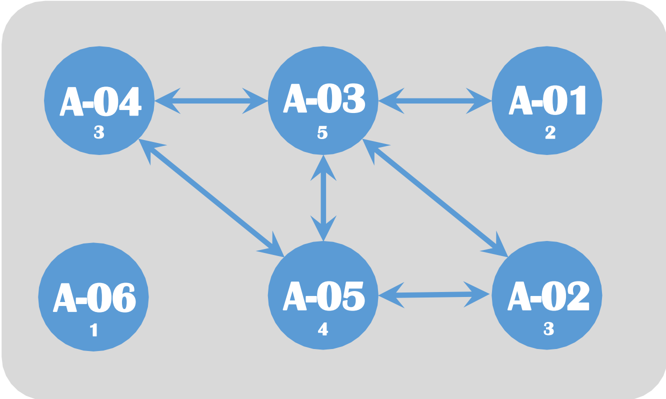

Figure 1: Explaining the Interdependency of sub-KPIs.

3.2 Criticality & Importance of Sub-KPIs

Consider another example of same six activities (sub-KPIs), but this time their criticality to operations is considered. Figure 2 presents an example of operation criticality of different activities. Activities A-03 and A-06 are critical for business unit operation, whereas, the activities A-01 and A-04 are necessary with A-02 and A-05 having intermediate importance. A sub-KPI for any critical activity requires continuous monitoring for operational excellence and improvement (**Note**: *the small numerals, under each activity in Figure 2 provide the critically index to different activities in an operating unit*).

Figure 2: Operational Criticality of different sub-KPIs.

3.3 Relevance Index for each Sub-KPI

Figure 1 and Figure 2 illustrated on how different activities are stacked in relation to each other, and their relative importance to operations. While embarking on developing a composite KPI for a business unit, following is considered as a “key” take-away from these examples:

- All activities (or sub-KPIs) within an operating unit are not equal, therefore, their interdependence must be considered carefully and weighed accordingly
- Operation criticality of each activity should be measured and accounted, while developing a composite KPI

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With the understanding of risk analysis [6,7] a relevance index for each activity can be define as follows:

$$\text{Relevance (R)} = \text{Interdependence (D)} \times \text{Criticality (C)} \qquad (1)$$

Example for Activity A-03:

$$R_3 = D_3 \text{ x } C_3$$

$$R_3 = 5 \text{ x } 3 = 15$$

where

D = Interdependence number, taken from the small numerals of Figure 1

C = Criticality, taken from the small numerals of Figure 2

and hence for the other activities

$R_1 = 2$, $R_2 = 6$, $R_4 = 3$, $R_5 = 8$ & $R_6 = 3$

And Total Relevance (R_T):

$$R_T = R_1 + R_2 + R_3 + R_4 + R_5 + R_6 \qquad (2)$$

and

$$RR_{TT} = \sum_{ii=1}^{nn} RR_{ii} = 37 \qquad (3)$$

where i = 1 to n, and n = 6 in this case

and also

Relative Relevance (RR_i) for each activity "*i*" is

$$RR_i = 100 \text{ x } R_i / R_T \qquad (4)$$

3.4 Development of a Composite KPI

Development of a composite KPI, representing multiple activities, requires relationship and relevance among activities. The interdependency and criticality, discussed above, will provide the basis for developing an equation for composite KPI. All activities, using their relevance as weighing factors, are summed as follows:

$$KPI_{comp} = \{(R_1 \text{ x A-01}) + (R_2 \text{ x A-02}) + (R_3 \text{ x A-03}) + (R_4 \text{ x A-04}) + (R_5 \text{ x A-05}) + (R_6 \text{ x A-05})\} / R_T$$

And also

$$KKKKKK_{cccccccc} = \frac{1}{RR_{TT}} \sum_{ii=1}^{nn} RR_{ii} \; xx \; AA_{ii} \qquad (5)$$

It is important to note that the information related to each activity, before using above equation to calculate the composite KPI, should be converted into the same measurement units (or scale). The preferred measurement unit for monitoring performance is "percentage", therefore, the above equation can be re-written as follows:

$$KKKKKK_{cccccccc} \; \sum^{nn} \frac{100}{RR_{TT}} \; _{ii=1} RR_{ii} \; xx \; AA_{ii} \qquad (6)$$

The same equation (eq. 6) can also be define using Relative Relevance (RR) as:

$$KKKKKK_{cccccccc} = \sum_{ii=1}^{nn} RRRR_{ii} \; xx \; AA_{ii} \qquad (7)$$

4. Application to Performance Monitoring of Radiation Safety

Radiation Safety Group of Inspection Department, Saudi Aramco performs numerous Radiation Protection (RP) activities on a routine basis, to support operating facilities. Following are some major RP activities, which are used to configure an un-biased & operation critical performance measurement index:

- RP01 Review of Radiation Safety Procedures
- RP02 Issuance of Radiation Work Permits
- RP03 Issuance of Radiation Storage Pit Permits
- RP04 Monitoring the use of Radiation Sources
- RP05 Import & Export of Radiation Sources
- RP06 Radiation Safety Training
- RP07 Radiation Safety Awareness Sessions
- RP08 Radiation Safety Assessments
- RP09 Radiation Safety Drills
- RP10 Radiography Service Provider RPO Approvals

As a first step in developing the un-biased & operation critical composite KPI is to collect input from all activity owners as well as the subject matter experts (SMEs) in the field of industrial radiography and radiation protection. The input will guide in understanding the interdependence and criticality of each RP activity, with reference to needs and requirements of operating facilities.

Table 1 provides the summary input from all activity owners and SMEs, with regards to the interdependence and criticality of radiation protection activities (**Note:** *the 'X' in the table indicates the activity interdependence*). The collected information is then used to calculate respective relevance (as defined in equation 1) of each activity, with total relevance (equation 3) and relative relevance (equation 4).

Table 1: Calculated Relevance of RP Activities

Radiation Protection Activities	RP 01	RP 02	RP 03	RP 04	RP 05	RP 06	RP 07	RP 08	RP 09	RP 10	Dependency	Criticality	Relevance	Relative Relevance
RP 01	X									X	2	3	6	12 %
RP 02	X	X								X	3	3	9	18 %
RP 03	X		X							X	3	3	9	18 %
RP 04	X			X						X	3	2	6	12 %
RP 05					X						1	2	2	4 %
RP 06						X					1	2	2	4 %
RP 07							X				1	1	1	2 %
RP 08	X	X	X	X				X	X		6	1	6	12 %
RP 09				X			X		X		3	1	3	6 %
RP 10	X									X	2	3	6	12 %
Total Relevance (R_T)													50	100 %

5. Performance Monitoring of RP Activities

Performance monitoring cannot be accomplished without defining a target. The performance targets for each RP activity should be set by considering the historical data, service criticality and value to operations. The relevance calculated in Table 2 provides the weightage of each activity in the composite KPI of equation (6) or equation (7). The same equation can be re-written to define the Radiation Protection Performance Index (RPPI), as follows:

$$RPPI_{Target} = \frac{100}{RR_T}\sum_{i=1}^{n} RR_i \times T_i \quad \text{or} \quad RPPI_{Target} = \sum_{i=1}^{n} RR_i \times T_i \qquad (8)$$

$$RPPI_{Actual} = \frac{100}{RR_T}\sum_{i=1}^{n} RR_i \times A_i \quad \text{or} \quad RPPI_{Actual} = \sum_{i=1}^{n} RR_i \times A_i \qquad (9)$$

where

T_i = Targeted value of radiation protection activity "i",

A_i = Actual value of radiation protection activity "i", and

RR_i = Relative Relevance of radiation protection activity "i".

And radiation protection activities are (as covered in Table 1) from RP01 to RP10.

This radiation protection performance index development is now used to setup target and applied as a tool for monitoring performance of safety group RP activities. It is very important that this new methodology of performance measurement should be tested on historical performance data for radiation protection activities, before applying the same for continuous performance monitoring and improvement.

Table 2 provides an illustration of targets defined for each RP activity, with respective actual performance numbers from the 1st quarter of year 2014 of radiation safety group RP activities (**Note:** *even though this quarter has missing data, but selected intentionally for this example to emphasis the significance of calculating relevance, discussed in the next paragraph*). Target and actual performance numbers of each activity are then combined by using equation (8) and equation (9) to calculate the composite target and the composite performance index.

Using calculated target of 89.4%, the same analysis is now extended and applied across the historical data of thirty quarters (testing period from 1st quarter of 2014 to the 2nd quarter of 2021), to monitor holistic performance of radiation safety group through radiation protection performance index (RPPI). Figure 3 provides RPPI values over the testing period and compare the same with the pre-defined target. **Note:** *the performance targets are revised in the 3rd quarter of 2016, to make it more challenging*.

6. Top Level Inferences from Data and Trend Analysis

Figure 3 provides a top-level view of radiation protection performance of radiation safety group RP activities (**Note:** *the yellow curve in Figure 3 is line connecting data points presented as blue bars*). A close analysis for actual RPPI numbers, provides with following information:

- RPPI values are meeting or exceeding the target,
- RPPI values over 1st 10 quarters are showing a positive trend (the green line in Figure 3), which allowed the user to comfortably re-calculate the targets (the red line in Figure 3).
- RPPI values for 2 quarters (Q1 and Q2) in 2014, as well as the 2nd Quarter of 2020 are barely meeting the targets.

Table 2: Calculated Composite KPI Target & Compared with Actual Performance

Radiation Protection Activities	Dependency	Criticality	Relevance	Relative Relevance	Targets (%)	Actual (%)
RP 01	2	3	6	12 %	90	100
RP 02	3	3	9	18 %	90	100
RP 03	3	3	9	18 %	90	100
RP 04	3	2	6	12 %	90	100
RP 05	1	2	2	4 %	90	NDA*
RP 06	1	2	2	4 %	100	100
RP 07	1	1	1	2 %	100	100
RP 08	6	1	6	12 %	75	100
RP 09	3	1	3	6 %	100	00
RP 10	2	3	6	12 %	90	100
Total (Composite)			50	100 %	89.4	90.0

* NDA ⇨ No Data Available

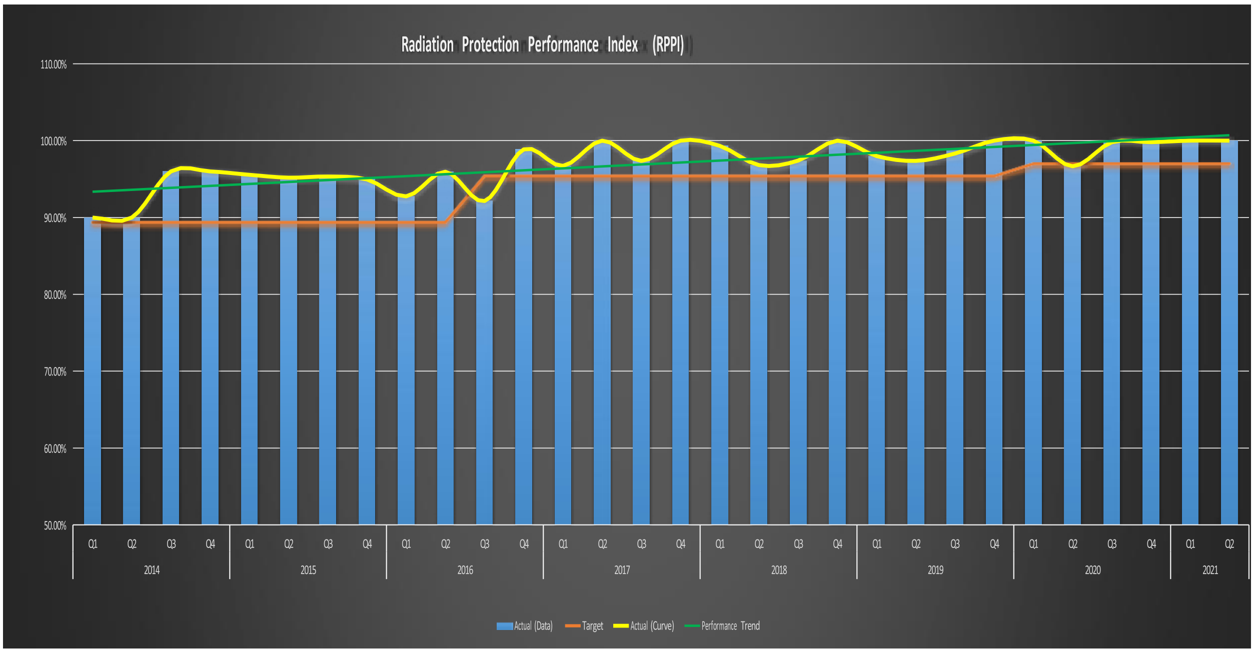

Figure 3: Comparison of RP Performance Index and Targets.

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The radiation safety group radiation protection activities are meeting the performance targets, as defined by this development. However, the close scrutiny of the Figure 3 concurrently with Table 2 provides the following evidence:

- The analysis didn't contain the data for activity RP05, and
- The activity RP09 has a score of "zero."

Further analysis of the comparison provided the following additional information:

- The data recording and reporting was not applied for activity RP05 at that time, and
- The activity RP09 has a target of 3 occurrences per year, hence the score of "zero" for the quarter in question.

In addition, it is also extracted from Table 2 that the relative relevance of activity RP05 is only 4 %, with a dependency of 1 and criticality 2. In addition, on a relevance scale of 1 to 9, the relevance of RP05 is only 2, which make this activity relatively less relevant as compared to activities RP02 and RP03.

7. Benefits of an Un-Biased & Operation Critical Composite KPI

The development of an un-Biased & Operation Critical Composite KPI carries several benefits:

- Reduces the influence of SMEs and activity owners for deciding on
  - selecting activities to monitor performances, and
  - assigning relative weightage (%), while configuring a composite KPI.
- The introduction and use of relative relevance
  - increases the visibility of operation critical activities, and
  - provide 'right' weightage (%) to individual activities comprising the composite KPI.
- Provide a dynamic and flexible method of performance monitoring by
  - Including all operation critical activities in accordance with their relative relevance,
  - offering possibility of including new activities, as and when they become operation critical or required to be monitored under regulations, and
  - excluding activities, which are no longer performed by the unit or became non-obligatory through code revisions

8. Conclusion

The use of clear, consistent and, most importantly, the relevant information is an important component of performance measurement, which involves monitoring the current level of performance and instituting changes where the performance is not in line with the predefined targets. However, it is important to recognize that the performance monitoring for a multidimensional entity is not straightforward and requires dealing carefully with operation criticality and influence of stakeholders for each activity. This is required to have the "right" performance picture, without any concern of manipulation and misinterpretation.

Composite performance indices are a beneficial communication instrument for conveying summary information in a relatively simple way. This effort of developing an un-biased & operation critical performance index has minimized the SME influence on proportionating different activities within the composition through relative relevance. The composite index offers a more rounded assessment of performance in presenting the big picture with the attention focused on operation critical activities.

The presented configuration is dynamic in nature and flexible to the varying operation needs, government regulations and industrial code requirement.

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