SOME APPROACHES TO ENSURE MISSION RELIABILITY OF CRITICAL MILITARY EQUIPMENT

Ph.D. Thesis

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DEPARTMENT OF MECHANICAL ENGINERING

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SOME APPROACHES TO ENSURE MISSION RELIABILITY OF CRITICAL MILITARY EQUIPMENT

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I hereby certify that the work which is being presented in the thesis entitled **Some Approaches to Ensure Mission Reliability of Critical Military Equipment** in the partial fulfillment of the requirements for the award of the degree of **DOCTOR OF PHILOSOPHY** and submitted in the **Department of Mechanical Engineering, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from December 2018 to April 2024 under the supervision of Prof. Bhupesh Kumar Lad, Professor, Department of Mechanical Engineering, Indian Institute of Technology Indore, and Prof. Makarand S. Kulkarni, Professor, Department of Mechanical Engineering, Indian Institute of Technology Bombay, Mumbai.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

25 April 2024

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This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

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List of Publications

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5. **Mohril, R. S.**, Solanki, B. S., Kulkarni, M. S. and Lad, B. K., "Residual Life Prediction in the Presence of Human Error Using Machine

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B. Publications other than Ph.D. Work:

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6. Majumdar, J., **Mohril, R. S.**, Lad, B. K. and Kulkarni, M. S., "Logistics, Reliability, Availability, Maintainability and Safety (L-RAMS) for Intelligent, Interconnected, Digital and Distributed (I2D2) empowered futuristic Military Systems" Accepted for publication in *IEEE Transactions on Engineering Management.* doi: 10.1109/TEM.2024.3370818. (Impact Factor = 5.8)

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List of Abbreviations

AF	Adjustment Factor
AFHEP	HEP wise Adjustment factor
AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
BSC	Binary-State Components
BSS	Binary-State Systems
C	Cannibalized Spare
CA	Current Age
CAG	Comptroller and Auditor General of India
CL	Confidence level
CMD	Central Materiel Department
DC	Duty Cycle
DE	Differential Evolution
DEFCON	Defence Readiness Condition
DL	Distributed Ledger
DOD US	Department of Defence, United States
DR	Deployment Role
EFC	Equivalent Full Charge
EPRD	Electronic Parts Reliability Data
F	Function – M: Mobility, F: Firepower, C: Communication, P: Protection
FPCON	Force Protection Condition
G	Genuine Spare
GA	Genetic Algorithm
GOCO	Government-Owned, Contractor-Operated
GUI	Graphical User Interface
HEP	Human Error Probability
HQ	Headquarter
HRA	Human Reliability Assessment

ICT	Information and Communication Technologies
IID	Identically and Independently Distributed
IM	Imperfect Maintenance
IoT	Internet of Things
MBT	Main Battle Tank
MHIDAS	Major Hazard Incident Data Service
MID	Maintenance ID
ML	Machine Learning
MLE	Maximum Likelihood Estimation
MR	Minimal Repair
MSC	Multi-State Components
MSS	Multi-State Systems
MTBF	Mean Time between Failure
MTTF	Mean Time to Failure
MTTR	Mean Time to Repair
NATO	North Atlantic Treaty Organization
NHEP	Nominal Human Error Probability
N-O	Non-OEM Spare
NPRD	Non-Electronic Parts Reliability Data
NSWC	Naval Surface Warfare Center
OEM	Original Equipment Manufacturer
PGA	Parallel Genetic Algorithm
PM	Preventive Maintenance
PoET	Proof of Elapsed Time
PoW	Proof of Work
PRA	Probabilistic Risk Assessment
PSF	Performance Shaping Factors
R	Refurbished Spare
RAMS	Reliability, Availability, Maintainability, and Safety
RBD	Reliability Block Diagram

RBD	Reliability Block Diagram
REDCON	Readiness Condition
RUL	Remaining Useful Life
SC	Smart Contract
SGX	Software Guard Extension
SM	Selective Maintenance
SMP	Selective Maintenance Problem
SPAR-H	Standardized Plant Analysis Risk – Human Reliability Analysis
TEE	Trusted Execution Environment
TTF	Time to Failure
XGBoost	Extreme Gradient Boosting Algorithm

List of Notations

$R(t)$	Reliability for time ‘t’
η	Scale parameter – Weibull Distribution
β	Shape parameter – Weibull Distribution
t_{mode}	Mode of the failure times
PP_1	Phase Parameter 01
$PP_{1,1}$	1st range of Phase Parameter 01
P_i	Phase ID
AF_{Px}	Phase-wise Adjustment Factor
$\eta_{Pdefault}$	Scale parameter of the system/component in a default phase
DC_{Px}	Phase wise Duty Cycle
AF_{Sx}	Spare wise Adjustment factor
$f(t)$	Probability Density Function
R_{Tank}	Reliability of the MBT
$N(i)$	Number of assemblies under consideration
$M(i,j)$	Number of components in the i^{th} assembly,
$R(i,j)$	Reliability of the j^{th} components in the i^{th} assembly
EA_i	Effective Age
M_d	Effective Mission Duration
y_i	actual data point
$\hat{y}_i^{(t)}$	Predicted value
$L\left(y_i, \hat{y}_i^{(t)}\right)$	Loss function for tree
$\Omega\,(f_i)$	Term for regularization
ω	Weight of the leaves
γ	Learning rate or shrinkage
λ	Regularization Coefficient

$\boldsymbol{\mu_{error}}$	Mean of errors
$\boldsymbol{\sigma}$	Standard Deviation
$\boldsymbol{C_{(i,j)}}$	Cost of j_{th} component of i_{th} assembly
$\boldsymbol{M_{(i,j)}}$	Binary Variable indicating Maintenance Decision
$\boldsymbol{R_{Des}}$	Desired Mission Reliability of the tank (higher threshold)
$\boldsymbol{T_m}$	Total maintenance time required
$\boldsymbol{T_{av}}$	Total maintenance time available

Abstract

In a world shaped by geopolitical uncertainties and evolving threats, the pursuance of war readiness has become the defining objective of defence forces across the globe. The experiences derived from previous war situations emphasize that true war readiness goes beyond sheer numerical superiority, focusing on the reliable performance of critical military assets. An important aspect of qualifying a critical military system as war ready lies in meticulously evaluating three fundamental factors: the system's mission capability, operational availability, and mission reliability. Traditionally, the primary focus has been on attaining operational availability of mission-capable systems, which is constrained by its emphasis on the system's current state, without necessarily ensuring future mission success. As a result, defence forces are currently observing a significant change in focus from just ensuring the operational availability of critical systems to the broader measure of mission reliability. Scientifically supporting this shift, this thesis presents a series of research-based studies that investigate scientific approaches tailored to the unique requirements of the defence forces. Through a focused examination of these approaches, the thesis aims to provide insights into how defence forces can effectively ensure the mission reliability of their critical military systems in order to effectively attain war readiness in a manner that aligns with the distinct challenges and complexities of the military landscape.

Firstly, this thesis introduces two comprehensive methodologies for predicting the mission reliability of critical military equipment. One methodology expands upon the existing mission reliability prediction method by integrating essential military-specific factors with the help of adjustment factors, while the other introduces a novel machine learning-based approach. These enhanced methods aim to provide accurate and contextually relevant prediction of mission reliability by considering a comprehensive set of identified military-specific factors, such as operations in diverse operating fields with extreme environmental conditions, multiple deployment roles requiring distinct set of functionalities, the use of refurbished, cannibalized or non-OEM spares, and human error in maintenance under strenuous situations. Numerical

investigations using these methodologies have been conducted on multiple pragmatic scenarios relevant to military operations. These investigations seek to establish the effects of essential military-specific factors on component life and, consequently, mission reliability.

Acknowledging the fact that the way to attaining and ensuring the desired mission reliability has an intricate relationship with the opted maintenance strategy, this thesis introduces a maintenance approach that addresses the imperative of war readiness in tandem with mission reliability. This mission reliability based selective maintenance approach works with the principle that the exploitation, as well as maintenance of mission-critical equipment, should be balanced in such a way that mission critical equipment is always ready for deployment on specific missions or can be made ready within a specified allowable deployment delay for maintenance as per readiness expectations. A parallel genetic algorithm is developed to optimize the associated selective maintenance strategy, identifying a cost-optimal set of maintenance activities. Demonstration of the proposed approach is presented with the help of cases of maintaining war readiness by ensuring the mission reliability of one of the most critical military equipment – the Main Battle Tank across multiple deployment roles. With the help of numerical experimentation, critical parameters of the proposed approach, like mission reliability thresholds, and allowable deployment delay for maintenance in readiness definition, are optimized for the considered demonstration cases. Significant changes in the key metrics, such as maintenance frequency, maintenance cost, maintenance duration, etc., were observed on varying the deployment role and terrains of missions. This validated the consideration of military-specific factors and concluded that the notion of a one-size-fits-all approach proves inadequate in the context of military maintenance management. Through comprehensive evaluation, the superiority of the present approach over the conventional time-based preventive maintenance policy is further established. By incurring ~6% lesser cost, the present approach resulted in maintaining the mission reliability of the MBT higher than the predefined threshold for more than 90% of the overall lifecycle in the considered time horizon. Studying the suggestions from the literature regarding the war readiness definition, the approach is developed to present the readiness level of the fleet in categorization as theoretical readiness and practical readiness. Leveraging the developed approach and outcomes of the numerical investigations, mechanisms are developed to provide war readiness of a fleet at a glance to the high authority decision-makers involved in the development of doctrines. Overall, the proposed approach offers strategic insights and an effective maintenance strategy tailored to military needs, presenting a substantial improvement over traditional time-based maintenance approaches.

Throughout the early stages of this research endeavor, including the field study undertaken to explore and investigate the subject area, a significant deficiency in crucial maintenance-related data has been starkly revealed, both in terms of quantity and quality. This data scarcity poses a major hindrance to the applicability of the developed approaches within the scope of this thesis and also impedes recent trends such as artificial intelligence-driven decision-making in defense forces based on contemporary analytics, which heavily rely on data. Recognizing data scarcity as a pivotal concern, this thesis adopts a proactive approach to address this issue on two fronts. Firstly, it systematically explores alternate approaches for probability distribution parameter estimation as perceived in the literature. Through meticulous examination, six alternate methods have been identified and are presented in a sequential manner, with the aim of estimating the probability distribution parameters crucial for reliability predictions. Furthermore, in an effort to provide a resolution to this challenge, this thesis introduces a blockchain-enabled maintenance management framework designed specifically for military equipment. After careful consideration of the causes of the data deficiency and the challenges behind it from the military operations viewpoint, technological choices are made to develop the blockchain framework. Availing of this framework will solve the issue of scarcity of accurate maintenance data, resulting in enhanced accuracy in crucial estimations like mission reliability, thereby improving war readiness and sustainability estimations of military organizations.

Overall, in this thesis, significant contributions are made in the form of scientific approaches aimed at ensuring mission reliability and achieving war readiness levels. Novel insights into mission reliability prediction, maintenance strategy optimization, and data management in military operations are provided, thus making valuable contributions to the broader understanding of war readiness management in defence forces.

❖

Chapter 1

Introduction

In this introductory chapter, the background, rationale, theory, gaps, objectives, and contributions of the present research are presented to highlight the challenges and significance of mission reliability based war readiness assessment for defence forces. In the end, the outline of the thesis is given.

1.1 Research Background and Motivation

Future of Warfare:

During the next two decades, military conflict will most likely be driven by the same factors that have historically prompted wars - ranging from resource protection, economic disparities, and ideological differences to the pursuit of power and influence. However, the manner in which wars are fought will undergo significant transformation driven by evolving doctrines and emerging technologies [1]. The continuous infusion of modern technologies into critical military assets highlights the ever-changing nature of military development, a pattern emphasized by NATO's Report on Science and Technology Trends from 2020 to 2040, clearly illustrating the swift modernization of defence forces [2].

The integration of Artificial Intelligence (AI) and Information and Communication Technologies (ICTs) has revolutionized military equipment, enabling them to operate as a cohesive and interconnected force. This shift towards network-centric warfare dominated by technologies enhances battlefield awareness and accelerates decision-making processes [3]; and promises to fundamentally change the nature of warfare in the future [4]. The adoption of cutting-edge technologies, such as active protection systems (APS) like the Israeli ‘Trophy’ system or the Russian ‘Arena’ system, exemplifies the modernization of military systems. These APS can detect and neutralize threats like anti-tank missiles and rockets, significantly enhancing the survivability of critical military equipment on the battlefield. For example, integrating such modern technologies with advanced sensor systems like thermal imaging and laser rangefinders has notably improved situational awareness for critical military equipment, enhancing their ability to detect and engage targets effectively, even in challenging environments. Modern equipment like India’s ‘Atharva’ – a hybrid marvel offering a promising blend of power, agility, and cutting-edge technology; and weaponry like India’s ‘Aditya’ are poised to make a significant impact on warfare. These advancements have expanded the horizons for doctrine makers in defence forces, prompting them to think beyond what was feasible a decade ago.

Nevertheless, as these advanced systems become more widespread and accessible, they will bring about additional complications, making more assets vulnerable, making combat potentially more deadly, and heightening the risk of escalation. Policymakers in the defence domain recognize the importance of anticipating these shifts in order to effectively plan for the future of warfare. Despite the widespread interest in this prediction, accurately forecasting the course of warfare remains a difficult challenge. Even technologically advanced militaries have struggled in this endeavor [5]. In this evolving landscape, where predicting when and how the war will happen is very difficult, it is evident that defence forces must prioritize their readiness as the most all-encompassing course of action.

War Readiness:

The core of the claim for prioritizing the military readiness lies in the basic principles of defence capabilities, which are summarized by the ability to achieve a specified wartime objective. The defence capability of any nation is made up of four essential components: force structure, modernization, readiness, and sustainability (Figure 1.1) [6].

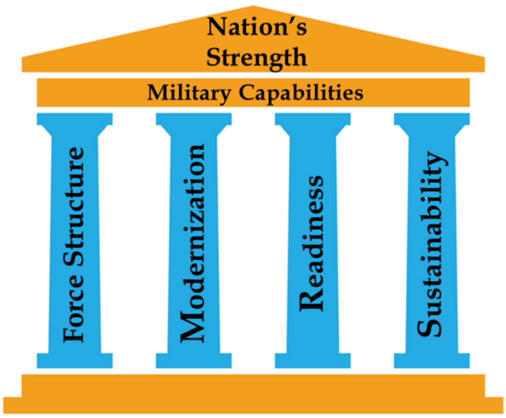

Figure 1.1 Four pillars of military capabilities

The experiences derived from previous war situations emphasize that true defence capability goes beyond sheer numerical superiority. Key historical conflicts, such as the Six-Day War of 1967 fought by Israel [7], the 2008 Russo-Georgian War [8], and the 1940 Winter War fought by Finland [9], serve as notable examples that reinforce this understanding. It becomes evident that the readiness of critical assets for deployment and their sustained operational capability until the achievement of war objectives plays a pivotal role in defining overall defense capability. In this context, readiness is defined as the ability of forces, armored vehicles, and weapon systems to deliver the output for which they were designed, including the ability to deploy and employ without unacceptable delays [6]. Whereas sustainability is defined as the staying power of the forces after deployment, often measured in days [6]. The sustainability of forces is heavily contingent upon their state of readiness. If a war were to break out while the forces were not ready as desired, their sustainability would be largely irrelevant. Therefore, the pursuance of war readiness has become the defining objective of military forces across the globe.

Although all four pillars of defence capability are essential, readiness provides defence forces with a decisive edge by instilling them with the element of surprise - a cornerstone of contemporary military doctrines. In the context of warfare, surprise is termed as 'strike the enemy at a time or place or in a manner for which he is unprepared. Surprise can be in tempo, size of force, direction or location of main effort, and timing' [10]. The element of surprise constitutes a pivotal aspect of warfare, conferring significant advantages to defence forces [11]. By catching adversaries off-guard and disrupting their operational tempo, the surprise element enables defence forces to seize the initiative and dictate the terms of engagement. Unless and until the desired high levels of readiness are attained, leveraging the element of surprise is nearly impossible. As a result, defence forces view the readiness metric as a critical component in developing neoteric doctrines.

Todd Harrison's article 'Rethinking Readiness' emphasizes the significant correlation between all aspects of the US defence budget and their war readiness, highlighting the sincere commitment of the defence forces to prioritize their readiness levels [12]. Within the context of defence forces, readiness is typically classified into three specific tiers: strategic, operational, and tactical. Harrison places particular emphasis on the importance of operational readiness, arguing that it is the most important among the three. He evaluates existing readiness models in the US military, highlighting their primary emphasis on supply chain logistics and personnel training, while comparatively overlooking the crucial element of operational readiness through asset management. This critique emphasizes the significance of reassessing current frameworks to guarantee thorough readiness throughout all tiers of military operations.

Although significant amounts of funding have been allocated to improve military readiness, defence forces around the world have faced difficulties in reaching optimal levels [13]. A report by the Government Accountability Office in the US identifies multiple factors causing a deficiency in achieving the desired readiness levels [13]. It is important to highlight the significance given to accurately considering external military-related factors and ensuring the realistic nature of readiness models. This report emphasizes the importance of creating a thorough strategy to tackle readiness weaknesses at the operational level. One more difficulty in current war readiness strategies is their primarily subjective nature. In order to substantially model and achieve enhanced operational readiness levels, bringing more objectivity is necessary [14].

The Department of Defense, United States, officially defines military readiness as the ability of military forces to fight and meet the demands of assigned missions [15]. This doctrinal perspective on readiness is based on assessing the extent to which a military unit, and collectively all units, can accomplish operational missions. Similar to the aforementioned approaches, this definition emphasizes numerous parameters within militaries, including equipment. However, it places relatively less emphasis on the approaches for achieving readiness.

To explicitly translate the readiness definition within the scope of equipment readiness, all of the above-mentioned definitions can be deconstructed and examined from a narrower yet more detailed perspective focusing on equipment readiness. In doing so, readiness in the context of military equipment can be understood as the ability of equipment or a fleet of equipment to be deployed on the designated mission at any given point in time to perform towards achieving the stated objective. Alternatively, it should be capable of deployment within a predefined short duration, allowing for adequate preparation. Where the extent of this predefined short duration adversely influences the actual extent of readiness, it is imperative to consider it given its potential trade-off with overall maintenance efforts.

Readiness – the Indian Context:

India is perhaps the only country in the world involved in severe territorial disputes with two nuclear-armed neighbors - which also have a close strategic relationship, if not an outright alliance [16]. Following the Galwan crisis between India and China in the summer of 2020, the specter of a two-front war reached a fever pitch among India's strategic community. According to certain media reports, in the past two decades, the Indian government examined the option of a limited-scale attack for several times following the enemy's escalation, but the lack of cold-start war readiness among Indian forces prompted decision-makers to reject that option [17]. Considering the frequency of escalations faced by the Indian defence forces in the past, cold-start readiness emerges as the primary preparatory choice. The numerous advantages that the cold-start war readiness brings to the offensive doctrine are quite evident. However, it is needless to mention that cold-start readiness has an equal, if not greater, impact on the outcomes of war when it comes to defensive doctrines.

The advancements made by the Indian defense forces in terms of modernization are notably commendable; however, concerns persist regarding their readiness levels. A report of the Comptroller and Auditor General of India on working of Army Base Workshops for the year ended March 2016 highlights several serious concerns regarding the backlogs and delays in maintenance of critical military equipment like main battle MBTs, posing serious questions on the overall readiness levels [18]. In a report that was tabled in the Indian Parliament, the CAG suggested that the army should have a detailed plan to keep the weapons system available for any eventuality [19]. Against this backdrop, the concepts of war readiness hold more weightage and gravity to the Indian defence forces.

War Readiness Assessments:

Given the evident importance that defence forces place on evaluating and enhancing their readiness for war, it is imperative to study the current approaches employed by defence forces globally for assessing their war readiness. Concerning the war readiness assessment approaches, there is a paucity of open-domain literature. Nonetheless, there are a few commentaries available, which provide insights into these approaches. Notably, analyses of approaches utilized by the US defense forces stand out among the sparse available literature. US defence forces used multiple readiness metrics for different situations and to cater to different verticals in the forces. Notable metrics include Defence Readiness Condition (DEFCON) [20], [21], Readiness Condition (REDCON) [22], and Force Protection Condition (FPCON). Among these, DEFCON holds particular significance, putting slight consideration on equipment readiness, while REDCON and FPCON emphasize personnel formations and their mobilization only.

With the very limited information available in the open domain, there is a great degree of variation in how DEFCON is interpreted. DEFCON, characterized by five escalating levels of readiness, serves as an alert state for the US armed forces, ranging from DEFCON 1 (most severe) to DEFCON 5 (least severe) [21]. These gradual levels indicate the readiness to match varying military situations; DEFCON 1 indicates maximum readiness for immediate action; DEFCON 2 indicates that the armed forces are ready to deploy and engage in less than six hours of time. Finally, DEFCON 5 indicates the lowest state of readiness. It is crucial to recognize that while DEFCON prioritizes personnel formation readiness, it tends to put less emphasis on achieving the overall readiness of mission-critical equipment. Indeed, none of the existing approaches in the public domain adequately address the readiness of essential equipment vital to military operations. In the context of Indian defence forces, Lt. Gen. NB Singh, in his article 'The Alchemy of Equipment Sustainment', highlighted the need of development of metrics to realistically portray how well equipment readiness capabilities support the doctrine [23].

Existing Approaches for Achieving War Readiness:

The traditional approaches to achieving war readiness for critical military equipment mostly revolve around achieving great equipment availability, which is primarily concerned with whether the equipment is up and operational at a particular time. However, this metric does not speak anything about the equipment's future performance during actual missions. For example, a fleet may have 100% availability due to no equipment failures at a given period, but this does not reflect how well the equipment functions during wartime operations. The Russia - Ukraine conflict is a striking example, where despite deploying initially operating mission critical equipment from Russia, reports show significant damage to their main battle MBTs, significantly affecting mission outcomes. Hence, while equipment availability remains essential, it's imperative to recognize its limitations in predicting future performance. Mission reliability, a statistical metric that appears to be more promising for military applications, is becoming more acceptable in the industrial sphere, and systematically focuses on the availability of equipment in the future (t>0). Charles T. Kelley's thorough research emphasizes the crucial difference between equipment availability and mission reliability. He showed that while initial availability has a modest effect on combat effectiveness, mission reliability has a severe impact on the combat effectiveness [24]. As a result, defence forces are currently observing a significant change in focus from just ensuring the operational availability of critical systems to the broader measure of mission reliability. Furthermore, it is critical to emphasize the importance of selecting technically capable equipment for deployment against a specific mission, as deploying equipment that is incapable of providing the functionalities required for mission accomplishment can result in undesirable outcomes. Thus, assessing the technical suitability of equipment before deployment is crucial for accomplishing intended mission goals.

In essence, in the context of war readiness in the contemporary warfare, a crucial aspect of qualifying a critical military equipment as war-ready involves meticulous evaluation of three fundamental factors: the equipment's mission capability, operational availability, and mission reliability.

Mission Reliability based War Readiness:

Mission reliability is defined as the probability that a system will perform its required mission-critical functions for the duration of a specified mission under conditions stated in the mission profile [25]. In its conventional context, reliability is commonly perceived as a function of time, a perspective that aligns with probabilistic principles. However, concerning military equipment, the DOD's guide for achieving Reliability, Availability, and Maintainability [26] advocate for a more nuanced definition of mission reliability. According to these guidelines, reliability should be conceptualized with respect to a clearly defined mission and the specific conditions under which the equipment will operate. This approach emphasizes that reliability is influenced by the environment and stresses encountered by a system during its mission. Since a mission profile typically outlines these factors comprehensively, it is advisable to evaluate reliability by considering all mission-specific elements rather than solely as a function of time.

The above stated comprehensive definition of mission reliability inherently encompasses the essential criteria for assessing the war readiness of critical military equipment. Mission reliability-based methodologies offer a paradigm shift in war readiness management, promising to supersede conventional approaches by changing the ways decision makers look at their war readiness. Despite the acknowledgment of mission reliability's suitability in war readiness management within the existing literature, scholarly works explicitly demonstrating its application remain scarce. With the evolving landscape of military technology and warfare dynamics, it is imperative for defence forces and researchers within the domain to explore diverse approaches aimed at achieving and ensuring mission reliability for critical military assets.

Role of Mission Reliability in overall Military Operations and Maintenance:

The importance of mission reliability in the administration of war readiness has been previously emphasized. However, the role of mission reliability extends beyond solely ensuring readiness for combat scenarios. Mission reliability is considered one of the most effective levers for effective sustainment [27]. It also plays a crucial role in the broader spectrum of military operations and maintenance, contributing to the effective execution of various important tasks and assisting decision-makers and policymakers in their decision-making. In the context of military operations, the reliability of equipment directly impacts the success and efficiency of missions. Moreover, in the context of maintenance, mission reliability serves as a guiding principle for optimizing maintenance schedules, resource allocation, and overall asset management strategies. By prioritizing mission reliability across all facets of military operations and maintenance, armed forces can enhance their overall operational effectiveness in an ever-evolving warfare landscape.

While operating and maintaining the critical military equipment, the authorities come across several crucial questions for further decision making. Mission reliability can directly assist in answering these questions leading to effective and data-backed decision making. Some of the important questions whose answers are layered under mission reliability are as follows.

- For a given mission profile, which is the best available equipment for the deployment?
- For a given mission profile, which fleet (regiment/squadron) is the best for deployment?
- Which fleet can be mobilized immediately so that it will not require high maintenance after mobilization?
- On the deployment of a particular equipment on a mission, what are the chances that the equipment will not encounter any failure during the mission?
- What all components are to be maintained before the deployment for successful execution of the mission?
- Which spares to carry along while executing the mission?

While the significance of mission reliability across various critical decision-making in military contexts is widely recognized, the current body of literature lacks comprehensive methodologies to effectively implement it for defence forces. Consequently, a pressing need arises for defence forces and researchers within the defence domain to evaluate approaches aimed at achieving and maintaining mission reliability for vital military equipment. While existing literature extensively addresses reliability prediction within conventional manufacturing and logistics spheres, it is crucial to acknowledge that the direct application of these reliability prediction models to critical military systems may be inappropriate. This incoherence arises from the failure of such models to incorporate the effect of several crucial military-specific factors.

This thesis attempts to bridge this gap by presenting a series of studies that investigate scientific approaches tailored to the unique requirements of the defence forces. As outcome of the investigations, this thesis aims to provide insights into how defence forces can effectively ensure the mission reliability of their critical military systems in a manner that aligns with the distinct challenges and complexities of the military landscape.

Data Scarcity – A Big Challenge:

Reliability engineering, being a data-centric domain, requires a sufficient amount of data, particularly failure and maintenance related data, for performing several of the analyses developed in the present research. The efficacy of the developed approaches is intricately linked to the quality and quantity of the underlying operations and maintenance data. This is more important in the domain of Reliability, Availability, Maintainability, and Safety (RAMS) management for military systems, where accurate data-analytics play a crucial role. However, it has been found that a lack of data poses substantial obstacles to defense forces, reducing their ability to make analytical decisions based on existing data. Recent trends like industry 4.0 are claiming the possibility to transform the current military capabilities [28]. However, these strategies expect high level of preparedness from data management perspective; and the absence thereof creates hinders the seamless application of such modern techniques. The absence of a mechanism for the systematic management of operations and maintenance data in defence organizations is the prime reason for the data unavailability, and it poses a formidable obstacle in the pursuit of comprehensive war readiness assessment and management in the age of analytics.

The defence sector faces unique challenges in managing a large set of maintenance related data securely for critical decision-making. Issues such as data registry, integrity, and security are more complex due to the vast amount of data generated by military organizations and the involvement of multiple partners in the overall value chain. The increasing number of equipment and their strategic deployment in diverse locations pose challenges for maintenance data management. The introduction of the Government-Owned, Contractor-Operated (GOCO) model in defence maintenance further complicates data management with concerns like data sharing, integrity, transparency, and increased bureaucratic processes. Handling maintenance data within such a vast and challenging scenario, especially with the anticipated level of detail, presents a considerable challenge. In the era of data analytics, mere possession of data is insufficient; it must also be presented in suitable electronic formats to ensure its efficacy. Eventually, if the necessary data is maintained with the desired level of accuracy and granularity by any traditional mechanism, especially considering its criticality in military operations, it must be stored in a highly secure environment.

Acknowledging data scarcity as a pivotal concern, this thesis takes a proactive stance by addressing this issue on two levels. The essence lies in recognizing that without a reliable source of ample and quality data, the envisioning and execution of scientific approaches for war readiness management remain an impregnable challenge.

1.2 Problem Description

As outlined in previous section, achieving war readiness is one of the paramount objectives for defence forces. In this context, the significance of assessing and ensuring mission reliability is visibly increasing. However, scholarly literature demonstrating mission reliability based war readiness management is not seen in the existing pool of literature. This research systematically identifies and addresses the evolving research problem in the context of the shift of conventional war readiness management from ensuring operational availability to mission reliability. Hence, this thesis presents comprehensive studies of some approaches to predict the mission reliability of critical military equipment, ensure it to be higher than desired, thereby achieving its war readiness.

To explicitly formulate the problem, a systematic literature review is carried out. Although very limited scientific literature about war readiness assessment and its way forward is openly available, some standard reports and commentaries from reputed organizations helped understand the landscape better. Additionally, in-depth discussions with the experts in the defence domain helped understanding the scenario in a better manner. However, for all the technological advancements attempted in this thesis, sufficient literature is available, which is thoroughly studied for the present research.

Critical findings and research gaps are as follows:

(A) Most of the literature in the domain of war readiness management keeps focus on achieving operational availability through traditional maintenance practices. Some scientific reports have perceived that mission reliability is a better metric for war readiness assessment. However, scholarly literature demonstrating mission reliability based evaluations is not seen in the existing pool of literature.

(B) The available mission reliability prediction methods do not suffice to be viable for critical military equipment, as they lack the ability to incorporate the effect of numerous key military-specific factors on mission reliability, resulting in compromised accuracy.

(C) The currently available maintenance optimization models pose a computational challenge by needing longer computation time, which is not appropriate for a fast-paced organization like defence. The advancement of modern machine learning algorithms opens up newer avenues for faster and more effective methods of mission reliability evaluation. These avenues are rarely investigated in the literature.

(D) The present maintenance approaches, like selective maintenance models, consider the mission reliability of systems. However, they do not fit into the exact modus operandi of the maintenance function of the defence forces as they do not correspond to the war readiness expectations.

(E) The literature acknowledges the challenges in RAMS domain posed by data scarcity. Although there are many frameworks available for effective data management, it does not suffice the adequacy to be viable for defence maintenance management, given the numerous challenges which are unique to the defence organizations.

1.3 Research Objectives

Based on the presented rationale and the findings from the literature review, the overall objective is as follows:

Development of a maintenance approach that exactly suits the modus operandi of defence forces in attaining and sustaining war readiness by ensuring the mission reliability of critical military equipment.

The overall objective is further divided into the following Sub Objectives (SO):

SO1: Development of a mission reliability prediction method with modeling the combined impact of identified military-specific factors on system reliability. Further, link the predicted system reliability to the functional reliability of the critical military equipment.

SO2: Development of mission reliability based selective maintenance planning approach to ensure desired mission reliability for critical military equipment against multiple mission profiles.

SO3: Critical analysis of the proposed approach by comparing its performance against the conventional maintenance practice.

SO4: Development of a comprehensive framework for military maintenance data management to increase the applicability of developed approaches and make military maintenance future-ready in the era of analytics.

1.4 Key Contributions and Broader Impact

The overall research toward fulfilling all of the above-stated objectives started with investigating the subject area, which included a detailed study of military literature available in the open domain and in-depth discussions with defence professionals involved in decision-making, operations, and maintenance. The investigation of the subject area not only helped understand the existing maintenance function and gather the required information for performing the research but also helped to refine the research objectives to effectively align them with the exact modus operandi of the defence forces.

In light of the serious scarcity of data from a quality as well as quantity viewpoint, this thesis presents a comprehensive study of alternate methods to estimate the required data for mission reliability prediction. Some hybrid models are presented that effectively leverage the knowledge of domain/field experts to estimate the parameters for probability distribution for the failure data in the absence of actual failure data – a fundamental need for parametric approaches for conventional reliability prediction methods. Following the acquisition of comprehensive insights into the maintenance function of military equipment and gathering essential data for reliability prediction, the efforts are directed toward fulfilling the stated research objectives.

The paramount objective of this research is to ensure the mission reliability of critical military equipment, thereby achieving its war readiness. In order to make the mission reliability prediction for military equipment accurate, literature strongly suggests incorporation of the military specific factors, which is rarely seen in the present literature. In order to address this expectation, with the subject area investigations, and literature review, essential military specific factors which are influential to the mission reliability of the critical military equipment are identified. Further, this thesis proposes two comprehensive methodologies for predicting mission reliability of critical military equipment. One methodology represents a scientific expansion of the existing mission reliability prediction method, while the other introduces a novel approach based on machine learning. Aiming to provide a more accurate and contextually relevant prediction of mission reliability, both of these enhanced methods incorporate a comprehensive set of identified military-specific factors, and maps their combined effect on mission reliability of critical military systems.

Acknowledging the fact that the way to attaining and ensuring the desired mission reliability has an intricate relationship with the opted maintenance strategy, this thesis attempts to propose a tailored maintenance approach that addresses the imperative of war readiness in tandem with mission reliability. This thesis proposes a novel mission reliability based selective maintenance approach which ensures that the critical military equipment under consideration should always possess the mission reliability of a desired predefined level. It balances the utilization and maintenance of critical military equipment in such a way that the equipment is always in the state of readiness with the desired predefined level of mission reliability. In order to effectively integrate the selective maintenance planning with the proposed approach, a comprehensive review of the state of the art literature on selective maintenance is performed and is presented in this thesis.

In order to demonstrate the effectiveness of the developed selective maintenance based approach for ensuring mission reliability and, ultimately war readiness at the fleet level of the equipment, a parallel genetic algorithm is used to implement the developed maintenance approach at the fleet level. The use of a parallel genetic algorithm has helped to analyze several of the key parameters in selective maintenance optimization without requiring significantly more computational time, irrespective of the significant increase in the problem complexity. An added contribution lies in the outcomes of this demonstration of the developed maintenance approach at the fleet level, as it facilitated the optimization of some of the key parameters in the selective maintenance problem.

While working in the domain of reliability engineering and maintenance management for military equipment, and investigating the subject area in the scope of the present research, it was identified that because of the absence of a mechanism for the systematic management of operations and maintenance data in defence organizations, data scarcity is a big concern. And this data scarcity poses a formidable obstacle in the pursuit of comprehensive war readiness assessment and management in the age of analytics. To provide a holistic solution to the problem of operation and maintenance data scarcity in the defence forces and to increase the applicability of the developed approaches, this thesis presents a novel blockchain enabled maintenance data management framework for military equipment, with the intent of making military maintenance future ready in the era of analytics.

On a broader scale, this thesis contributes significantly in several key aspects. Firstly, it introduces comprehensive mission reliability prediction approaches that have wide-ranging applications within the military domain. These approaches are designed to enhance the overall war readiness management by ensuring the mission reliability of critical military equipment through scientifically validated methodologies. The outcomes derived from the analysis using these developed prediction methods have unveiled valuable insights and non-obvious learnings. These insights are expected to contribute to further advancements in research related to maintenance management and war readiness within military organizations. The thesis also addresses a critical gap identified in the literature, which emphasizes the need for more advanced techniques to manage war readiness assessment models effectively. While literature acknowledges this need, it falls short in providing practical suggestions on how to achieve it. This thesis fills this gap by presenting scientific approaches that can augment the existing war readiness assessment practices. Furthermore, this thesis serves as a valuable ready reference for defence forces globally that are endeavoring to enhance their war readiness management strategies. By uniquely integrating reliability engineering and maintenance management with the critical domain of war readiness in military management, this thesis makes a novel contribution that significantly enhances the overall understanding of this crucial area within the research community.

1.5 Organization of Thesis

The thesis is broadly divided into six chapters. The current chapter introduces the reader to the rationale of the work, outlines the research objectives, and briefly enumerates the overall contribution. Chapter 2 presents comprehensive insights into the existing maintenance function of critical military equipment like armored vehicles. Chapter 3 presents the developed approaches for mission reliability prediction while incorporating the combined impact of several identified military-specific factors. This chapter also presents a novel machine learning based approach for mission reliability prediction. With the outcomes of numerical investigations, the effect of various military-specific factors on systems life and mission reliability is presented. Chapter 4 proposes the novel mission reliability based selective maintenance approach, presents the demonstration of the proposed approach on a fleet of main battle MBTs, and with the numerical experiment, highlights optimization of the critical parameters in the formulated problem. Chapter 5 presents a blockchain enabled comprehensive framework for military maintenance data management to increase the applicability of developed approaches and make military maintenance future-ready in the era of analytics. Chapter 6 draws conclusions from the overall research and discusses some of the important future directions for expanding the work done within the scope of this thesis. Figure 1.2 depicts the overall flow of the organization of the thesis.

1.6 Summary

The introduction chapter provides a brief overview of the research journey in the scope of the present thesis. It begins with providing the rationale for the present work, explaining the reasons behind undertaking this study. This sets the stage for the subsequent discussion on the research background and motivation, where existing knowledge gaps and the need for further investigation are highlighted. This leads to the establishment of clear research objectives, outlining the goals and aims that the study seeks to achieve. Furthermore, the key contributions of the research and its broader impact are briefly outlined. It emphasizes the innovative approaches that this research brings to the field. Finally, the organization of the thesis is presented, providing a structured overview of how the content is divided into chapters to address the research objectives and present the findings systematically.

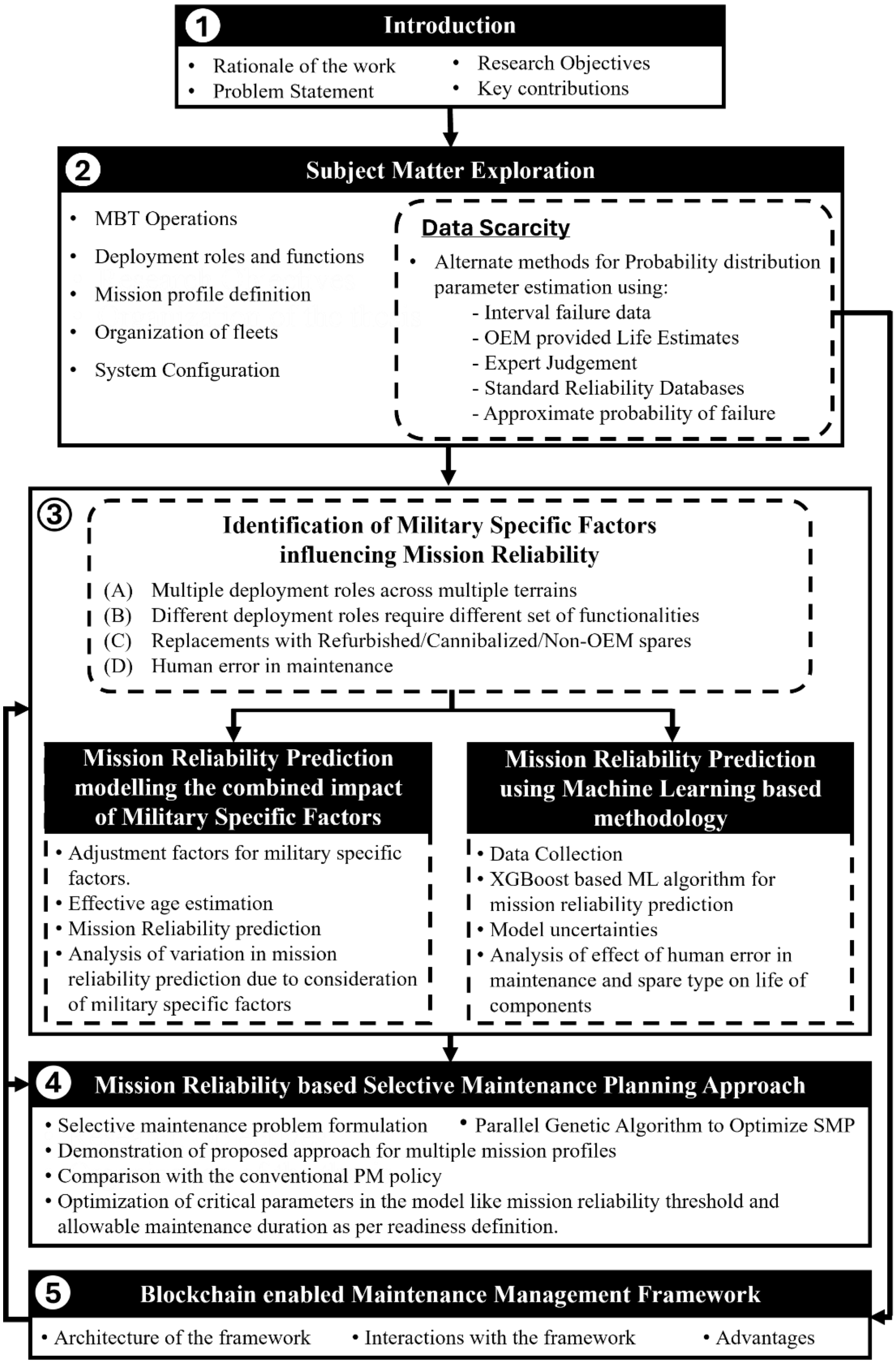

Figure 1.2 Organization of the thesis.

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Chapter 2

Main Battle Tank Operations

- Subject Matter Exploration

This chapter lays the foundation for the thesis by examining the overall operation function of critical military equipment. It draws upon two key sources of information: publicly available military documents and discussions with expert industry professionals involved in both the manufacturing and decision-making sides of defence. The chapter focuses on gleaning insights from these sources that are directly relevant to the methodological approaches presented in later chapters of the thesis.

As discussed in the preceding section, this thesis proposes some approaches for war readiness management through effective management of mission reliability of critical military equipment. Although the overall objective is to develop approaches which are generic in nature and should be able to be applied to a wide range of mission critical equipment, for the development and further demonstration of the approaches within the scope of this thesis, Main Battle Tanks (MBT) have been chosen as the subject matter. This consideration is based on the large proportion of the MBTs among all the mission-critical equipment in the defence forces. Given that the developmental effectiveness of the approaches hinges upon understanding the operational and maintenance functions of MBTs, it is imperative to delve into these aspects. Consequently, this chapter discusses the overall operation function of MBTs, which is acquired from the military documents which are available in the open domain [29], [30], [31], and in-depth discussion with the professionals working in the manufacturing as well as decision making of the defence domain. Despite the extensive amount of data and insights garnered through these activities, the chapter selectively presents insights pertinent to the developed approaches which are further discussed in this thesis. This comprehensive exploration of the subject matter not only facilitated the acquisition of requisite information and data for approach development and demonstration but also largely helped to refine the objectives of this study in order to align them well with the exact modus operandi of defence forces for overall war readiness management.

2.1 Employment Scenarios

The overall lifecycle of an MBT, along with many other mission-critical military equipment, during its employment phase can be classified into two primary categories: *Peacetime* and *Wartime*. The majority of equipment utilization occurs during peacetime, encompassing routine operations, mission exercises, and training activities. Consequently, the majority of equipment maintenance activities are also conducted during peacetime, with the objective of ensuring the equipment remains operational and available for wartime deployments, for which it is primarily intended. In peacetime, MBTs are utilized for routine operations and participation in predefined training exercises. Further delineation of the employment phase reveals four distinct scenarios [32], as depicted in Figure 2.1.

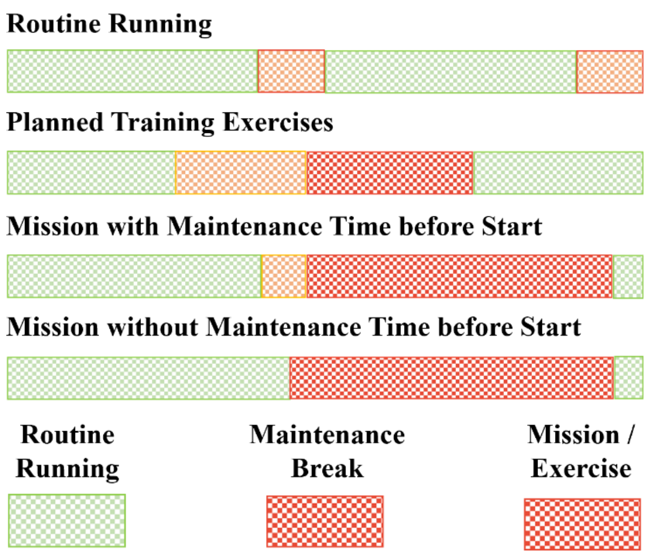

Figure 2.1 Employment Scenarios

- Routine running:

In this scenario, MBTs are not deployed on missions or training exercises. Instead, they are solely tasked with performing routine runs. Maintenance of the MBT follows a predefined schedule. Following maintenance, the MBT resumes its normal routine runs. In this scenario, the timeline for scheduled maintenance events, the duration of maintenance events, and the subsequent operational run duration of the MBT are all predetermined and known. A significant portion of the MBT lifecycle in the employment phase is dedicated to performing this scenario.

- Planned training exercises:

During training exercise, an MBT has to complete its assigned mission that closely simulates actual battle situations. The only distinction between a real mission and a training exercise is that the training exercise follows a pre-defined schedule, and the MBT must operate appropriately. As the schedule for the training exercise is known well-before, there is a chance to complete all essential maintenance tasks to ensure that the MBTs are well-prepared for the upcoming exercise.

- Mission with maintenance time before start:

As previously discussed, predicting the outbreak of war is inherently difficult, and this uncertainty extends to determining the timing of MBT deployments for missions. Once a mission is assigned, there is often a very limited window of opportunity to prepare the equipment for participation. Depending on the available timeframe before the mission, decisions regarding performing maintenance activities must be made. This scenario introduces the possibility that there may not be adequate time to complete all desired maintenance activities before the mission commences.

- Mission without maintenance time before start:

This scenario arises when there is no time for maintenance prior to the mission commencement. Under these circumstances, no maintenance activities can be performed on the MBTs before they embark on the mission in an emergency situation, necessitating their deployment in their existing condition.

This extreme scenario underscores the importance of cold-start readiness, wherein MBTs must be maintained during peacetime to ensure they are not only capable of initiating but also completing missions of certain duration in the event of an unforeseen outbreak of war.

2.2 Deployment Roles

MBTs are expected to serve multiple deployment roles (DR) across their lifecycle. At its most fundamental level, the roles MBT performs in war time can be classified into Attack and Defense role. In both of these roles, MBTs are deployed on different mission types. For a particular MBT, the different possible mission types are as follows [30]:

DR 1. Tank to Tank Combat

MBT is involved in direct combat with enemy's MBT on war field.

DR 2. Deep Penetration

MBT is involved in travelling deep into enemy's territory; and battling deep in enemy territory.

DR 3. Close Fire

MBT is involved in intensive firing on enemy's resources including infrastructure.

DR 4. Infantry Protection

MBT or group of MBTs has to provide protection to critical resources including infantry.

DR 5. Reconnaissance

MBT is sent for military observation of a region to locate the enemy or to perform preliminary surveying or research.

2.3 Functions

In order to successfully perform any of the aforementioned deployment roles, an MBT performs the following four different functions independently or sometimes simultaneously [29].

F1. Mobility

The primary ability of an MBT enabling rapid maneuverability on the battlefield to swiftly engage enemy targets or reposition as needed.

F2. Firepower

The ability to fire using potent armaments such as main guns, machine guns, and anti-MBT missiles, allowing them to engage and destroy enemy vehicles, and personnel formations effectively.

F3. Protection

The ability of an MBT to provide armored protection to several things including itself, other MBTs, infantry, some soft resources, own posts etc.

F4. Communication

The ability of an MBT to seamlessly coordinate with other units and command centers, enabling real-time information exchange, target acquisition, and tactical decision-making.

2.4 Organization of MBTs

The organization of MBTs within military forces typically follows a hierarchical structure designed to optimize operational effectiveness and command coordination. Although the names may vary, prime militaries in the world follow a very similar organization of their MBTs, where slight variations in numbers may be found. Understanding the various levels of MBT fleets and their organization is crucial, as the majority of decision-making regarding deployment occurs at the fleet level.

At the lowest level, a strategic grouping of three to four MBTs is referred to as a troop or platoon. Three to four of these groups collectively constitute a squadron or company, which serve as the basic tactical units assigned for mission roles. Additionally, three to four of these groups are combined to form a regiment or brigade, which also includes some MBTs from the headquarters command [31]. To mitigate ambiguity arising from variations in these titles, the organization of MBTs as utilized by the Indian Army, based on available knowledge in open domain literature [33], is adopted within the scope of this thesis, as shown in Figure 2.2.

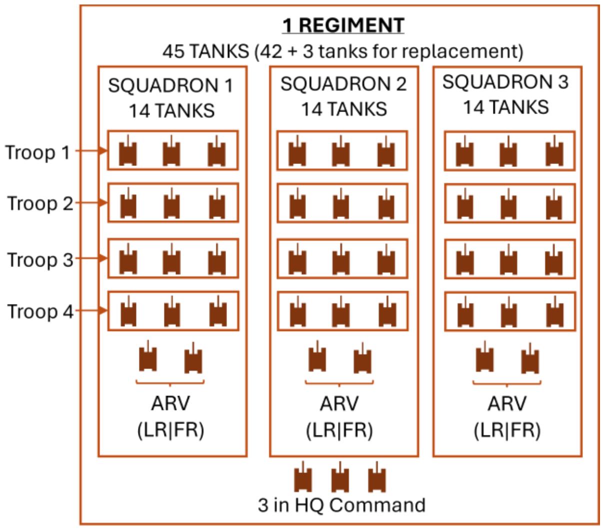

Figure 2.2 Organization of MBTs

2.5 Mission Profile Definition

The operational planning and execution of a fleet of MBTs in militaries heavily relies on the mission profile definition. The process entails the methodical identification and outlining of objectives, activities, and requirements for MBTs to effectively accomplish specified mission goals. As the present study deals with mission reliability prediction, it is imperative to understand all the factors which are required to define a actual mission for fleet of MBTs.

- Deployment Role: Attack / Defence
- Mission Type: Tank to Tank / Deep Penetration / Close fire / Reconnaissance / Infantry Protection
- Distance to travel: Probable distance the MBT has to maneuver.
- Mission Duration: Probable duration the MBT has to operate.
- Mission Location: Exact location where the mission needs to carry out.
- Equivalent Full Charge (EFC) Requirement: Expected firing rounds.

2.6 System Configuration

In the context of mission reliability prediction, the creation of a Reliability Block Diagram (RBD) constitutes a pivotal step. The reliability function derived from the RBD serves as the basis for mission reliability prediction. A comprehensive understanding of the system configuration of the equipment is essential for constructing the RBD. The system configuration encompasses a list of all assemblies and their respective sub-assemblies. Achieving a finer granularity in the system configuration enhances the accuracy of predictions. In this study, the system configuration of an MBT as presented by [32] is utilized. Based on discussions with experts, slight modifications have been incorporated into this system configuration, including a few additional sub-assemblies. The system configuration used in the scope of this study is presented in Annexure A.

2.7 Probability Distribution Parameter Estimation

Probability distribution parameter estimation is a fundamental component of the traditional parametric approach utilized in reliability prediction, as it offers valuable insights into the behavior of systems and components over time. This process encompasses the selection of an appropriate probability distribution that aligns with the observed data characteristics, followed by the application of statistical techniques to estimate the parameters associated with the chosen distribution. These statistical techniques encompass methods such as Maximum Likelihood Estimation (MLE), Least square method, probability plotting, among others. The accuracy of the estimated parameters is significantly influenced by the quality and quantity of lifetime data available for the component under consideration.

Despite the availability of probability distribution parameters for the majority of components as presented by [32], estimating them for the added components posed a significant challenge due to insufficient quality and quantity of lifetime data. Furthermore, literature pertaining to lifetime data or probability distribution parameters of components utilized in MBTs is not readily accessible in the open domain. Unfortunately, in many instances, the absence of a systematic maintenance and failure data collection mechanism poses a significant challenge, resulting in a scarcity of accurate lifetime data. This deficiency complicates the process of effective reliability prediction. To overcome the said challenge of data unavailability, literature perceived that the expertise of domain specialists within these industries could be systematically used and integrated with the statistical models to fetch the required estimates [34], [35], [36], [37], [38]. Therefore, within the scope of the present research, a comprehensive review of the literature is conducted to explore alternative non-conventional methods for estimating probability distribution parameters for reliability prediction. Six methods are presented in a sequential manner, with established priorities, to facilitate a comprehensive understanding of their applicability and effectiveness in estimating probability distribution parameters for reliability predictions; which are relevant to the defence maintenance function. In this research context, the primary method prioritized for parameter estimation involves utilizing MLE when exact lifetime data for the component is available in adequate quality and quantity. Considering the mechanical nature of the components in the system configuration under consideration, the Weibull distribution is assumed to be the underlying probability distribution, as it can effectively model increasing, decreasing and constant failure rates based on the value of shape parameter.

2.7.1 Alternate Method 01 – Using Interval Lifetime Data

When lifetime data is available in the form of intervals, often encountered due to limited observation capabilities, the use of the MLE method for parameter estimation holds applicability. Interval data arises when the exact failure times of components are unknown, and only information on the time intervals within which failures occurred is available. This scenario commonly arises when component inspections are made at discrete intervals. In such cases, MLE provides a robust approach to estimate the parameters of the probability distribution that best fits the observed interval data [39].

2.7.2 Alternate Method 02 – Using OEM Provided Life Estimates

The Original Equipment Manufacturer (OEM) of the component possesses the design data pertaining to the component, which includes certain life estimates derived from laboratory testing results. These life estimates serve as valuable inputs for estimating the distribution parameters. Specifically, the life estimates denote the percentage of the population that has survived until a specified time, with "L10 life" representing an industry-standard value indicating the time at which 90% of the parts are surviving, or conversely, 10% of the parts have failed. Knowledge of any two such life estimates result in a system of two equations with two unknowns. Eq. 1 presents the reliability function for Weibull distribution [40]. For instance, when the user specifies the L10 life, the reliability of the component for that duration can be deemed as 0.9 (Eq. 2), while specifying the L90 life corresponds to a reliability of 0.1 for the component within the specified time duration (Eq. 3). Consequently, by inputting any two life estimates, two reliability equations can be formulated using the reliability function. Solving these equations simultaneously yields the two parameters, namely the scale parameter (η) and shape parameter (β).

$$R(t) = exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \quad \text{Eq. 1}$$

$$0.9 = exp\left[-\left(\frac{L10\ Life}{\eta}\right)^{\beta}\right] \quad \text{Eq. 2}$$

$$0.1 = exp\left[-\left(\frac{L90\ Life}{\eta}\right)^{\beta}\right] \quad \text{Eq. 3}$$

2.7.3 Alternate Method 03 – Using OEM Provided Life Estimates and Expert Judgement

Maintenance personnel tasked with the maintenance of these MBTs possess significant expertise regarding the equipment and its failure patterns [41]. While these maintenance experts, along with others in the design domain, may have extensive practical experience with the equipment, it is not expected from them to possess knowledge of the underlying failure distributions. In cases where only one life estimate is available from the OEM, only one reliability equation can be generated. To obtain the other reliability equation, expert judgment can be relied upon. The expert judgement in the form of answers to some of the following questions can be used to create the other equation [38], [42].

- What is the maximum survival time observed by the expert?
- What if the time at which the component is most likely to fail?
- How many failures are observed by the expert?
- How much preventive replacements are observed by the experts? And at what time?

The maximum observed life of a component suggested by the expert indicates a high probability of failure at that time, leading to the generation of an equation for failure probability based on this information as Eq. 4. Additionally, with information about number of failures and the highest survival time observed by the experts, failure probability can be estimated using Benard's approximation for median rank estimation, as suggested by [42].

$$F(t) = 1 - exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \qquad \text{Eq. 4}$$

Similarly, the most likely life of the component as stated by the expert suggests the mode value of the time-to-failure distribution, resulting in the creation of another equation as Eq. 5.

$$t_{mode} = [\frac{\beta - 1}{\beta}]^{1/\beta} \times \eta \qquad \text{Eq. 5}$$

In case of no failures seen, the minimum life observed of component stated by the expert along with the number of preventive replacements seen by the individual expert leads to the usage of zero failure test where the reliability of that component can be estimated using the number of failures seen by the individual expert and the confidence level (CL). The equation for estimating the zero failure reliability is given as Eq. 6 and Eq. 7.

$$1 - CL = R^{n} \qquad \text{Eq. 6}$$

$$1 - CL = P(X \le C) = \sum_{X=0}^{C} \frac{n\,!}{X!\ (n - X)!} P^{X}(1 - P)^{n-X} \qquad \text{Eq. 7}$$

As discussed earlier the life estimate provided by the OEM has higher priority for parameter estimation, here for solving the two equations with two variables, one equation from OEM life estimate is always used and for the other equation any one of the three equations discussed above in this section can be used.

2.7.4 Alternate Method 04 – Using Expert Judgement

In instances where even one life estimate is unavailable, one can rely solely on expert judgment. In such cases, the expert need to provide responses to at least two of the questions outlined in sub-section 2.7.3. Based on the expert's answers to these questions, the corresponding equations (among Eq. 4, Eq. 5, Eq. 6, Eq. 7) are formulated and solved concurrently to estimate the necessary probability distribution parameters [38], [42].

2.7.5 Alternate Method 05 – Using Standard Reliability Databases

Standard reliability databases such as the NPRD (Non-Electronic Parts Reliability Data) [43], EPRD (Electronic Parts Reliability Data) [44], NSWC (Naval Surface Warfare Center) handbook for reliability prediction [45], and several MIL standards provide valuable resources for estimation of probability distribution parameters in instances where actual field lifetime data and all the other data mentioned in above subsection is unavailable. These databases contain extensive records of failure rates, failure modes, and other reliability-related information for a wide range of components and systems. By leveraging the data compiled within these databases, probability distribution parameters can be estimated. Majority of these reliability databases provides the failure rate for the components. Additionally, a set of failure modes is also provided, among which a particular failure mode and its respective shape parameter need to be identified first. On acquiring the knowledge about failure rate and the shape parameter, remaining another parameter - scale parameter can be estimate as follows:

$$Mean = \frac{1}{Failure\ rate} \qquad \text{Eq. 8}$$

$$Mean = \eta \times \Gamma\left(\frac{1}{\beta} + 1\right) \qquad \text{Eq. 9}$$

where,

$$\Gamma(n) = \int_0^\infty e^{-x}\ x^{(n-1)}\ dx \qquad \text{Eq. 10}$$

$$\eta = \frac{1}{Failure\ Rate\ \times \Gamma\left(\frac{1}{\beta} + 1\right)} \qquad \text{Eq. 11}$$

2.7.6 Alternate Method 06 – Using Approximate Probability of Failure

In an extreme case, where none of the data required in above discussed methods are available, including the case where the expert is also not confident enough o provide the required judgement, this priority six method can be used which has its links to fundamentals of reliability prediction as statistical probabilistic inference. The expert can specify the probabilities of failure of a component for different time duration and the model will estimate the parameters from those failure probabilities. The data expected for this type of estimation is described with the help of an example below.

Table 2.1. Approximate Probability of Failures

Interval	Probability of Failure
What is the probability of failure in interval 0 to A?	0.1
What is the probability of failure in interval A to B?	0.2
What is the probability of failure in interval B to C?	0.5
What is the probability of failure in interval C to D?	0.2

Using the standard method of Least square fitting [40], the given data can be used to estimate the probability distribution parameters.

❖

Chapter 3

Mission Reliability Prediction Approaches

In this chapter, two novel methodologies for predicting the mission reliability of critical military equipment are presented. First, a detailed discussion of several military-specific factors that significantly impact mission reliability is presented. Subsequently, the development of the two new mission reliability prediction approaches is described. Finally, the results of numerical investigations utilizing these methods are presented. The impact of the identified military-specific factors on mission reliability is then highlighted through analysis of these results. This investigation provides valuable insights for both operational as well as maintenance planning within the military context.

The work presented in this chapter is published in two parts. Firstly, under the title *"Residual Life Prediction in the Presence of Human Error Using Machine Learning"* in "Proceedings of 4th IFAC Workshop on Advanced Maintenance Engineering, Services and Technologies - AMEST 2020", University of Cambridge, September 2020. doi: 10.1016/j.ifacol.2020.11.019. Secondly, under the title *"XGBoost based residual life prediction in the presence of human error in maintenance"* in "Neural Computing & Applications" vol. 35, pp. 3025–3039. doi:10.1007/s00521-022-07216-2.

The overall objective of the present thesis deals with the notion of achieving desired war readiness by ensuring mission reliability of critical military equipment. Consequently, within the scope of this research, mission reliability prediction becomes a pivotal aspect. This chapter delineates the development of two distinct approaches developed for the prediction of mission reliability of critical military equipment.

3.1 Mission Reliability of Military Equipment

In today's scenario, reliability engineering is a well-established, multi-disciplinary scientific discipline which aims at providing an ensemble of formal methods to address the following questions [46], [47], [48]:

- Why systems fail, e.g. by using the concepts of reliability physics to discover causes and mechanisms of failure and to identify consequences;
- How to develop reliable systems, e.g. by reliability-based design;
- How to measure and test reliability in design, operation and management;
- How to maintain systems reliable, through maintenance practices.

In the context of present thesis, research focuses on the last question listed above, and attempts to provide scientific approaches to maintain critical military systems reliable, through maintenance practices.

Reliability is traditionally viewed as a time-dependent function, aligning with established probabilistic principles. However, concerning military equipment, the DOD's guide for achieving Reliability, Availability, and Maintainability [26] advocates for a more nuanced understanding of mission reliability. According to these guidelines, reliability should be framed within the context of a well-defined mission profile and the specific operational conditions under which the equipment will be deployed. This approach highlights that reliability is shaped by the environmental factors and operational challenges encountered by a system during its mission execution. Since a mission profile typically encompasses these factors comprehensively, it is recommended to evaluate reliability by considering all mission-specific elements rather than solely as a time-dependent function [26].

Leveraging insights from the DOD's guide [26], a literature review was undertaken to explore factors affecting reliability predictions, aiming to improve the accuracy of mission reliability prediction. This review identified several military-specific factors that significantly impact the mission reliability of critical military equipment. Although literature recognizes the impact of certain factors individually, their collective influence on mission reliability has not been thoroughly examined in the current literature. Additionally, there is a gap in the existing literature concerning a mission reliability prediction approach that aligns with the operational practices of military organizations, which would integrate the combined effects of essential military-specific factors. As previously highlighted, mission reliability plays a pivotal role in the present approaches for war readiness management. Therefore, achieving accuracy in mission reliability prediction is paramount. Therefore, rather than employing conventional mission reliability prediction approaches [32], this thesis introduces a tailored mission reliability prediction methodology. This methodology incorporates the combined impact of following four essential military-specific factors, leading to more accurate and realistic predictions.

(i) Deployment across multiple terrains characterized by extreme environmental conditions.
(ii) Different deployment roles requiring different functionalities.
(iii) Use of Refurbished/Cannibalized/Non-OEM Spares in maintenance.
(iv) Human error in maintenance.

These are discussed in detail hereunder.

3.1.1 Deployment across multiple terrains

Given the dynamic nature of warfare and the geographical constraints faced by nations, critical military equipment like MBTs are deployed across diverse locations across borders which are characterized by different terrains. Often, escalating situations necessitate the deployment of a fleet of MBTs from one terrain to another. These terrains are characterized by extreme environmental conditions, as observed in specific instances such as the deployment of T-72 MBTs by the Indian Army in the East Ladakh region in 2019 [49]. These MBTs were previously deployed in different regions with distinct environmental conditions, highlighting the adaptability required of military equipment [50]. Similarly, during the Gulf War, US Army's M1 Abrams tanks encountered harsh desert conditions in Iraq and Kuwait, posing challenges uncommon in their native operational environment [51]. Such examples underscore the necessity for critical military equipment, including MBTs, to operate effectively across diverse terrains with varying environmental conditions.

The impact of extreme environmental conditions on component aging and subsequent reliability is well-documented in literature [52], [53]. Extensive research into the reliability of mining equipment has revealed that environmental conditions during operation, including factors such as temperature, humidity, dust levels can significantly impact the reliability of the system, machine, or its components [52]. However, most traditional and even some modern reliability estimation models designed for conventional manufacturing systems, prioritize the consideration of a particular environmental conditions considering the stationary nature of systems over those operating in diverse terrains. In contrast, for MBTs and other critical military equipment, the environmental factor significantly influences mission reliability and should be factored into reliability prediction models to enhance accuracy [32].

Furthermore, it is imperative to acknowledge that environmental conditions can fluctuate not only across terrains but also due to seasonal changes within each terrain [54]. For example, there can be a temperature difference of nearly 50°C in Indian desert terrain between summer and winter seasons. While the robust design of MBTs is engineered to adapt to such diverse conditions, the impact on performance and component degradation within the system can significantly vary. Various well-received reliability databases provide the multipliers to the failure rate of the components operating under different possible environmental conditions [43]; which acknowledges the effect of environmental conditions onto the system/component's reliability. Therefore, simply considering the terrain of operation is insufficient for accurate mission reliability prediction. Instead, incorporating seasonal variations in environmental conditions is crucial, as different seasons can substantially alter overall environmental factors impacting equipment reliability and performance. Therefore, a comprehensive approach considering both terrain and seasonal variations is essential for precise mission reliability prediction and maintenance decision-making in military operations.

In addition to the environmental factors like the terrain and season in which the MBT operates, various other operational factors also play a crucial role in determining the degradation characteristics of its components. For instance, the engine load is a known significant factor in the overall degradation of the system. Critical military equipment often operates in diverse deployment roles, each requiring different levels of load. Considering the extensive range of critical military equipment, there are multiple factors that must be taken into account when formulating the mission reliability function.

The consideration of multiple such factors into mission reliability prediction can be considered slightly analogous with the reliability estimation for phased mission systems; whose treatment is well handled in the literature [55], [56], [57]. In the light of absence of well structured definitions of phased missions in the context of varied military equipment, the present research works on the different treatment for reliability prediction. However, taking inspiration from this concept, the effective way to incorporate the combined effect of all the essential environmental as well as operational factors, the concept of operation phase is used. Here, a phase for a system can be defined by a combination of all the operational and environmental parameters that affect the life of the system / component. For instance, in the case of an engine and its subsystems, the phase parameter could be the percentage capacity or load at which the engine operates. Continuous operation of the engine at higher loads for prolonged periods accelerates component degradation. Similarly, environmental conditions such as temperature can also serve as phase parameters, as operating in higher temperature environments significantly affects the lifespan of certain components.

In order to quantify the phase parameters and integrate it to the mission reliability formulation, phases are defined as following. Firstly, all the phase parameters are listed (Table 3.1) along with their units and ranges to incorporate their variable effect on the component's life and ultimately the mission reliability.

Table 3.1 Phase parameter definition

Phase Parameter ID	Phase Parameter	Measuring Unit	Parameter Range ID	Range Lower limit	Range Upper Limit
PP_1	Ambient Temperature	*°C*	$PP_{1,1}$	*-40*	*5*
			$PP_{1,2}$	*6*	*40*
			$PP_{1,3}$	*41*	*58*

Finally, each phase (P_i) is created as a unique combination of every range (a) of every phase parameter defined (b). Where 'a' ranges from 1 to the total number of phase parameters, and 'b' ranges from 1 to the total number of levels in the parameters range. In the case of two phase parameters, P_i will be a combination of $PP_{a,b}$. An example of phase assuming two phase parameters, where in addition to the phase parameter defined in Table 3.1, one more phase parameter – absolute humidity (in two parameter range IDs are defined) is given in Table 3.2.

Table 3.2 Phase definition

Phase ID	Phase Parameter 01	Phase Parameter 02
P_1	$PP_{1,1}$ *(Temp in range -40 to 5 °C)*	$PP_{2,1}$ *(Relative humidity in low range)*
P_2	$PP_{1,1}$ *(Temp in range -40 to 5 °C)*	$PP_{2,2}$ *(Relative humidity in high range)*
P_P	:	:

Throughout its operational life cycle, an MBT operates within specific phases as defined. As previously discussed, transitioning between phases directly impacts the lifespan of system components and overall system performance. To effectively account for this influence, an Adjustment Factor (AF) known as the *'Phase-wise Adjustment Factor'* is implemented. In this research, the Weibull distribution serves as the model for reliability analysis considering the mechanical nature of the components under consideration and the all encompassing ability of the distribution. The scale parameter η *(Eta)* represents the characteristic life of the component and is directly associated with its lifespan. The *Phase-wise Adjustment Factor* is utilized to mitigate the impact of phase transitions and standardizes each phase relative to a predetermined default phase (baseline phase). This adjustment factor is determined by calculating the ratio between the scale parameter of the system/component in a given phase and that in the default phase Eq. 12.

$$\boldsymbol{AF_{P_x}} = \frac{\eta_{P_x}}{\eta_{P_{default}}} \qquad \text{Eq. 12}$$

In system operations, components may not be continuously active throughout a mission or may experience varying loads compared to their rated capacities during operation. To account for these scenarios, a parameter known as the Duty Cycle *(DC)* is commonly employed. For example, certain components are utilized only during specific phases, such as during engine ignition when ambient pressure is extremely low. Consequently, these components are activated selectively during particular phases, influencing the overall duty cycle of MBT components. The duty cycle is formally defined as the ratio of the operational duration of a given component to the total operational duration of the parent system. This value is always positive, with a default value of 1 indicating continuous operation at the rated load. Any deviation from this default value reflects different load conditions relative to the rated load or total operational time. For example, a duty cycle of 0.5 suggests that a component operates only half of the time during the system's operation. When considering phase-wise operations, a multiplier termed as the 'Duty Cycle Multiplier' is utilized to quantify the impact of duty cycle variations resulting from phase changes Eq. 13.

$$\boldsymbol{DC_{P_x}} = \frac{Total\ duration\ the\ system/component\ operates\ in\ P_x}{Total\ duration\ the\ parent\ system\ operates\ in\ P_x} \qquad \text{Eq. 13}$$

Both of these multipliers are further recorded for all the possible phases in a given context for a particular critical military system, as given in Table 3.3.

Table 3.3 Phase wise Adjustment factor and Duty Cycle Multiplier Definition

Phase ID	PP_1	PP_2	Phase wise Adjustment Factor ($\boldsymbol{AF_{P_x}}$)	Duty Cycle Multiplier ($\boldsymbol{DC_{P_x}}$)
P_1 *Default Phase*	$PP_{1,1}$	$PP_{2,1}$	AF_{P_1}	DC_{P_1}
P_2	$PP_{1,1}$	$PP_{2,2}$	AF_{P_2}	DC_{P_2}
P_3	$PP_{1,2}$	$PP_{2,1}$	AF_{P_3}	DC_{P_3}
P_4	$PP_{1,2}$	$PP_{2,2}$	AF_{P_4}	DC_{P_4}

The process outlined above for systematically capturing the impact of operational and environmental phases can be effectively applied across a wide spectrum of military equipment. Nonetheless, for the MBTs considered within this study, after evaluating available data and engaging in thorough discussions with domain experts, it becomes evident that all phases can be delineated by taking into account the terrain and season in which the MBT is deployed. Typically, MBTs operate across diverse terrains such as plains, deserts, high-altitude areas, forests, and shores, while experiencing seasonal changes encompassing summer, winter, and monsoon periods. A normal season can serve as the benchmark or baseline season for MBTs operations.

3.1.2 Different deployment roles require different functionalities

As delineated in Section 2.2, MBTs are anticipated to fulfill multiple deployment roles (DR) throughout their lifecycle, encompassing both offensive and defensive scenarios. These roles include tank-to-tank combat, deep penetration, close fire, infantry protection, and reconnaissance, which collectively cover a wide range of deployment roles in attack and defense situations. To effectively execute any of these deployment roles across different operational phases, an MBT must independently or concurrently perform four key functions: mobility, firepower, protection, and communication.

Table 3.4 delineates the correlation between the necessity of various functionalities across different deployment roles. It is evident that not every function is indispensable for every deployment role. If a specific mission profile does not necessitate a particular functionality, then performing maintenance solely on the components associated with that functionality would not yield significant benefits, given the mission requirements and limited maintenance duration. For instance, if an upcoming MBT mission involves reconnaissance, focusing maintenance efforts on the assemblies or sub-assemblies related to firepower functionality would not maximize the benefits in achieving the desired mission reliability from a practicality viewpoint. While this approach may improve the mission reliability metric, its practical applicability in the field may not be optimal. Hence, it is imperative to integrate the mission reliability of equipment with its various functionalities and estimate it in terms of functional reliability. The current mission reliability formulation attempts to establish this linkage by initially mapping all functionalities to the system's sub-systems and components. Subsequently, utilizing this mapping, the mission reliability function is customized for each prediction based on the specified mission profile.

Table 3.4 Correlation between functionalities and deployment roles

	F1	F2	F3	F4
DR1	✓	✓	✓	✓
DR2	✓	✓	✓	✓
DR3	✓	✓	✓	
DR4	✓		✓	
DR5	✓			✓

3.1.3 Use of Refurbished/Cannibalized/Non-OEM Spares

As suggested by [26], mission reliability should not only be perceived as a function of time, but also function of several other factors including maintenance. Most of the literature on reliability analysis and maintenance modelling considers that every replacement of the component is done using new and genuine spares. In the context of military equipment maintenance, this assumption does not always hold true [18]. Considering several factors related to limited maintenance duration, compact due dates, complex procurement procedures, financial aspects, etc., practices like cannibalization and refurbishment flourish. Sometimes due to necessity or sometimes considering a sustainable practice, components are replaced with refurbished or remanufactured spares. The reconditioning of the spare part may be done by OEM or the user. Generally, in military scenarios, in addition to this, cannibalization of spares is also practiced. Where a component from some equipment is taken out and installed with another equipment without any significant maintenance. In some situations of unavailability of spare largely due to discontinuation of product or remote locations, the user is forced to replace the component with some non-OEM spare. These refurbished/non-OEM spares generally follow some different lifetime probability distribution compared to the genuine new spares [58], [59]. Whereas, the cannibalized spare comes with already utilized age. There is a major influence of using such components on their residual life and the overall system performance [60]. Considering the unavoidability of these practices in the context of military maintenance function, it is important to integrate their effects in the mission reliability prediction for military equipment [32]. The present mission reliability formulation considers the possibility of replacement of any spare using new – genuine (G) or refurbished (R) or cannibalized (C) or non-OEM (N-O) spare. To account for the effect of using such spares with different lifetime distribution on the system reliability, *Spare wise Adjustment factor* is used. However, in the case of using the cannibalized spare, there is no change in the lifetime distribution as the product is very same. Therefore, for cannibalized product, there is no requirement of an adjustment factor; and the cannibalized age of the component can be added to the initial age of the component (Table 3.5).

Table 3.5 Spare wise Adjustment Factors

Sr. No.	**Spare Type**	**Spare wise Adjustment factor AF_{S_x}**
1	New - Genuine	AF_{S_G}
2	Refurbished	AF_{S_R}
3	Non-OEM	$AF_{S_{NO}}$
4	Cannibalized	AF_{S_G} Effective Age = Cannibalized Age

Figure 3.1 represents the depiction of the effect of using the different types (G/R/C/N-O) on the component's effective age across the chronological time of usage. For ease of illustration, it is assumed that, in this particular case of cannibalization, the spare is replaced with a cannibalized part that has acquired the same operating age.

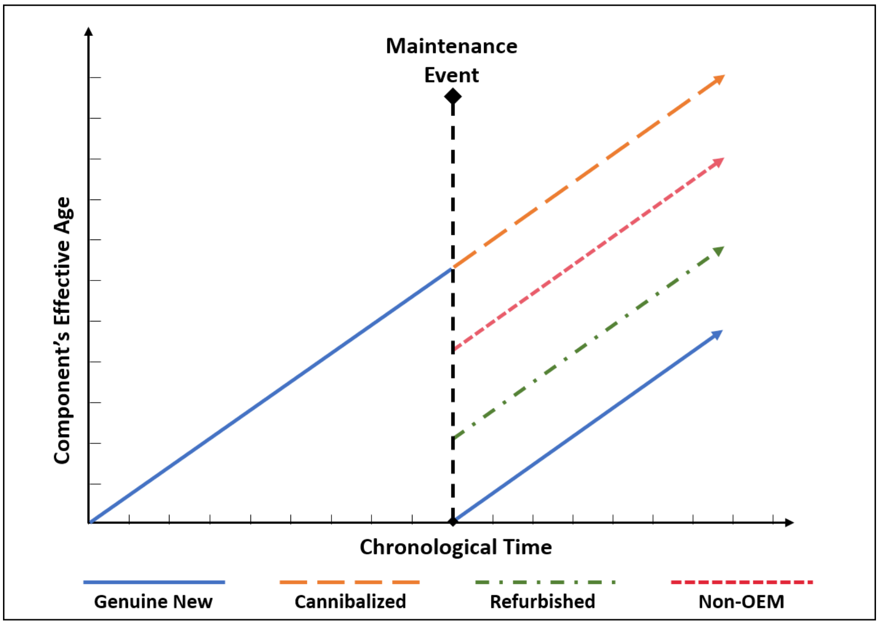

Figure 3.1 Effective Age for different spare types

3.1.4 Human error in maintenance

Humans are susceptible to making errors, and wherever human intervention is involved in maintenance activities, there is always a potential for human error. Such errors during maintenance can result in failures or accelerate the degradation of a component, affecting its overall performance [61]. Extensive literature underscores the human error as a significant contributor to system failures [62], [63], [64]. Dhillon et al. [65] highlighted the significant impact of human error on system failures across various industrial sectors. In fossil power plants, human error contributes to 20% of all system failures and can lead to up to 60% of total annual power loss due to maintenance-related errors [65]. Similarly, in the mining industry, human-related causes account for 25-35% of machine breakdowns [66]. Koval et al. conducted a study indicating that human error causes approximately 7.4% of computer system failures [67]. Furthermore, data from the Major Hazard Incident Data Service (MHIDAS), as cited by [68], reveals that 22% of accidents in refineries are attributed to human errors. Additionally, human error is identified as the root cause in 41% of failures in the pipeline industry [62]. These findings underscore the critical role of addressing human factors in enhancing system reliability and safety across diverse industrial domains. Despite the recognized impact of human error during maintenance on component life, its integration into reliability formulations is often overlooked to a great extent in domains other than nuclear power generation. Conventional reliability modeling and analysis primarily rely on probability distribution parameters provided by the OEM or derived from historical failure data, which do not consider the influence of human error in maintenance. Reliability models that fail to account for this factor are unlikely to provide accurate predictions. In military maintenance contexts, where maintenance tasks can be stressful and strenuous [69], considering the limited maintenance duration, stress on the maintenance personnel, ergonomically poor conditions, the possibility of human error in installation or maintenance activities is relatively higher [70]. Therefore, there is a critical need to incorporate the effect of human error in maintenance into reliability predictions for critical military equipment [32]. This research aims to address this need by integrating the effect of human error in maintenance into mission reliability predictions for critical military equipment.

The effectiveness of a human operator in executing a specified task within defined conditions and time constraints plays a critical role in determining the overall reliability of a system [71]. This effectiveness is formally termed as Human Reliability, which is essentially the complement of Human Error Probability (HEP). The term human reliability is defined as the probability that a person (1) correctly performs some system required activity in a specified time period and (2) performs no extraneous activity that can degrade the system [72]. HEP is the probability that a given task within a specific time interval was accomplished with errors [73]. Factors which influence the likelihood of a failure occurring are so called Performance Shaping Factors (PSFs) [74]. These PSFs encompass environmental or personal factors that can either positively or negatively impact a human operator's performance [74]. Figure 3.2 [62] depicts various human performance factors leading to the human error in any industrial activity.

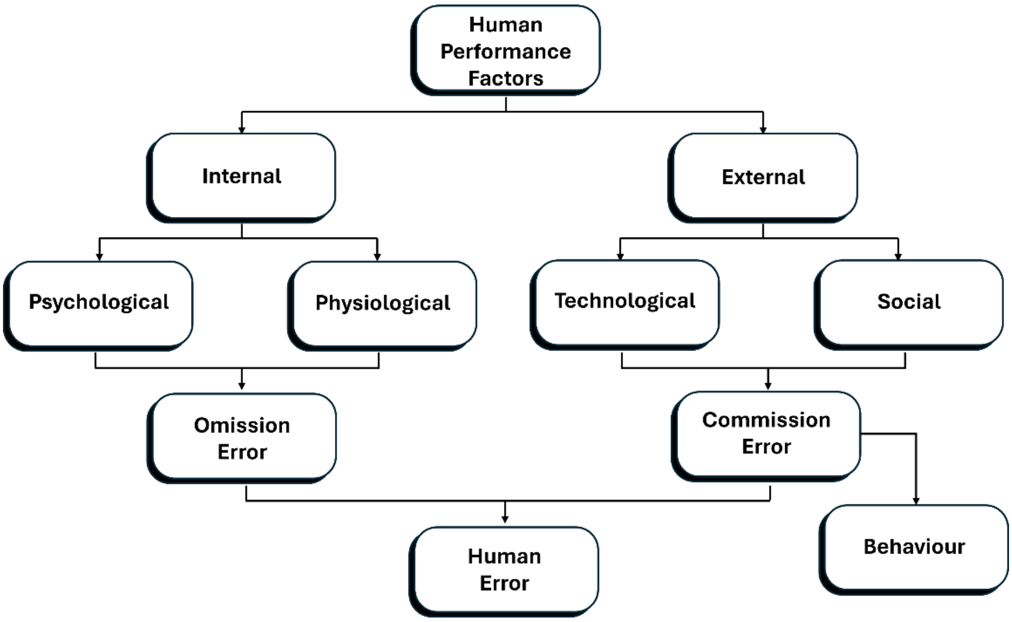

Figure 3.2 Human performance factors leading to human error

Identifying and analyzing these factors constitute a fundamental aspect of all HRA methodologies. To adequately integrate human error in maintenance within the mission reliability prediction framework, it is crucial to comprehend the existing methodologies for quantifying human error and conducting its analysis. Therefore, a literature review was undertaken on the literature discussing evolution of HRA, different methodologies, and their formulations.

To date, over 50 distinct HRA methods have been proposed and are typically classified into three generations, with each generation addressing the shortcomings of earlier methods and advocating necessary advancements. The initial generation of HRA methods primarily relied on simplistic qualitative approaches, utilizing expert judgment and subjective analysis for identifying human errors [62]. Many methods in this generation were influenced by risk assessment methodologies like Probabilistic Risk Assessment (PRA), a trend that continued into subsequent generations of HRA methods. Second-generation methods focused on quantifying human error probability by considering cognitive processes and Performance Shaping Factors (PSFs) such as workload, stress, sociological and psychological factors, and illness. The third generation of HRA methods recognized the importance of interrelated PSFs and their dependencies, leveraging Bayesian networks to model these relationships effectively. Bayesian networks facilitate capturing the interdependencies among PSFs in a structured manner, enhancing the understanding of their impacts on human reliability. Figure 3.3 provides an overview of the evolutionary progression of prominent HRA methodologies across these three generations.

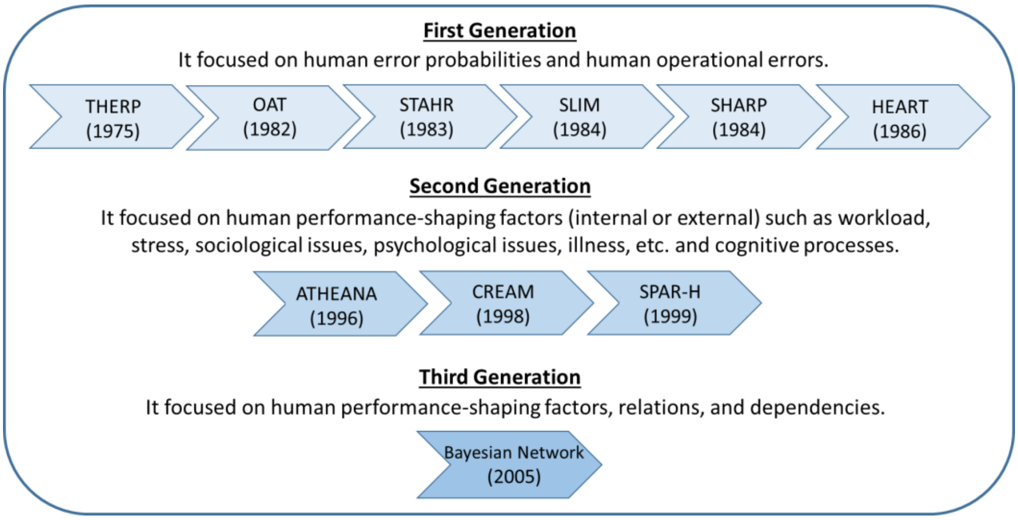

Figure 3.3 Evolution of HRA methodologies in three generations

Several articles have conducted reviews and analyses of HRA methods within the manufacturing domain. French et al. [75] conducted a seminal review of HRA methods that did not make domain-specific assumptions. Nevertheless, their findings are valuable and apply to the manufacturing domain as well. Di Pasquale et al. [76], [77] offer a comprehensive overview of techniques for analyzing human reliability in manufacturing, including assembly systems. Their work underscores that while numerous HRA methods exist, many fails to capture the dynamics of ongoing accidents or general human behavior. Extending their previous work, Di Pasquale et al. [77] systematically reviewed HRA approaches specifically for manual assembly systems, demonstrating the efficacy of HRA methods in predicting human error probability and identifying critical error-influencing factors in such systems. Franciosi et al. [78] proposed a taxonomy of PSFs relevant to HRA in industrial maintenance, including factors such as available task time, ergonomics, and task complexity. Their analysis emphasizes the significance of considering human error in maintenance activities due to the non-negligible impact of different error types on the studied systems. Petruni et al. [79] utilized the Analytic Hierarchy Process (AHP) to assist in evaluating and selecting appropriate HRA methods for the automotive industry. Such approaches are increasingly relevant given the growing number of available HRA methods.

Despite active research in HRA, none of the mentioned articles comprehensively covers both system and human reliability assessment for manufacturing systems [71]. This gap underscores the need for a standardized method that adequately captures the effect of HEP on the mission reliability of manufacturing systems, highlighting an area where literature lacks a standardized approach.

In the scope of the problem under consideration, to map the effect of human error (estimated in the form of HEP) on the life of the component and further its mission reliability, an *Adjustment Factor (AF_{HEP})* is used. A large range of HRA methodologies provide quantitative assessment of the occurrence of human error in any of the industrial activity in the form of HEP. Although the present methodology is capable of making use of HEP estimated using any of the standard HRA methodologies, in this particular context, Standardized Plant Analysis Risk – Human Reliability Analysis (SPAR-H) is used for HEP calculation. This selection is particularly based on the outcomes from the comparative studies presented in [68], [80]. SPAR-H is a model for HRA invented by U.S. Nuclear Regulatory Commission in conjunction with the Idaho National Laboratory [81]. SPAR-H method considers eight PSFs: available time, stress, complexity, experience/training, procedures, ergonomics, fitness for duty, and work processes. After collecting ratings for each of these PSF and categorizing the task as action or diagnosis task for Nominal Human Error Probability (NHEP) selection, HEP value can be calculated using Eq. 14 [81].

$$HEP = \frac{NHEP \ \times PSF_{composite}}{NHEP \left(PSF_{composite} - 1\right) + 1} \qquad \text{Eq. 14}$$

$$where, PSF_{Composite} = \prod_{1}^{8} PSF_i \qquad \text{Eq. 15}$$

NHEP for Action = 0.0001

NHEP for Diagnosis = 0.001

Generally, following any maintenance activity, an inspection procedure is conducted. During these inspections, errors are often identified and subsequently rectified as well. Consequently, the effective HEP is estimated as Eq. 16 based on the calculated HEP and the probability of detecting the human error.

$$Effective\ HEP\ =\ [Estimated\ HEP]\times[1-Probability\ of\ detection] \qquad \text{Eq. 16}$$

Finally, the AF_{HEP} is estimated using Eq. 17

$$AF_{HEP}\ =\ [Effective\ HEP]\times[Expert\ judgement\ for\ effect\ of\ HEP] + [1-Effective\ HEP] \qquad \text{Eq. 17}$$

In the absence of required data, this methodology makes use of expert judgement as suggested by [38], and the effect of particular HEP on the component is captured through expert judgement. Here, the expert states the judgement regarding the effect of HEP in a particular range on the component life in the form of an adjustment factor to the scale parameter of the component.

3.2 Mission Reliability Prediction incorporating the effect of essential military-specific factors

Reliability is defined as the probability that a component or system will perform a required function for a given period of time (t) when used under stated operating conditions [82]. It is the probability of a nonfailure over time. Eq. 18 expresses this relationship of reliability with time in mathematical form where, T is a continuous random variable – time to failure of the component or system.

$$R(t) = Pr\{T \geq t\} \qquad \text{Eq. 18}$$

where,

$$R(t) \geq 0, R(0) = 1, and\ \lim_{t\to\infty} R(t) = 0$$

Reliability function represents area under the curve defined by the probability density function *f(t)* (Eq. 19).

$$R(t) = \int_{t}^{\infty} f(t')dt' \qquad \text{Eq. 19}$$

The methodology for conducting reliability analysis on equipment or a fleet of equipment involves a systematic approach comprising six key steps [83]:

(1) Understanding the system and identifying subsystems and faults within it, and creating the reliability block diagram.

(2) Collecting, sorting, and classifying Time to Failure (TTF) data for each subsystem and fault.

(3) Analyzing the data to verify the assumption of Identically and Independently Distributed (IID) data.

(4) Fitting the TTF data of subsystems and faults with appropriate theoretical probability distributions.

(5) Estimating reliability for each subsystem and the overall system using the best-fit distribution.

(6) Identifying critical subsystems and faults and formulating an enhanced maintenance policy to improve overall system reliability.

In the above six step methodology, step 1 – 4 are combinedly worked upon and presented in Annexure A.

In context of step 5 - estimating reliability for each subsystem and the overall system using the best-fit distribution, this study models the reliability function considering the Weibull distribution. Eq. 1 presents the reliability function for 2P - Weibull distribution. The probability density function is given by Eq. 20.

$$f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \qquad \text{Eq. 20}$$

In order to estimate the reliability of a component which has already accumulated some age (Age), conditional reliability of that component is estimated as given in Eq. 21

$$R(t|Age) = \frac{R(t\ + Age)}{R(Age)} \qquad \text{Eq. 21}$$

In case of a 2 – parameter Weibull distribution, this conditional reliability function takes the form as:

$$R(t|Age) = \frac{e^{-\left(\frac{t+Age}{\eta}\right)^{\beta}}}{e^{-\left(\frac{Age}{\eta}\right)^{\beta}}} \qquad \text{Eq. 22}$$

The mission reliability of the whole MBT (R_{Tank}) for the future mission profile is estimated from the mission reliability of every component according to the MBT's reliability block diagram and all the parameters mentioned in Annexure A. Ultimately, mission reliability of a MBT (R_{Tank}) is estimated using Eq. 23.

$$R_{Tank} = \prod_{i=1}^{N_{(i)}} \left(\prod_{j=1}^{M_{(i,j)}} \left(R_{(i,j)}\right) \right) \qquad \text{Eq. 23}$$

where,

$N_{(i)}$ is the number of assemblies,

$M_{(i,j)}$ is the number of components in the i_{th} assembly,

$R_{(i,j)}$ is the reliability of the j_{th} components in the i_{th} assembly,

R_{Tank} is the reliability of the MBT.

The standard approach for reliability prediction, as outlined above, is widely recognized within the domain. However, when essential military-specific factors are integrated into the mission reliability formulation, the process becomes notably intricate. At various decision points where mission reliability needs to be predicted, the formulation must consider a broad spectrum of factors. For example, as discussed previously, MBTs operate in diverse terrains that are marked by extreme environmental conditions. Within these terrains, they require to navigate through multiple operating phases, and maintenance activities are conducted at different echelons as necessary. As a result, when attempting to predict the mission reliability of MBTs operating within such varied deployment scenarios, it becomes challenging to incorporate these complexities within a single mathematical function. Figure 3.4 illustrates the overall complexity involved in mission reliability prediction for MBTs, incorporating the combined impact of essential military-specific factors.

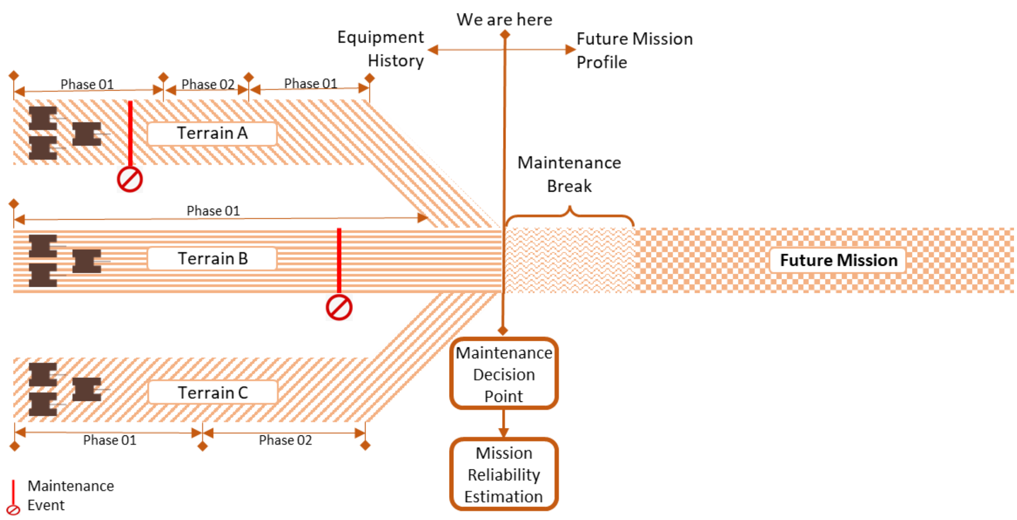

Figure 3.4 Overall complex scenario for mission reliability prediction

In formulating mission reliability prediction within such a complex scenario, characterized by the aforementioned military-specific factors, extensive data and information must be captured. As various MBTs operate in diverse military fields across different terrains, degradation rates vary. Moreover, maintenance activities predominantly occur in field maintenance workshops, complicating maintenance record tracking across workshops. Additionally, varying levels of human error in maintenance further contribute to the complexity of mission reliability prediction. To address this complexity, systematic registration of MBT operation information is essential. This need stems from the objective of integrating the impact of essential military-specific factors into the mission reliability prediction process. Figure 3.5 illustrates the comprehensive information required for mission reliability prediction, categorized into data related to equipment history and data related to future missions. Within the equipment history, three key characteristics are considered, namely environmental, operational, and maintenance data. This encompasses information such as the terrains where the equipment has operated, the operational phases it has undergone, and detailed logs of all maintenance events including the actions taken and HEP in those actions. Moreover, regarding a future mission, it is assumed that all necessary information is available. This future mission profile information is organized into three main verticals: deployment characteristics, usage requirements, and environment profile. The data within these categories includes elements such as the MBT's role, mission type, terrain and season specifics, mission duration, travel distance, and EFC requirement.

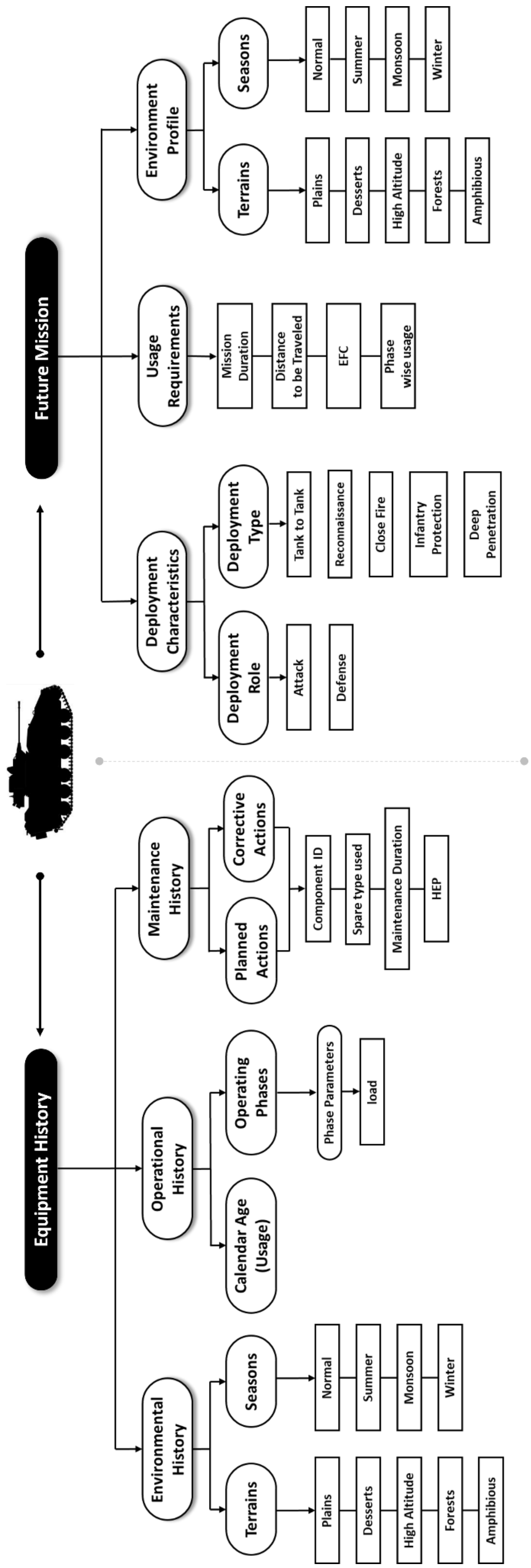

Figure 3.5 Information for mission reliability predictions.

As all the considered essential military specific factors influence the degradation of the system while utilization, age of a component / system is a good way to consider the effect of all these factors on the component / system. Therefore, in the proposed methodology for mission reliability prediction, the effect of all the considered military-specific factors is incorporated in the age of systems / components in the equipment, i.e. MBT.

In the context of present research, it is crucial to acknowledge that the degradation of systems due to the impact of all the aforementioned essential military-specific factors is experienced during their utilization. The age of components or systems is considered an effective method for incorporating the combined effect of these factors on the overall reliability. Therefore, in the proposed methodology for predicting mission reliability, the influence of all identified military-specific factors is incorporated by correlating them with the age of systems and components of the MBT.

3.2.1 Effective age estimation

The concept of virtual age has been introduced by Kijima et al. as a means to quantify the effect of a maintenance on the future lifetime of a repairable system [84]. To clarify on the notion, it is worth pointing out that several authors in the statistical literature refer to the virtual age as the effective age [85], encompassing the effects induced by interventions beyond maintenance. While the former term is specifically utilized in models based on the principles established by Kijima et al., the latter term is more commonly used across various contexts. Moreover, the concept of effective age pertains to defining the virtual age function as outlined by Kijima et al. or in its subsequent relevant extensions. The primary objective of effective age modeling is to develop a stochastic model that can effectively describe and analyze recurring events with interventions to comprehend the dynamics introduced by these interventions [85]. In the proposed methodology, effective age serves as a parameter that incorporates the impact of all essential military-specific factors into the degradation of the MBT during its utilization. The operational age of the system/component after factoring in all military-specific factors is referred to as effective age. Given the objective of estimating the mission reliability of a component and subsequently the MBT, the developed methodology calculates the effective age of all components in the MBT. To determine the effective age of components, three aspects require careful consideration: (i) Environmental history, (ii) Operational history, and (iii) Maintenance history.

In order to comprehensively address the three aforementioned characteristics, a usage monitoring mechanism has been developed. Illustrated in Figure 3.6, this mechanism systematically records the status of the MBT at regular observation intervals. Alongside the MBT status, various other pertinent information is also logged, such as the timestamp of inspection, the operational phase, and the assignment of a Maintenance ID (MID) based on the system's operational status. This MID serves as a representation of the maintenance action executed and is primarily utilized to denote the type of spare utilized during maintenance operations. Table 3.6 provides an overview of the interpretations associated with each MID. For instance, MID ‘0’ indicates the MBT is operational without any failures; ‘F’ signifies a detected failure, while ‘D’ denotes a failed state with delayed maintenance. The remaining MIDs specify the specific maintenance activities carried out and identify the type of spare employed for replacement. In scenario 1, during observation interval #3, the MBT is recorded as being in a failed state. However, by observation interval 4, the MBT has undergone maintenance and is operational again, with the component replaced using a new and genuine spare. The corresponding Human Error Probability (HEP) is also estimated for this maintenance activity. In scenario 2, at observation interval 1, the MBT is noted to be in a failed state. During observation interval 2, the MID ‘D’ signifies a delay in the required maintenance activity. Subsequently, by observation interval 3, the MBT has been restored after maintenance, with the faulty component replaced with a cannibalized spare. Each data record includes the date, precise time, and maintenance duration for every maintenance event.

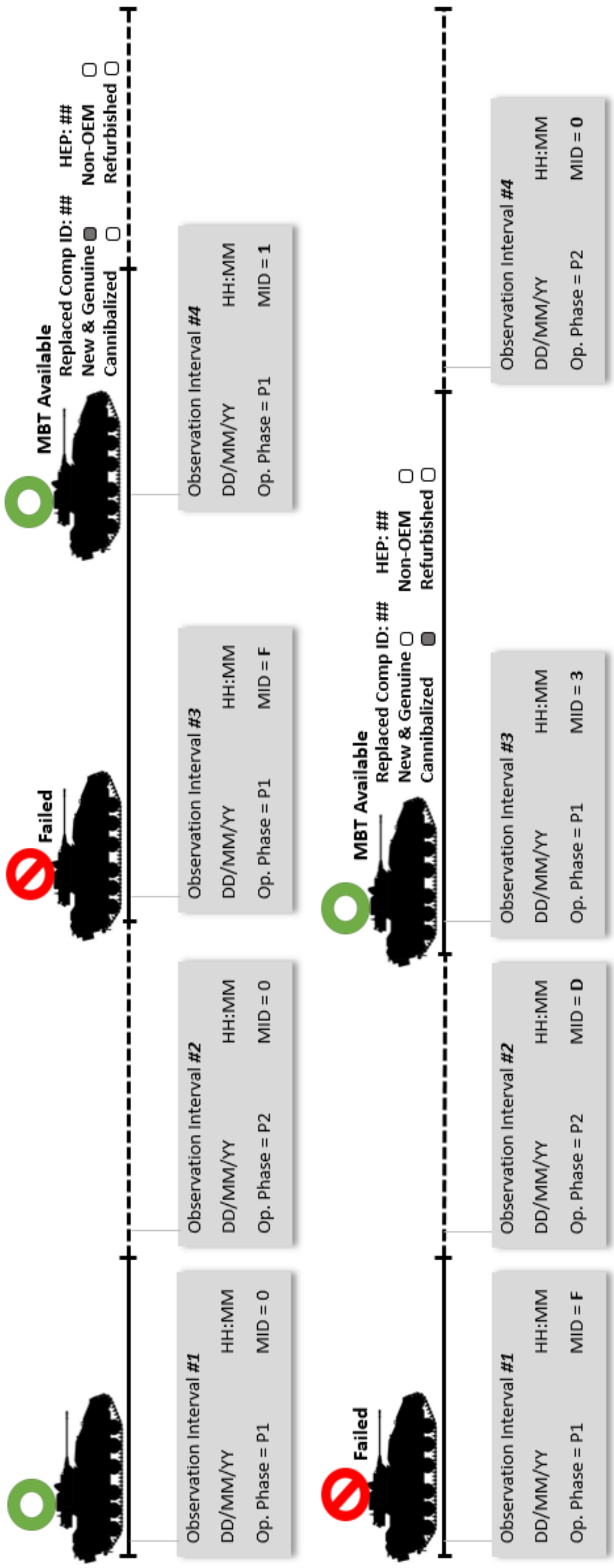

Figure 3.6 Systematic capturing of information for effective age estimation

Table 3.6 Interpretation of Maintenance IDs

MID	System State at Interval Start Time	Failure Observed?	Maintenance Performed?	Replaced?	If replaced, Refurbished?	If replaced, Cannibalized?	If replaced, Non-OEM?
0	1	0	0	-	-	-	-
F	1	1	0	-	-	-	-
D	0	-	0	-	-	-	-
1	0	-	1	1	0	0	0
2	0	-	1	1	1	0	0
3	0	-	1	1	0	1	0
4	0	-	1	1	0	0	1
5	0	-	1	1	1	1	0
6	0	-	1	1	0	1	1
7	0	-	1	1	1	0	1
8	0	-	1	1	1	1	1

Based on the data records depicted in Figure 3.6, the Current Age (*CA*) for any component within MBT refers to the amount of time or usage that has elapsed since the component was first placed into service. And it is calculated to represent the actual utilization of the component in terms of time. Utilizing information regarding operational phases, spares utilized in maintenance activities for replacements, and the HEP associated with each maintenance activity, the relevant adjustment factors and duty cycle multipliers are extracted from Table 3.3, Table 3.5, and Eq. 17. Ultimately, the effective age of every component in an MBT is estimated as shown in Eq. 24.

$$Effective\ Age(EA_i) = \frac{CA\ \times DC_{phase}}{AF_{phase}\ \times AF_{maintenance} \times AF_{HEP}} \qquad \text{Eq. 24}$$

In the traditional approach, reliability prediction is based on time-based usage adjusted for operational phases and the duty cycle. However, this approach does not account for the effects of using refurbished, cannibalized, or non-OEM spares, nor for human error during the installation process.

As previously discussed, mission reliability is fundamentally a function of time. For estimating the mission reliability of a MBT, the complete mission profile is translated into one time duration. The mission profile for which the reliability of the particular MBT is to be predicted, is known in the form of three different attributes, viz: deployment characteristics, usage requirements and environment profile. For instance, consider a mission profile where the MBT is expected to be ready for an attack role, necessitating the use of all four functionalities. This mission may require the MBT to travel 150 kilometers in desert terrain during the summer season, with a continuous operation duration of 36 hours. Given this mission profile, the operational phase in which the MBT will operate and the mission duration are known. With this information, the corresponding adjustment factor for phase wise operation AF_{Phase} is determined. Accordingly, the effective mission duration (M_d) is estimated for every component of MBT considering its duty cycle. The formulation for effective mission duration is as follows:

$$Effective\ Mission\ Duration(M_d) = \frac{Mission\ duration \times DC_{phase}}{AF_{phase}} \qquad \text{Eq. 25}$$

Once the M_d is known for every component (using Eq. 25), mission reliability of every component can be predicted using Eq. 22 and translated into mission reliability of MBT using Eq. 23.

3.3 Machine Learning approach for mission reliability prediction for MBT

As outlined in previous sections, ensuring accuracy in predicting mission reliability for critical military equipment holds paramount importance due to its direct impact on high-level decision-making processes such as maintenance management, readiness assessment, and deployment strategies. Inaccuracies in predicted mission reliability can lead to undesirable outcomes in these strategic domains. Incorporating the effects of military-specific factors is crucial to achieving the desired accuracy in mission reliability predictions. Figure 3.5 illustrates the comprehensive array of military-specific factors essential for mission reliability prediction. Given the current situation of lack of adequate data, the methodology proposed in section 3.2 relied on adjustment factors derived from expert judgment. However, recognizing the necessity for highly accurate predictions, transitioning from expert judgment-based adjustment factors to the parameters derived from the actual data is imperative in the foreseeable future. Nevertheless, deriving such parameters from actual data poses significant challenges, especially given the complexity of military maintenance functions for MBTs. Moreover, future decision-making models will necessitate understanding the collective or individual impacts of these military-specific factors on system life, performance, and reliability to inform critical decision-making processes. While the methodology in section 3.2 is very much able to incorporate the combined effect of the essential military specific factors on the mission reliability of MBT, it will be difficult for it to establish the exact quantitative effect of any particular military specific factors on the life of the component under consideration.

Establishing the aggregate and independent effect of all essential military-specific factors on component reliability using conventional methodologies can be highly complex and may lead to inaccurate results. The conventional approach involves estimating an additional probability distribution parameter for each military-specific factor affecting a component's life. However, the existing parameter estimation methods pose mathematical challenges in estimating these additional parameters. Generally, the MLE is used for parameter estimation. Parameter estimation in the case of Weibull distribution for the two parameters Scale and Shape using MLE itself is a tedious process. These estimates often involve complicated nonlinear functions based on observed data. As the number of parameters to be estimated increases in the likelihood function, the complexity of solving the function also escalates [86]. Numerical methods are usually employed to solve the likelihood function, but they come with issues such as instability in estimated parameters [86] and high sensitivity to seed parameter choices [87]. This complexity has often led to the oversight of this effect in reliability estimations and maintenance management practices.

The advent of machine learning (ML) has opened up several avenues to handle such mathematically complicated problems with ease. Building upon this advancement, a machine learning methodology is devised for Remaining Useful Life (RUL) based mission reliability prediction. In the recent times, researchers have successfully applied machine learning algorithms for residual life predictions in broad domains [88] such as belts [89], gears [90], batteries [91]. A thorough examination of existing models in the literature has informed the design of the proposed machine learning model for RUL prediction and subsequent mission reliability assessment. Based on the nature of maintenance data, including operational phases, replacements with refurbished/cannibalized/non-OEM spares, and the HEP in every maintenance activity, a decision tree-based ensemble machine learning model emerges as the optimal choice, which provides the prediction of component's RUL with satisfactory accuracy, thereby contributing to enhanced mission reliability prediction.

3.3.1 Proposed Machine Learning based Methodology

This section describes the proposed ML based methodology for predicting RUL and further the mission reliability while incorporating the effect of essential military specific factors. In this methodology, the required data is collected and processed for the ML algorithm; the decision tree based boosted ensemble algorithm is developed, trained and tested on the pre-processed data; and ultimately, using the trained model, RUL is predicted and according to the user-defined future mission profile, Mission reliability prediction is done. Key steps in the methodology are discussed here in detail.

3.3.1.1 Decision Tree Algorithm

For achieving accuracy in prediction problems, selecting an effective ML algorithm is critical. In this work, decision tree based algorithm is used for RUL prediction. Decision tree-based algorithms are a popular choice in regression tasks, including RUL prediction, due to their inherent ability to model complex, non-linear relationships within data. They operate by recursively partitioning the data into subsets based on feature thresholds, allowing them to capture intricate patterns in the failure and degradation behaviour of components. For RUL prediction, decision tree algorithms excel because they can effectively handle high-dimensional feature sets and are less sensitive to data scaling, making them highly adaptable to varied maintenance and operational histories. Additionally, decision tree models provide interpretability, as the decision-making paths within the tree structure can be easily visualized, supporting insights into which features most significantly influence the predictions. This makes decision tree-based models a robust choice for regression-based RUL prediction tasks where transparency and handling of non-linear relationships are critical. The goal of the decision tree is to develop a model which can predict the target variable by learning certain decision rules inferred from the data structures [92]. With the decision tree algorithm, the predictor space, i.e. the entire population, is segmented into multiple homogeneous sets based on appropriate differentiators [93]. The fundamental structure and the terminology of an individual decision tree is shown in Figure 3.7 (A) [90]. There are three types of nodes in any decision tree. The entire population of the dataset is represented by the root node which is split into multiple nodes using differentiators. Each decision node represents the test on the attribute and results into the subsequent branches depending on the true/false result of the test. The nodes which do not get segmented any further are known as terminal or leaf nodes. Generally, the terminal node represents the decision to be made. In case of RUL prediction, the life of the component itself is represented by the terminal node, whereas the decision nodes represent several parameters deciding the life, like the range of HEP, spare type, etc., as shown Figure 3.7 (B).

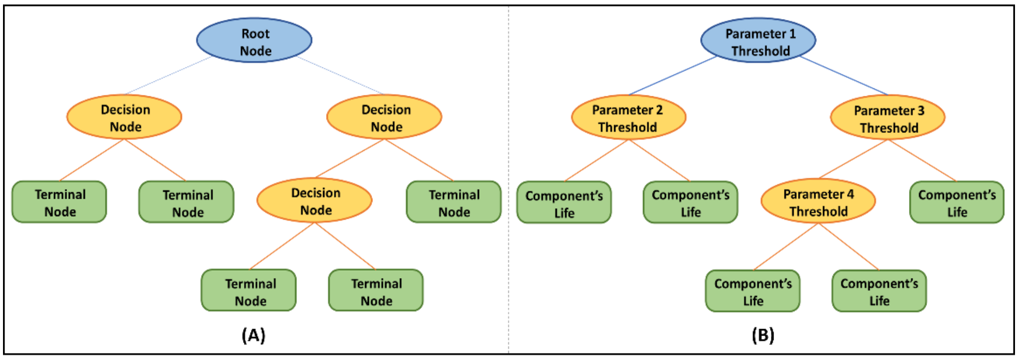

Figure 3.7 (A) Fundamental structure and terminology of a decision tree (B) Sample decision tree

In literature, it has been pointed out that a single decision tree is highly susceptible to overfitting [94]. To mitigate this risk, ensemble models combining multiple trees have been favored. Studies indicate that ensemble machine learning models outperform single prediction algorithms [94]. When employing ensembles, boosting algorithms are commonly utilized to amalgamate individual trees due to their high flexibility and interpretability [95]. Boosting algorithms, like Gradient boosting, are known to enhance the predictive power of a model by converting weak learners into strong learners [96]. The ensemble decision tree model generates multiple trees sequentially, aiming to minimize the residual error from the previous tree in each iteration. In this study, the decision tree ensemble learning approach is adopted to analyze maintenance and operation data related to the component. Gradient boosting, as an extension of boosting algorithms, is a widely adopted method known for its effective and accurate predictions [94], [95]. This method leverages the gradient descent algorithm to optimize differentiable loss functions.

3.3.1.2 XGBoost: Extreme Gradient Boosting Algorithm

XGBoost is recognized as a scalable machine learning system for tree boosting that requires significantly fewer resources compared to many existing systems [97]. Due to its substantial impact in various renowned machine learning and data mining challenges worldwide, XGBoost has emerged as the preferred choice among data scientists across different domains. Over the past six years, its applications have expanded significantly in diverse areas such as healthcare [98], industrial [99], communications [100], transportation [101], among others. The exceptional performance of XGBoost in supervised learning, particularly in prediction tasks, has led to its adoption in this study for residual life prediction.

XGBoost operates as a gradient boosting library where the system learns sequentially by constructing successive decision trees. A detailed understanding of its functionality and underlying principles can be found in [97]. It is a decision tree-based algorithm that builds an ensemble of trees in a sequential manner to enhance prediction accuracy. Each subsequent tree in the XGBoost model aims to correct the errors made by the previous trees, achieving this through gradient boosting, which minimizes the residuals of the prior predictions. By learning from the errors iteratively, XGBoost efficiently converges to a model that can capture complex dependencies and interactions within the data. Importantly, XGBoost includes several optimizations, such as regularization, shrinkage, and weighted quantile sketch for handling sparse data, which improve both the model's predictive performance and its robustness. In the context of RUL prediction, XGBoost's ability to adaptively model non-linear degradation patterns make it particularly suited for accurately forecasting the remaining life of components based on their historical maintenance and operational data. Each decision tree within XGBoost maps random input data to distinct nodes and generates corresponding continuous scores. These scores determine the thresholds for tree classification. Predictions are made with each tree, and using the training data, residuals or errors are computed as the disparities between predicted and actual data points. The model is trained iteratively, generating new trees while considering the residuals or errors from the preceding tree. Figure 3.8 illustrates the overall workflow of the XGBoost algorithm.

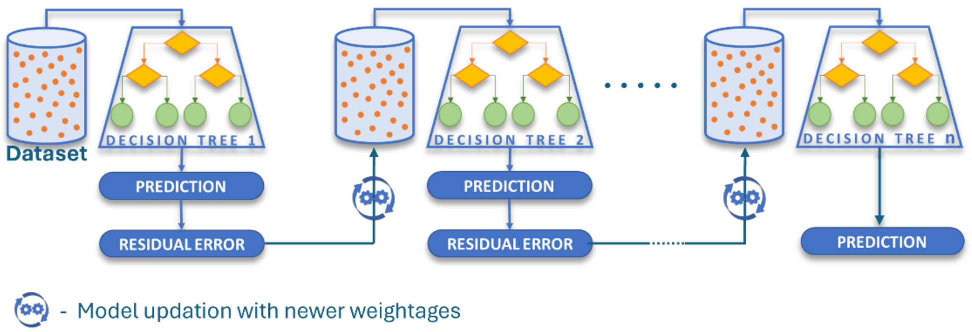

Figure 3.8 Working of XGBoost

The training of the model progresses by generating newer trees, with the primary aim of minimizing prediction errors. This consecutive tree generation is guided by the objective of minimizing the error in the predictions. XGBoost supports multiple loss functions, each catering to different regression objectives. Common choices include Mean Squared Error (MSE), Mean Absolute Error (MAE), and Huber loss. MSE is widely used for general regression due to its sensitivity to large errors, which can be beneficial for applications where outliers carry meaningful information. MAE, on the other hand, is more robust to outliers, making it a suitable choice in cases with substantial noise or uncertainty. In this study, MSE was selected as the loss function for the XGBoost model, as it is well-suited for capturing the variance in the time-to-failure data and emphasizes larger errors, which are critical in RUL prediction to ensure that the model is attuned to the most impactful deviations. This choice aligns with the goal of minimizing the prediction error in RUL, where accurate reliability predictions are essential for effective maintenance planning. The objective function of the XGBoost model is the summation of an error function and a model complexity function. The objective function to be minimized is given as Eq. 26 [102].

$$Obj = \sum_{i}^{t} L\left(y_i, \hat{y}_i^{(t)}\right) + \sum_{i}^{t} \Omega\left(f_i\right) \qquad \text{Eq. 26}$$

Where, y_i is the actual data point, $\hat{y}_i^{(t)}$ is the predicted value and $L\left(y_i, \hat{y}_i^{(t)}\right)$ is the loss function for tree t. $\Omega\left(f_i\right)$ is the term for regularization whose objective is to reduce the complexity of the tree function, and it is estimated as Eq. 27.

$$\Omega\left(f\right) = \gamma T + \frac{1}{2} \lambda \, || \, \omega \, ||^2 \qquad \text{Eq. 27}$$

Here, T is the number of leaves; the weight of the leaves is given by ω. γ is the learning rate or shrinkage which is used for tree pruning, and λ is the regularization coefficient that prevents the overfitting of the model.

3.3.1.3 Data Requirements

The data-driven approach of XGBoost necessitates well-structured data to facilitate its learning and precise prediction process. As previously highlighted, our proposed methodology seeks to forecast the RUL of components by integrating the collective influence of essential military specific factors: (i) diverse operational phases, (ii) types of spare parts utilized, and (iii) human error during maintenance activities. To effectively train the XGBoost algorithm and establish correlations between the component's lifespan and these factors, a meticulously documented dataset encompassing maintenance and operational details specific to the system/component is essential. For the proposed approach, the requirement of the data of the component across its lifecycle is depicted in Figure 3.9.

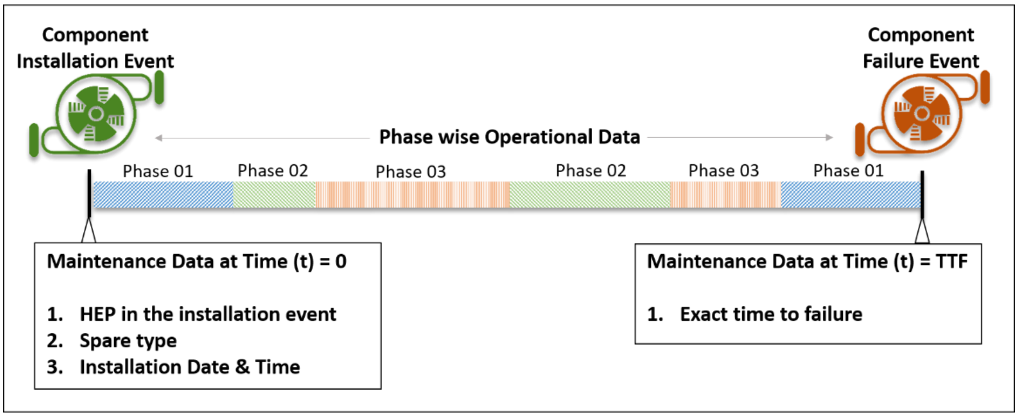

Figure 3.9 Requirement of component's data across its lifecycle

Based on the requirements depicted in Figure 3.9, the systematic data is expected in the format given in Table 3.7.

Table 3.7 Component wise data requirement

Component Details				**Phase wise Operating History across lifespan**			**TTF**
Comp Name	**Comp ID**	**Spare Type**	**HEP**	**P1 (%)**	**P2 (%)**	**P3 (%)**	
AAA1	FP456	N	0.6	38	44	18	415
AAA1	FP457	R	0.75	64	05	31	368

To predict the RUL of the component, it is necessary to provide details about the current status of the component, including its current age. Given the current age of the considered component, the algorithm slices the component wise data (Table 3.7) at the time equal to current age, into history and future profile. This processed data sliced at a given age (format shown in Table 3.8) is the primary input to the XGBoost model. As per the quality of the data, it requires some pre-processing before it is used in the model. Generally, data cleaning, including outlier removal is done with the specified interquartile range, and some of the encodings are done at this stage. The formatted and pre-processed data is then used for training the XGBoost model. A significant portion of the data is used for the training of the model. To gain the desired accuracy in the predictions, hyperparameters of the models play a vital role. Some of the prominent hyperparameters in the XGBoost are the number of decision trees in the model, maximum depth of a tree, learning rate, minimal instance rate, subsample ratio, regularization coefficient, etc. After hyperparameter tuning, the model is tested for accuracy using a portion of the dataset reserved for testing purposes. Once the desired accuracy is achieved, the prediction for residual life can be made for the component for which the user defines the expected future mission profile.

Table 3.8 Processed data input to algorithm

Component Details			**Operating History**			**Phase wise operation after sliced age**			**TTF**
Comp Name	**Spare Type**	**HEP**	**P1 (%)**	**P2 (%)**	**P3 (%)**	**P1 (%)**	**P2 (%)**	**P3 (%)**	
AAA1	N	0.6	42	48	10	60	25	15	415
AAA1	R	0.75	40	32	28	52	20	28	368

3.3.1.4 Uncertainties in mission profile definition

As the ultimate aim of the methodology is to predict the RUL of component and further its mission reliability, definition of the mission profile is an important step. The definition of mission profile for equipment like MBT is discussed previously. However, in reality, the user can specify the number of phases the component is supposed to operate in, but it is difficult for the user to specify the exact proportion of mission duration in every operating phase. Additionally, such user inputs for future expectations about real life missions are often coupled with the uncertainties and variabilities. These uncertainties and variabilities are based on the ability of the user to provide the input with accuracy. Any machine learning model seeking to establish an effective connection between the military specific factors and component’s life, should be able to effectively handle these uncertainties and variabilities. To effectively deal with the uncertainties and variabilities in the user input for future expected mission profile, in this model, three different cases are considered as follows:

Case 1: The user provides the exact future mission profile. Here the exact mission duration and the proportion of operating phases in a small range are made available.

Case 2: The user provides the future mission profile in a range of mission duration along with the ranges of proportions in each operating phase.

Case 3: The user provides only the mission duration of the future mission profile and the user is unable to specify the proportions of mission duration in each of the operating phases.

In the ideal scenario, denoted as case 1, all necessary information is accurately provided to the model. However, in cases 2 and 3, even if the user is not able to provide the exact number of phases the component is expected to operate, the model has the provision of estimating the number of phases using the ranges of operating parameters provided by the user for across the mission duration. In case 2 and 3, if the user specifies the wrongly estimated proportions in every phase, the maintenance decision is likely to be significantly influenced. To mitigate these challenges in cases 2 and 3, the current methodology utilizes probability distributions for the proportion of operating time in each phase. These distributions can be derived from historical phase-wise operational data, as depicted in Figure 3.10. When the user cannot specify the exact mission profile, pre-estimated distribution parameters for phase-wise operations are employed to generate realistic proportions of mission duration in all operational phases. By leveraging these underlying probability distributions, the algorithm simulates multiple scenarios with different phase-wise operations. For each scenario, the RUL is predicted, and based on its comparison with the mission duration, mission reliability is estimated as proportions.

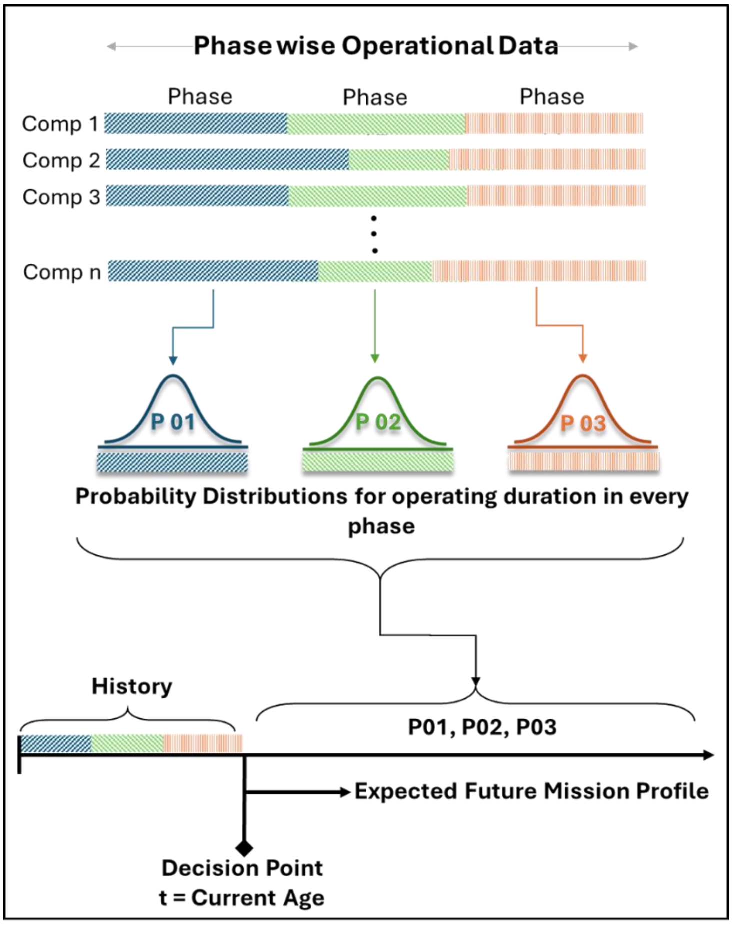

Figure 3.10 Mission profile definition with phase wise usage from probability distributions.

3.3.1.5 RUL based mission reliability prediction

Finally, in this step, the component's RUL is forecasted using a trained and validated XGBoost model based on each data input. To enhance the realism of mission reliability prediction, it is imperative to incorporate uncertainties into the predicted RUL. Consequently, a confidence interval is computed for each prediction to gauge model uncertainty. Due to the challenge of knowing the underlying probability distribution for predicted RUL consistently, this study utilizes Chebyshev's inequality [103] for estimating the desired confidence interval. According to the Chebyshev's inequality, for any real number k > 0,

$$Pr(|P - \mu| \geq k\sigma) < \frac{1}{k^2} \quad \text{Eq. 28}$$

In probability theory, the Chebyshev's inequality guarantees that, for a wide class of probability distributions, no more than $\frac{1}{k^2}$ of the distribution's values can be more than k standard deviations away from the mean [104]. Using the mean and the standard deviation obtained using the errors in the predictions from the XGBoost model, the confidence interval for 2σ is estimated as $(\mu_{error} \pm 2\sigma_{error})$. Where the error of prediction is estimated as the difference between the predicted life and the actual life in the testing dataset. And the standard deviation of this prediction error is used to estimate the confidence interval. Using the limit of 2σ gives the confidence that a minimum of 75% of predictions will lie in this range [103]. For mission reliability prediction, the lower bound of residual life serves as the basis. The process entails predicting mission reliability by juxtaposing this lower bound of RUL against the anticipated future mission duration across one thousand simulated scenarios. The mission reliability of the component is determined by the proportion of scenarios where the lower bound of RUL exceeds the mission duration. Utilizing a non-parametric approach in mission reliability prediction introduces a risk index with each prediction. The decision-maker can set a risk index threshold based on the component's criticality. As data management becomes more streamlined, this uncertainty is expected to diminish, thereby enhancing the accuracy of mission reliability prediction.

3.3.2 Demonstration of proposed methodology

To demonstrate the proposed methodology, the prediction of RUL and subsequent mission reliability for a mission-critical component utilized in a specific MBT is undertaken. This component represents the lowest maintainable unit from a maintenance standpoint. Given that the current methodology relies on a machine learning algorithm, it necessitates sufficient systematic data to train the model effectively. To achieve this, a maintenance data simulator is developed as part of this study. The simulator is designed to mimic the generation of field failure records and operational data within a military-specific environment. An essential aspect of the data simulator is its capability to handle uncertainties and variations in the correlation of multiple factors that influence the component's life effectively.

3.3.2.1 Data Simulator

This subsection addresses the development of a data simulator aimed at generating adequate maintenance and operational data. The data simulator is designed to enhance the realism of simulated data from a military perspective by incorporating all previously discussed essential military-specific factors.

One crucial aspect is the identification and capture of operating phases for the component under consideration. For this component, the sole phase parameter identified as influencing its life is the percentage of load on the engine where the component is installed. Based on the ranges of this phase parameter, the component operates within three phases denoted as P1, P2, and P3. P1 represents the baseline phase, while P2 and P3 denote the extreme phases. Analyzing some of the maintenance and operation history from the system housing the component, a phase transition probability matrix for the component is assumed for data simulator and presented in Table 3.9.

Table 3.9 Phase transition probability matrix

	Phase 01	**Phase 02**	**Phase 03**
Phase 01	0.5	0.3	0.2
Phase 02	0.2	0.5	0.3
Phase 03	0.3	0.2	0.5

As previously mentioned, changes in the operating phase have varying impacts on the component's life and consequently affect system reliability. The failure characteristics of the considered component are provided by the OEM and follow a 2P-Weibull distribution. However, the scale parameter provided by the OEM pertains only to the baseline phase. Utilizing this scale parameter across different and extreme phases would introduce inaccuracies in subsequent estimations. Due to insufficient maintenance data, conventional parameter estimation methods are limited in estimating parameters for different phases accurately. To address the phase-wise impact on the component's life, a multiplier known as the *'Phase Eta Multiplier'* (EM_P) is introduced to adjust the scale parameter of the failure time distribution. This multiplier aims to normalize component usage across phases relative to the baseline phase and accommodate the effects of phase changes. The determination of these Phase Eta Multipliers typically relies on expert judgment, following the methodology outlined by Lad and Kulkarni [38]. Given the challenge of precisely defining multipliers for phase-wise operations, the simulator allows for the use of multipliers from a specified range or probability distribution, thus managing uncertainty regarding the distinct operational phases' effects on the component's life. The estimated Phase Eta Multipliers for all three phases are detailed in Table 3.10.

Table 3.10 Phase Eta Multipliers

Phase	**Phase Eta Multiplier**
Phase 01 [EM_{P01}]	01 → Baseline Phase
Phase 02 [EM_{P02}]	0.83 – 0.87
Phase 03 [EM_{P03}]	0.73 – 0.77

To account for the impact of refurbished or Non-OEM spares, a multiplier known as the '*Spare-wise Eta Multiplier*' (EM_S) is used, which adjusts the scale parameter accordingly. These multipliers are determined through expert judgment and are outlined in Table 3.11. When a component is replaced with a cannibalized spare, its actual age is set to the accumulated age pre-replacement. In such case of cannibalization, assuming no maintenance is conducted, the component maintains its original quality and follows the same probability distribution as before. Defining precise multipliers for different spare types is challenging due to the probabilistic nature of component lifetimes. Experts may propose a range of multipliers reflecting the effect of using different spare types on component life. In the developed simulator, the provision is made to use this spare wise eta multiplier from a range suggested by the user. This provision handles the uncertainty in the effect of using other than genuine or new spare on component's life.

Table 3.11 Spare-Wise Eta Multiplier

Spare Type	**Spare-Wise Eta Multiplier**
G: Genuine [EM_{GS}]	01
R: Refurbished [EM_{RS}]	0.75 - 0.80
N-O: Non-OEM [$EM_{N\text{-}OS}$]	0.45 – 0.55

To consider the impact of human error in maintenance on system/component reliability, a factor known as the '*HEP Eta Multiplier*' (EM_{HEP}) is introduced, which adjusts the scale parameter accordingly. Table 3.12 presents the HEP Eta multipliers for different ranges of HEP during the installation activities of the component, as estimated through expert judgment. The simulator utilizes this multiplier from a specified range or predefined probability distribution. This approach helps address the uncertainties and variabilities associated with defining the effect of HEP on the component's life.

Table 3.12 HEP Eta Multiplier

HEP	**HEP Eta Multiplier [EM_{HEPRi}]**
0 - 0.1	01
0.1 - 0.3	0.93 – 0.98
0.3 – 0.6	0.88 – 0.92
0.6 - 0.9	0.81 – 0.87
0.9 – 1.0	0.73 – 0.80

In this data simulator, all the aforementioned multipliers are used only in order to make the simulated data more realistic from the military perspective. The developed maintenance data simulator simulates the data with the first event as installation of the component (genuine/refurbished/cannibalized/Non-OEM – based on estimated probabilities) at time 00:00 hrs. on day 01. At the time of installation of the component, the simulator simulates one HEP estimate. The component starts operating in one of the three identified phases. The simulator simulates the operations of the fuel pump in all the three phases based on the phase transition probabilities (Table 3.9). At the end of day 01, the age of the component is calculated phase wise, and according to the corresponding phase eta multiplier, the age of component (for that day only) is converted to the age in the baseline phase. Based on the probability distribution parameters, the time to failure of the component is inversely estimated using Eq. 29 [32]. The lifetime distribution parameters provided by the OEM for the considered component are, Scale parameter (η)= 350 hrs. and Shape parameter (β) = 4. These distribution parameters are used in Eq. 29 for the simulation.

$$t = \left\{\left[-ln\left(R \times e^{-\left(\frac{T}{\eta}\right)^{\beta}}\right)\right]^{1/\beta}\right\} \times \eta - T \qquad \text{Eq. 29}$$

Here, R is assumed reliability of the component which is a random variable generated using a uniform distribution (0 - 1). If the estimated time to failure is higher than 24 hrs (duration of that day), the component is considered as survived and not failed. This continues till the estimated time to failure is higher than 24 hrs. When the time to failure is less than 24 hrs. the component is considered failed on that day. In this case, the time to failure value (which is less than 24 hrs.) is added to the age of the component after converting that age according to the baseline phase. As the maintenance data is simulated using the actual lifetime distribution parameters, the simulated maintenance data is expected to closely adhere with the real data. The sample of simulated data for the fuel pump is shown in Table 3.13.

Table 3.13 Simulated Data

Installation Data

Component Name	Spare Type	Installation Date & Time	HEP
Comp A1	New	DD-MM-YY 00:00	0.605

Operational Data

Day	Interval	Parameter 01	Phase	Status
1	1	30	1	Working
	2	30	1	Working
	3	62	2	Working
	:			
	:			
14	1	93	3	Failed
TTF			**317 hrs.**	

Installation Data

Component Name	Spare Type	Installation Date & Time	HEP
Comp A2	Refurbished	DD-MM-YY 01:00	0.502

Operational Data

Day	Interval	Parameter 01	Phase	Status
1	1	25	1	Working
	2	71	2	Working
	:	:	:	:

3.3.2.2 User Input and RUL based mission reliability prediction

To predict the RUL using developed XGBoost methodology, and further the mission reliability, the model requires the future mission profile for the component as an input to the methodology. Once the future mission profile for a component is provided by the user, the algorithm fetches the historical data for the component from the database. With this, the installation time of the component, HEP in its installation activity, its current age, its spare type, and historical phase wise operational data of the component is available to the model. Considering the mission profile, the overall datapoint for RUL prediction by the user is formatted in Table 3.14.

Table 3.14 User input for RUL prediction

Component Name (Spare Type)	**HEP (installation)**	**Current age (hrs)**	**Operational History**		
			Phase 01 (%)	**Phase 02 (%)**	**Phase 03 (%)**
Comp A (G)	0.277	80	33.75	33.75	32.5
Future Profile					
Mission Duration (hrs)	**Expected to operate in**				
	Phase 1 (%)	**Phase 2 (%)**	**Phase 3 (%)**		
250	40	45	15		

The algorithm considers the current age of the component, and with this current age, it slices the data (at the time equal to current age) into history and future profile. Table 3.15 shows the sample for sliced data based on the current age of the component, which is the primary input to the algorithm.

Table 3.15 Processed data after slicing based on the user input

Component Details			**Operating History**			**Operating Env after sliced age**			**TTF**
Comp No.	**Spare**	**HEP**	**P1 (%)**	**P2 (%)**	**P3 (%)**	**P1 (%)**	**P2 (%)**	**P3 (%)**	
1	G	0.63	32.5	41.2	26.2	33.1	32.0	34.7	330.3
2	G	0.21	42.5	32.5	25.0	27.4	35.5	37.0	341.7
3	R	0.31	62.3	12.7	25.0	0	0	0	77.02

To start with the XGBoost model training, a basic model is initialized with default model parameters. Moreover, the basic model's parameters have been tuned to further improve the model accuracy and reduce the prediction error. The model also implemented cross validation for better accuracy. For the best prediction results, the hyperparameters are tuned as follows:

maximum tree depth = 6

number of estimators = 4500

learning rate = 0.1

regularization coefficient = 0.08

minimum child weight = 5

subsample = 1

subsample ratio of columns = 0.7

After hyperparameter tuning of the model, 20% of the dataset is used for testing the accuracy of the model. Mean absolute error of the prediction is estimated using Eq. 30, and found to be equal to 18 hrs., which is ~5% of the characteristic life of the component, and hence considered as acceptable.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \qquad \text{Eq. 30}$$

Where, y_i and x_i are predictions and true TTFs respectively. n is total number of datapoints.

For the above input (Table 3.14), the model predicted the residual life equal to 175 hrs. where the actual residual life of the component in the data is 178.7 hrs. The confidence interval for this residual life prediction is estimated as discussed in section 3.3.1.5.

For mission reliability prediction, considering the uncertainty in mission profile definition from user, one thousand scenarios are simulated where the installation data and the operating history of the component remain constant, and the scenario is different because the operating proportion in every phase is different depending on the uncertainty in mission profile definition. Finally, the user input is formatted as given in Table 3.16 and inputted to the XGBoost model for RUL prediction.

Table 3.16 Simulated user input for RUL prediction

Comp	**Spare**	**HEP**	**Operating History**			**Current Age**	**Mission Duration**	**Future Profile**			**RUL**
			P1_H	**P2_H**	**P3_H**			**P1_R**	**P2_R**	**P3_R**	
1	G	0.63	0.325	0.412	0.262	80	240 ± 10	0.331	0.320	0.348	?
2	G	0.63	0.325	0.412	0.262	80	240 ± 10	0.482	0.412	0.106	?
:	:	:	:	:	:	:	:	:	:	:	:
1	G	0.63	0.325	0.412	0.262	80	240 ± 10	0.523	0.206	0.271	?

For the given simulated user input, the XGBoost model predicts the RUL against all the scenarios. Here, in the considered example, 1000 scenarios are generated. Where, first eight columns in Table 3.16 are constant and the scenario is distinct based on the variation in column 9 – 11. Once the RUL for every scenario is predicted, the confidence interval for each of the scenarios is estimated using Chebyshev's inequality. The lower bound of the RUL in every scenario is then compared with the higher end of mission duration (here, 250 hrs), and accordingly the proportions of scenarios where predicted RUL is higher than the mission duration are calculated. In the present example, mission reliability of the component is predicted to be 0.93, with a risk of 7%. A threshold for this risk index need to be set by the user depending on the criticality of the component.

3.4 Discussion

In this section, we presented two distinct approaches for predicting mission reliability of critical military equipment while considering the collective impact of essential military-specific factors. The first approach involves employing specific adjustment factors for each military-specific factor and integrating them with the effective age of components in the system, which is then applied in the formulation of conditional mission reliability. On the other hand, the second approach utilizes an XGBoost-based machine learning algorithm for predicting RUL, which is subsequently utilized for mission reliability prediction. Both approaches offer unique advantages and drawbacks. While the second approach is computationally efficient and relieves the user from the complex statistical treatments associated with the first approach, it necessitates a substantial amount of data. Once an adequate dataset is available, this machine learning-based approach promises ease of use and effective implementation. This approach is envisioned to seamlessly integrate with new-generation autonomous decision-making systems in the military organizations. However, in the absence of such a rich dataset, the first approach remains a viable and effective option. In this study, we utilize both approaches to evaluate the impact of the considered essential military-specific factors on component life and the mission reliability of the MBT.

By employing the first approach, mission reliability is assessed across various scenarios involving diverse terrains, seasons, and deployment roles for the MBT. To examine the relationship between mission reliability and terrain/season, multiple scenarios are analyzed where the mission duration remains constant at 36 hours and the MBT has already operated for 200 hours. Detailed input data for mission reliability prediction, along with system configuration and respective adjustment factors, is outlined in Annexure A. User defined mission profile for one such extreme scenario is mentioned below:

> *An MBT has to execute a 36-hour mission in a deep penetration deployment role, specifically in an attack formation within the desert region during the month of May. Ensuring uninterrupted operational capability of the MBT without any failures is imperative throughout the mission duration.*

Transitioning from a scenario involving plains terrain and normal season to one involving desert terrain and summer season resulted in an approximate 12% alteration in mission reliability prediction. This underscores the crucial role of terrain and season considerations in predicting mission reliability for the MBT, as illustrated in Figure 3.11 across four distinct scenarios.

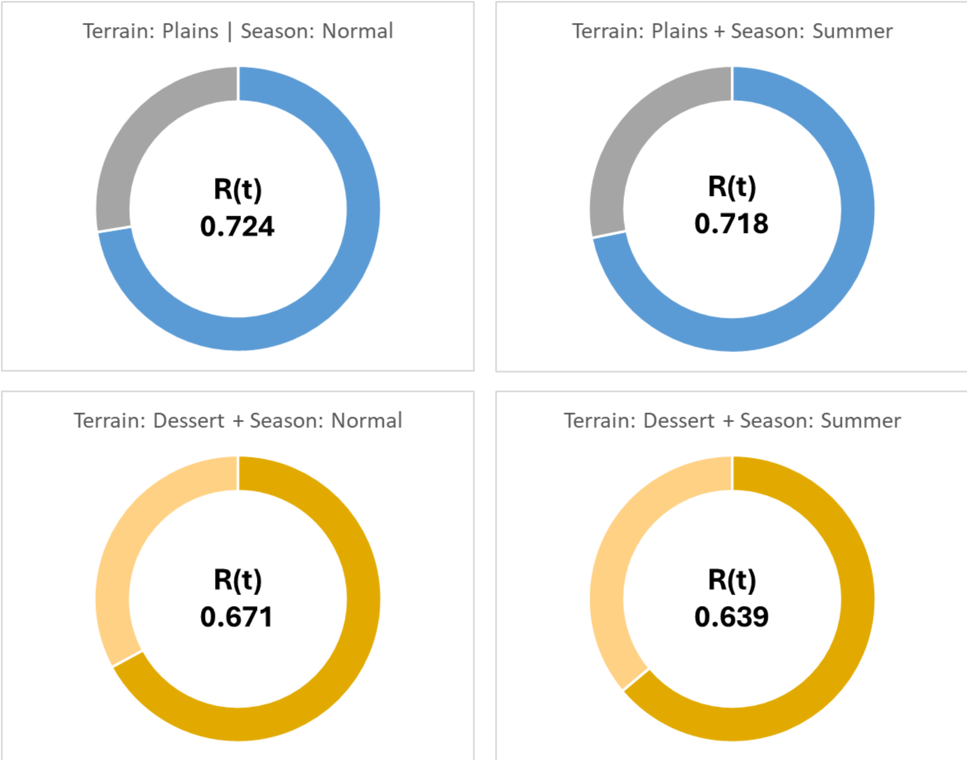

Figure 3.11 Change in mission reliability with change in terrain and season

In a separate investigation, the decline in mission reliability across three distinct deployment roles has been analyzed. The mission reliability of an identical MBT undertaking a 36-hour mission but in varying deployment roles has been predicted and graphed, as depicted in Figure 3.12. The analysis clearly illustrates a reduction in mission reliability across all three deployment roles, each following a unique trajectory. For instance, in role 1, encompassing all four functionalities, the mission reliability dipped below the critical threshold of 0.8 after 135 hours of operation, while for role 2 (requiring mobility, firepower, and protection), it occurred at 156 hours, and for role 3 (focused on mobility and communication), the threshold was reached at 181 hours of operation. This distinct variation in mission reliability decline underscores the significance of factoring in diverse deployment roles when predicting mission reliability for critical military equipment like MBTs. Such considerations are particularly crucial in military contexts where these equipment types often operate in specific deployment roles for prolonged periods, especially during peace time.

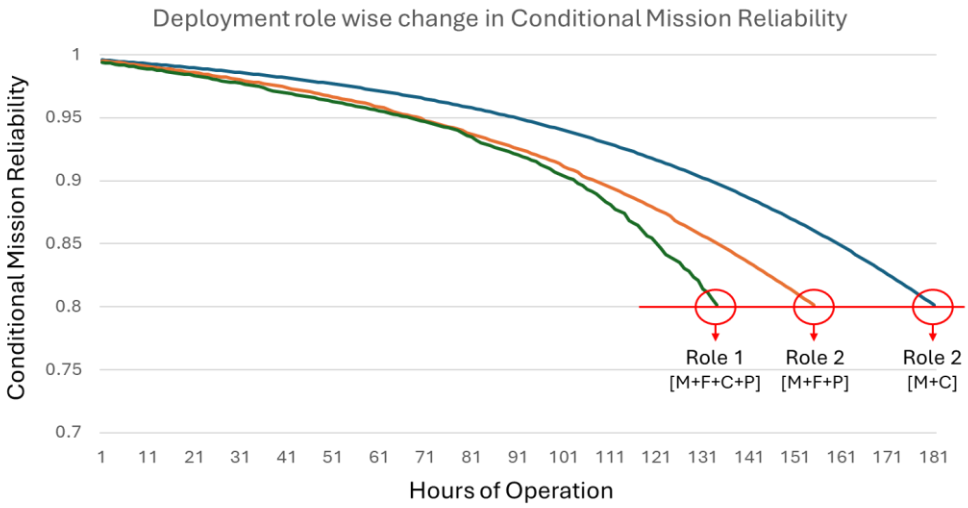

Figure 3.12 Deployment role wise change in conditional mission reliability

To examine the impact of different levels of human error in maintenance on residual life of the component using the proposed machine learning based approach, numerical experiments were conducted. The experiments utilized the developed XGBoost algorithm to predict the residual life of the considered component across 18 distinct scenarios. These scenarios encompassed three types of spare parts: genuine, refurbished, and non-OEM. Cannibalized spare parts were not considered as a separate category due to the considerations discussed in section 3.1.3, where the impact of cannibalized spares is contingent upon their initial age, characterized as genuine if the initial age is zero. For all three spare types, the current age was set to 80 hours, and the phase-wise operating profile remained constant. By varying the HEP value six times, ranging from no human error conditions to very high HEP, the prediction of the component's life was conducted. The trends in the life predictions are graphically represented in Figure 3.13, with each sub-diagram having a different scale on the Y-axis to accommodate the graphical data effectively.

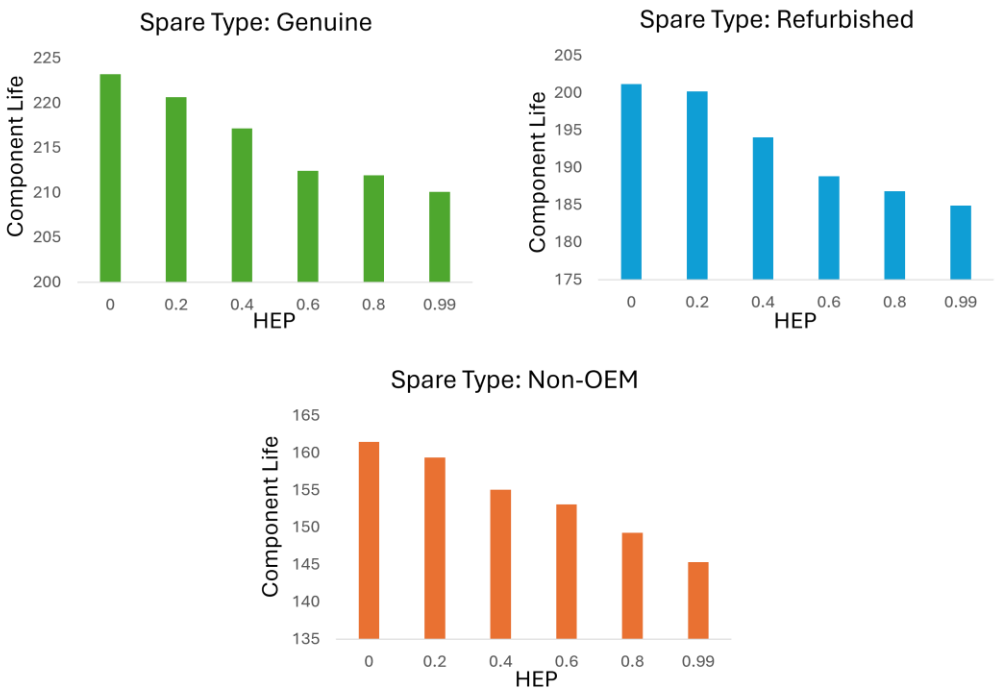

Figure 3.13 Effect of varying HEP on component's life

The observable impact of varying Human Error Probability (HEP) on the component's life and consequent residual life, as predicted by the proposed methodology, indicates a consistent trend. As the HEP increases, there is a corresponding decrease in the component's life across all scenarios. This observed pattern not only reinforces the expected behavior but also serves to validate the accuracy of the developed algorithm.

In another observation, the influence of human error on the component's life was analyzed in relation to the spare type. Through the same numerical experiment (refer to Figure 3.13), it was noted that for genuine spares, the variation in predicted component life between scenarios where human error is negligible (HEP = 0.01) versus when it is considered significant (HEP = 0.9) could reach up to 5.8%. This disparity was more pronounced for refurbished spares at 8.0%, and notably higher for non-OEM spares, approaching almost 10% (Figure 3.14). The increasing percentage change in life underscores the necessity of accounting for human error to avoid erroneous mission reliability estimations. In terms of managerial implications, the utilization of non-OEM spares in environments prone to human error during maintenance is discouraged. Given the substantial impact of human error on component life across all scenarios, acknowledging this factor in maintenance considerations is imperative.

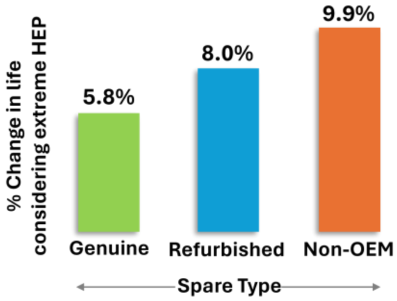

Figure 3.14 Spare-wise % change in life considering extreme HEP

In the numerical experiments, a notable observation emerged regarding the impact of human error on component life relative to the component's age. Figure 3.15 illustrates that as the age of the component increases, the effect of human error becomes more pronounced. This trend is evident when comparing the component's RUL under minimal HEP conditions to scenarios where HEP is considered significant. For instance, with genuine spares, at an age of 80 hours, the RUL change is approximately 4.05%. This change increases to 7.27% at 120 hours of age and further escalates to 10.43% at 160 hours. A similar trend, although with different magnitudes, is observed for refurbished and Non-OEM spares. For Non-OEM spares, the analysis includes component ages of 40, 60, and 80 hours. Due to the shorter lifespan of Non-OEM spares compared to genuine and refurbished ones, there were fewer data points available for Non-OEM spares with ages exceeding 200 hours. Consequently, the model's ability to predict RUL for aged Non-OEM spares was unstable, resulting in less accurate predictions. Nonetheless, the trend of HEP effects with increasing component age remained consistent for Non-OEM spares when considering shorter component ages. From a managerial perspective, it is imperative to incorporate the HEP effect in maintenance planning, particularly for aged components. This consideration holds heightened importance for military organizations, which frequently utilize vintage equipment. Neglecting to account for HEP can lead to inaccurate mission reliability predictions and impede critical maintenance management efforts. Therefore, emphasizing this consideration in mission reliability prediction and critical maintenance management is crucial for effective decision-making and equipment maintenance within such organizations.

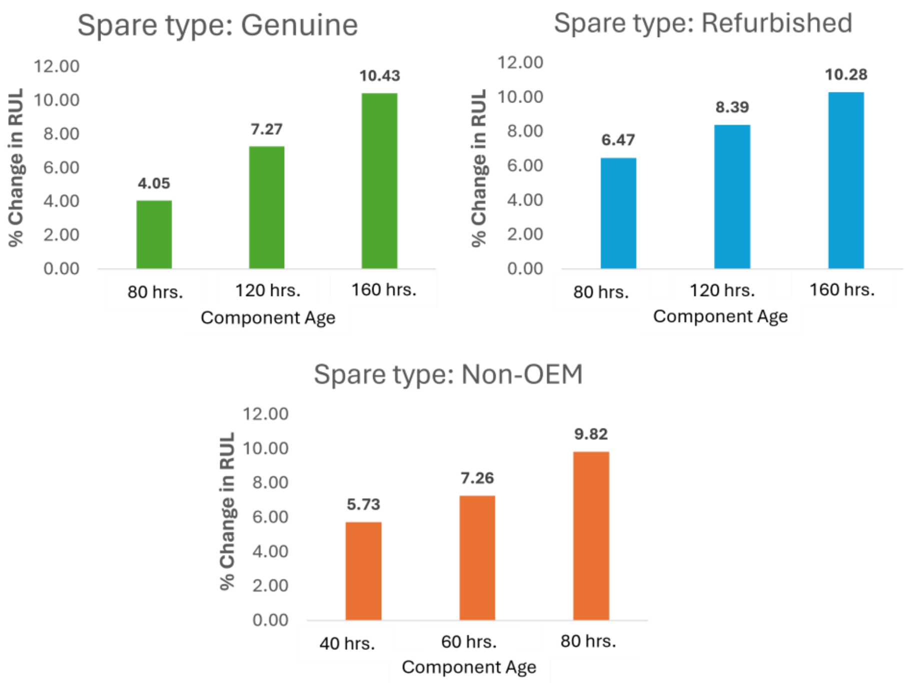

Figure 3.15 Effect of human error with increasing age of component

3.5 Summary

The paramount objective of this research is to ensure the mission reliability of critical military equipment, thereby achieving its war readiness. In order to make the mission reliability prediction for military equipment accurate, literature strongly suggests incorporation of the military as well as nation-specific factors, which is rarely seen in the present literature. This chapter tackles this limitation by introducing two comprehensive methodologies for predicting mission reliability of critical military equipment. One methodology represents a scientific expansion of the existing mission reliability prediction method, while the other introduces a novel approach based on machine learning. Aiming to provide a more accurate and contextually relevant prediction of mission reliability, both of these enhanced methods incorporates a comprehensive set of identified military-specific factors as follows: (i) Operations in diverse operating fields featuring extreme environmental conditions, (ii) Multiple deployment roles exhibiting multiple functionalities, (iii) Use of cannibalized, refurbished, or non-OEM spares instead of new-genuine spares, and (iv) Human error in maintenance of critical equipment in strenuous situations.

In the first methodology, the mission profile for which the readiness of the particular equipment is to be assured is determined in the form of three different attributes, viz: deployment characteristics, usage requirements, and environment profile. Accordingly, the effective mission duration is estimated for which every component's reliability is predicted. This approach involves employing specific adjustment factors for each military-specific factor and integrating them with the effective age of components in the system, which is then applied in the formulation of conditional mission reliability. Further, considering the RBD of the equipment characterized by series–parallel configurations, its mission reliability is predicted.

In the second methodology, a novel XGBoost based algorithm for residual life prediction of critical military equipment is developed and used, which is further used in simulation for mission reliability prediction. Given the current age of the considered component, the algorithm is designed to slice the operational data into history and future profiles. This processed maintenance data sliced at a given age is the primary input to the XGBoost model. After training the model and achieving the desired accuracy in predictions, the prediction for residual life is done. In light of the uncertainties involved in the mission profile definition, the presented algorithm is developed capable of handling a good extent of these uncertainties and variabilities. Once the residual life is predicted, confidence bounds are set on the predicted residual life, and further, it is compared with the derived mission duration to predict the mission reliability. On multiple tests, the model predictions are found to be in the desired level of accuracy and mean absolute errors are found well within the desired limits.

The numerical investigations using the developed mission reliability prediction methods have revealed that the terrain in which an MBT operates plays a pivotal role in determining its mission reliability. Significant variations in mission reliability have been observed across different terrains, indicating the necessity for tailored reliability assessments for specific roles in diverse environmental contexts. Deployment roles have been identified as crucial determinants of mission reliability. Noteworthy differences in mission reliability outcomes have been observed when transitioning between deployment roles. This underscores the importance of considering deployment roles in evaluating mission reliability in terms of functional reliability.

The developed model is further used to investigate the effect of human error in maintenance and spare type on the life of the component. Outcomes of numerical investigations suggests that the magnitude of the varied impact of human error in maintenance on component life depends upon the choice of spare type, viz. genuine, refurbished, cannibalized, and non-OEM options. Additionally, the impact of human error on component life is observed to be amplified with the increasing age of the component, emphasizing the necessity of factoring in this effect, particularly in maintenance planning for critical equipment with aging components.

❖

Chapter 4

Mission Reliability based Selective Maintenance Planning Approach

This chapter presents a novel mission reliability based selective maintenance approach for military equipment. The chapter discusses how the predicted mission reliability is utilized to achieve and sustain war readiness through selective maintenance strategies. A review of the relevant selective maintenance literature is presented. Following problem formulation, key parameters are optimized, and the overall approach is then demonstrated for multiple operational scenarios. Comparative evaluation establishes the superiority of this approach over traditional time-based methods. The chapter then demonstrates a mechanism for rapid fleet-level readiness assessment for high level decision makers. Finally, numerical analyses illustrate the influence of critical parameters on managerial decision-making.

A part of the work presented in this chapter is published under the title "*Novel Selective Maintenance Approach to Ensure Mission Reliability of Armoured Vehicles Considering Multiple Deployment Roles in Distinct Operating Profiles*" in "Defence Science Journal" vol. 74(4), pp. 447-459, 2024, DOI: 10.14429/dsj.74.19370.

The overall objective of the research outlined in this thesis is to develop an approach tailored to suit the modus operandi of defence forces in attaining and sustaining war readiness by ensuring the mission reliability of critical military equipment. This chapter elaborates on how the predicted mission reliability of critical military equipment, as determined through the previously presented methodologies, is utilized in approaches to achieve and sustain war readiness. The pivotal aspect of effectively managing military equipment and ensuring their readiness to the desired standard lies in the selection and subsequent management of an effective maintenance approach.

If the overall objective of attaining and sustaining war readiness by ensuring the mission reliability of critical military equipment is translated into a base level actionable program, in its simplest manner, it essentially means guaranteeing that the considered critical military equipment consistently exhibits a higher level of mission reliability than what is required for its deployment in wartime scenarios. Accomplishing this signifies that the equipment, or a fleet of such equipment, is war-ready with the desired level of confidence. However, during peacetime operations, in the form of routine running or regular exercises, these critical equipment experience degradation, leading to a reduction in their mission reliability against some predefined mission profiles. This underscores the crucial role of the maintenance function to maintain the mission reliability of critical equipment while its utilization resulting in its degradation, resulting in fall of mission reliability.

Maintenance function has been always coupled with equipment downtime and resource cost. A whole lot of literature in maintenance management strives to balance this tradeoff, however, scholarly literature discussing overall maintenance management which suits the exact modus operandi of military organization in achieving mission reliability and ultimately, war readiness is not available. Consequently, while the maintenance function is viewed as the solution to ensure the mission reliability of critical military equipment, it raises several critical questions for which answers are lacking in the existing literature. These questions include determining the appropriate level of mission reliability to be maintained, defining acceptable downtime during maintenance activities in line with war readiness expectations, evaluating whether the accepted downtime level during maintenance impacts the war readiness metric, establishing acceptable maintenance costs, determining the optimal maintenance frequency, and other related considerations.

Existing maintenance policies are not directly applicable to meet the expectations of war readiness and address the crucial questions mentioned earlier. The literature on maintenance modeling primarily focuses on maintenance policies for conventional manufacturing and logistics spheres, and thus, its intricacies are tailored to that domain. However, these maintenance models, primarily designed for conventional manufacturing systems, cannot be easily adapted for the maintenance of critical military systems, particularly mission-critical systems where war readiness is of utmost importance. Numerous challenges such as, challenging conditions for repair personnel with limited maintenance duration availability, extreme operational environments, uncertain spare parts availability at remote maintenance locations, and others contribute to the distinct nature of maintenance in military systems compared to manufacturing systems. Additionally, factors such as usage patterns of military equipment further compound these differences. The overall lifecycle of critical military equipment can be classified into two categories, peacetime and wartime, which bring the extremely varied stress levels to the equipment. The majority of the usage of the equipment happens in peacetime in the form of routine running, mission exercises, etc., and hence, most of the maintenance of the equipment is performed in peacetime only, but with the objective of keeping the equipment ready for wartime operations for which it is actually intended. Looking at the usage patterns, battlefield situations, maintenance practices, and on top of that the expectation from the maintenance function, it is evident that the conventional maintenance practices are not sufficient for ensuring the war readiness of the critical military equipment.

There exists a necessity for a tailored maintenance approach that aligns with the exact modus operandi of military organizations by integrating crucial military-specific factors, while also meeting the expectations of war readiness for critical military equipment. This chapter aims to fulfill this requirement by introducing a novel mission reliability based selective maintenance approach. This approach is tailored for military equipment and effectively integrates the essential military-specific factors, thereby addressing the identified need effectively. The technical insights into the operational mechanism of the proposed approach are presented in the following sections.

4.1 Mission reliability based maintenance planning

The present approach works with the principle that the exploitation, as well as maintenance of mission-critical equipment, should be balanced in such a way that if, at any point in time, the equipment is ordered to be deployed on a certain specific mission, it should be ready; otherwise, it should be able to be ready in a specified maintenance duration as per readiness expectation. Here, the readiness of a critical equipment is seen from two different yet related viewpoints; one being its immediate ability to be deployed and the other being its ability to achieve deployable status within a short maintenance timeframe. In this context, inspired by real-world military operations, mission readiness for an MBT is defined as either being fully prepared for immediate deployment on predefined mission profiles or capable of being made mission-ready within a predefined short maintenance window. For instance, if an MBT is not currently prepared but can be made mission-ready within a specified short time frame through maintenance, it qualifies as mission-ready due to the mission start time being greater than the allowable maintenance duration.

In the proposed approach, the methodology involves continuous monitoring of the mission reliability of every critical equipment in the fleet under consideration for predefined mission profiles. Depending on the utilization of the equipment, the mission reliability against the predefined mission profiles starts decreasing. Considering the objective of maintaining the mission reliability to the desired levels always, whenever the mission reliability against the predefined mission reaches a predefined lower threshold of mission reliability, a maintenance event is triggered. In this triggered maintenance event, necessary maintenance activities are performed that increase the mission reliability of the equipment to a predefined higher threshold of mission reliability. Upon reaching this higher reliability level, the equipment becomes available for utilization once again. Subsequently, when the mission reliability decreases again for predefined mission profiles to the lower threshold, another maintenance event is triggered. In this way, the equipment is not allowed to be utilized beyond a predefined lower mission reliability threshold. However, the triggered maintenance event is coupled with the downtime of the considered critical equipment, which is undesirable. Therefore, the utilization of the equipment is systematically managed in such a way that the duration for triggered maintenance event should be attempted to be smaller than the allowable maintenance window as per the readiness definition. In other words, it can be stated that the equipment is not allowed to be utilized beyond a certain point, from where maintaining it to the desired higher reliability threshold within a predefined maintenance time is difficult. This approach ensures that the equipment under consideration is either prepared for deployment on specific predefined mission profiles with the desired mission reliability or is undergoing maintenance, where the maintenance process is designed to be completed within a small maintenance window, aligning with the readiness definition and ensuring prompt deployment of the equipment thereafter. Figure 4.1 depicts the approach with the trend of mission reliability of equipment against a mission profile.

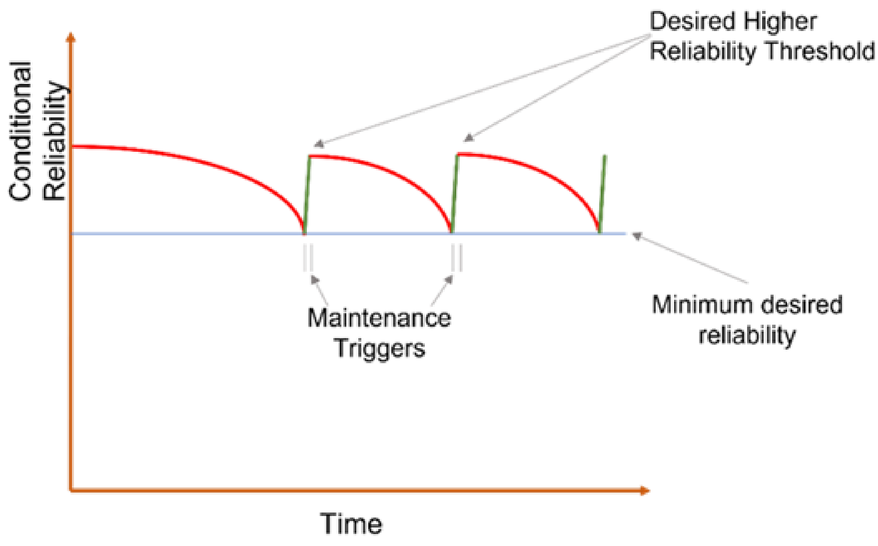

Figure 4.1 Mission reliability based maintenance planning

While examining the trajectory of declining mission reliability, depicted in Figure 4.1, it is crucial to note the significant variations in mission reliability decline associated with changes in deployment roles, as illustrated in Figure

3.12. Deployment roles are expected to highly influence the mission reliability of the same equipment (Figure 4.2). The current approach systematically accounts for this influence by monitoring mission reliability across a predefined set of deployment roles.

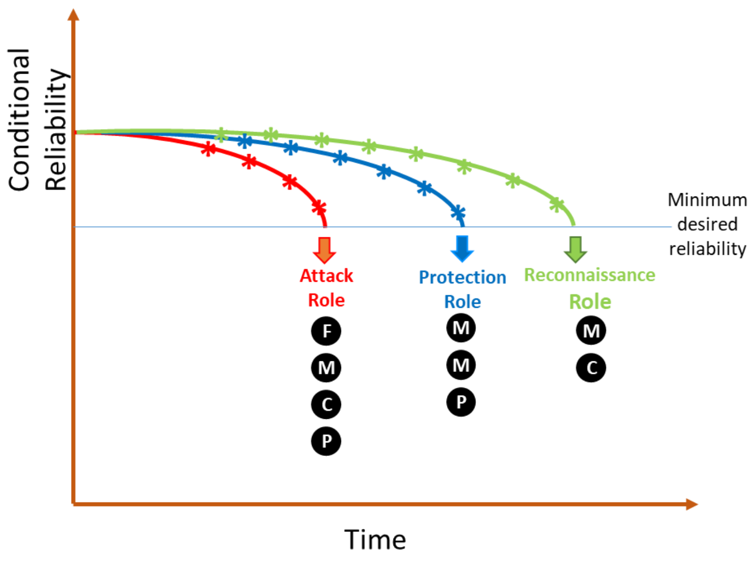

Figure 4.2 Change in conditional mission reliability wrt different deployment roles

Upon the trigger of a maintenance event, a pivotal decision revolves around selecting a suitable set of maintenance activities for the equipment. The primary goal here is to execute necessary maintenance tasks that elevate the mission reliability of the equipment to meet the higher mission reliability threshold within the specified duration outlined in the readiness definition. However, this maintenance event is always coupled with resource constraints such as limited maintenance duration, budgetary constraints, spare parts availability, etc. Consequently, considering the maintenance scenario and its associated constraints, a maintenance optimization problem is formulated at the onset of each triggered maintenance event. By solving this optimization problem, a set of optimal maintenance activities is identified, enabling the attainment of the higher threshold of mission reliability through their execution.

4.2 Selective maintenance planning

The key to effectively managing military equipment and ensuring their mission preparedness to the desired level is the selection of an effective maintenance approach. In various industrial applications, systems are often required to execute a sequence of predefined missions with a maintenance break between them. To maintain a system at an acceptable operating condition during its production or during succeeding missions, necessary maintenance actions must be performed on deteriorated components during these maintenance breaks. However, it is not always the case that all of the components will be replaced with new ones, especially when resources such as time, budget, spares, and maintenance personnel are limited. Nonetheless, maintaining the components is essential to ensure a high probability of a system successfully completing a subsequent mission. In this scenario, managers must decide which components should be flexibly maintained according to actual conditions rather than following a fixed schedule all the time. This maintenance strategy is known as Selective Maintenance (SM), a policy of attempting to 'do more with less' [105]. Literature suggests the applicability of selective maintenance (SM) for military systems [32], [106], [107]. The overall scenario of SM along with its criteria influencing and steering the maintenance decision making process are depicted in Figure 4.3. When compared to various other maintenance policies, SM exhibits unique characteristics that render it highly practical in certain real industrial scenarios. These distinctive features primarily include its mission-oriented approach and condition-based maintenance policy. Considering the nature of the maintenance scenario and its associated constraints, formulation of selective maintenance problem (SMP) is justified. A comprehensive examination of the state-of-the-art literature on SM was conducted to effectively formulate the SMP and seamlessly integrate it into the developed approach.

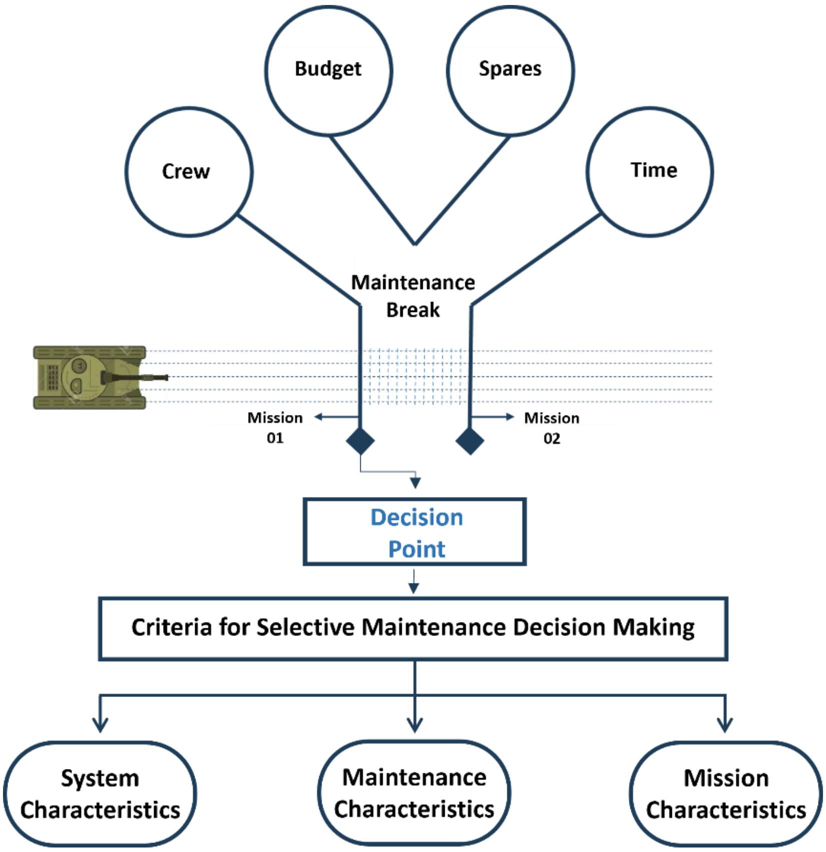

Figure 4.3 Selective Maintenance - Scenario and Criteria

4.2.1 State-of-the-art review on selective maintenance

The SM is particularly suited for the maintenance of multi-component systems following an alternating sequence of missions and breaks [105]. To enhance the ability of such systems to successfully complete their subsequent missions, maintenance actions are carried out on components during scheduled breaks. However, limited maintenance resources such as time, budget, spare parts, and repair crews restrict the number and levels of maintenance activities that can be performed before the next mission. The optimal selection of components to maintain is known as the SMP and can be traced back to [108]. The primary goal is to maximize system reliability for upcoming missions or minimize overall maintenance costs for maintenance activities to be carried in the present maintenance break, considering various pertinent maintenance and logistics constraints. Solving the resulting optimization problems, even for the fundamental version of the SMP, is often exceedingly challenging. The last two decades have witnessed a significant interest from researchers in the maintenance domain towards making the SMP more comprehensive and pragmatically applicable. Following the original SM approach, many new SM optimization models and solutions have been extensively explored from various research and application prospects. The two major exploration directions are formulation characteristics, and solution approaches. While advancing the research on SM on these two directions, researchers worked on expanding the application of SMP for complex real industrial systems considering uncertainties in various characteristics at multiple levels. The systematic detailed review on literature discussing SMP can be found in [105], [109], [110]. Figure 4.4 presents the categorization of SMP formulation characteristics and solution approaches [110].

The very first work on SM presented a mathematical model to selectively determine a subset of replacement actions for a series – parallel configured system composed of identical components with a constant failure rate [108]. However, industrial systems in reality often feature non-identical components. Subsequently, research extended the SM problem to address systems composed of non-identical components connected in series – parallel configuration [111]. Series – parallel systems are the most studied in the SM literature, as many real world systems can be modelled as series – parallel configurations. Following the initial work on SM, many researchers modelled their SMP on such configuration [32], [112], [113], [114], [115], [116], [117]. A limited number of studies delve into the SMP for complex reliability architectures. [118] expanded the initial SMP to encompass subsystems within complex structures. Further, to efficiently address the SMP for large, intricate structures, which include serial k-out-of-n systems with non-identical components, a nonlinear SMP is converted into a multidimensional knapsack problem [119]. While the majority of SM investigations depict system configuration through RBD, a few studies opt for alternative methodologies such as dynamic fault tree [120], tree and leaf representation [121], and directed graph modeling [122].

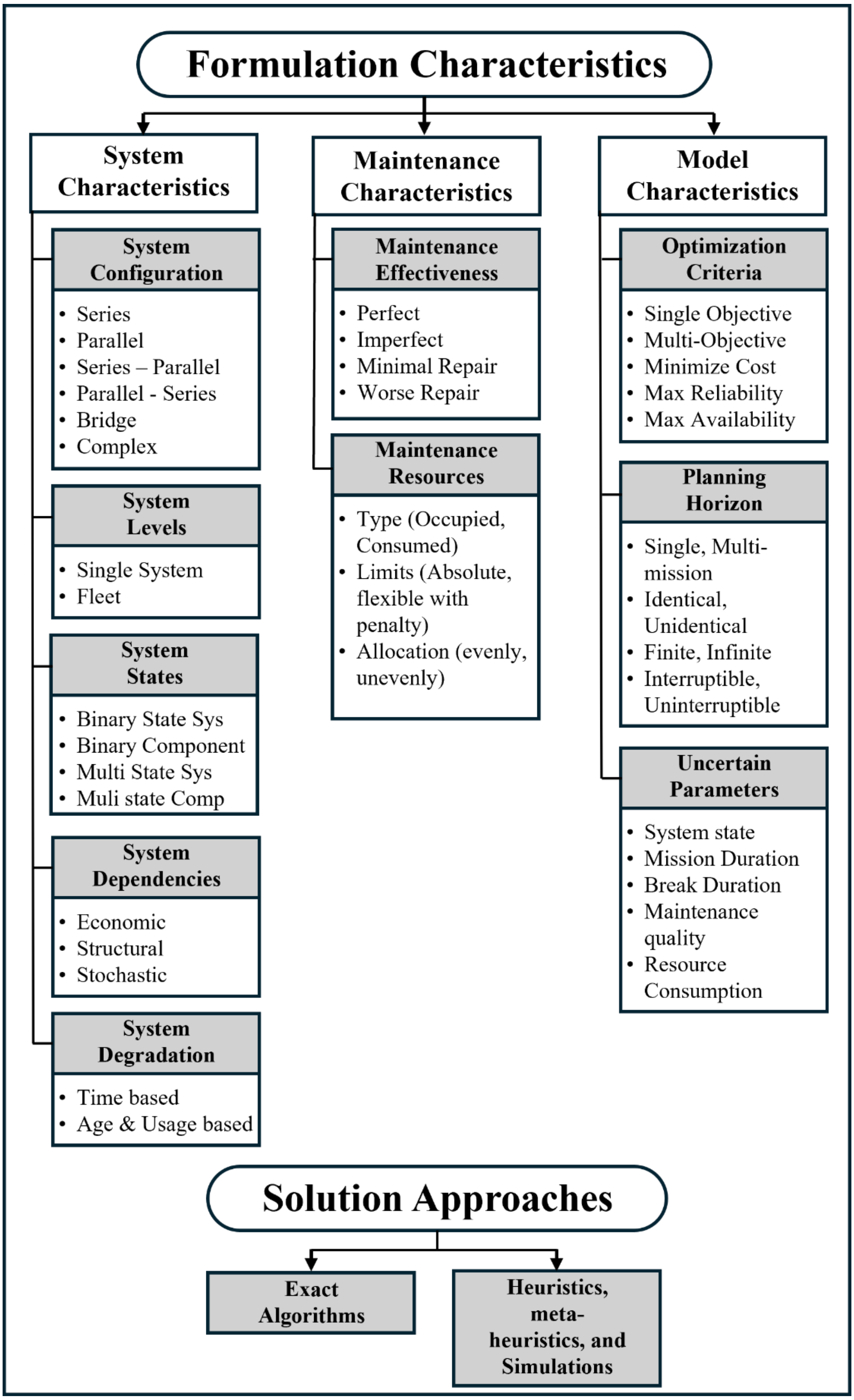

Figure 4.4 Categorization of SMP formulation characteristics & solution approaches

Early advancements in SM were constrained to binary-state systems with binary-state components (BSS-BSC), where the system and its components could exist in either a failed or functional state. However, certain industrial systems and components exhibit continuous degradation over time, leading to the classification of Multi-State Systems (MSS). MSS encompasses systems with a multi-state nature alongside binary-state components (MSS-BSC) or both multi-state systems and components (MSS-MSC). Consequently, the SMP was applied to numerous MSS scenarios to optimize maintenance decisions. [123] presented a methodology to address SM decisions within MSS-BSC featuring non-coherent states. [124] expanded the SMP to encompass multi-mission multi-state systems, while [125] explored single-mission SMP in an MSS with binary-state components. These studies commonly assess system performance using capacity or productivity metrics, prevalent in energy transmission, manufacturing, and power generation systems. Building upon this work, the investigation of SMP for MSS was extended to include MSC in an MSS (MSC-MSS) rather than solely BSC [126]. Subsequent studies have delved deeper into SMP considerations for MSS, with [127] examining SMP within an MSS where components experience variable loading conditions leading to degradation based on their operational state and applied load.

The maintenance function plays a pivotal role in characterizing the deterioration in the state of a system. The original SM model [108] focused solely on replacing failed components. Subsequent developments by [128] extended the model to include Minimal Repair (MR) and Preventive Maintenance (PM). Eventually, [129] proposed the inclusion of Imperfect Maintenance (IM) in the SMP. They presented a case study where the SMP was applied for the maintenance of a power generation coal transportation system. Here, the authors integrated the IM into the SMP with the use of the Kijima Type II model [84]. They used Genetic Algorithms (GA) to solve the optimization problem and additionally presented the effect of considering IM on the SM outcomes. It was observed that the incorporation of IM in SMP achieves more accurate outcomes as it has a direct influence on maintenance cost and break duration. To incorporate the effect of IM in SMP, [126] used an age reduction factors which manipulates the effective age of every component after every maintenance action. An approach - Hybrid hazard rate was also used to capture the effect of IM, where every IM action characterized the change in the base hazard rate of the component [130]. A majority of the models considered the predefined level of IM; whereas, SMP was also demonstrated where the level of IM is stochastic, as it could be highly uncertain [131].

In addition to the levels of IM, several parameters in the SMP are inherently uncertain such as mission and break durations, system state determination and resource consumption. Neglecting the stochastic and/or uncertain nature of many such parameters can lead to the overestimation of system reliability. Specifically, stochastic aspects like mission length and maintenance duration have been underexplored in the literature on SM. Some studies have addressed this by incorporating probability distributions such as Gamma and Triangular distributions to model uncertain durations [132], [133], [134], [135]; while others have used discrete random variables [136] or fuzzy values [137], [138]. Studies have shown that the stochastic nature of failure times, mission duration, operation time lead to uncertainty about the effective age of components at the beginning of the next mission [139]. The sequence of maintenance actions also impacts the chance of completing maintenance actions if there is stochasticity [140].

A limited body of literature within SM has focused on addressing the intricate challenge of system state determination. This has been achieved through various methodologies such as formulating nonlinear, discrete, chance-constrained programming optimization models to handle diagnostic uncertainties related to built-in test equipment [141], employing Bayes' theorem and probability analysis to derive component state distributions from uncertain diagnostic outcomes [142], and proposing fuzzy Mult objective models to optimize the fuzzy reliability of individual subsystems and developing robust SM strategies to identify optimal maintenance actions for binary-state systems under imperfect observations [143].

All of the intricate considerations in the above discussed literature on SM contribute to multiplying the complexity of the formulations of the SMPs. One of the main challenges faced by SMP models is their difficulty in achieving optimal solutions, especially for large-scale industrial problems involving extensive systems and numerous realistic considerations. Rice [144] demonstrated that the basic SMP is NP-hard, indicating that the computation time increases exponentially as the number of variables grows, a characteristic shared by its extensions. Different methodologies and techniques are used for solving the SMP, which could be clustered into two groups: exact and heuristics approaches as shown in Figure 4.4. A vast majority of the SMP in the literature used exact algorithms and meta-heuristics, whereas a limited research work can be found that uses simulation based algorithms and deep learning.

The early stages of research development in SM were predominantly marked by the utilization of exact algorithms, such as total enumeration [108], shortest path method [145], and search space reduction [146]. Subsequently, researchers continued to employ exact methods in their SMPs, including the max-min approach [147] and branch and bound type procedures [148]. The computationally expensive nature of most SMP exact solution methods limits their applicability to small sized problems. As a result, alternative approaches such as general heuristics, meta-heuristics, simulation, and deep-learning-based methods are employed to efficiently obtain near-optimal solutions. Subsequent to the fundamental work on SM, several studies use general heuristics to handle SMPs [149], [150]. Knowing the benefits of using meta-heuristics over the general heuristics, the majority of the SMPs were solved using the evolutionary algorithms. [151] first used GA to find the best maintenance strategy for a large-scale SMP. Subsequently, many studies used GA to solve large-size instances of the SMP [32], [106], [152], [153]. In addition to GA, DE, another evolutionary algorithm, is used intensively in SM optimization. [154] used the DE for the first time as a solution approach for large size instances of the SMP, following this various other studies used DE for SM optimization [126], [133]. Besides evolutionary algorithms, other meta-heuristics are also used such as simulated annealing algorithm [139], [155], particle swarm optimization [141], [156], and ant colony optimization [157]. Recently, some of the modern hybrid techniques also have been used to solve SMP efficiently. A SMP, which is a dynamic optimization problem, is formulated as a discrete time finite horizon Markov decision process; and a deep reinforcement learning method is used to find the optimal maintenance action [158]. [159] demonstrated application of hybrid deep learning with differential evolution algorithm for SMP. Some approaches with maintenance priority of components are developed which guides the algorithm to select the components for maintenance [160], [161].

The literature on SM showcases substantial research advancement aimed at refining and enhancing this policy's maturity and practicality. However, its applications across various industrial domains remain limited in the literature. Despite being recommended for military equipment, the actual implementation of SM on operational military systems is documented only in a couple of research papers. The primary focus of SM studies tends to revolve around manufacturing and transportation systems. While the presented review of the literature on SM helps setting a strong foundation for the SMP for the problem under consideration, it is crucial to note that each industrial domain differs, and a particular maintenance policy may not be universally applicable. Therefore, for optimal outcomes, the maintenance policy must be tailored while considering specific domain-related factors.

The operation of missions in many real-world applications often involves different mission requests, planning horizons, and mission types that need to be considered simultaneously during SM decision-making. Furthermore, the modeling approach for system reliability may vary across missions based on specific requirements. However, existing literature on SM has somewhat overlooked the variety of mission profile characteristics. Therefore, exploring SM with regard to different mission types and working conditions presents a promising avenue for further research.

Various approaches have been discussed to solve this nonlinear programming problem of SM. However, there lacks a universal approach that simultaneously addresses result reliability and computational complexity. In real life industrial systems, the component count can be substantial, significantly expanding the potential solution space. Interestingly, it's evident that different methods are not mutually exclusive but rather complementary and interconnected. Thus, to overcome the limitations of individual solution methods and leverage diverse approaches, further investigation into a hybrid solution method, integrating different methods, may offer an efficient resolution. Moreover, the emergence of parallel computing and machine learning presents promising avenues for exploration in this domain.

4.2.2 SMP Formulation

The initial point in the triggered maintenance event is referred to as maintenance decision point. Here, the SMP is optimized to find an optimal subset of maintenance activities, on execution of which, the higher mission reliability threshold can be achieved. The objective of the present SMP is to find a cost-optimal set of maintenance actions that achieves MBT's mission reliability greater than the higher mission reliability threshold in a shorter time than the given one according to the readiness definition. The formulation of the SMP under consideration at the maintenance decision point is as follows:

$$Min\ C = \sum_{i=1}^{N(i)} \left(\sum_{j=1}^{N(i,j)} \left(\left(C_{(i,j)} M_{(i,j)} \right) \right) \right) \qquad \text{Eq. 31}$$

Such that,

$R_{Tank} \geq R_{Des}$

$T_m \leq T_{av}$

Where,

$C_{(i,j)}$: Cost of j_{th} component of i_{th} assembly

$M_{(i,j)}$: Binary Variable indicating Maintenance Decision

$M_{(i,j)}$ = 0, if component is not replaced in this maintenance activity; and 1 if the component is replaced in this maintenance activity

R_{Tank}: Mission Reliability of the tank predicted using Eq. 23

R_{Des} : Desired Mission Reliability of the tank (higher threshold)

T_m : Total maintenance time required

T_{av} : Total maintenance time available

$R_{(i,j)}$: Conditional reliability of of j_{th} component of i_{th} assembly

M_d : Effective mission duration

$Age_.$: Effective age of component

η & β : Weibull distribution parameters

Given that the mission reliability based SM approach operates based on the mission reliability estimated using previously discussed approaches, which are tailored to integrate all essential military-specific factors, the outcomes of the SMP are comprehensively informed by these factors. In addition to the previously considered four military specific factors in mission reliability prediction (refer section 3.1), one more factor is considered in this SMP. In the case of maintenance of an MBT, more than one maintenance person/crew works simultaneously. Hence, the total time to perform all the maintenance activities (T_m) is estimated, assuming three crews working simultaneously on different maintenance activities of one MBT.

4.2.3 Parallel Genetic Algorithm for optimization

To solve the formulated SMP, GA is used, as it is largely acknowledged in the literature on SM. For demonstrating the developed approach on a single MBT, this developed GA is used. However, the expansion of the solution space with an increase in the number of components, along with the provision of using multiple type of spares, make the chromosomes complex, posing challenges, as GA tends to require significantly more time. This poses difficulties for conducting numerical investigations across multiple scenarios. Consequently, in this study a Parallel Genetic Algorithm (PGA) is developed and used to optimize the SMP efficiently.

A PGA works by harnessing the power of parallel computing to expedite the process of optimization. It operates based on the principles of GAs, which mimic natural selection and evolution to iteratively improve solutions to complex problems. In a PGA, the population of potential solutions is divided into subpopulations that can be processed concurrently on multiple processors or cores. This parallel processing enables simultaneous execution of genetic operations such as selection, crossover, and mutation on different parts of the population. The key steps in a PGA include initializing a population of candidate solutions, evaluating their fitness using a predefined objective function, selecting individuals for reproduction based on fitness, applying genetic operators to generate new solutions, and iterating these steps until a satisfactory solution is found or a convergence criterion is met. All these algorithms try to solve the same task and after they've completed their job, the best individual of every algorithm is selected, then the best of them is selected, and this is the solution to a problem. This approach is often called 'island model' because populations are isolated from each other, like real-life creature populations may be isolated living on different islands. This is one of the most popular approaches to parallel genetic algorithms, even though there are others. Figure 4.5 depicts the overall working of PGA in multiple islands.

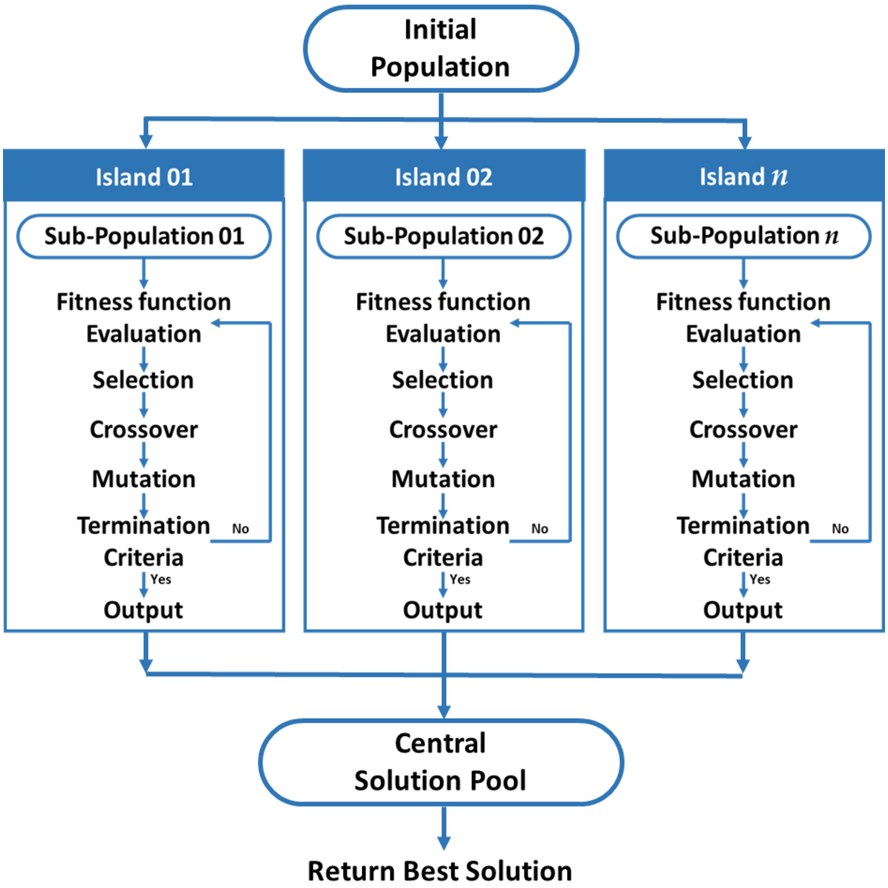

Figure 4.5 Working of Parallel Genetic Algorithm

By leveraging parallelism, PGA can achieve significant speedup and scalability, making it well-suited for tackling large-scale optimization problems across various domains. It offers a potent approach to tackle computationally intensive optimization problems by harnessing parallel computing capabilities.

In the scope of this thesis, a python library for PGAs – PGAPy 2.4 is utilized on an Intel I5 processors with four cores, where four islands are created.

4.3 Demonstration of the proposed approach

This section aims to demonstrate the effectiveness of the proposed approach in managing the readiness of an MBT during routine peacetime usage while maintaining its desired readiness level for some predefined missions. Initially, all necessary information for mission reliability prediction and SM optimization is collected, including parameters of 2-P Weibull distribution, maintenance duration, costs associated with different maintenance actions, and various adjustment factors for operational phases, distinct spares, and human error in maintenance. The complete dataset for the MBT is provided in Annexure A2. Utilizing this dataset, the MBT's utilization and required maintenance until its first scheduled overhaul are analyzed using the present approach. As detailed in section 4.1, continuous monitoring of the MBT's mission reliability for a predefined mission is conducted. Whenever the mission reliability falls below the lower threshold, a maintenance event is triggered. Employing PGA, SM optimization is carried out to determine the cost-optimal subset of maintenance activities required to achieve the higher mission reliability threshold. Upon completion of these maintenance activities, the MBT is once again available for utilization with its mission reliability exceeding the higher threshold for the specified mission.

In demonstration case I, the MBT is required to be ready for the following mission profile.

> *Case I: An MBT has to be ready with the mission reliability of* ***0.8*** *for a mission of* ***deep penetration*** *in* ***attack role*** *in the* ***plain region*** *and* ***normal season****, for continuous operation of* ***36 hours****, with the allowable deployment window of* ***04 hours*** *for necessary maintenance.*

This mission profile definition provides several important variables in the proposed formulation. The considered MBT is presently working in peacetime and performing its routine running of 20 mins every day. However, the user's mandate is to maintain the tank in a state of readiness for the defined mission profile. Specifically, if this MBT is instructed for deployment on the specified mission, it should have a minimum mission reliability of 0.8. In case it falls short, there is an allowable maintenance window of 4 hours for necessary maintenance to achieve readiness. Despite the required mission reliability being 0.8, routine running causes a decline in mission reliability. Following the proposed approach, maintenance is performed whenever mission reliability reaches 0.8, enhancing it to a higher threshold. For this demonstration case, the higher mission reliability threshold is assumed to be 0.9, with the lower threshold at 0.8 as per user specifications.

Upon implementing the proposed mission reliability based SM approach for the specified duration of the MBT during routine peacetime, it was noted that a total of 12 maintenance events were triggered. The specific details regarding these maintenance events can be found in Table 4.1.

Table 4.1 Details of Maintenance actions in Demonstration Case I

Maintenance Event	**Maintenance Action**
1	L3 (R) | L4 (R) | N3 (G)
2	A10 (G) | D2 (NO) | D3 (G) | L1 (G) | L5 (G) | N3 (G)
3	A6 (G) | D4 (G) | D5 (G) | D7 (G) | L2 (NO) | N2 (G) | N3 (G)
4	A2 (G) | A3 (G) | A5 (G) | F5 (G) | L3 (G) | N3 (G)
5	A4 (R) | A8 (R) | L4 (NO) | N3 (G)
6	A10 (R) | D2 (R) | D3 (R) | L1 (G) | L5 (G)
7	A7 (NO) | D4 (R) | D5 (G) | L3 (R) | L4 (R)
8	D7 (G) | L2 (R) | N2 (G) | N3 (G)
9	A2 (R) | A3 (NO) | A6 (R) | D3 (R) | L5 (G) | N3 (G)
10	A5 (G) | A10 (G) | D2 (NO) | L1 (G) | L3 (G) | L4 (G) | N3 (G)
11	A4 (NO) | A8 (NO) | D4 (NO) | D5 (NO) | F5 (NO) | N3 (R)
12	A7 (R) | D3 (R) | D7 (R) | L2 (NO) | L3 (R) | L4 (G) | L5 (G)

In summary, when the mission reliability of the MBT initially dropped to 0.8, the first maintenance event was triggered. Through SM optimization, it was determined that replacing components L3, L4, and N3 would result in achieving a mission reliability of 0.9, meeting the higher mission reliability threshold. Furthermore, the approach proposed that in the absence of new genuine spares, which alternative spare types would also achieve the desired higher mission reliability threshold. The letters denoted in brackets alongside the component IDs indicate the type of spare that can be utilized in such circumstances. For instance, the maintenance action of L3(R) in the first maintenance event suggests that installing a refurbished spare for L3 would suffice if a new genuine spare is unavailable. However, it is always recommended to use new genuine spares as they lead to a higher reliability enhancement, thereby delaying the triggering of the next maintenance event.

Considering the requirement based on user defined mission profile, 04 hours of deployment window for maintenance is allowed. Consequently, measures are taken to ensure that each maintenance event is completed within or below this 4-hour timeframe. The maintenance events which resulted in achieving the higher mission reliability threshold within the allowable deployment window for maintenance are termed here as successful events. However, certain components within the system have a TTR exceeding this allowable maintenance window. As a result, it is expected that some maintenance events will exceed the 4-hour window. Nevertheless, through SMP optimization, efforts are directed towards assessing the feasibility of keeping the maintenance duration within the designated deployment window. In the present demonstration case I, out of twelve maintenance events, only four events resulted in maintenance duration of more than 4 hours, resulting in ~67% maintenance events as successful events. Further details regarding the maintenance cost and maintenance duration implications of executing these maintenance plans at each trigger are illustrated in Figure 4.6.

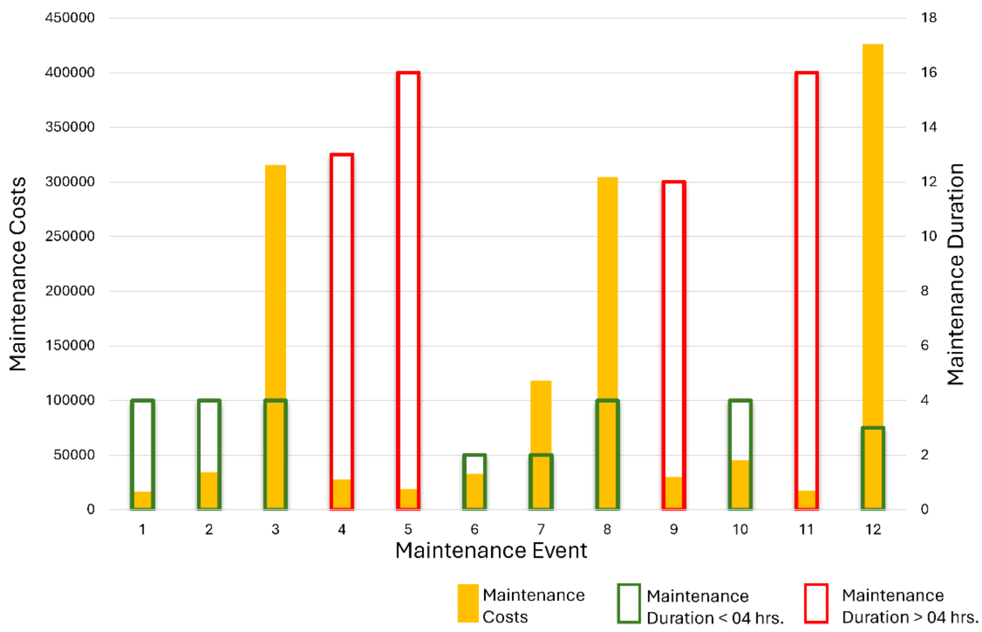

Figure 4.6 Details of Maintenance events in Demonstration Case I

As discussed, an MBT has to undergo multiple deployment roles in distinct terrains characterized by extreme environmental conditions. In order to demonstrate the application of the proposed approach for deployment roles in different terrains, the approach is applied to the same MBT but for deployment roles in different terrains.

In demonstration case II, the MBT is required to be ready for the following mission profile.

> *Case II: An MBT has to be ready with the mission reliability of* ***0.8*** *for a mission of* ***deep penetration*** *in* ***attack role*** *in the* ***dessert region*** *and* ***summer season****, for continuous operation of* ***36 hours****, with the allowable deployment window of* ***04 hours*** *for necessary maintenance.*

On performing the same analysis for the same duration till first designated overhaul, a significant change is observed in the maintenance events. Figure 4.7 depicts the details of every maintenance event like maintenance cost and duration in this analysis.

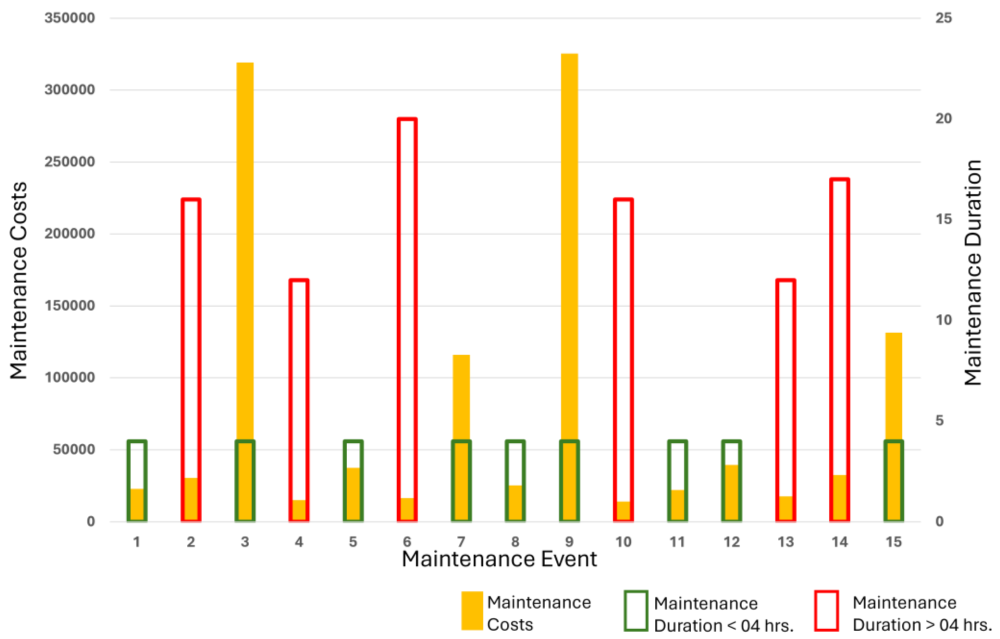

Figure 4.7 Details of Maintenance events in Demonstration Case II

In this scenario, where the terrain changes to desert and the season shifts to summer as illustrated in Figure 4.7, out of fifteen maintenance events, six events could not achieve the required level of mission reliability within the 4-hour window.

Upon comparing the outcomes of analyses in both of the demonstration cases, a significant difference in key metrics is observed despite achieving readiness. With the transition from plains to desert terrain and normal to summer season, metrics such as the maintenance frequency increased by ~25%. Consequently, planned downtime also rose by ~53%. Furthermore, the total cost incurred in all maintenance events increased by ~21%. These variations underscore the importance of considering terrain and seasonal changes in MBT utilization during maintenance planning and management.

Upon analyzing the approach for the same deployment role but in different terrains, a significant change in key metrics was observed. Figure 4.8 illustrates the changes in four key metrics for three different terrains with respect to the plain terrain: maintenance frequency, the percentage of events where the readiness level cannot be achieved within the allowable deployment delay for maintenance, the total maintenance cost incurred in all maintenance events, and the total planned downtime across the considered time horizon. In

Figure 4.8, it is evident that all four key metrics vary remarkably with the change in terrain, with all metrics skewed towards the scenario with desert terrain characterized by the most extreme environmental conditions. This observation highlights the need for systematic independent analysis of the approach for cases where multiple or different terrains are involved. The notion of a ‘one-size-fits-all’ approach proves inadequate in the context of military maintenance management, as notable disparities are found in key metrics such as maintenance cost, planned downtime, and maintenance frequency when planning maintenance for the same equipment deployed across different terrains.

The analyses conducted offer insights into the management of MBTs from a spares management perspective as well. While it is generally advisable to utilize genuine spares for maintenance activities, traditional practices like refurbishment and cannibalization, as well as the use of Non-OEM spares, may be necessitated by specific circumstances. In such cases, the insights derived from the analyses can aid decision-making processes. For critical equipment that frequently changes operations across multiple terrains, refurbishment or cannibalization may not be viable solutions. However, in situations where refurbishment is necessary, these spares may be suitable for equipment operating in less critical roles. For example, there are some equipment like infantry combat vehicle, which slightly shares the design and a few important spares with the MBTs, but some of them are classified to operate in a lesser critical operations. In compelling situations, decision makers may opt to allocate the genuine spares to the mission critical MBTs while providing refurbished spares to the less critical infantry combat vehicles, where it is known that the terrain of operation is not going to be changed frequently. Contrarily, for the MBTs for which the change in terrain and seasons is frequently expected, replacements with the genuine spares should be considered a priority choice.

Figure 4.8 Operating terrain wise comparison

As previously discussed, an MBT has to undergo multiple deployment roles in distinct terrains. The different deployment role necessitates different set of functionalities in order to accomplish the deployment role. In order to demonstrate the application of the proposed approach for different deployment roles, the approach is applied to the same MBT but for a deployment role.

In demonstration case III, the MBT is required to be ready for the following mission profile.

> *Case III: An MBT has to be ready with the mission reliability of **0.8** for a mission of **reconnaissance** in **defence role** in the **plain region** and **normal season**, for continuous operation of **36 hours**, with the allowable deployment window of **04 hours** for necessary maintenance.*

On performing the same analysis for the same time horizon, a significant change is observed in the maintenance events. In this case, for the same time horizon, only eleven maintenance events are triggered; out of which, for eight events, the maintenance could be completed within the allowable deployment delay for maintenance, and the required reliability was achieved. Figure 4.9 highlights all the other relevant details in this case of demonstration.

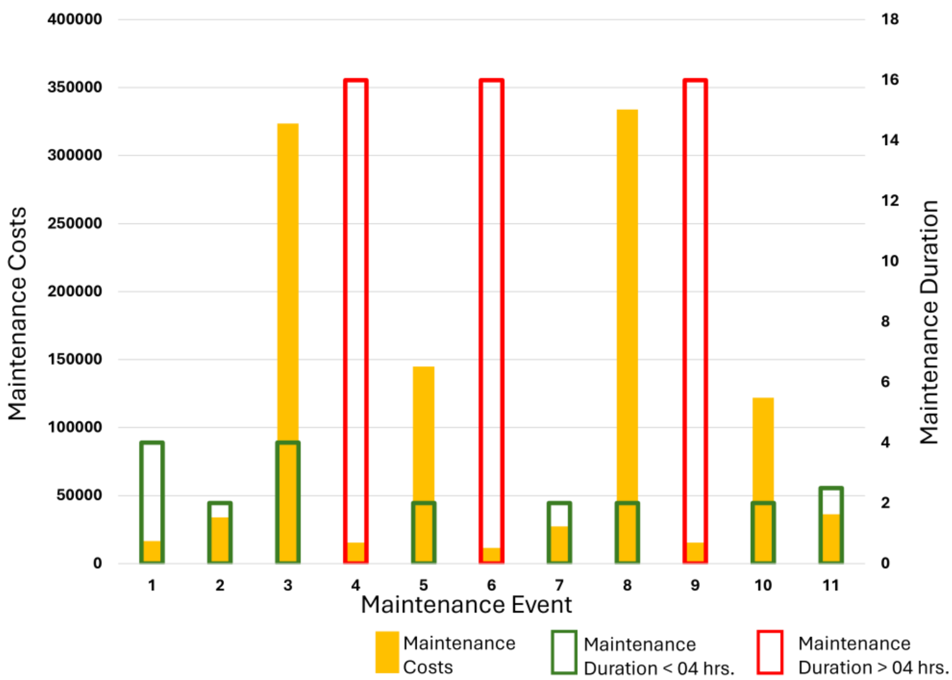

Figure 4.9 Details of Maintenance events in Demonstration Case III

With the outcomes of all the three demonstration cases, it is evident that the desired level of readiness for a given time horizon can be achieved for the critical military equipment by employing the proposed mission reliability based SM approach.

4.3.1 Optimization of mission reliability thresholds

The mission reliability threshold is a crucial parameter in the proposed approach, with both lower and higher thresholds playing a pivotal role in its effective execution. Systematically setting these thresholds involves considering their tradeoff with key metrics like maintenance frequency, cost, and planned downtime. While the lower threshold is dictated by fleet-level mission requirements, the user plays a role in optimizing the higher threshold. The manner in which a mission for an MBT is stated has been discussed previously. However, when it comes to the actual scenarios, where the missions are handled at the fleet level by higher commands, mission definitions encompass broader fleet-level considerations, as exemplified below:

> *The* ***squadron*** *needs to carry out an* ***attack role*** *of* ***deep penetration*** *mission of* ***36 hrs****. of continuous operation, in the* ***High-Altitude*** *region. Where the squadron will be covering a distance of* ***50 kms****. In order to successfully accomplish the mission,* ***at least 11 MBTs*** *should be working with full functionalities at the end of the mission with confidence more than 80%. Allowable deployment delay for maintenance is 04 hours.*

Similar to the previously discussed mission for an MBT, this mission profile commanded to the fleet of MBTs provides all the variables required to the proposed mission reliability based SM approach. It provides additional important information regarding the requirement of total number MBTs for accomplishing the mission. This information facilitates estimating the lower threshold of mission reliability which is to be maintained across the time horizon under consideration. The information provided can be translated into the classical form of *k out of n* configuration. In the above discussed example of fleet level mission profile, there are fourteen MBTs in a squadron and one MBT for replacement from HQ, out of these fifteen MBTs, at least eleven MBTs are expected not to encounter any of the failures, with the confidence of 80%. This makes the case of 11 out of 15 tanks with confidence of more than 80%. This configuration can be estimated using Binomial distribution, and for the present example, the expectation comes out to maintain all the MBTs in the squadron with the mission reliability of more than 80%. Therefore, the lower threshold of mission reliability is set to be 0.8. So that while implementing the proposed approach on the considered squadron, the mission reliability of all the MBTs should not fall below 0.8.

The user is required to systematically establish the higher threshold for mission reliability. While aiming for the highest possible threshold of mission reliability may seem intuitive, its implications on the other key metrics need to be critically evaluated. To conduct this evaluation, the developed PGA-based optimization approach is applied to a squadron of MBTs. Initially, the approach is employed across all squadron MBTs at three different higher mission reliability thresholds - 0.85, 0.9, and 0.95, while maintaining a constant lower threshold at 0.8, as per the user-defined mission profile. To encompass a diverse set of MBTs based on age, reflecting varied initial mission reliability levels, the squadron's MBTs are considered with varying ages. Table 4.2 illustrates the calculated data for a specific case (Lower threshold = 0.8, and higher threshold = 0.9) as an example of this analysis.

Table 4.2 Fleet level data for optimizing higher threshold of mission reliability (Case I)

Higher mission reliability threshold = 0.90					
MBT ID	**Initial Rel.**	**M. Events**	**Success Ev**	**Cost**	**Downtime (Hrs)**
1	0.995057	13	8	941010	91.6
2	0.990075	13	8	906290	88.6
3	0.995057	13	8	892600	85.6
4	0.981903	13	8	933750	91.6
5	0.991836	13	8	902400	91.6
6	0.993498	13	8	896280	86.6
7	0.988821	13	8	914340	91.2
8	0.974287	14	8	994750	87.6
9	0.984134	13	8	1040350	95.6
10	0.986232	13	8	903000	93.6
11	0.979527	13	8	965600	95.6
12	0.976994	13	8	972600	95.6
13	0.995057	13	8	912300	94
14	0.971393	14	9	1004900	91.6

Upon conducting an analysis of the approach's execution on the same squadron with varied higher thresholds of 0.85 and 0.95, corresponding data sets were gathered. The collected data from all three scenarios underwent a thorough evaluation concerning four crucial metrics: average total maintenance events (maintenance frequency), the percentage of events successfully completed within the allowable deployment delay, average maintenance cost, and average planned downtime. The graphical representation of this analysis is depicted in Figure 4.10. Notably, it is evident that the 0.85 option is suboptimal when considering maintenance frequency, successful event percentages, and average downtime. Comparatively, between the 0.9 and 0.95 options, there is no significant deviation in maintenance frequency and successful event percentages. However, upon assessing the tradeoff between average maintenance cost and average downtime, the 0.9 threshold emerges as the most optimal choice among these three levels.

Figure 4.10 Comparison between three options for higher threshold (0.85 | 0.9 | 0.95)

Following the determination of 0.9 as the optimal higher threshold for mission reliability, a more precise estimation was sought through a similar analysis. This analysis was conducted using closely related thresholds of 0.89, 0.9, and 0.91 to determine the optimal higher threshold of mission reliability. The graphical representation of this analysis is depicted in Figure 4.11. Reducing the choice of criteria, the metrics – maintenance frequency and % successful events suggest no change in all the three cases. The two metrics – average maintenance cost and average downtime, curtail the option of 0.91 being optimal among the three. Looking at the slight tradeoff between average maintenance cost and average downtime, 0.9 emerges as the optimal choice for higher threshold of mission reliability.

Figure 4.11 Comparison between three options for higher threshold (0.89 | 0.9 | 0.91)

4.3.2 Optimization of allowable deployment delay for maintenance

Efforts in war readiness management are primarily geared towards achieving cold start war readiness, although this may not be applicable to all critical equipment. For certain critical equipment, militaries allow a small duration before deployment. This situation could arise due to the fleet formation, where deployment occurs after front-runner fleets are deployed, or it might be linked to specific events that offer some preparation time. Hence, in many scenarios, equipment fleets are granted a brief period before actual deployment, during which maintenance activities can be carried out to ensure readiness. This concept introduces the notion of allowable deployment delay for maintenance. In the previous analysis, this duration was assumed to be 4 hours, a value derived from extensive discussions with domain experts. However, this duration of allowable deployment delay for maintenance plays instrumental role in overall maintenance management of critical military equipment. Therefore, it is imperative to systematically study the effect of varying this duration, and accordingly optimize it for executing the proposed approach effectively.

The concept of allowable deployment delay for maintenance is a significant aspect in war readiness management, complementing the importance of cold start readiness. It introduces two sub-concepts: theoretical readiness and practical readiness, which are closely interdependent and aid doctrine makers in assessing the overall state of readiness. Theoretical readiness represents the equipment population ready for deployment with the desired mission reliability at the present time (t=0). In contrast, practical readiness represents the equipment population that can be made ready for deployment at a specified time in the very near future (t>0). For instance, if a mission is scheduled to start in the next four hours, theoretical readiness would include equipment currently meeting the desired mission reliability. On the other hand, practical readiness would also include equipment that can achieve the desired mission reliability within the next four hours through maintenance activities. For example, in a squadron, if there are 10 MBTs whose mission reliability is higher than 0.8, the theoretical readiness is estimated to be 10/14 = 71.42%. However, there are two MBTs with mission reliability of 0.78 and 0.76, which require 02 hours and 03 hours respectively for maintenance in order to achieve the mission reliability of 0.8 or higher, the practical readiness will count these MBTs as ready considering the fact that these MBTs will require maintenance duration lesser than the mission start duration, and all the required maintenance resources are available. Hence, the practical readiness will be estimated to be 12/14 = 85.71%. It is very important to understand that, although these metrics do not directly affect the reality, they provide valuable insights to military strategists for informed decision-making in doctrine development.

The selection of allowable deployment delay for maintenance within readiness definitions significantly impacts practical readiness levels at the fleet level. While opting for higher values may obviously appear to elevate practical readiness levels, considering its delusional effect on overall war readiness, it is important to assess the tradeoff it has with the other important metrics. Therefore, firstly the effect of varying this allowable deployment delay for maintenance on average practical readiness is assessed in multiple scenarios featured with changing deployment roles. Additionally, the lower peaks of practical readiness are also critically studied, as it is not desirable to experience a dip in that. Figure 4.12 presents the comparison of scenarios where initially, the allowable deployment delay for maintenance is varied from 04 hours to 06 hours and 08 hours, for deployment role of tank-to-tank battle; later it was varied in the same levels but for a deployment role of reconnaissance.

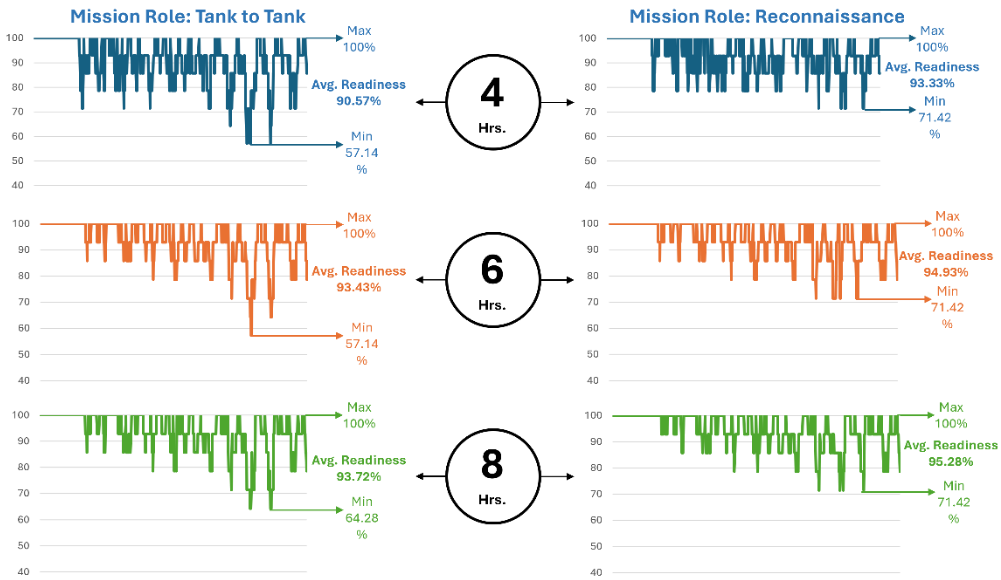

Figure 4.12 Change in average practical readiness with change in allowable deployment delay for maintenance

In Figure 4.12, it is evident that increasing the allowable deployment delay for maintenance leads to a slight rise in the average practical readiness of the fleet. However, there is a minimal change observed in the dip of the practical readiness due to the relatively stable minimum levels. This indicates that the increase in allowable deployment delays for maintenance has an insignificant impact on the fleet's average practical readiness levels. While extending the duration of allowable deployment delay could notably enhance average practical readiness levels, it is crucial to recognize that such an increase may create a misleading impression of readiness. Although practical readiness levels may appear to be inflated on paper, this could lead to challenges during actual deployment, requiring more time and potentially resulting in undesirable outcomes.

While the obvious inclination to extend the allowable deployment delay for maintenance in readiness definition may be strong, it is crucial to avoid excessive increases beyond a certain threshold, which inherently remains in a minimal bound. Optimization of this duration is essential, taking into account the specific context of the situation. To determine the optimal value among 4, 6, and 8 hours in the present context of managing the readiness of the MBTs, numerical investigations have been conducted.

After conducting an analysis of the approach's execution on the same squadron with varied allowable deployment delays for maintenance of 4, 6, and 8 hours, while keeping the lower and higher mission reliability thresholds constant at 0.8 and 0.9 respectively, corresponding datasets were collected. These datasets underwent thorough evaluation regarding four crucial metrics: average total maintenance events (maintenance frequency), the percentage of events successfully completed within the allowable deployment delay, average maintenance cost, and average planned downtime. The graphical representation of this analysis is depicted in Figure 4.13.

Figure 4.13 Comparison between three options for allowable deployment delay for maintenance

Notably, it is evident that the maintenance frequency metric showed no change in all three cases. However, considering the tradeoff between the remaining three metrics, a duration of 4 hours for the allowable deployment delay for maintenance was found to be optimal. While the average maintenance cost metric suggests that 8 hours is a good choice, the resulting average downtime is not desirable. Therefore, based on this analysis, a duration of 4 hours for the allowable deployment delay for maintenance is considered optimal.

4.4 Fleet level readiness at a glance

The preceding sections have demonstrated the efficacy of the current approach in managing the readiness of critical military equipment fleets, such as MBTs, by ensuring their mission reliability. For decision-makers and policymakers within defense forces, maintaining fleet readiness and having real-time insight into future readiness levels are equally critical. The proposed approach not only ensures fleet readiness for critical military equipment but also offers a systematic method to evaluate fleet-level readiness across diverse scenarios, encompassing various deployment roles and equipment fleets. This section further explores how the current approach can be leveraged to provide a comprehensive snapshot of fleet-level readiness to higher authorities involved in decision-making processes.

The mission reliability based SM approach outlined in this research facilitates the efficient management of equipment readiness across diverse deployment roles and mission profiles, allowing the specification of one role as the primary deployment role. In this approach, a maintenance event is triggered when the mission reliability for the primary deployment role falls below the lower mission reliability threshold, aiming to restore it to the desired higher threshold. Despite undergoing maintenance, the equipment's mission reliability for alternative deployment roles may still exceed the specified lower threshold. This implies that under exceptional circumstances where maintenance cannot be immediately conducted, the equipment may not be fully ready for its primary deployment role but can maintain readiness for other deployment roles at the desired mission reliability level. For instance, if the mission reliability of an MBT for tank-to-tank battle deployment drops below the lower threshold, its mission reliability for roles such as infantry protection or reconnaissance may still remain above the desired level. Consequently, although the MBT may not meet readiness requirements for its primary attack role, it can still be considered prepared for other roles such as attack or defense formations. Figure 4.14 visually illustrates this scenario for clarity.

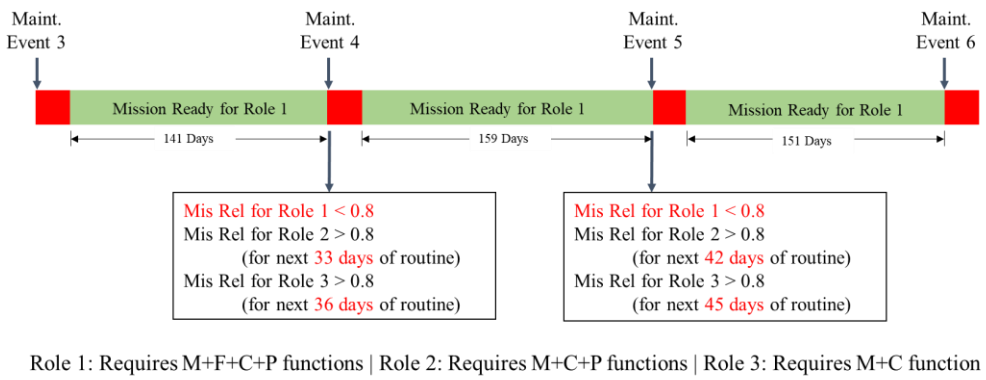

Figure 4.14 Readiness levels for multiple deployment roles

Expanding upon this rationale, the results derived from executing the proposed approach on various fleets of critical military equipment can be consolidated to devise a framework for illustrating fleet-level readiness assessment across multiple deployment roles. This framework would significantly aid high-level decision-makers in formulating doctrines based on the real-time state of readiness for multiple fleets of critical equipment such as MBTs. Figure 4.15 provides a graphical depiction of the mechanism for assessing fleet-level readiness at a glance. This depiction showcases the readiness status of all MBTs within a fleet across three distinct deployment roles. By employing the methodology elucidated in Figure 4.14, this representation gauges the fleet's readiness by assessing the status of each MBT in the fleet at any given moment. In Figure 4.15, initially, all MBTs are shown to be fully ready for the three predefined deployment roles, indicating 100% readiness across all roles. However, in the subsequent scenario, MBT 01 and MBT 02 enter a maintenance phase due to a drop in mission reliability below the lower threshold, resulting in reduced readiness for deployment role 1. Nonetheless, both MBTs retain their desired mission reliability for deployment roles 2 and 3, maintaining 100%

readiness for these roles. Through this framework, decision-makers in defense forces can accurately ascertain the precise state of readiness of their fleet.

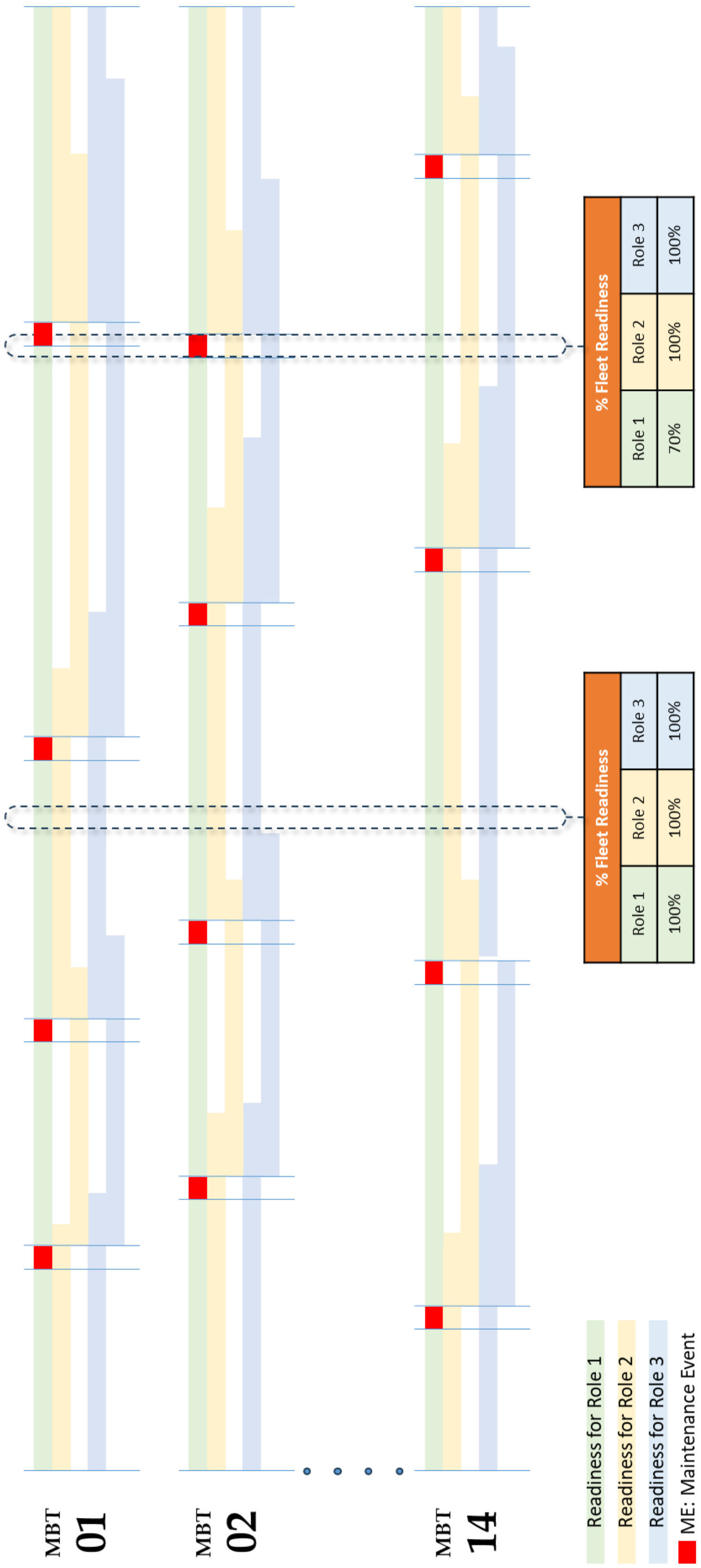

Figure 4.15 Fleet level readiness assessment at a glance

4.5 Comparison with traditional approach

Based on the outcomes observed in the demonstrated cases, it becomes evident that the current approach effectively provides the required assurance regarding the readiness of critical equipment by ensuring the desired level of mission reliability. Nevertheless, to evaluate its practicality for implementation in real-world scenarios, a fundamental question must be addressed: *"Does this approach outperform the conventional one?"* In order to scientifically address this question, this section undertakes a comparative analysis between the proposed approach and a representative conventional maintenance approach.

Given the substantial quantity of equipment and the intricacies involved in overall maintenance management, a prevalent practice in military equipment maintenance is the adoption of a time-based preventive maintenance policy [18], [162]. This policy involves the classification of components into multiple PM groups, each with a distinct maintenance frequency. In the context of the considered representative time-based maintenance policy, PM groups are categorized from 01 to 04, with respective maintenance frequencies of 2, 3, 4, and 5 years. When an MBT undergoes maintenance according to this policy, all components within the designated PM group are simultaneously replaced. Table 4.3 delineates the maintenance groups in accordance with this representative time-based maintenance policy. Additionally, there exist some more PM groups with maintenance intervals surpassing the time horizon considered in the current demonstration cases; hence, these groups are not enumerated here.

Table 4.3 Representative conventional time based preventive maintenance policy

PM Group 1			
Sr. No.	**Comp ID**	**Cost**	**TTR (hrs)**
1	D3	9000	01
2	L4	9000	01
PM Group 2			
Sr. No.	**Comp ID**	**Cost**	**TTR (hrs)**
1	A3	8000	12
2	D2	14000	01
3	D4	2300	01

4	L3	6000	01
5	N2	1900	0.25
6	N3	1500	04
PM Group 3			
Sr. No.	**Comp ID**	**Cost**	**TTR (hrs)**
1	A2	2500	12
2	A4	3500	16
3	A5	6000	0.5
4	A6	8000	01
5	A7	100000	01
6	D5	1000	01
7	D7	1000	01
8	F5	4000	7.6
9	L1	3500	01
10	L2	300000	02
PM Group 4			
Sr. No.	**Comp ID**	**Cost**	**TTR (hrs)**
1	A8	5000	16
2	A10	5500	01
3	L5	900	0.5

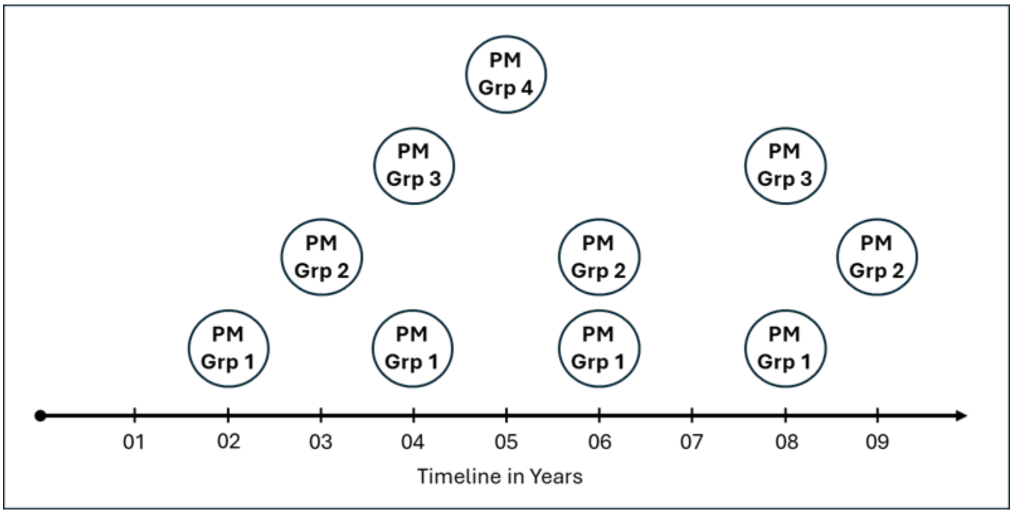

Figure 4.16 Timeline of PM Group triggers

Upon analyzing the same MBT to adhere to this representative time-based maintenance policy, various key metrics were assessed. In order to strictly follow this time-based maintenance policy for an MBT within a time horizon similar to the demonstration cases, a total planned (fixed) maintenance cost of 1009800 is required. The planned (fixed) downtime required to follow this policy is 82 hours. However, even with strict adherence to the time-based maintenance policy, the mission reliability of the MBT is found to be dropped significantly, as this policy primarily emphasizes operational availability rather than mission reliability. Specifically, the mission reliability of the MBT for a mission duration of 36 hours of continuous operation (identical to demonstration case I) just before the initial PM event drops to 0.451. Subsequently, to achieve the desired mission reliability of 0.9, a maintenance duration of at least 18 hours would be required. Following the first maintenance event as per the PM policy, the mission reliability of the MBT for the attack role would improve to 0.7. From this juncture, an additional 12 hours of maintenance break is necessary to attain the desired mission reliability of 0.9. Moreover, the mission reliability of the MBT just before the second PM event (at the conclusion of the third year of usage) declines to 0.3. Post the second PM break, the mission reliability would increase to 0.39. However, achieving the higher mission reliability threshold from this point onwards becomes exceedingly challenging, hindering the prompt deployment of the fleet of MBTs on missions without encountering unacceptable delays. These circumstances leads to the previously mentioned undesirable situation where the MBT cannot be deployed for its intended wartime mission.

On the contrary, with the developed approach, for ~ 90% of the time horizon, the mission reliability of the MBT is higher than 0.8, from where the desired mission reliability can be achieved within 4 hours. (for 67% of maintenance triggers); and the MBT can be called mission ready as per the readiness definition. With this approach, ~ 09% of the time horizon, the mission reliability of the MBT is lesser than 0.8, whereas, with the representative conventional PM policy, ~ 83% of the time horizon, the mission reliability of the MBT is lesser than 0.8 (Figure 4.17). It is apparent that the existing approach results in excellent readiness management of the MBT, while outperforming the conventional time based PM policy in terms of achieving mission reliability and ultimately readiness. Looking at the economic aspect of the approaches, the proposed approach guaranteed delivers this readiness level with almost the same costs when compared to representative conventional PM policy.

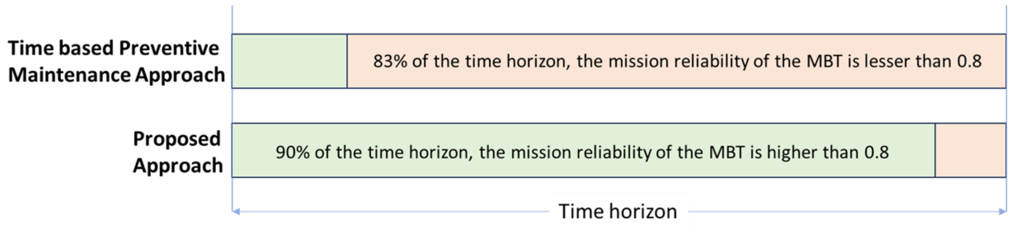

Figure 4.17 Mission reliability wise comparison with the time-based PM approach

4.6 Summary

Acknowledging the fact that the way to attaining and ensuring the desired mission reliability has an intricate relationship with the opted maintenance strategy, this chapter introduces a maintenance approach that addresses the imperative of war readiness in tandem with mission reliability. This mission reliability based SM approach works with the principle that the exploitation, as well as maintenance of mission-critical equipment, should be balanced in such a way that if, at any point in time, the equipment is ordered to be deployed on a certain specific mission, it should be ready, otherwise, it should be able to be ready in a specified allowable deployment delay for maintenance as per readiness expectation. Whenever the mission reliability of any equipment in the fleet touches down the predefined lower threshold of mission reliability due to its usage, the developed algorithm triggers a maintenance event, where a SMP is optimized using PGA to find a cost optimal set of maintenance activities to perform on MBT to uplift its mission reliability to the higher threshold for a predefined mission profile.

On analyzing the proposed approach where the readiness expectation is set for a particular deployment role, and the terrain is kept varying, significant changes in the key metrics were observed. Similarly, significant changes in the same key metrics were observed on varying the deployment role. This validated the consideration of military-specific factors and concluded that the notion of a one-size-fits-all approach proves inadequate in the context of military maintenance management. Notable disparities are found in key metrics such as maintenance cost, planned downtime, and maintenance frequency when planning maintenance for the same equipment deployed across different terrains.

The mission reliability threshold stands as a critical parameter within the proposed approach, where the lower and higher thresholds hold significant importance for its optimal execution. Establishing these thresholds systematically entails evaluating their trade-offs with essential metrics such as maintenance frequency, cost, and planned downtime. The lower threshold is primarily determined by fleet-level mission specifications, while optimizing the higher threshold involves the user's active role. While aiming for the highest possible threshold of mission reliability may seem intuitive, the results of numerical experimentation shed light on the adverse implications of excessively high thresholds on average maintenance costs and planned downtime. Although such thresholds may decrease the total number of maintenance events over a given time horizon, it is imperative to recognize the trade-offs involved and optimize them for each specific scenario. To optimize the higher mission reliability threshold, the proposed approach is analyzed on all the MBTs in a squadron on three different levels of higher mission reliability threshold (0.85, 0.90, and 0.95). Finally, an optimum level of a higher threshold is derived by critically examining all the aforementioned four important metrics.

Additionally, the allowable deployment delay for maintenance that suits the readiness expectation is also optimized. Studying the suggestions from the literature regarding the war readiness definition, the approach is developed to present the readiness level of the fleet in categorization as theoretical readiness and practical readiness. The effect of varying the maintenance duration on this categorization is explicitly studied and the outcomes are presented in this chapter. The selection of allowable deployment delay for maintenance within readiness definitions significantly impacts practical readiness levels at the fleet level. While opting for higher values may obviously appear to elevate practical readiness levels, it is essential to acknowledge the potentially misleading nature of this parameter. Leveraging the developed approach and outcomes of the numerical investigations, mechanisms are developed to provide war readiness at a glance to the high authority decision-makers involved in development of doctrines.

Through comprehensive evaluation, the superiority of the present approach over the conventional time-based preventive maintenance policy is further established. By incurring ~6% lesser cost, the present approach resulted in maintaining the mission reliability of the MBT higher than the predefined threshold, for more than 90% of the overall lifecycle in the considered time horizon. The present approach provides the strategic decision-makers with the insight necessary to be war ready with the desired mission reliability and provides a superior and effective maintenance strategy as compared to conventional time-based maintenance.

Chapter 5

Blockchain Enabled Maintenance Data Management Framework

This chapter presents a novel framework that leverages blockchain technology to revolutionize maintenance data management within military organizations. The chapter commences by analyzing the specific challenges that hinder traditional military maintenance data management practices. Subsequently, the technological choices made to design the proposed blockchain architecture are meticulously detailed. Following this, a comprehensive overview of user interactions with the framework is presented. Finally, the chapter culminates by highlighting the significant benefits this framework offers for military maintenance data management. In particular, the chapter emphasizes how this framework enhances the applicability and effectiveness of the various methodologies developed throughout this thesis.

The work presented in this chapter is published in two parts. Firstly, under the title "*Fleet Maintenance Data Management Framework: A Novel Approach*" in "Proceedings of International Conference on Precision, Meso, Micro and Nano Engineering -COPEN 2019", IIT Indore, 2019. Secondly, under the title "*Blockchain Enabled Maintenance Management Framework for Military Equipment*" in "IEEE Transactions on Engineering Management" vol. 69, no. 6, pp. 3938-3951. doi: 10.1109/TEM.2021.3099437.

All of the approaches proposed in the previous sections of this thesis deal with the domain of mission reliability and maintenance modeling, which are predominantly data-driven. The efficacy of the developed data-driven approaches is intricately linked to the quality and quantity of the underlying operations and maintenance data. This holds especially true in the overall domain of RAMS management, where analytics plays a crucial role. The attainment of effective war readiness is contingent upon proficient RAMS management. Nonetheless, this study consistently encountered a dearth of requisite data, both in terms of quality and quantity. It has been found that a lack of data poses substantial obstacles to defense forces, reducing their ability to make analytical decisions based on existing data. Recent trends like industry 4.0 are claiming the possibility to transform the current military capabilities [28]. However, these strategies expect preparedness of military workshops for the modern technological tools like data analytics using Artificial Intelligence and Machine Learning. In order to accommodate these prospective changes, data centric decisions will need the data from current maintenance scenarios. Furthermore, the unavailability of adequate data severely limits the practical application of the comprehensive approaches developed and proposed in the scope of this thesis. The absence of a mechanism for the systematic management of operations and maintenance data in defence organizations could be the prime reason for the data unavailability, and it poses a formidable obstacle in the pursuit of comprehensive war readiness assessment and management in the age of analytics. The essence lies in recognizing that without a reliable source of ample and quality data, the envisioning and execution of scientific approaches for war readiness management remain an impregnable challenge. Acknowledging data scarcity as a pivotal concern, this thesis takes a proactive stance by addressing this issue by presenting a research backed modern solution which not only increase the applicability of the developed approaches but also makes the military maintenance management future ready in the era of analytics.

5.1 Challenges in Data Management

With the rising cognizance and prospects of data-driven decision-making, the importance and awareness about data management is growing.

With the upsurging generation of big data and the rising concern over its security, the challenges in data management are increasingly pressing across all the sectors. One of the sectors which has a potential of transforming itself through increasing use of data-driven techniques in crucial decision-making, is the defense sector. Therefore, like all the other industrial domains, the defense sector needs to effectively manage the security critical data. However, in view of the gravity of the data generated by military organizations, the challenges in data management, especially with data registry and further data security, are multifold when compared to other industrial domains [163]. The challenges further increase due to the involvement of large in-house hierarchy, the involvement of multiple value chain partners, multi-echelon operations, etc. With the emergence of the GOCO model in defence maintenance [164], the issue of data scarcity will be compounded by issues like data sharing, data integrity, transparency in management, an increase in bureaucratic authentications, etc.

The persistent upgradation of militaries results into higher number of equipment; which makes the maintenance of these equipment a challenging task. Moreover, the strategic deployment of these equipment at distinct and extreme locations across the country makes maintenance scenarios more challenging. Managing maintenance data for such huge challenging scenario that too with expected granularity is cumbersome. Since militaries work in multiple hierarchical authority levels, monitoring and validating every maintenance activity by higher authority is arduous. However, this monitoring and validation is needed to run the maintenance program with the desired punctuality. In order to maintain this punctuality, a mechanism is required which can validate and record the maintenance activities with minimized human intervention and still has the check from higher authorities.

Above all, in the era of data science, just having the data is not adequate. It is also important to have it in appropriate formats. Still, the use of hand-written maintenance logs is not very uncommon. To make it usable for analytics based on contemporary techniques, this maintenance data needs to be electronically recorded in a proper format with accuracy and details. If by any traditional maintenance management mechanism the required data is maintained with desired accuracy and granularity, this data being crucial military data, it has to be stored in utmost secured environment [165]. This becomes further essential in current situations with the emergence of GOCO model where involvement of third party vendors and service providers is increasing in military maintenance. The third-party service providers who deal with the maintenance or inventory of the military equipment need access to equipment usage data. This requires a controlled, monitored, and authenticated channel for the involvement of external agencies where only limited access is granted to them.

Considering the aforementioned scenario of maintenance function in military organizations and the associated challenges, there is a profound need for a tailor-made comprehensive maintenance management framework, which indeed suffices the need for inputs to advanced contemporary techniques while unraveling the aforementioned issues. The framework is essentially required to unravel the issues like scarcity of the maintenance data, traceability of the military equipment/components, difficulty in monitoring and validating every maintenance activity by higher authorities, maintaining security of the stored data even in the presence of third-party vendors and service providers.

5.2 Representative Maintenance Scenario in Military

This section aims to depict a typical representative scenario of maintenance of MBTs in military organizations. Comprehending this scenario is important for the development of the proposed architecture for maintenance data management.

Considering the obvious security reasons, the maintenance units for MBTs are considered to be located far from the border region. Hence, the maintenance of the MBTs is carried out at distinct locations. The names used by militaries for their personnel formations, equipment formations and maintenance locations varies markedly depending on the country. The terms used here are generic. The scenario is presented in Figure 5.1.

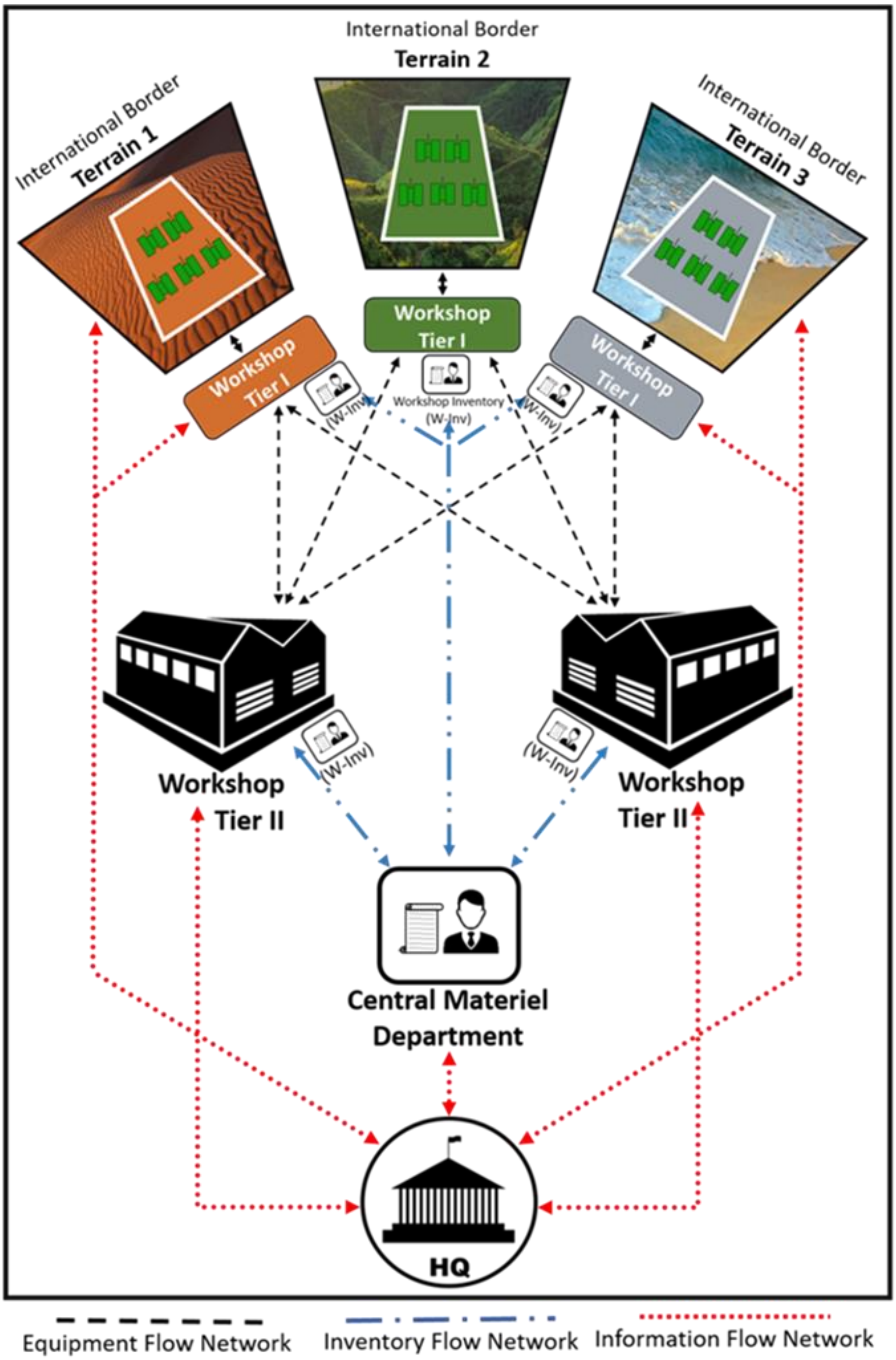

Figure 5.1 Representative scenario of military equipment maintenance

Field: Considering the fundamental function of the MBT, it is deployed in areas across a wide range of border regions known as fields. The MBT needs to work in distinct terrains in different fields. The minor repairs or replacements needed at the field can be done under the supervision of a field manager.

Tier I Workshop: Some routine inspections and replacements are carried out at these workshops. These are located in close vicinity of the deployment. Generally, one workshop is considered to be allotted to one field. Here, the workshop manager works under the supervision of Workshop Commandant - the top deciding authority of tier I workshop.

Tier II Workshop: For the major replacements as well as overhauls, the MBTs are sent to these Tier II workshop, which are quite far from the border region due several strategic reasons including security. Here the workshop manager works under the supervision of Workshop Commandant - the top deciding authority of tier II workshop.

Central Materiel Department (CMD): The spare inventories for all these maintenance activities gets administered by an inventory manager at central materiel department, which is again located at different location than the workshops. Its main function is to administer the quality and quantity of spares at workshop inventory (inventory associated with every workshop – W-Inv).

Headquarter (HQ): Although the maintenance activities are carried out at aforementioned locations, the central higher authority at the HQ monitors all these maintenance activities remotely from a central location. Several key decisions regarding readiness, finance, organizational culture etc. are taken by central authority at HQ.

For the majority of the maintenance tasks, whether scheduled or not, the MBT has to relocate a lot. Therefore, over its complete life cycle the MBT has to be at multiple locations undergoing different tasks. Making all the huge data generated by distinct players available for all the players wherever required is not an easy task. Therefore, it is needed to store this data and share it with the workshops or external agencies whenever needed while maintaining appropriate security measures.

This maintenance scenario leads to several issues whose solution leads to enhanced efficiency in these maintenance practices. Because these vehicles need to relocate for the majority of the time, performing different tasks, which could be an assigned mission or a scheduled maintenance, it could be difficult for the higher authorities to trace and calculate the exact status of the vehicle. This issue of traceability is of two types. First, to trace the vehicle for its current location and working status; and second, to trace the journey of systems or subsystems inside a vehicle, in the light of practice of cannibalization and refurbishment in the military maintenances. Because of several reasons like emergency, due dates, unavailability of spares, etc. a component from one equipment can get installed in another with or without repairing. When this kind of replacements happens for times, maintaining the traceability of data gets more complex; and not maintaining this information makes this maintenance data less potent. When the MBT is sent to the workshops, the field unit that owns the MBT expects the information regarding the status of the MBT. The corresponding authority is also interested to know whether the workshop is able to respond to every maintenance work required, whether the workshop is able to deliver back the MBT in expected duration, whether the workshop is having all the required spares etc. Many times, the field unit is also interested in participating in the maintenance decisions. In case, the workshop is not able to perform all the required maintenances due to whichever reasons, the field unit authority will be required to communicate to the workshop on a common platform.

5.3 Blockchain Enabled Maintenance Management Framework

In light of the aforementioned maintenance scenario and its associated challenges, this thesis proposes a blockchain enabled maintenance management framework as a viable solution. This section delineates the developmental approach employed in creating this framework, encompassing a comprehensive examination of its technological aspects. In order to develop the framework comprehensively, some choices among the available technologies are made, and those are discussed in this section.

5.3.1 Blockchain Technology

The advent of blockchain technology presents a momentous solution to resolve several issues associated with data management in a novel manner. Blockchain concept is getting increased attention, where the work is distributed in nature, because it enhances security and privacy [166], increases systems fault tolerance, provides a faster settlement and reconciliation, creates a scalable network [167] and helps in saving cost and time by removing intermediaries [168]. Employing blockchain, the transactions which mandatorily needed the centralized architecture and trustworthy third-party applications can now work in a decentralized manner, and that too with the same or increased level of inevitability [166]. With its unique package and characteristics, blockchain can be seen disrupting many traditional data management approaches. Considering the increasing awareness about blockchain technology, the core technology has been discussed and explained by many [166], [169], [170], [171]. Therefore, this thesis does not attempt to explain the basic mechanism of the technology. Casino et al. [172] have presented an excellent mindmap abstraction of different applications of blockchain where significant work is being carried. It has already found several industrial applications as financial services for the banking industry [173], [174], in healthcare for decentralized and secured data sharing [175], [176], [177], industry 4.0 manufacturing systems [178], IoT [179], traceability systems for food supply chains [180], logistics operation [181], [182], data management in government institutions where data in large volume is involved [183], identity management [184], agricultural ecosystem [185], for traceability of imported goods [186]. Several literatures on blockchain applications affirm its suitability for its application in the manufacturing sector [187], [188], [189]. In a nutshell, industrial situation where there is a need of a single source of truth, trusted transactions, immutable ledger store, and near real-time data sharing, blockchain application is going to have many more advantages than the conventional database systems [190].

Considering the nature of the challenges related to the data management in defense organizations, blockchain technology is being contemplated as a profound solution. Therefore, defence ministries in several countries such as USA, Russia, China, etc. and some of the military alliances like NATO have shown interest in using blockchain technology towards the goal of enhancing military strengths [191]. Defence executives surveyed by Accenture cite blockchain as one of the top emerging technologies which they are focused on to support greater industry growth and efficiency [192]. Studies indicate that more than 80% of the companies which work in the defense industry plan to integrate Blockchain into their different processes in 2021 [193]. Presently, the areas in the defense sector where the application of blockchain is being studied and implemented are cyber defense, tactical networks [194], communication, IoT [195], Supply Chain Management, Logistics etc. [191]. Furthermore, there are areas in the defense sector where the application of blockchain technology promises to deliver desirably effective solutions. One such area is the maintenance function in defense organizations. Despite several challenges associated with the maintenance data management in defense sector, this area is still untouched as far as the application of the blockchain in defense is concerned.

As discussed, the literature shows the efforts made by researchers to use blockchain for providing solutions to various challenges in the industrial as well as the defense sector. However, the literature providing a systematic approach to make use of blockchain to strengthen the data governance in maintenance data management for militaries is not available. Considering the numerous challenges involved in maintenance data management especially in the military organizations, there is a need for a well-researched and systematic approach to make use of blockchain technology. As a solution, this thesis presents a blockchain enabled maintenance management framework for military equipment, which focuses on making the military maintenance function more comprehensive and future ready. As the awareness and interest in the blockchain technology are growing, this research provides a detailed approach as a ready reference to any military organization to develop their own blockchain enabled maintenance management system.

5.3.2 Architecture of the Framework

In order to develop the framework comprehensively, some choices among the available technologies are made, and those are discussed in this section.

Blockchain applications are categorized as public, private, and federated or consortium blockchain [196]. In this case of military organization, where the blockchain is proposed to manage military maintenance data, federated blockchain is favored among all, as it is not centralized as private; and only authorized nodes can participate, making it permissioned decentralized blockchain. All the nodes in this blockchain are identified users. Moreover, irrespective of the size of the network, the transaction gets validated in the duration of the order of milliseconds [170], [197].

In order to achieve agreement of all the required nodes on any transaction, some consensus is required. To reach up to a consensus in a distributed environment is a challenge before blockchain. To resolve this issue, blockchain uses various consensus algorithms. For example, the cryptocurrency Bitcoin used Proof of Work (PoW) as a consensus algorithm [166]. There are several other consensus algorithms available such as Proof of Stake, Proof of Activity, Proof of Burn, Proof of Capacity, Practical byzantine fault tolerance, etc. [198] However, the one which is often used with the permissioned blockchain is the Proof of Elapsed Time (PoET). These consensus algorithms facilitate all the nodes in the blockchain to reach upto accordance about the existing state of the ledger. If any node of the blockchain attempts to add some information, it is very important for all the other nodes to agree on this information before it is permanently added into the blockchain. This consensus on incorporating every transaction into the blockchain brings the transparency and hence the trust in the network. The choice of consensus algorithm should depend on the type of blockchain and organizations' expectations about the speed, efficiency, and trust in the blockchain operations. Unlike the several popular blockchains where cryptocurrencies are involved, in the presented military scenario, none of the nodes is working to win some rewards for mining. Additionally, one cannot expect the availability of high-end computational devices in all the fields considered in the present military maintenance scenario. In the present scenario, the consensus algorithm is required to ensure the transparency in the verification process of all the registered maintenance data.

For the proposed framework, considering the need and nature of the consensus, PoET is considered more suitable. PoET is known an energy saving consensus algorithm without intensive mining process. In the present context for military organizations, there is a need for a consensus algorithm that works without demanding the expensive computational power, and without the involvement of any kind of tokens. Here, the nodes are not working to win the rewards for mining in the blockchain, and hence PoET is highly applicable as the network will not have any tokens to burn or hoard, and the hardware or energy required is also minimal [171]. The PoET consensus algorithm is used in this framework with the prime objective of bringing the transparency in the process of validating every transaction before it permanently gets into the blockchain.

PoET was developed by Intel in 2016, primarily for the permissioned blockchain. This is considered as an efficient form of the Proof of Work, while removing the need of computationally expensive mining intensive process with the randomized timer system. PoET works in conjunction with the Intel's Software Guard Extension (SGX); which allows the trusted code to run independently irrespective of the system or platform it is working on. SGX has the ability to digitally attest that the trusted code is running properly without any manipulation in the trusted execution environment [199]. The memory where the trusted code is stored in the Trusted Execution Environment (TEE) is even safe from malicious attacks. The PoET algorithm generates a random waiting time for each considered node in the blockchain, and the node with the shortest waiting time wakes up first and is allowed to commit the newer block to the blockchain, broadcasting the necessary information to the complete network. This complete process happens in a completely randomized manner and PoET algorithm has several further analytical checks to ensure the security and trustworthiness in the process. Its integration with TEE typically ensures that there is no manipulation to the trusted code. Furthermore, literature suggest that the PoET algorithm is capable of scaling the network upto thousands of nodes in a network. For more detailed discussion on working of PoET and other important consensus algorithm [199] can be referred to. In the proposed framework, PoET is used to reach upto a consensus in all the validation processes by making them completely randomized to bring transparency in the network. For example, when the user creates any transaction for some maintenance activity performed on an MBT, it requires the successful validation to permanently get into the blockchain. In this framework, the superior authority to the user who created the transaction at the same workshop performs the validation. In order to bring accuracy in the data stored in blockchain and to make validation process more uncompromising, the framework ensures that while creating the transaction, the user does not know about who is going to validate the particular transaction. Therefore, the validating node is selected randomly from all the available nodes with the superior authorities at the same workshop. In order to bring transparency and trust in these random selection processes for selecting validating nodes, PoET is used.

The choices made for the proposed framework provide enhanced security and recoverability to the military maintenance data. Any single modification in any of the transactions by any of the nodes is going to disrupt the complete blockchain, and hence, no one can modify any transaction without everybody's knowledge. All the verified transactions are cryptographically sealed with the help of hashing using available hashing algorithms like SHA-256 which returns the hash value of 256 bits. Moreover, the proposed blockchain based framework ensures the prevention of loss of data due to any reason with the help of one of the fundamental blockchain characteristics. If anything like a malware attack or damage happens to a ledger in a node, it will automatically fetch the latest ledger from the network bringing it to the latest version despite having lost its own. This makes the blockchain intrinsically secured and satisfies the claim that the use of this blockchain makes military maintenance data more secure and recoverable.

Nick Szabo [200] introduced the concept of Smart Contract (SC) as 'a computerized transaction protocol that executes the terms of a contract.' Smart contracts enabled blockchain technology to minimize extrinsic engagement by automatic validation and execution. A smart contract facilitates translating contractual clauses into embeddable code. One of the main features of this technology is self-tracking the fulfillment of the predetermined requirements and decision making according to a predefined algorithm [200]. By using smart contracts, the need for trusted intermediaries between transacting parties is minimized. With the use of such smart contracts, military authorities can prevent their efforts in validating every maintenance activity and can rely more on the external agencies with necessary trust while keeping required transparency.

Based on the aforementioned choices within blockchain technology, the proposed framework is designed. In a particular case, this proposed framework considers seven distinct nodes to represent five different locations in the network (Figure 5.2).

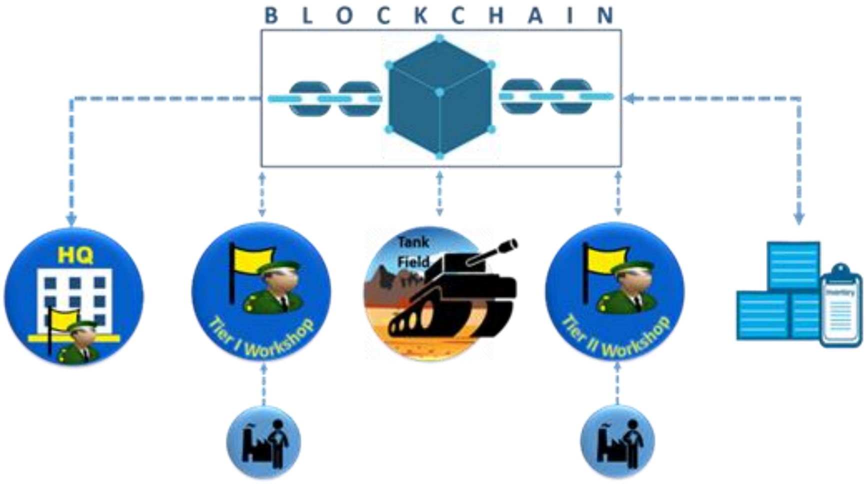

Figure 5.2 Structure of the framework

Based on their authority, permission for the node to read, write, or validate in the blockchain is defined. Table 5.1 shows all the locations involved, actors in the blockchain, and their respective read/write/validate permissions in the particularly considered case of maintenance of MBTs.

Table 5.1 Locations, Actors, and their Permissions in the Framework

Sr. No.	**Location**	**Authority**	**Permission**		
			Read	**Write**	**Valid-ation**
1	Field	Field Manager	Y	Y	Y
2	Field Workshop	Maintenance Manager	N	Y	N
		Workshop Commandant	Y	N	Y

3	Base Workshop	Maintenance Manager	N	Y	N
		Workshop Commandant	Y	N	Y
4	Head Quarter	Concern Higher Authority	Y	N	N
5	Central Materiel Dept.	Inventory Manager	Y	N	Y

5.3.3 Access Control Policy

To regulate access to the proposed blockchain based framework from a security perspective, an access control policy is defined. This policy regulates permission to interact with the distributed ledger and make transactions verified by the respective nodes. Additionally, this policy provides the authentication level to every node that decides the node's category as a full node or partial node. A full node has access to the complete ledger, whereas a partial node has only the respective subset of the distributed ledger.

In the present permissioned blockchain framework, the Principal Administrator (PA) is the full node, which is authorized to set the access control to every other node in the network. On the creation of every node, the PA defines the authentication level of the node and provides a Node Identity (NId) over a secure channel. The whole process of NId generation is performed with the trusted code in the trusted execution environment, which cannot be manipulated. The NId also represents the authentication level of the respective node. The PA maintains the permissioned database of all the NIds and their corresponding authentication level. Five authentication levels (L1 – L5) are pre-defined in this framework, nodes with authentication levels of L1, L2, L3 are partial nodes, and L4, L5 nodes are full nodes. L1 and L2 nodes are set as the partial nodes, which has access to a subset of the ledger related to the equipment at the location of the respective node and has the permission to write into the blockchain by accessing the GUI. The authentication level of L1 permits the user to write the transaction in the form of a job card or maintenance activity using the GUI. The authentication level of L2 is assigned to the user with higher authority at every field and workshop; with this authentication level, the user can read the transaction to validate it. These nodes have access to read/write/validate the data only related to the equipment in their possession. All the nodes with the authentication level of L4 & L5 are set as the full nodes, which has the complete distributed ledger at their node and has complete access to it. L4 authentication level is assigned to the nodes where the organizational authorities are interested in analytics over the data in the blockchain. For analytics, these nodes may require data from all the nodes in the blockchain. The nodes with the L5 authentication level have access to the status of every equipment and group of equipment irrespective of their location. User with the top authorities in the military organization is assigned with the L5 level. L3 is the authentication level which is assigned to the third parties or external agencies involved in the maintenance and spare procurement process for the military equipment. In order to perform their analytics, access is given to these nodes, which are continuously monitored by the L4 nodes, and only the filtered data is made available to them to perform analytics.

Whenever any node generates any maintenance activity transaction, the respective node receives an encrypted transaction key from PA, and this transaction key is stored in a database with PA. This transaction key becomes the part of the header of the transaction. At the time of validation of this transaction where the consensus algorithm selects one validation node, a smart contract checks for the transaction key associated with this transaction. The smart contract allows the transaction to be validated only if the transaction key is found in the PA database; otherwise, it rejects the transaction and raises the alarm to the PA for false entry of transaction. This process ensures that no unauthorized transaction is registered in the blockchain.

5.4 Interactions with the Framework

In the considered representative maintenance scenario, when the MBT is working in the field, it is in the authority of the MBT commander. Whenever maintenance is required to the MBT, either scheduled or corrective, the MBT is taken to the field manager, who decides the future operation of the MBT. The authority at the field knows the issues about the MBT better, so this framework provides a platform for the field authority like MBT commander or the field manager to provide breakdown reasons if the MBT has failed and needs corrective maintenance and a list of repairs and replacement (corrective/preventive) expected. This expectation of the field authority can be recorded in the form of a digital job card. Within the same job card, using the GUI, the field manager can specify the expected return date, which can become a tentative due date target for the workshop authorities. On submission of the job card by the field manager, it becomes a transaction attribute and gets into the memory pool in the form of a JSON object (a sample JSON object for the job card is given here).

```
{
"TankID": "T123", "Tank_Group": "ABC",
"Tank_Status":"Working", "
"BreakdownReasons": {"1 value": "None"},
"MaintenanceRequired":
{"1 value": "perform minor replacement 01",
 "2 value":"Replace Hose B15" },
"MaintDestination": "Tier I Workshop",
"DispatchedDate": "01-Jan-2020",
"ReturnExDate": "15-Jan-2020"
}
```

This transaction attribute gets into the blockchain after its validation by someone among the corresponding top authorities in the respective field. This validation includes the correctness of the entries made in the job card, along with the availability check of the workshop and reasonable expected return dates. When the MBT sent by the field manager reaches its destined workshop (Tier I/II), the authority at the workshop has to receive it, and after some inspection of the MBT about its overall condition and the specified maintenance requirements in the job card, the receipt needs to be recorded on the blockchain. This receipt needs some more information related to what all maintenance is required, what maintenance activities can be performed considering the load on the workshop and the spare availability etc., and whether the mentioned expected delivery date can be achieved. After inspecting everything along with the job card, the workshop manager can specify the possible delivery date. Once this receipt is registered on the blockchain, the current location of the MBT will be changed from 'transit' to the respective workshop; therefore, the nodes at higher authorities with the specific authentication level (L4 and L5) will be able to see the current status of the MBT. All the maintenance activities performed on the MBT needs to be recorded in the specific format that collects the maintenance data comprehensively. The user interface shown in Figure 5.3 specifies the several information entities the workshop authority can register, which gets recorded in the blockchain. The form in Figure 5.3 consists of a sub form titled as 'Maintenance Data Manager', which has field for entering every maintenance activity done on the respective MBT. This sub form helps in fetching various important information required later for several analytics. It also records repair or replacement of the lowest maintainable unit, which is the lowest replaceable or repairable entity. This facilitates the framework in recording the maintenance data with the highest granularity. Along with the maintenance start and finish duration, it also records the category of replaced component, whether it is an original component or refurbished/cannibalized/duplicate component. Post-maintenance inspection and testing are crucial tasks to perform, and this form needs to be checked twice by the maintenance personnel for completion of maintenance tasks and, later on, completion of testing. Once the maintenance personnel submits this form, it is stored as a transaction attribute to the memory pool of the blockchain. After the workshop higher authority and inventory manager validate the transaction one after the other, it is registered with the blockchain. Here, to bring transparency in the validation process, as discussed earlier, the PoET consensus algorithm is used. This allows only one among all the available nodes with higher authorities at the same workshop to validate the complete transaction and add it to the blockchain. The consensus algorithm randomly selects one node among the available nodes with higher authority at the same location with the typical procedure of PoET as discussed earlier. This randomized process ensures the transparency and accuracy in the registered data, since every node which is creating the transaction is totally unaware about who is going to validate their transactions. The JSON object generated on submission of the following form (Figure 5.3) is similar to one, which is given for the job card, with some additional attributes.

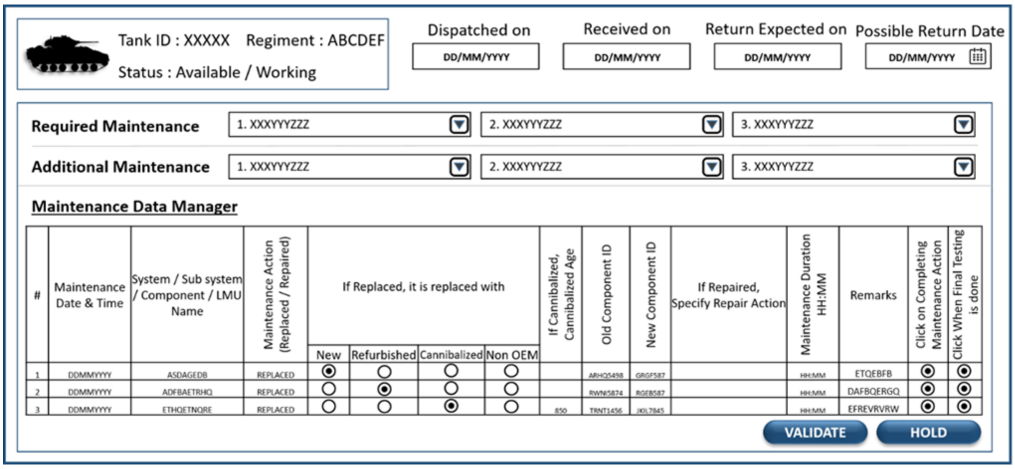

Figure 5.3 Maintenance data manager form with the job card

Blockchain technology is known for its inherent way to provide the data integrity without requiring any external party to control the transaction [175]. The present framework makes use of this technology to its fullest to provide the data integrity. In the context of data management, data integrity refers to overall completeness, consistency, accuracy and trustworthiness of the data. The logical structure of the framework is developed such that every maintenance personnel has to register every maintenance related activity for every equipment whose maintenance is performed, so the consistency of the data gets maintained properly.

Additionally, the validating authority does not give a clear pass to the data unless it is checked for its completeness and accuracy. Since every transaction of the data is linked with the maintenance personnel who registered the data and authority who validated the data, the trustworthiness of the data gets achieved. The use of consensus algorithm in validation process brings transparency and the trust in the network. Immutability being one of the key characteristics of the blockchain, keeping the data transactions unchanged is primarily achieved; hence the claim of bringing data integrity gets satisfied and the achieved integrity gets along with the registered data forever.

In the complete maintenance process, the Inventory Manager (authority at CMD) plays a very crucial role. The quantity and quality of the spares required for all of this maintenance are taken care of by the CMD, which is centrally working, as mentioned in an earlier section. The inventory manager has to validate the form submitted by the workshop manager and then it gets validated by the workshop commandant. In this validation, the inventory manager checks for the replaced and newly installed part's IDs and compares them with the IDs in ordered stock. By this validation, the inventory manager has the complete check on the quality of the parts by ensuring that only centrally procured parts have been used instead of locally purchased or refurbished or cannibalized. In case of refurbishment or cannibalization, part ID of that component helps tracking its complete history; hence, appropriate quality in spares can be maintained. As every maintenance activity is getting registered with the blockchain, and the inventory manager is one of the nodes, the inventory status file for the spare parts at the central inventory manager varies. Hence, inventory managers can monitor the stock of every spare in real time without being present at every workshop. In this proposed framework, several smart contracts are used to automate the validation process. One of the smart contracts used for validation and monitoring at the inventory manager node is shown in Figure 5.4.

```
struct Part
 {   uint128 id;
     string status;   }
 bool flag = false;

 function checkPartExists(uint128 removedPartid,
                                    uint128 installedPartid, Part [ ] data)
 {   Part removedPart;
     Part installedPart;
     for(unit i = 0; i< data.length; i++)
         {     if(data[i].id === removedPartid)
               {    if(data[i].status === 'old')
                    {   removedPart = data[i];    }      }
  if(data[i].id === installedPartid)
    {   if(data[i].status === 'new')
      {      installedPart = data[i];    }      }
   }
  if(!removedPart)
   { flag = true; }
  if (installedPart)
    {  installedPart.status = 'old';  }
  else
    { flag = true;  }
return (flag,installedPart)
}
```

Indicates need of escalation of the issue to higher authority

Results into deducting the part Id from new part stock list

Figure 5.4 Smart contract example

This smart contract (developed in Solidity) helps in validating the authenticity of spares used in equipment maintenance. The function *'checkPartExists'* gets part IDs of removed and installed parts from maintenance records submitted by workshop manager node and the inventory status file for all the parts (registered by CMD). It loops over the provided data to check whether the part IDs entered by the user while submitting the maintenance data form exists in the inventory status file or not. If both the part IDs are found in the data, (which implies use of authentic spares), it changes the status of the new part that has been installed to 'old', deducting the part ID from the new parts section in the inventory status file. In the event of not finding the part ID (removed / installed) in the inventory status file (which indicates the inauthenticity of the spares), the smart contract raises the flag as true, indicating the need for escalation of the issue to the corresponding higher authority. This smart contract helps the inventory manager at CMD node to validate the large quantity of maintenance transaction with minimized human intervention that too in lesser time. In the form of these smart contracts, some algorithms with transaction protocols works for the validation process, resulting in a more uncompromising way of validation.

Because the workshop manager is updating every maintenance activity on the maintenance data manager sub form, the field manager as well as headquarter authority can monitor the status of maintenance of the MBT in real time. When the listed maintenance tasks are completed on the MBT, the workshop authority can set the status of MBT as ‘ready to deliver’. When the MBT is ready to deliver, the field manager can check whether all the expected maintenance activities are carried out or not. Only after getting completely satisfied with the performed maintenance activity, the field manager can accept the MBT to be returned to the field. Here, there is a scope for using a smart contract to validate the completeness of the work listed in job card. In case of any conflict here, both the parties can negotiate online in the presence of head quarter authority and can settle on common grounds. Otherwise, these issues can be escalated to the head quarter, where the authority at head quarter will be involved in this negotiation or settlement.

Although all of these maintenance activities happening at the distinct workshops are continuously monitored by the HQ authorities, they are more interested in knowing the readiness or availability at the group levels of the MBTs. They are also interested in knowing the status of an MBT whether it is working or not; if it is under maintenance, where is the maintenance happening etc. The proposed framework presents the GUI based status monitoring to the HQ authority as shown in Figure 5.5.

If the HQ authorities want to know the maintenance history of a particular MBT, it can also be fetched from the blockchain using its unique ID, as shown in the format given in Table 5.2.

Figure 5.5 Sample status report to the HQ authorities

Table 5.2 Maintenance history of an equipment

Last Five Transactions				
Sr. No.	**Date**	**Location**	**Status**	**Maintenance Action**
1	05/01	Received on Field Workshop	Down	Medium Repair 1 Scheduled
2	16/01	Field Workshop	Working	Medium Repair 1 Completed
3	17/01	Sent to Field from Field Workshop	Working	NA
4	20/01	Reached on Field	Working	NA
5	30/01	Field	Working	Routine Inspection Done

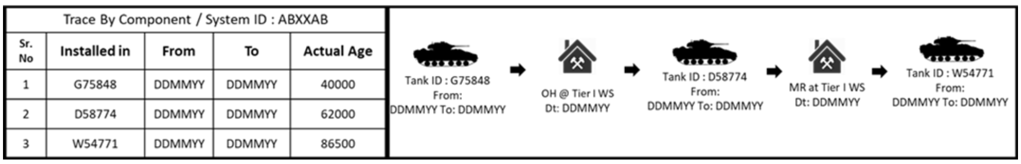

Figure 5.6 Component Traceability

As discussed in the earlier sections, traceability of any system or sub system inside an MBT is a major issue. Information related to the transfer of any system or sub system from one MBT to another; and history of every equipment inside an MBT from its inception can be fetched from the blockchain framework using its unique ID. Figure 5.6 depicts the ability to trace every system within this framework, where a trace of component is described as its journey from one MBT to other through the workshops.

This framework considers almost every participant in this maintenance scenario as one distinct node. When every participant knows that the transaction done by him/her is getting validated by the corresponding higher authority, which is again monitored/validated by their higher authorities; and none of the transactions can be modified later due to the choice of consortium or federated blockchain; it provides great transparency as well as trust in every participant irrespective of their position in the hierarchy. Moreover, this blockchain enabled framework provides authentication for the nodes used by the external agencies, placing necessary validation checks (by military authorities) at several steps and monitoring the data accessed by them. Hence, resolves the issue of third-party involvement without tampering security or transparency of the complete network. In this way, the third-party maintenance agency or external suppliers can make use of the military maintenance data for several analytics at their end without actually possessing or extracting the whole data. Hence, the claim of blockchain bringing transparency and trust in the organization gets satisfied. The complete flow of maintenance data getting registered in blockchain through several validations is presented in the Figure 5.7.

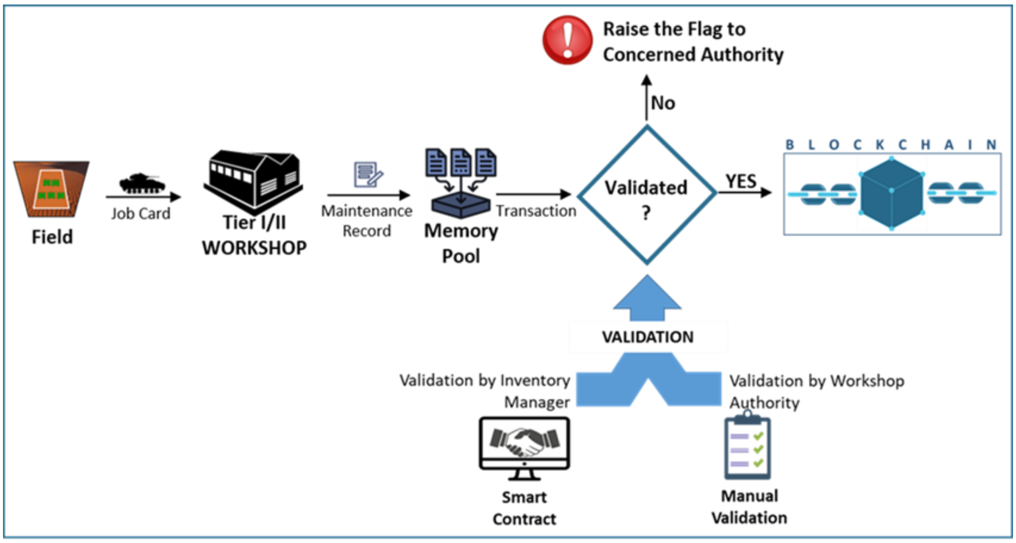

Figure 5.7 Maintenance data registry in the blockchain through validations

This blockchain enabled framework makes use of several characteristics of blockchain technology like Distributed Ledger (DL) and smart contracts; and hence promises the faster and efficient exchange of information. This framework promises an efficient way to enable the user with the required information at the right time with desired security. This efficient exchange of information through the distributed ledger and validation through smart contracts is depicted in Figure 5.8.

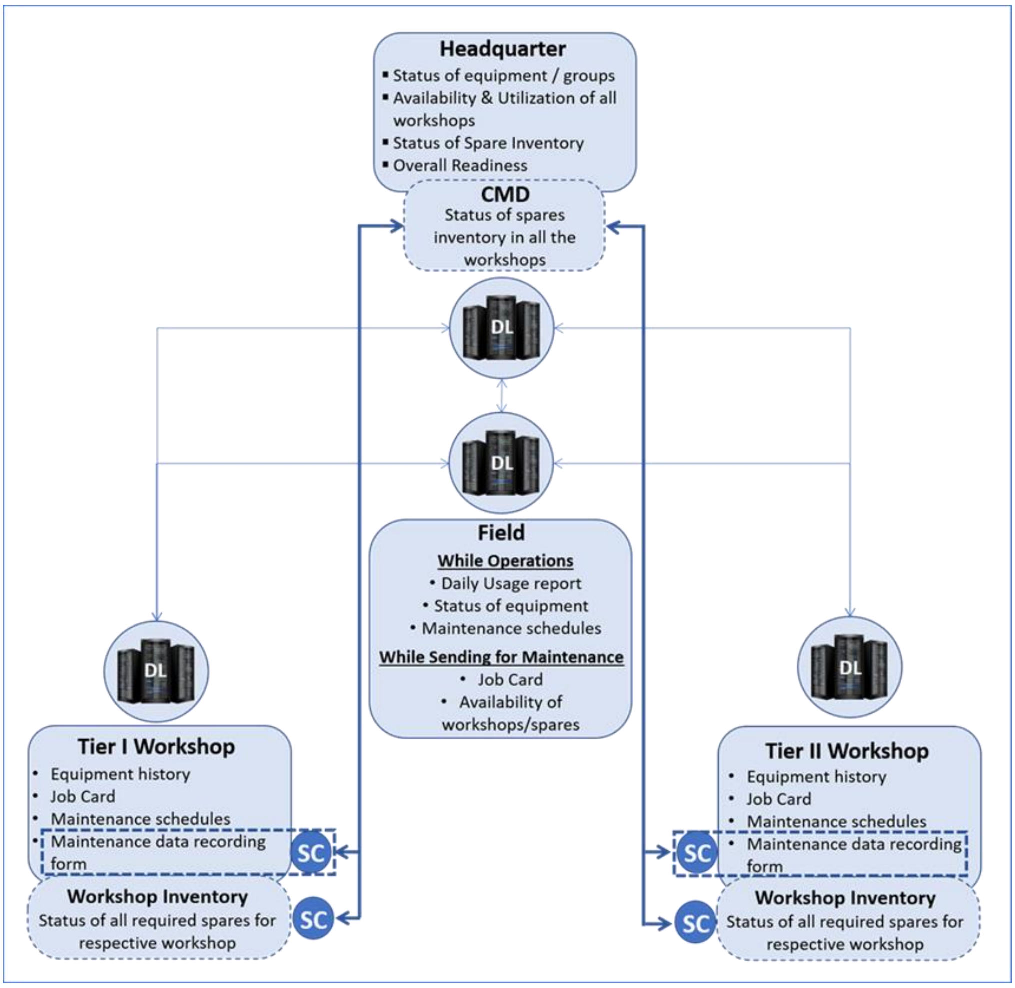

Figure 5.8 Information exchange through distributed ledger

This framework offers more cost-effective solutions as compared to conventional maintenance management solutions. Firstly, this framework reduces the involvement of resources needed to operate, scale and secure the network; secondly, transparency across the network also reduces the cost of further verification. In addition, there are several other benefits in the form of accurate analytics, which can be fetched from the proposed blockchain framework. Various benefits and analytics based on the information from the proposed blockchain are discussed in the next section.

5.5 Advantages of the Proposed Framework

The proposed framework serves several momentous advantages over the conventional database systems. The primary advantages are those which are inherited from the concept of blockchain, and secondary advantages are the efficient analytics based on the adequate data from the proposed blockchain and ease in several decision-making based on that.

5.5.1 Inherent Advantages of the Blockchain

Data security is one of the most needed characteristics for military data management frameworks where all the data stored is highly confidential. Blockchain is knows as intrinsically a very secure technology. The proposed framework claims to offer the highest level of security to the registered maintenance related data. Data security has the attributes known as the trio of confidentiality, integrity and availability. Confidentiality is used to protect data from unauthorized disclosure. Integrity is used to prevent users from changing data and in a broader sense it refers to overall completeness, consistency, accuracy and trustworthiness. Availability guarantees that data is accessible to authorized users whenever and wherever required. To provide all the three attributes of the data security to the stored military maintenance data, the proposed framework provides a logical structure while using the inherent characteristics of the blockchain technology. Confidentiality is the prime elementary property of data security, which is offered by this framework. The present access control policy ensures that the data stored in the blockchain is not accessible to any of the unauthorized party. With this policy, only authorized nodes can read/write/validate the transaction. Additionally, the predefined authentication levels associated with nodes strictly ensures that only the respective subset of ledger is available to the respective node. The present blockchain enabled framework ensures that the data entered in the form of transaction is encrypted, and hence the data modification is a difficult task. As this framework is based on consortium or federated blockchain, a single modification in any of the transaction by any of the node is going to disrupt the complete blockchain, and hence no one can modify any transaction without everybody's knowledge. At predefined intervals, verified transactions are cryptographically sealed with the help of hashing. For example, if maintenance personnel make a transaction for a maintenance activity performed at tier I workshop, where a particular component is replaced with a cannibalized one. Later this transaction in encrypted form is stored in the blockchain after successful validation by higher authority at the same tier I workshop and inventory manager. Once this encrypted transaction is stored in the blockchain, no one can make any modification in this transaction. For any reason, if anyone including the higher authority in the organization tries to trace this transaction and modify it, the encrypted transaction cannot be decrypted and manipulated. If someone tampers this transaction, the complete blockchain will be disrupted. With this disruption, the data from the distributed ledger of node with same authentication level will be fetched and replace the disrupted ledger in the node. With this feature of reproducing data upon the loss of data due to tampering at any node, this framework provides great data reliability to the stored maintenance data. Again, in this newly fetched ledger, the transaction will possess the same data, as it was earlier. Moreover, all the nodes in the network will get to know about this attempt. Hence, in this manner the immutability to the maintenance data is maintained in the blockchain. Tampering with the whole data in all the distributed ledgers simultaneously is practically impossible. In this manner the stored data is undisclosed to any unauthorized entity, maintaining high-level confidentiality. With the presented access control policy, every user of this framework has very limited and monitored access to the actual required data. Like, the node with the L1 authentication level, has a very limited access to the data which is related to the equipment that has direct connection with the same node. This node is not permitted to read the data from other fields or workshops and validate any of the maintenance transaction. The presented policy provides authenticated monitored access to the third parties involved in maintenance and inventory management for analytics purpose. The access to these parties is only granted with the necessary validation checks at several steps. These third parties are assigned with the authentication level of L3, which can only access the data that is on demand filtered by respective L4 node.

Hence, the framework resolves the issue of data access to external agencies without tampering with security or transparency of the complete network. Consequently, with the application of blockchain technology, the confidential data stored in the framework is highly secured.

For accuracy in high level decision-making, data integrity is very important. The logical structure of the framework consisting of data entry along with necessary validations ensures the consistency and completeness of the data registered. When every participant knows that every transaction made is getting validated by the corresponding higher authority, which are again monitored / validated by their higher authorities; and none of the transactions can be modified later due to the immutability in the blockchain; it provides great trustworthiness to the data and to every participant irrespective of their position in the hierarchy along with the transparency in the whole network. This covers all the aforementioned four attributes of data integrity, which is served to the stored crucial military maintenance data. Distributed ledger is one of the core characteristics of blockchain technology. By integrating the several authentication levels in the access control policy with the distributed ledger, this framework ensures that the only required data is available to every node whenever needed. This brings the third attribute of data security i.e., data availability.

5.5.2 Analytical Advantage of the Blockchain

Several characteristics of blockchain technology used in this framework like distributed ledger, smart contracts, data immutability, etc. make the analytics smoother and enhances the accuracy in estimations resulting in improved decision-making. In this section, several pragmatic analytics based on the data from the proposed blockchain and decisions based on that are discussed.

The first and foremost advantage of the developed blockchain enabled framework is that it enhances the applicability of all the developed approaches in the scope of this thesis by guaranteeing the availability of required data from a quality as well as quantity viewpoint. The proposed framework is capable of maintaining the maintenance data with high granularity and hence, able to provide the maintenance data very accurately. The entries in the blockchain can be queried to get information like the installed date and replacement date, along with the reason for the replacement. This accuracy surely reflects in the estimation of highly critical estimations like degree of repair, fleet availability, mission readiness, etc. Certain policy decisions for maintenance management, spare management or crew management can be taken with higher confidence with the available accurate maintenance data. Blockchain enables the user to use this data at particular nodes with great security. Because the maintenance data registered is validated at every step, the framework brings enhanced accuracy in the estimation. For the military equipment where the degree of restoration, which indicates the effect of any repair on the age of the equipment plays a vital role, improved estimations and their availability at required multiple nodes enhances the quality of overall maintenance planning. Because the maintenance actions are performed at different locations by different maintenance personnel and authorities, having the accurate estimates like degree of restoration wherever required (using distributed ledgers) helps in planning the maintenance efficiently. As the framework helps in estimating TTF with great accuracy, several OEM specified life estimates like Mean Time to Failure (MTTF) or Mean Time between Failure (MTBF) can be estimated and compared with the expected range, and corresponding measures can be taken. With these accurately estimated metrics, maintenance planning becomes more effective.

This framework enables the user to escalate several maintenance management related issues to higher authorities. However, these escalations indicate irregularities in the workflow. In order to quantify these irregularities, this framework with the help of some programmed counters makes a provision for recording the number of events where maintenance issues have been escalated to the HQ. Several other important analytics-based data driven decision-making in a more accurate manner is possible with the use of this framework. Although there are numerous analytical decision-making queries which this blockchain can answer, for example some of those analytical queries are mentioned here.

• What percentage of the time are the MBTs dispatched back after maintenance within the expected duration?

• After overhaul, in how many MBTs new engines are installed?

• How many systems / Components are replaced with cannibalized spares?

• How many times was the Inventory unable to provide the required spares?

• Are there any cases of delay and conflict in validation by the workshop authorities?

• Does the Mean Time to Repair - (MTTR) (for the specific component) matches with organizational policy? (Based on Maintenance duration recorded in the maintenance data manager).

5.6 Summary

With this research, a novel attempt is made to introduce blockchain technology to maintenance data management in military organizations. The framework presented here is a tool to assist military organizations in recording their equipment failure and maintenance data with the desired granularity, accuracy, and punctuality. Developed framework will solve the issue of scarcity of accurate maintenance data, resulting in enhanced accuracy in crucial estimations like mission reliability, thereby improving war readiness and sustainability estimations of military organizations. While this framework attempts to resolve the issue of traceability of equipment at different levels, it makes the maintenance data more potent.

In addition, the framework delivers several inherent advantages of the blockchain technology, such as data integrity to military maintenance management, along with bringing transparency and trust to the organization. The selection of a federated blockchain allows only a few authenticated nodes to access the data and also addresses third-party involvement problems by providing multiple authentication levels to the nodes in the network, hence resolving the problem of data sharing and security across the network. By this approach, the framework allows third-party vendors or OEMs to run their analytics on the actual data without having actual access to the critical military data. The proposed framework attempts to encompass the viewpoint of almost every actor in the military maintenance scenario. This work considers seven actors in the MBTs' representative maintenance scenario. The roles of each actor in maintenance and interaction in the maintenance scenarios are comprehensively discussed for the proposed blockchain framework. The use of smart contracts for validation with minimized human intervention is presented in this study. Here only one smart contract is presented; there is scope for finding the situations where more smart contracts can be used. The choice of PoET as a consensus algorithm makes the framework more energy and cost efficient. The ability of the proposed framework to provide accurate and sufficient maintenance data on distributed ledger will further motivate the researchers to develop more accurate and novel approaches for reliability and maintenance modeling for military equipment.

Although the framework utilizes most of the benefits of blockchain technology to improve the maintenance management of military equipment, there are a few issues associated with this technology in military maintenance data management. Most importantly, the package of all the benefits of using blockchain technology comes at a high establishment cost. The way this technology works, it requires a high number of computation systems proportionate to the size of the network. All the nodes are required to work simultaneously, where computationally expensive algorithms for consensus and encryptions need to run. This, in turn, requires a large amount of computational power. The energy costs and their environmental implications cannot be simply ignored. A major challenge lies in investing such high costs in establishing such frameworks while military organizations migrate to this from their existing systems. However, all the high environmental costs associated with this technology are linked to its ability to provide the desired high-end security to the crucial military data stored in the blockchain. Moreover, in this proposed framework, the technological choices are made such that the requirement of high computational power is minimized. It is hoped that the future rewards of employing this framework in the form of better decision-making with accurately and securely stored maintenance data will make this investment all worthwhile. Moreover, observing the persistent advancement in the research on blockchain technology, it can be believed that this requirement of high establishment cost will be reduced in the future.

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Chapter 6

Overall Summary, Conclusions, & Future Scope

The objective of this chapter is to provide a summary of the work reported in this thesis in terms of technological context from defence perspective, research contributions, and utility of the research. In the end, limitations and future scope of the study are given.

6.1 Summary and Conclusions

The outcomes of the research in this work advances the existing body of knowledge by developing a tailored maintenance approach that exactly suits the modus operandi of defence forces in attaining and sustaining war readiness by ensuring the mission reliability of critical military equipment. Considering the pivotal role played by mission reliability in the effective management of war readiness, this thesis presents two novel methodologies for mission reliability prediction for critical military equipment while incorporating the combined effect of essential military-specific factors. With this consideration, a non-trivial problem of predicting the mission reliability of critical systems experiencing continuous exposure to multiple domain-specific factors is solved. This comprehensive consideration enhances the accuracy and contextual relevance of the overall analysis. Additionally, this research contributes to the existing pool of knowledge by presenting the non-obvious and non-intuitive learnings from the numerical experimentations performed on the demonstration case of maintenance of a main battle tank – one of the most critical military equipment. Finally, this thesis attempts to address the challenging problem of maintenance data management in the context of the military maintenance function by presenting a blockchain-enabled maintenance management framework for military equipment. In general, this research work can be assessed in the following contexts.

6.1.1 Technological context from a defence perspective

Present research adds the following innovative technical outcomes to the body of knowledge, which would be very important from the defence context.

(A) Mission reliability prediction considering the combined effect of essential military-specific factors.

The present methodology for mission reliability prediction presents a comprehensive approach for integrating the effect of all the domain-specific factors into mission reliability. This methodology presents a way to capture the effect of these domain-specific factors in the form of respective adjustment factors integrated with the effective age of the component, which is further used in the conditional reliability formulation. The outcomes derived from the numerical investigation conducted using this developed mission reliability prediction methodology have confirmed the effectiveness of integrating domain-specific factors. The results have shown significant variations in mission reliability when transitioning across different scenarios, including variations in terrains and operational seasons. This highlights the critical role of considering terrain and season factors when predicting mission reliability for critical military equipment. Furthermore, the study revealed distinct decreases in mission reliability for equipment operating in the same terrain and season but across different deployment roles. This underscores the importance of accounting for diverse deployment roles in mission reliability predictions for critical military equipment, such as MBTs. Such considerations are particularly crucial in military contexts where these equipment types often operate in specific deployment roles for prolonged periods, especially during peace time.

(B) XGBoost based machine learning methodology for mission reliability prediction.

The machine learning-based methodology presented in this study introduces a novel approach for mission reliability prediction, particularly in scenarios with computationally complex formulations involving the integration of essential military-specific factors. Traditionally, such integrated modeling would require extensive computation time, potentially compromising prediction accuracy. This methodology contributes to the existing literature by leveraging XGBoost, demonstrating its effectiveness in mission reliability prediction and expanding its application in reliability engineering domains. The favorable outcomes of the model underscore the suitability of XGBoost for similar applications in reliability engineering. Additionally, this methodology addresses the challenging task of quantifying the precise impact of various factors, such as human error in maintenance and the utilization of non-genuine spares, on component life and subsequent mission reliability. The numerical investigations conducted highlight the dependency of the impact of human error in maintenance on the type of spare used, including genuine, refurbished, cannibalized, and non-OEM options. From a managerial perspective, the findings strongly discourage the use of non-OEM spares in environments where human error during maintenance is prevalent due to their detrimental effects on component life and mission reliability.

(C) Mission reliability based selective maintenance planning approach

The present approach scientifically addresses how defence forces can effectively ensure the mission reliability of their critical military systems in order to effectively attain war readiness in a manner that aligns with the distinct challenges and complexities of the military landscape. The outcomes of numerical investigation using the developed approach provide several crucial insights into the effective implementation of the proposed approach. It is found that the key metrics for execution of the proposed approach significantly change with the change in terrain, season of operation, and deployment role. This concludes that the notion of a one-size-fits-all approach proves inadequate in the context of military maintenance management. For executing the developed approach, analyses need to be made with situation-specific factors derived from a mission profile for the deployment. Regarding the choice of higher threshold of mission reliability in the context of the present approach, aiming for the highest possible threshold of mission reliability may seem intuitive, but the results of numerical experimentation shed light on the adverse implications of excessively high thresholds on average maintenance costs and planned downtime. Although such thresholds may decrease the total number of maintenance events over a given time horizon, it is imperative to recognize the trade-offs involved and optimize them for each specific scenario. Moreover, the selection of allowable deployment delay significantly impacts practical readiness levels at the fleet level, requiring careful consideration to avoid potential misleading impressions of readiness. While opting for higher values may obviously appear to elevate practical readiness levels, it is essential to acknowledge the delusional nature of this parameter. While extending the duration of allowable deployment delay could notably enhance average practical readiness levels, it is crucial to recognize that such an increase may create a misleading impression of readiness. Although practical readiness levels may appear inflated on paper, this could lead to challenges during actual deployment, requiring more time and potentially resulting in undesirable outcomes. The proposed approach not only guarantees fleet readiness but also enables fleet-level readiness assessment across various deployment roles and equipment fleets, aiding high authority decision-makers in doctrine development. Importantly, the present approach ensures equipment readiness while surpassing traditional time-based maintenance policies in war readiness levels and maintenance cost—a critical factor.

(D) Blockchain enabled maintenance management framework for military equipment

This research is a novel attempt made to introduce blockchain technology to maintenance management in military organizations. Blockchain technology is found to be a momentous solution to address several military-specific challenges causing the several issues in maintenance data management. Availing of this framework will solve the issue of scarcity of accurate maintenance data, resulting in enhanced accuracy in crucial estimations like mission reliability, thereby improving war readiness and sustainability estimations of military organizations.

6.1.2 Utility of the research work

The systematic approaches developed in the scope of the present research will help in the following manner:

1. The mission reliability prediction methodologies enables the decision makers in defence forces to predict the mission reliability of their critical equipment with enhanced accuracy and contextual relevance. Which can be further used to numerous decision making events other than the presented approach for war readiness management.
2. The developed mission reliability prediction methodology has the potential to help the users other than in defence domain, where critical assets experiences the unique domain specific factors.

3. The developed machine learning based methodology for mission reliability prediction not only makes the prediction process computationally effective, but also opens up newer avenues of using machine learning in the domain of reliability engineering especially in the domain of human reliability.
4. Proposed novel mission reliability based selective maintenance approach is the first-of-its-kind work that demonstrates the systematic management of mission reliability for effective achievement of overall war readiness while considering multiple deployment roles, in a cost-effective manner.
5. In light of the serious challenges posed by data scarcity, the developed blockchain enable framework presents a scientific ready reference to the defence organization which are planning to develop some solution to circumvent this issue. This ready reference is hoped to enable the user with scientifically studied technological choices for development of their blockchain framework.
6. The presented study of alternate methods for probability distribution parameter estimation will serve as a comprehensive guide for reliability estimation in the industrial scenarios characterized with the absence of adequate data.
7. By harnessing the approaches and insights provided by this study, defence organizations can bridge the gap between theoretical concepts and practical implementation in the domain of reliability engineering, thereby realizing tangible improvements in their overall war readiness.

6.2 Limitations and Future Scope of the study

The primary focus of this work has been the development of approaches to ensure mission reliability and war readiness. Hence, after discussing the developed approaches, demonstration cases are presented for a specific type of MBT. Given the extensive materiel strength of defence forces worldwide, analyzing the implementation of these developed approaches for other types of critical equipment would yield further insights.

The absence of real data has impeded the analyses within the present scope in various aspects. The utilization of actual data in the analyses of the developed approaches, instead of expert judgment-based data, may lead to more realistic insights. However, it is noteworthy that the approaches and methodologies developed have been crafted in a manner such that their behavior remains consistent even with the use of real data, ensuring their effectiveness and reliability. For instance, due to the lack of data and reliance on a single published dataset, certain parameters such as TTR (Time to Repair) variances have not been factored in. However, with the inclusion of real-life data, these variances would be accounted for, leading to more nuanced and detailed insights.

The application of developed mission reliability based selective maintenance approach on the field would result into high levels of war readiness, however, the induced change in maintenance patterns would affect the current spare parts management systems. The effect of application of the developed approaches on the spare parts management including war wastage reserves is worth exploring.

The current approaches focus on managing critical equipment during peacetime. Extending these approaches to cover wartime scenarios would be a valuable area for exploration. This extension would require integrating casualty models with the developed approaches to provide a comprehensive framework for managing critical equipment in both peacetime and wartime conditions.

In the context of the developed maintenance data management framework, while blockchain technology offers significant benefits, its implementation comes with a high establishment cost due to the need for extensive computational systems. All nodes must run computationally intensive algorithms simultaneously, leading to considerable energy costs and environmental implications. The proposed framework adopts technological choices aimed at minimizing the need for extensive computational power. The anticipated benefits, such as enhanced decision-making based on accurately and securely stored maintenance data, justify this investment. Additionally, given the ongoing advancements in blockchain technology research, it is foreseeable that the high establishment costs associated with blockchain implementation will decrease over time.

Annexure

System Configuration of MBT:

Sub-Assembly #	Sub-Assembly ID	Component ID	Shape Parameter	Scale parameter (hrs)	Time to Replace (hrs)	Cost of Replacement (Rs.)
1	A	A1			8	1000000
2		A2	4.09	630.1	12	2500
3		A3	5.5	559.8	12	8000
4		A4	4.75	630.1	16	3500
5		A5	5.2	715.2	0.5	6000
6		A6	5.97	577.1	1	8000
7		A7	5.4	703.8	1	100000
8		A8	5.7	761.8	16	5000
9		A9	6.3	3180	2	2700
10		A10	3	804.4	1	5500
11	B	B1			9	560000
12		B2	4.42	3079	12	1500
13		B3	4.56	4919	2	3500
14		B4	4.56	4919	1	3500
15		B5	4.56	4919	2	6200
16	C	C1	5.94	6962	10	350000
17	D	D1			6	60000
18		D2	4.4	477.1	1	14000
19		D3	5.94	386.7	1	9000
20		D4	4.84	580	1	2300
21		D5	4.4	618	1	1000
22		D6	4.62	4919	1	3000
23		D7	4.62	628	1	1000
24		D8	4.62	4919	1	25000
25		D9	5.94	2320	1	2000
26	E	E1	5.5	1663	9.5	50000
27	F	F1	5.94	8122	9.5	3500
28		F2	4.4	6361	9	95000
29		F3	5.94	8122	7.5	23000
30		F4	2	8304	7	10500
31		F5	4.59	743.1	7.6	4000
32		F6	5.94	8122	10	8000
33		F7	4.62	4697	10.5	20000
34		F8	4.36	4697	10.5	125000

35		F9	4.4	3180	10	18000
36		F10	4.4	3180	11	35000
37	G	G1	6.52	4570	10	45000
38		G2	6.52	4570	10	7500
39	H	H1	6.52	4570	10.5	50000
40		H2	6.52	4570	10.5	8000
41	I	I1	6.52	4570	10	450000
42		I2	5.94	1531	11	20000
43	J	J1	5.18	4086	10	210000
44		J2	5.94	1531	10.5	3000
45	K	K1	3.92	3912	10.5	15000
46		K2	4.71	3818	5	25000
47		K3	4.62	2608	5.5	5200
48		K4	4.55	2897	6	55000
49		K5	4.55	2897	8	500000
50	L	L1	4.27	612	1	3500
51		L2	4.4	636	2	300000
52		L3	4.09	482	1	6000
53		L4	4.53	357	1	9000
54		L5	2.5	831.5	0.5	900
55	M	M1	5.22	3000	1	12575
56		M2	5.62	4919	1	2400
57	N	N1	7.48	6116	9.5	65000
58		N2	6.71	537	0.25	1900
59		N3	2.1	479	4	1500
60	O	O1	3.6	3060	1	8000
61		O2	3.2	4455	1	17000
62		O3	4.7	4162	1.5	30000
63		O4	2.9	3930	2	21000
64		O5	5.2	3501	1	9000

Cost of replacement of different spares:

Sub-Assembly #	Sub-Assembly ID	Component ID	Cost of Replacement with New Genuine Spare	Cost of Replacement with Refurbished Spare	Cost of Replacement with Cannibalized Spare	Cost of Replacement with Non-OEM Spare
1	A	A1	1000000	800000	600000	500000
2		A2	2500	2000	1500	1250
3		A3	8000	6400	4800	4000
4		A4	3500	2800	2100	1750
5		A5	6000	4800	3600	3000
6		A6	8000	6400	4800	4000
7		A7	100000	80000	60000	50000
8		A8	5000	4000	3000	2500
9		A9	2700	2160	1620	1350
10		A10	5500	4400	3300	2750
11	B	B1	560000	448000	336000	280000
12		B2	1500	1200	900	750
13		B3	3500	2800	2100	1750
14		B4	3500	2800	2100	1750
15		B5	6200	4960	3720	3100
16	C	C1	350000	280000	210000	175000
17	D	D1	60000	48000	36000	30000
18		D2	14000	11200	8400	7000
19		D3	9000	7200	5400	4500
20		D4	2300	1840	1380	1150
21		D5	1000	800	600	500
22		D6	3000	2400	1800	1500
23		D7	1000	800	600	500
24		D8	25000	20000	15000	12500
25		D9	2000	1600	1200	1000
26	E	E1	50000	40000	30000	25000
27	F	F1	3500	2800	2100	1750
28		F2	95000	76000	57000	47500
29		F3	23000	18400	13800	11500
30		F4	10500	8400	6300	5250
31		F5	4000	3200	2400	2000
32		F6	8000	6400	4800	4000
33		F7	20000	16000	12000	10000
34		F8	125000	100000	75000	62500
35		F9	18000	14400	10800	9000
36		F10	35000	28000	21000	17500
37	G	G1	45000	36000	27000	22500
38		G2	7500	6000	4500	3750
39	H	H1	50000	40000	30000	25000
40		H2	8000	6400	4800	4000

41	I	I1	450000	360000	270000	225000
42		I2	20000	16000	12000	10000
43	J	J1	210000	168000	126000	105000
44		J2	3000	2400	1800	1500
45	K	K1	15000	12000	9000	7500
46		K2	25000	20000	15000	12500
47		K3	5200	4160	3120	2600
48		K4	55000	44000	33000	27500
49		K5	500000	400000	300000	250000
50	L	L1	3500	2800	2100	1750
51		L2	300000	240000	180000	150000
52		L3	6000	4800	3600	3000
53		L4	9000	7200	5400	4500
54		L5	900	720	540	450
55	M	M1	12575	10060	7545	6287.5
56		M2	2400	1920	1440	1200
57	N	N1	65000	52000	39000	32500
58		N2	1900	1520	1140	950
59		N3	1500	1200	900	750
60	O	O1	8000	6400	4800	4000
61		O2	17000	13600	10200	8500
62		O3	30000	24000	18000	15000
63		O4	21000	16800	12600	10500
64		O5	9000	7200	5400	4500

Phase wise DC and AF for extreme scenarios:

Sub-Assembly #	Sub-Assembly ID	Component ID	$DC_{P_{Normal}}$	$AF_{P_{Normal}}$	$DC_{P_{Dessert}}$	$AF_{P_{Dessert}}$
1	A	A1	1	1	1	1
2		A2	1	1	1	0.7
3		A3	1	1	1	0.75
4		A4	1	1	1	0.8
5		A5	1	1	1	0.9
6		A6	1	1	1	0.8
7		A7	1	1	1	1
8		A8	1	1	1	0.9
9		A9	1	1	1	0.9
10		A10	1	1	1	0.7
11	B	B1	1	1	1	1
12		B2	1	1	1	0.8
13		B3	1	1	1	1
14		B4	1	1	1	1
15		B5	1	1	1	1
16	C	C1	1	1	1	1
17	D	D1	1	1	1	1
18		D2	1	1	1	0.9
19		D3	1	1	1	1
20		D4	1	1	1	1
21		D5	1	1	1	1
22		D6	1	1	1	1
23		D7	1	1	1	0.9
24		D8	1	1	1	0.9
25		D9	1	1	1	1
26	E	E1	1	1	1	1
27	F	F1	1	1	1	1
28		F2	1	1	1	1
29		F3	1	1	1	1
30		F4	1	1	1	1
31		F5	1	1	1	1
32		F6	1	1	1	1
33		F7	1	1	1	1
34		F8	1	1	1	1
35		F9	1	1	1	1
36		F10	1	1	1	1
37	G	G1	1	1	1	1
38		G2	1	1	1	1
39	H	H1	1	1	1	1
40		H2	1	1	1	1

41	I	I1	1	1	1	1
42		I2	1	1	1	1
43	J	J1	1	1	1	1
44		J2	1	1	1	1
45	K	K1	1	1	1	1
46		K2	1	1	1	1
47		K3	1	1	1	1
48		K4	1	1	1	1
49		K5	1	1	1	1
50	L	L1	1	1	1	1
51		L2	1	1	1	1
52		L3	1	1	1	1
53		L4	1	1	1	1
54		L5	1	1	1	1
55	M	M1	1	1	1	1
56		M2	1	1	1	1
57	N	N1	1	1	1	0.8
58		N2	1	1	1	0.9
59		N3	1	1	1	0.9
60	O	O1	1	1	1	1
61		O2	1	1	1	1
62		O3	1	1	1	1
63		O4	1	1	1	1
64		O5	1	1	1	1

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