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Novel Selective Maintenance Approach to Ensure Mission Reliability of Armored Vehicles Considering Multiple Deployment Roles in Distinct Operating Profiles

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ABSTRACT

Given the gravity of the element of surprise in modern warfare, military forces worldwide are constantly attempting to achieve and maintain operational readiness of their critical military equipment. Selective Maintenance (SM) is considered an effective approach for achieving system operational readiness. Effective use of the SM approach for military equipment requires considering various military-specific factors such as multiple deployment roles, distinct operating profiles, human reliability, and the use of refurbished or non-OEM spares. This makes the SM approach for military systems very challenging. This paper presents an approach that formulates the SM problem intending to achieve and maintain the required level of operational readiness for predefined future missions from a military viewpoint. This approach employs a novel methodology that estimates the mission reliability of military equipment while modeling the combined impact of several important military-specific factors. This complex yet necessary integration of various military-specific factors makes the present approach accurate and apt to the exact modus operandi of the armed forces. The developed approach is demonstrated for the maintenance of armored vehicles deployed on distinct missions under different operating conditions. Numerical investigations illustrate the efficacy of the present approach and highlight its advantages over the conventional maintenance approach.

Keywords: Military maintenance; Mission reliability; Selective maintenance optimization

1. INTRODUCTION

Readiness is one of the foremost priorities for military systems[1]. In modern times, where warfare is dominated by the element of surprise, forces are striving hard not only to achieve but also to sustain the operational readiness of critical military equipment[2]. For any critical military system to qualify as war ready, three factors are meticulously observed and ensured: the system's mission capability, operational availability, and mission reliability. In the strive to achieve and effectively manage these factors, the maintenance function plays an instrumental role.

The key to effectively managing military equipment and ensuring their mission preparedness to the desired level is the selection of an effective maintenance approach and further its management. Ample literature on maintenance management, which focuses on the maintenance function of manufacturing systems, is available. A comprehensive review of the literature discussing available maintenance policies, their management, and optimization can be found in Reference 3-4. From the variety of available maintenance policies, the literature suggests the applicability of Selective Maintenance (SM) for military systems that operate in mission modes[5-6]. However, SM models developed for conventional manufacturing systems can not be readily used for the maintenance of military systems.

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Several challenges, like limited availability of maintenance duration, strenuous conditions for repairpersons, extreme operating conditions, uncertain availability of spares at the maintenance locations, which are remote in many cases, etc., make the maintenance function in military systems different from the manufacturing system maintenance. Factors like usage patterns of military equipment compound this difference.

The overall lifecycle of critical military equipment can be classified into peacetime and wartime. 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. It is highly undesirable if any war-critical equipment operating in peacetime is not ready or cannot be ready in some specific limited time when needed for its deployment on some wartime mission. Hence, it is expected from the maintenance function that the war-critical equipment is maintained to be combat-ready even in its peacetime exploitation. Unlike the manufacturing systems, critical military equipment operates in multiple deployment roles like attack, defence, reconnaissance, etc., and in distinct terrains like plains, deserts, high altitudes, amphibious, etc., characterized by extreme environmental conditions.

Additionally, a major emphasis on equipment readiness for extreme situations, while the exact schedule for operations in a future mission is unknown, makes the maintenance function in military organizations more challenging. Therefore, while using any maintenance approach for military systems, it is important to consider several military-specific factors.

The well-established time-based preventive maintenance policies may not always guarantee to ensure high levels of mission reliability for mission-critical military equipment. In addition, the maintenance models discussed in the literature are predominantly designed for generic manufacturing systems and, hence, do not take into account the aforementioned essential military-specific factors. Employing such maintenance models readily for the maintenance of military systems will undermine the accuracy of decision making. Considering the scenario mentioned above and expectations from the maintenance function, there is a need for a tailor-made maintenance approach for military systems, which not only ensures that critical military systems continue to operate as expected but also ensures keeping all of its equipment in a state of readiness at all times. To achieve the requisite level of accuracy in military decision-making, the approach must be able to model jointly the military-specific factors described above.

This paper presents a novel mission reliability based selective maintenance approach which provides an effective solution to this requirement on the readiness front. 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.

The present approach involves continuous monitoring of the mission reliability of the critical equipment against some predefined mission profiles. Whenever the mission reliability reaches the lower threshold, SM optimization is performed to estimate the optimal subset of maintenance activities to be performed on the equipment, which uplifts the mission reliability of the equipment to the desired higher threshold. In this manner, the mission reliability of critical equipment is never allowed to drop less than a threshold. The prime metric in SM is mission reliability. This work presents a methodology to estimate the mission reliability of military equipment while modeling the combined impact of important military-specific factors. Consideration of military-specific factors like operation in multiple operational phases, use of refurbished/cannibalized/non-OEM spares, human error in maintenance, etc., makes this methodology well-suited and accurate for military applications. Although the present approach can be used for the maintenance and readiness of a varied range of critical military equipment, in this paper, the present approach is demonstrated for the maintenance of armored vehicles, viz. Main Battle Tanks (MBT). In order to validate the present approach, its demonstration is compared to the conventional maintenance approach.

2. MILITARY SPECIFIC FACTORS

Over the complete lifecycle, the MBT experiences its exploitation in peacetime and wartime. Although the MBT is made with the sole purpose of employing it in a war, the majority of the exploitation of the MBT is done in peacetime only. Therefore, most of the maintenance activities on the MBT are also performed in peacetime. In peacetime, the MBTs are consistently utilized, and this utilization is majorly in the direction of exercising the wartime scenarios. The overall employment of the MBTs can be classified into four scenarios: normal routine employment, training exercise, mission with prior maintenance break, and mission without prior maintenance break, known as cold start mission. In any of these four deployment scenarios, MBT is expected to work without any failure during the assigned mission. During the deployment or maintenance of MBT in any of these scenarios, several military-specific factors play an important role, as discussed below.

2.1 Operation Across Multiple Terrains

MBTs are required to operate across multiple terrains characterized by extreme environmental conditions. Such diverse operating conditions have a considerable influence on the system's performance and reliability. Literature has shown that these operating and environmental factors affect the reliability of the considered system or component significantly[7]. Various well-received reliability databases provide multipliers to the failure rate of the components operating under different possible environmental conditions[8], which acknowledges the effect of environmental conditions on the system/component's reliability. In order to make the maintenance planning and decisions more accurate and realistic, this effect of diverse operating and environmental conditions needs to be considered in SM formulation.

In this formulation, the combined effect of operating and environmental conditions is linked to the MBT's deployment in terms of Phase. 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 example, the load could be an operational parameter for an engine and its associated components, and ambient temperature could be an environmental parameter for several of the systems in MBT. In order to quantify the phase parameters and integrate them into the SM formulation, we define the phases as follows. Firstly, all the phase parameters are listed (Table 1) along with their units and range to incorporate their variable effect on the

Table 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

component's life and, ultimately, the mission reliability.

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 $PP_{a,b}$.

Across its lifecycle, an MBT operates in one of these defined phases. A change in the phase reflects a change in the reliability of the components of the system. To capture this effect, an *Adjustment Factor (AF)* called as *'Phase wise Adjustment Factor'* (AF_{Phase}) is used. In this study, 2P-Weibull distribution is used to model the reliability of non-repairable systems or components that are mechanical in nature. It is characterized by two parameters: scale parameter (η) and shape parameter (β). The scale parameter – *Eta* is the characteristic life of the component, which is related to the life of the component. The AF_{Phase} adjusts the effects of a phase change and normalizes each phase into a pre-selected default phase. It is estimated as the ratio of the scale parameter of the component for the respective phase to the scale parameter of the component in the default phase (1).

$$AF_{P_x} = \frac{\eta p_x}{\eta p_{default}} \tag{1}$$

Additionally, there are some components that are operated only in some particular phases. Therefore, the phase change also affects the duty cycle of the components of the MBT. In general, the duty cycle is defined as the ratio of the operating duration of the considered component to the total operating duration of the parent system. Here, in the case of phase wise operation, to capture the effect of change in the duty cycle led by a change in the phase, a multiplier called as *Duty Cycle Multiplier* (DC_{Phase}) is used (2).

$$DC_{P_x} = \frac{\text{Total duration the system/component operates in } P_x}{\text{Total duration the parent system operates in } P_x} \tag{2}$$

For the MBTs considered in this study, it is observed that all the phases can be easily defined by considering the terrain and season in which the MBT operates. Generally, MBT operates in different terrains like planes, deserts, high-altitude areas, forests, and shores. The different seasons are summer, winter, and monsoon. A normal season is considered as a baseline season for MBT's operations.

2.2 Multiple Deployment Roles

MBTs are expected to serve multiple deployment roles across its lifecycle. In order to successfully perform any of the deployment roles, an MBT performs different functions independently or sometimes simultaneously. A reliable system means being able to perform its intended functions[9]. Typically, an MBT is expected to perform five deployment roles: DR1: Tank to Tank Combat, DR2: Infantry Protection, DR3: Reconnaissance, DR4: Close Fire, DR5: Deep Penetration; and provide four functionalities: F1: Mobility (M), F2: Firepower (F), F3: Protection (P), F4: Communication (C). Table 2 presents the mapping for requirement of functionalities for different deployment roles. This mapping does not state that a particular functionality is not required in a particular deployment role. It states that the particular deployment role does not require a particular functionality with very high mission reliability, as its probability of use is relatively less.

Table 2. Mapping for functionalities for different deployment roles

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

2.3 Usage of Refurbished/Non-OEM/Cannibalised Spares

Most of the literature on SM considers that every replacement of the component is done using new and genuine spares. In the context of military maintenance, this assumption does not always hold true. Considering several factors related to limited maintenance duration, compact due dates, complex procurement procedures, financial aspects, etc., practices like refurbishment, cannibalisation, and using non-OEM spares flourishes[10]. Many times, these reconditioned or non-OEM spares follow different lifetime distributions[11]. To account for the effect of using such spares with different lifetime distributions on the system reliability, Spare wise Adjustment factor is used. Table 3 presents the adjustment factors for the different spare types.

Table 3. Spare-wise adjustment factors

Spare type	Spare-wise adjustment factor AF_{S_x}
New - Genuine	AF_{S_G}
Refurbished	AF_{S_R}
Non-OEM	$AF_{S_{NO}}$
Cannibalized	AF_{S_G} Age = Initial Age + Cannibalized Age

2.4 Human Error in Maintenance

Humans are liable to make errors. In every maintenance activity, wherever human intervention occurs, there is always some chance of human error. This human error in maintenance may lead to failure or accelerate the failure of the respective component while degrading its performance[12]. In the case of military maintenance, this consideration holds more weight as performing maintenance of military equipment is sometimes very stressful and strenuous, leading to higher chances of committing an error. Therefore, there is an imperative need to integrate the effect of human error in maintenance into the reliability estimations and further to the SM formulation.

Human Reliability Analysis (HRA) methodologies provide the quantitative assessment of the occurrence of human error in any industrial activity in the form of Human Error

Probability (HEP)[13]. HEP for any activity is the probability that a human error will occur while performing the activity. There are many HRA methodologies available to estimate the HEP[13]. To map the effect of human error (estimated in the form of HEP) on the life of the component, an Adjustment Factor (AF_{HEP}) is used in this study. Generally, after any maintenance activity, an inspection is done. In this inspection, many a time, the error is detected and then rectified as well. Therefore, the effective HEP is estimated as (3) using the estimated HEP.

$$Effective\ HEP = [Estimated\ HEP] \times [1 - Probability\ of\ Detection] \quad (3)$$

Finally, the AF_{HEP} is estimated using Eqn. (4)

$$AF_{HEP} = [Effective\ HEP] \times [Expert\ Judgement\ for\ effect\ of\ HEP] + [1 - Effective\ HEP] \quad (4)$$

In the absence of required data, this methodology makes use of expert judgement, and the effect of HEP on the component is captured through expert judgement. Here, the expert states the judgement regarding the effect of HEP in a particular range

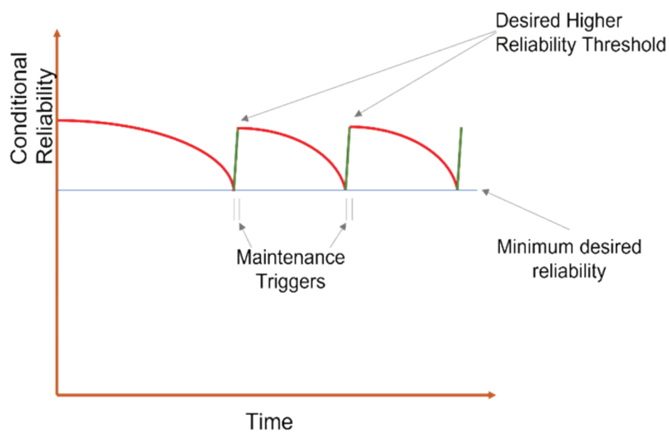

Figure 1. Maintenance event triggering w.r.t. conditional reliability.

on the component life in the form of an adjustment factor to the scale parameter of the component.

3. MISSION RELIABILITY BASED SELECTIVE MAINTENANCE APPROACH

The present approach involves continuous monitoring of the mission reliability of every equipment for predefined mission profiles. When the mission reliability reaches a predefined lower threshold, 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. However, the maintenance break is always full of constraints to perform all the maintenance. Hence, initially, an SM problem is formulated and solved for optimization to get a cost-optimal subset of maintenance activities that satisfies all the conditions. Once the higher reliability threshold is achieved, the equipment is made available for its utilization. In this way, the equipment is not allowed to be utilized beyond a predefined lower mission reliability threshold. In other words, it can be stated that the equipment is never allowed to be utilized beyond a certain point, from where maintaining it to the desired higher reliability threshold within a predefined time is difficult. Figure 1 depicts the approach with the trend of mission reliability of equipment against a mission profile.

To execute this approach, mission reliability estimation and further its use in maintenance optimization play an instrumental role. The details of these are discussed in the following subsections.

3.1 Effective Age Estimation

As all the considered military-specific factors influence the degradation of the system during utilization, the age of a component/system is a good metric to consider the effect of all these factors on the component/system. Kijima introduced the idea of a virtual age to model the effect of maintenance activities on the component's life[14]. Later, researchers illustrated the impact of maintenance actions and modeled that through virtual age[15]. Therefore, in the proposed mission reliability estimation

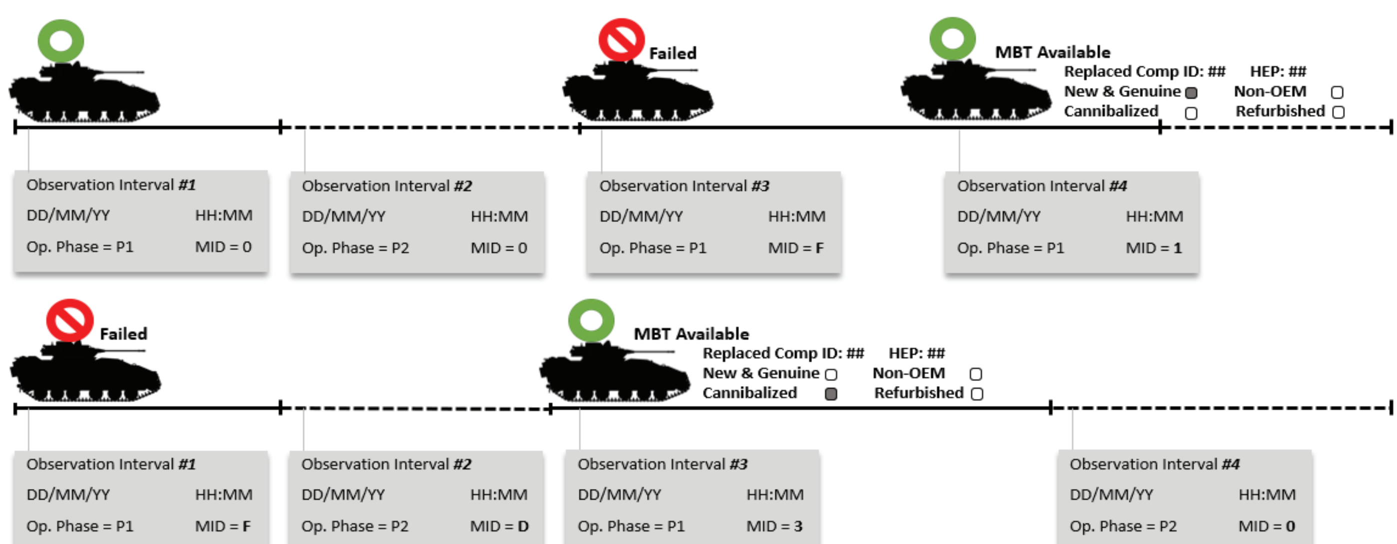

Figure 2. Systematic capturing of information for effective age estimation.

methodology, the effect of all the considered military-specific factors is incorporated in the age of the component/system in the equipment. The operating age of the component/system after incorporating the effect of all the military-specific factors is termed here as *effective age*. In order to estimate the effective age of the components in the system, three aspects need to be captured carefully: (i) phase wise operating history, (ii) maintenance history, and (iii) calendar age of the components.

Figure 2 depicts the systematic capturing of these three aspects using the developed usage monitoring mechanism. As shown in Fig. 2, in every observation interval, the status of the MBT is recorded with information like the date and time of inspection, the operating phase, and based on the operating status of the system, a maintenance ID (MID) is also recorded. MID represents the status of the MBT for its operations and maintenance. For every maintenance action, HEP is also recorded. Additionally, it shows the details of maintenance actions, like the spares used in the maintenance activities.

With all the data records, as shown in Fig. 2, the calendar age is estimated. Based on the operational phases, spares used in the maintenance activity for replacement, and the HEP in the corresponding maintenance activity, the corresponding adjustment factors are determined, and then the effective age of the component is estimated as shown in Eqn. 5.

$$\text{Effective Age } (EA_i) = \frac{CA \times DC_{Phase}}{AF_{Phase} \times AF_{Maintenance} \times AF_{HEP}} \quad (5)$$

where, *CA (calendar age)* refers to the usage of the component since its installation. Values of DC_{phase}, AF_{phase}, $AF_{maintenance}$, and AF_{HEP} are accordingly determined.

3.2 Mission Reliability Estimation

As the name of the present approach suggests, mission reliability plays a determining role in the overall approach. As this approach deals with the reliability of military systems, which mainly consists of mechanical components which fail with the usage with wear and tear as the primary failure mechanism, Weibull distribution is used here[16]. Weibull distribution is able to take care of increasing or decreasing failure rates[17]. For a 2-parameter Weibull distribution, the probability density function is given by Eqn. 6, and the reliability function for any component is given as Eqn. 7.

$$f(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (6)$$

$$R(t) = e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad (7)$$

where: t is the time duration for which reliability is to be estimated. Here, t = mission duration.

η is the scale parameter,

β is the shape parameter.

In order to estimate the reliability of a component that has already accumulated some age (*Age*), the conditional reliability of that component is estimated as given in Eqn. 8.

$$R(t|Age) = \frac{R(t+Age)}{R(Age)} \quad (8)$$

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

$$R(t|Age) = \frac{e^{-\left(\frac{t+Age}{\eta}\right)^{\beta}}}{e^{-\left(\frac{Age}{\eta}\right)^{\beta}}} \quad (9)$$

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. As per the system configuration of the MBT, multiple assemblies are connected as series configuration; and every assembly consists of multiple components connected in series configuration. Eqn. 10 can be used to estimate the mission reliability of system with such reliability block diagram. Ultimately, the mission reliability of a MBT (R_{Tank}) is estimated using Eqn. 10.

$$R_{Tank} = \prod_{i=1}^{N_{(i)}} \left(\prod_{j=1}^{M_{(i,j)}} \left(R_{(i,j)}\right)\right) \quad (10)$$

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.

Reliability is a function of time. For mission reliability estimation, a future mission profile is required to be known in detail. Figure 3 depicts all the information available regarding the equipment history and future mission profile for an MBT.

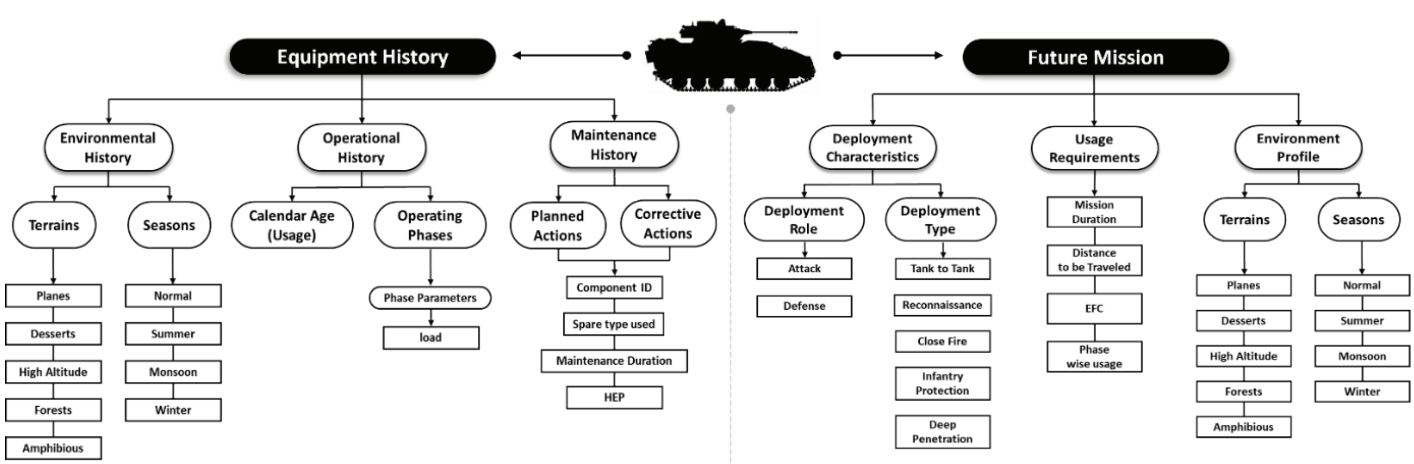

Figure 3. Information available at the maintenance decision point.

As shown in Fig. 3, the mission profile for which the readiness of the particular MBT is to be assured is known in the form of three different attributes, viz: deployment characteristics, usage requirements, and environment profile. For example, the mission profile for which the MBT is maintained to be ready is of attack role where all four functionalities are required, and it will need to travel for 150 km in desert terrain in the summer season. The MBT is required to operate for continuous operation of 36 hrs. Based on the given mission profile, it is known which phase the MBT will operate in and what the duration of the mission is. 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 effective mission duration is formulated as Eqn. (11):

$$\text{Effective Mission Duration } (M_d) = \frac{MissionDuration \times DC_{Phase}}{AF_{Phase}} \tag{11}$$

Once M_d is known for every component, the mission reliability of every component can be estimated using Eqn. 9 and translated into the mission reliability of MBT using Eqn. 10. Further, the mission reliability of a MBT for a predefined mission is continuously monitored. As discussed earlier in this section, once this mission reliability touches the lower mission reliability threshold, a maintenance event is triggered.

3.3 Selective Maintenance Optimization

Upon the triggering of a maintenance event, one of the key decisions to be made is regarding the selection of the optimal set of maintenance activities to be carried out on the MBT. Here, the prime intent is to perform the required maintenance activities to enhance the mission reliability of the MBT to the higher mission reliability threshold in the presence of all the constraints in the maintenance break. In every triggered maintenance event, the resources to be utilized are limited. Additionally, the obvious objective of minimizing the downtime of the MBT is always there. Considering the necessity of maintenance of momentum on battlefields, SM emerges as the optimally effective solution, especially when modeled with dynamics of deployment roles, terrains, spare support, and human reliability. Therefore, taking into account the nature of operations of the equipment under consideration and the objective of the maintenance event, the SM problem is formulated and then solved in this approach.

To formulate the SM problem effectively, we thoroughly studied the state-of-the-art literature on SM. To efficiently manage the maintenance function for the industrial systems, which operate in a sequence of missions, SM was introduced[18]. A detailed review of literature discussing SM[19-20].

Al-Jabouri, *et al.* systematically categorized the overall literature on SM based on two SMP features: formulation characteristics and solutions approaches[20]. Formulation characteristics are composed of three groups of characteristics related to the system, maintenance, and model. System characteristics deal with features like configuration, dependencies, states, levels, etc. 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[18]. Series-parallel configurations are the most explored systems in the literature on SM, as most of the real-world systems are configured as series-parallel systems. Only a limited number of research have endeavored to explore the SM for complicated real-life systems characterized by intricate reliability configurations. Cassady et al. expanded the original SMP by including intricate configurations to make it more suitable for real-life systems[21]. Diallo, *et al.* propose a transformation of the multidimensional knapsack problem to efficiently solve the SMP for intricate and redundant structures that consist of k out of n configurations with non-identical components[22]. Many industrial applications involve the utilization of fleets of assets, for which maintenance decisions need to be made for all the components and assemblies in the particular fleet, which enhances the mathematical complexity of optimizing the SMP. Researchers made successful attempts to solve the complex SMPs where the decision-making domain is for the fleets of assets[21-22]. Khatab, *et al.* presented a novel SMP model for the fleet level while considering several imperfect maintenance levels and multiple repair channels[22]. Zhang, *et al.* presented a novel SMP for military aircraft fleets while considering limitations regarding repair facilities and repairpersons, taking into account the uncertainties related to stochasticity in mission durations and breaks on the battlefield[23]. Further, the SMP was modeled for industrial systems where the systems and components belong to multi-state nature[24]. It was extended to explore the effect of variable loading conditions on the MSS[25].

Consideration of the level of maintenance is crucial as it actually influences the effective age of the systems and ultimately influences the maintenance decisions. Khatab, *et al.* introduced the inclusion of imperfect maintenance to SMP, which was based on the age reduction approach[26]. Later, several models that considered the multiple levels of maintenance in SMP were presented[5,24,27-28]. The third characteristic is about the model. The majority of the SMP formulations are modeled as single-objective optimization problems where the objective is to maximize the system's reliability or minimize the maintenance costs. There are some other models with different objectives, like environmental impacts[29] and minimizing the number of repair times[30]. To make the application of SM more effective in real-life systems, the stochastic component in mission duration, as well as maintenance break duration, was also incorporated in SMP[31].

Down the line, researchers attempted to effectively manage the combinatorial complexity in solving SM optimization. In the domain of maintenance optimization, the application of meta-heuristics such as Particle swarm optimization[32], Genetic Algorithm[33-34] has been investigated effectively. On a similar line, some diverse heuristics and meta-heuristics have been explored to efficiently solve the SMP in lesser computational time, such as Differential Evolution[27], Genetic Algorithm[35], Simulated Annealing algorithm[36], Particle swarm optimization[37].

In the past two decades of the progression of SM research, various application domains other than manufacturing systems have been explored. Recently, an SM model leveraging the combined benefit of predictive analytics and deep learning has been presented for aircraft engine systems[38]. Modern application for nuclear reactor systems is also explored[39]. The use of deep reinforcement learning is done to dynamically solve the SMP over a finite time horizon for a coal transportation system[40]. Sharma, *et al.* applied SM to military systems for forecasting spare parts management[16]. However, most of the literature on SM focuses on its application to manufacturing systems. As discussed, to achieve the best-desired outcomes, the maintenance policy also needs to be applied in consideration of critical military-specific factors.

The objective of the present selective maintenance problem is to find a cost-optimal set of maintenance actions that achieve 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 selective maintenance problem under consideration at the maintenance decision point is as follows:

$$Min\ C = \sum_{i=1}^{N(i)} \left(\sum_{j=1}^{N(i,j)} \left(C_{(i,j)} M_{(i,j)} \right) \right) \tag{12}$$

Subject to:

$$R_{Tank} \geq R_{Des} \tag{13}$$

$$T_m \leq T_{av} \tag{14}$$

where:

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

$M_{(i,j)}$: Multiplier to the cost of i_{th} component of j_{th} assembly based on the spare type,

M_0: Component is not replaced,

T_m: Total time to perform all the selected maintenance activities,

T_{av}: Total time duration available. Here, the time duration is as per the readiness definition,

R_{Des}: Higher mission reliability threshold,

R_{Tank}: Mission reliability of the MBT against the mission profile.

While solving the above optimization problem, some practical assumptions are considered, those are listed here:

(i) 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.

(ii) All the genuine spares are available with the inventory. (The unavailability of any of the spares can be indicated through the user input file).

With usage, components accumulate some age, and hence, for the estimation of mission reliability of an MBT, the effective age (from Eqn. 5) is used, and mission reliability is estimated as conditional reliability, as shown in Eqn. 15.

$$R(M_d|Age) = \frac{e^{-\left(\frac{M_d + E\_Age}{\eta}\right)^{\beta}}}{e^{-\left(\frac{E\_Age}{\eta}\right)^{\beta}}} \tag{15}$$

To solve the formulated SM problem, the Genetic Algorithm (GA) is used, as it is largely acknowledged by the literature on selective maintenance.

4. DEMONSTRATION OF THE PROPOSED APPROACH

To demonstrate the efficacy of the present approach, this section presents the application of this approach to the maintenance of an MBT. The prime intent of this section is to showcase how a particular MBT can be maintained during routine peacetime utilization while keeping its desired readiness level by applying the present approach. Firstly, a reliability block diagram of a particular MBT is developed, and accordingly, all the data required for mission reliability estimation and selective maintenance optimization is gathered. The complete dataset for an MBT is given as Annexure I[16]. Based on the dataset, with the present approach, the utilization of an MBT for the duration till its first designated overhaul is analysed.

For demonstration case I, the MBT is required to be ready for a deployment role of deep penetration for a continuous operation of 36 hrs. The mission is in plains, and the season is normal. As the MBT is in a deep penetration role, all four functions (M/F/C/P) are required. The higher and lower mission reliability thresholds are set as 0.9 and 0.8, respectively. As per the readiness definition, the allowable delay in deployment is 04 hrs. If the MBT can be maintained to be ready with a higher mission reliability threshold with a maintenance break of 4 hrs., it will be considered available.

On implementing the present approach for the decided time till the first designated overhaul of the MBT in routine peacetime, it is observed that a total of 12 maintenance events were triggered. The details of these maintenance events are given in Table 4.

It can be read as: when the mission reliability of the

Table 4. Details of maintenance actions in demonstration case I

Maint. 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 (C) | D3 (R) | L1 (G) | L5 (G)
7	A7 (NO) | D4 (C) | D5 (G) | L3 (R) | L4 (R)
8	D7 (G) | L2 (C) | N2 (G) | N3 (G)
9	A2 (C) | A3 (NO) | A6 (C) | D3 (C) | 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 (C) | D3 (C) | D7 (R) | L2 (NO) | L3 (R) | L4 (G) | L5 (G)

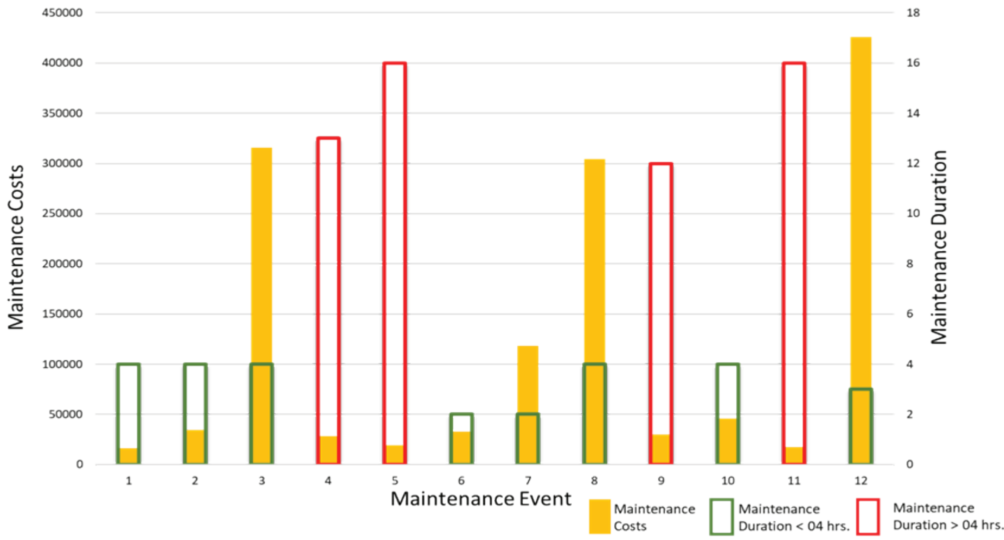

Figure 4. Details of maintenance events in demonstration case I.

MBT reached down to 0.8 for the very first time, the first maintenance event was triggered. SM optimization suggested that the replacement of components L3, L4, and N3 will result in achieving a mission reliability of 0.9, which is the higher mission reliability threshold. Additionally, the approach suggested that in case of non-availability of a new genuine spare, the use of other spare types will also suffice the objective of achieving the higher mission reliability threshold. The letters mentioned in the bracket, along with the component ID, suggest which type of spare can be used in such a situation. In the first maintenance event, the maintenance action of L3 (R) suggests that in case of unavailability of a new and genuine spare of L3, installation of a properly refurbished spare will also suffice the objective. However, installation of a new and genuine spare is always recommended as it results in achieving a higher reliability enhancement, which will result in prolonging the trigger of the next maintenance event. Additional details of the consequence of executing the maintenance plans at every trigger in terms of cost and duration are shown in Fig. 4.

In the considered case I, out of twelve maintenance events, only four events resulted in a maintenance duration of more than 4 hrs.

Furthermore, using this analysis, spare management can also be done proactively. The analysis also results in informing

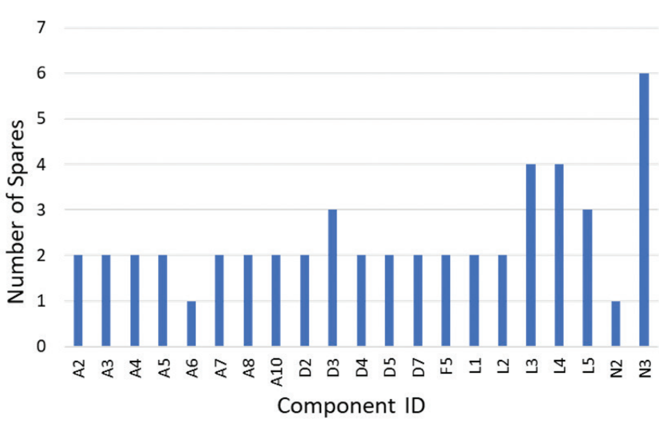

Figure 5. Spares requirements in demonstration case I.

about the expected requirements of spares for a longer time horizon. Fig. 5 gives information about the requirements of spares for a particular MBT for the defined time horizon.

In order to demonstrate the application of the present approach for deployment roles in different terrains, the approach is applied to the same MBT but for deployment roles in different terrains like high altitude, forest, amphibious, and deserts. In the analysis, all the inputs are kept constant as of demonstration case I, and only the terrain has been changed. We found the largest difference in several of the key metrics when the approach was tested for MBT, which is to be kept ready for the same as the previous deployment role but in desert terrain, and the season is summer.

As the terrain changed from plains to desert, and the season changed from normal to summer, key metrics like the total number of maintenance events triggered increased by 25%. Eventually, the planned downtime also increased by ~ 53%. In this scenario, the total cost incurred in all the maintenance events is also increased by ~ 21%. This variation in the results validates the need to consider terrains and seasons of the MBT utilization. Fig.6 depicts the changes in four key metrics viz: total number of maintenance events required till first designated overhaul, % events where the readiness level cannot be achieved in less than or equal to 04 hrs., total maintenance cost incurred in all the maintenance events, and total planned downtime across the time horizon under consideration. In Fig. 6, it can be observed that all four key metrics vary remarkably with the change in terrain. All the metrics are visibly skewed towards the scenario with dessert terrain. It shows that, although the prime objective of achieving readiness of the MBT is achieved, the approach needs to be independently analyzed for cases with multiple or different terrains. The 'One size fits all' approach will not prove to be good when implementing the approach for MBTs in different terrains or operating in distinct operational phases.

Similar to terrains, the values of metrics significantly vary with the change in deployment roles. For a case where the present approach is applied to an MBT (demonstration case II), which needs to be maintained ready for a mission

Figure 6. Operating profile wise comparison.

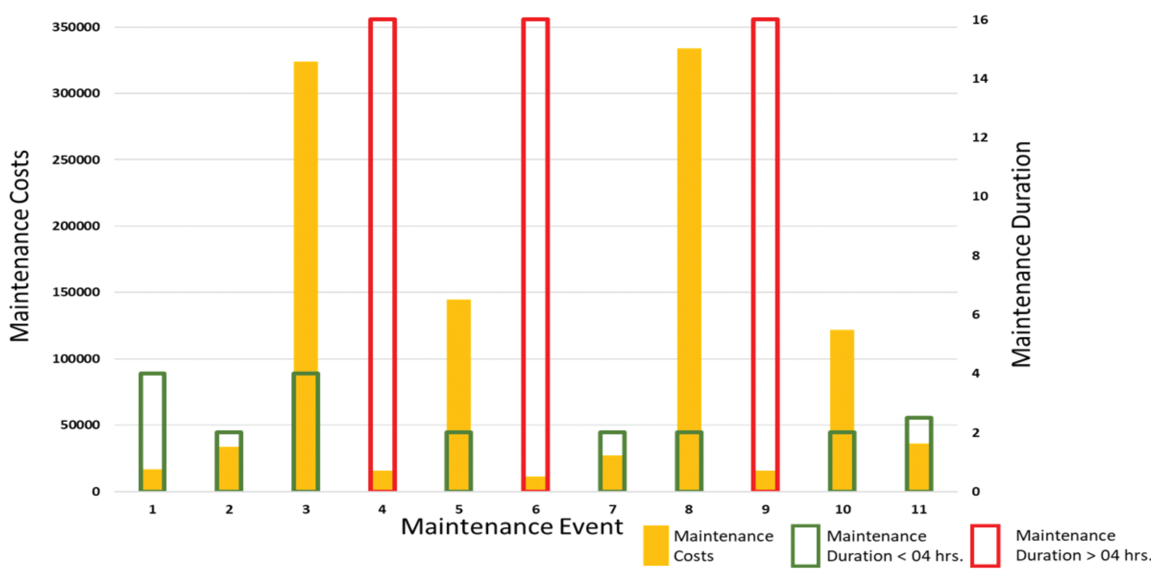

Figure 7. Details of maintenance events in demonstration case II.

of reconnaissance role of 36 hrs. of continuous operation in planes, the results differ while achieving the readiness of the MBT. 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 in less than 4 hours, and the required reliability was achieved. Figure 7 highlights all the other relevant details in this case of demonstration.

4.1 Comparison With the Conventional Maintenance Approach

This section presents a comparison of the proposed approach against the representative conventional maintenance approach. Considering the large number of equipment and the complexity involved in overall maintenance management, a time-based preventive maintenance policy is used for the maintenance of these military equipment. In the considered representative time-based maintenance policy, there are multiple PM groups. Once the MBT is taken for a maintenance event, as per this representative policy, all the components in the same group are replaced at once. Table 5 presents the maintenance groups asper this representative time-based maintenance policy.

Table 5. Maintenance groups for time-based preventive maintenance policy

PM Group 1		PM Group 3		PM Group 4	
Interval: Every 2 yrs.		Interval: Every 4 yrs.		Interval: Every 5 yrs.	
Sr. No.	Component ID	Sr. No.	Component ID	Sr. No.	Component ID
1	D3	1	A2	1	A8
2	L4	2	A4	2	A10
PM Group 2		3	A5	3	L5
Interval: Every 3 yrs.		4	A6		
1	A3	5	A7		
2	D2	6	D5		
3	D4	7	D7		
4	L3	8	F5		
5	N2	9	L1		
6	N3	10	L2		

In addition to the four maintenance groups mentioned in Table 5, there are some more whose maintenance interval is higher than the time horizon in the consideration of the present demonstrated cases. Hence, those maintenance groups are not mentioned here.

On analysing the same MBT to follow this representative time-based maintenance policy, some of the key metrics are estimated. To punctually follow this time-based maintenance policy for a MBT for the time horizon of eight years, a total planned (fixed) maintenance cost of 1009800 is required. The planned (fixed) downtime to follow this policy is 82 hrs. However, even after punctually following the time-based maintenance policy, the mission reliability of the MBT drops to very low levels, as the focus of this time-based maintenance policy is largely on operational availability and not mission reliability. The mission reliability of the MBT for the same mission of 36 hrs. of continuous operation (same as demonstration case I) just before the first PM event drops to 0.451. From here, to achieve the desired mission reliability of 0.9, at least 18 hrs. of maintenance duration will be required. Even after the first maintenance event, as per the PM policy, the mission reliability of the MBT for the attack role will be enhanced to 0.7. From this point, at least 12 hrs. of maintenance break is required to achieve the desired mission reliability of 0.9. Furthermore, the mission reliability of the MBT just before the Second PM event (at the end of the third year of usage) drops to 0.3. After the second PM break, the mission reliability will be enhanced to 0.39. From where it is impossible to achieve the higher mission reliability threshold and deploy the MBT on the mission without any unacceptable delays. In such a situation, the earlier discussed undesirable situation will arise where the MBT cannot be deployed on the wartime mission for which it is actually intended.

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. It is apparent that the existing approach results in excellent readiness management of the MBT. 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.

5. CONCLUSIONS

The novelty of this paper lies in incorporating dynamics of multiple deployment roles, deployment across multiple terrains, usage of multiple spare types, and human error into the framework of SM. 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. Moreover, the modeling so achieved also lends itself as a vital input to test the operational scenario models from the viewpoint of logistics support. Numerical investigations on multiple scenarios show that the considered multiple deployment roles and distinct operating profiles significantly influence the mission reliability of the equipment and further impact the maintenance decisions. The depiction of the proposed approach implies that implementing it will effectively guarantee the desired level of mission reliability of the equipment over the specified time horizon, hence reaching the desired levels of operational availability. By utilising the approach, the mission reliability is assessed based on all the equipment functions, leading to the sustainment of the mission capability. Therefore, the successful implementation of the approach will guarantee that the critical military equipment meets all three previously mentioned factors, which are meticulously assessed to determine the equipment's war readiness.

In a nutshell, while the defense forces across the globe are striving towards achieving higher readiness levels, the present approach offers an effective way to actually achieve it on the ground. In future research, it would be worth exploring the application of the present approach to a fleet of critical equipment and investigating how the presentapproach results in achieving the readiness of the overall fleet.

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Annexure I

System configuration			Functional association				Replacement cost				2-P Weibull Dist. Param.				Adjustment factors (Demonstration Case I)				
Comp ID	Assembly	Component	Mobility	Communication	Firepower	Protection	New & Genuine	Refurbished	Non-OEM	Cannibalized	Weibull Shape Parameter	Weibull Scale Parameter	Age	TTR	AF_{p1}	AF_{p2}	AF_{p3}	AF_{p4}	$DC_{multiplier}$
1	A	A1	Y		Y		1000000	800000	600000	500000			0	8	1	1	1	1	1
2		A2	Y		Y		2500	2000	1500	1250	4.09	630.1	0	12	0.95	0.7	1	1	1
3		A3	Y		Y		8000	6400	4800	4000	5.5	559.8	0	12	0.95	0.75	1	1	1
4		A4	Y		Y		3500	2800	2100	1750	4.75	630.1	0	16	1	0.8	1	1	1
5		A5	Y		Y		6000	4800	3600	3000	5.2	715.2	0	0.5	1	0.9	1	1	1
6		A6	Y		Y		8000	6400	4800	4000	5.97	577.1	0	1	1	0.8	1	1	1
7		A7	Y		Y		100000	80000	60000	50000	5.4	703.8	0	1	1	1	1	1	1
8		A8	Y		Y		5000	4000	3000	2500	5.7	761.8	0	16	1	0.9	1	1	1
9		A9	Y		Y		2700	2160	1620	1350	6.3	3180	0	2	1	0.9	1	1	1
10		A10	Y		Y		5500	4400	3300	2750	3	804.4	0	1	0.95	0.7	1	1	1
11	B	B				Y	560000	448000	336000	280000			0	9	1	1	1	1	1
12		B2				Y	1500	1200	900	750	4.42	3079	0	12	0.98	0.8	1	1	1
13		B3				Y	3500	2800	2100	1750	4.56	4919	0	2	1	1	1	1	1
14		B4				Y	3500	2800	2100	1750	4.56	4919	0	1	1	1	1	1	1
15		B5				Y	6200	4960	3720	3100	4.56	4919	0	2	1	1	1	1	1
16	C	C				Y	350000	280000	210000	175000	5.94	6962	0	10	1	1	1	1	1
17	D	D	Y				60000	48000	36000	30000			0	6	1	1	1	1	1
18		D2	Y				14000	11200	8400	7000	4.4	477.1	0	1	1	0.9	1	1	1
19		D3	Y				9000	7200	5400	4500	5.94	386.7	0	1	1	1	1	1	1
20		D4	Y				2300	1840	1380	1150	4.84	580	0	1	1	1	1	1	1
21		D5	Y				1000	800	600	500	4.4	618	0	1	1	1	1	1	1
22		D6	Y				3000	2400	1800	1500	4.62	4919	0	1	1	1	1	1	1
23		D7	Y				1000	800	600	500	4.62	628	0	1	1	0.9	1	1	1
24		D8	Y				25000	20000	15000	12500	4.62	4919	0	1	1	0.9	1	1	1
25		D9	Y				2000	1600	1200	1000	5.94	2320	0	1	1	1	1	1	1
26	E	E	Y				50000	40000	30000	25000	5.5	1663	0	9.5	1	1	1	1	1
27	F	F1	Y				3500	2800	2100	1750	5.94	8122	0	9.5	1	1	1	1	1
28		F2	Y				95000	76000	57000	47500	4.4	6361	0	9	1	1	1	1	1
29		F3	Y				23000	18400	13800	11500	5.94	8122	0	7.5	1	1	1	1	1
30		F4	Y				10500	8400	6300	5250	2	8304	0	7	1	1	1	1	1
31		F5	Y				4000	3200	2400	2000	4.59	743.1	0	7.6	1	1	1	1	1
32		F6	Y				8000	6400	4800	4000	5.94	8122	0	10	1	1	1	1	1
33		F7	Y				20000	16000	12000	10000	4.62	4697	0	10.5	1	1	1	1	1
34		F8	Y				125000	100000	75000	62500	4.36	4697	0	10.5	1	1	1	1	1
35		F9	Y				18000	14400	10800	9000	4.4	3180	0	10	1	1	1	1	1
36		F10	Y				35000	28000	21000	17500	4.4	3180	0	11	1	1	1	1	1
37	G	G1			Y		45000	36000	27000	22500	6.52	4570	0	10	1	1	1	1	1
38		G2			Y		7500	6000	4500	3750	6.52	4570	0	10	1	1	1	1	1
39	H	H1			Y		50000	40000	30000	25000	6.52	4570	0	10.5	1	1	1	1	1
40		H2			Y		8000	6400	4800	4000	6.52	4570	0	10.5	1	1	1	1	1
41	I	I1			Y		450000	360000	270000	225000	6.52	4570	0	10	1	1	1	1	1
42		I2			Y		20000	16000	12000	10000	5.94	1531	0	11	1	1	1	1	1
43	J	J1	Y				210000	168000	126000	105000	5.18	4086	0	10	1	1	1	1	1
44		J2	Y				3000	2400	1800	1500	5.94	1531	0	10.5	1	1	1	1	1
45	K	K1	Y				15000	12000	9000	7500	3.92	3912	0	10.5	1	1	1	1	1
46		K2	Y				25000	20000	15000	12500	4.71	3818	0	5	1	1	1	1	1
47		K3	Y				5200	4160	3120	2600	4.62	2608	0	5.5	1	1	1	1	1
48		K4	Y				55000	44000	33000	27500	4.55	2897	0	6	1	1	1	1	1
49		K5	Y				500000	400000	300000	250000	4.55	2897	0	8	1	1	1	1	1
50	L	L1	Y		Y		3500	2800	2100	1750	4.27	612	0	1	1	1	1	1	1
51		L2	Y		Y		300000	240000	180000	150000	4.4	636	0	2	1	1	1	1	1
52		L3	Y		Y		6000	4800	3600	3000	4.09	482	0	1	1	1	1	1	1
53		L4	Y		Y		9000	7200	5400	4500	4.53	357	0	1	1	1	1	1	1
54		L5	Y		Y		900	720	540	450	2.5	831.5	0	0.5	1	1	1	1	1
55	M	M1	Y		Y		12575	10060	7545	6287.5	5.22	3000	0	1	1	1	1	1	1
56		M2	Y		Y		2400	1920	1440	1200	5.62	4919	0	1	1	1	1	1	1
57	N	N1	Y		Y		65000	52000	39000	32500	7.48	6116	0	9.5	1	0.8	1	1	1
58		N2	Y		Y		1900	1520	1140	950	6.71	537	0	0.25	1	0.9	1	1	1
59		N3	Y		Y		1500	1200	900	750	2.1	479	0	4	1	0.9	1	1	1
60	O	O1		Y			8000	6400	4800	4000	3.6	3060	0	1	1	1	1	1	1
61		O2		Y			17000	13600	10200	8500	3.2	4455	0	1	1	1	1	1	1
62		O3		Y			30000	24000	18000	15000	4.7	4162	0	1.5	1	1	1	1	1
63		O4		Y			21000	16800	12600	10500	2.9	3930	0	2	1	1	1	1	1
64		O5		Y			9000	7200	5400	4500	5.2	3501	0	1	1	1	1	1	1