The Effect of Imperfect Maintenance on a System's Condition considering Human Factors

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Human Factors (HF) have a significant impact on the maintenance quality and are recognized as a specific cause of Imperfect Maintenance (IM). Technician inexperience, poor procedure quality, or environmental factors are exemplary HF and can lead to insufficient repair or inspection. However, due to limited data, many studies describe HF only qualitatively as a possible cause of IM or highly simplify the effect of HF. This paper attempts to analyze the effect of HF on the system's restoration level in order to provide a more realistic post-maintenance operating system condition. Furthermore, the economic savings potential of a fully automated condition-monitoring approach and the subsequent reduction of adversarial HF within the maintenance process will be analyzed. As use case serves the tire pressure maintenance task of an Airbus A320. Based on fuzzy logic, an IM model is developed, considering the effect of HF individually on restoration and inspection tasks using human reliability assessments. The aircraft maintenance eco-system is simulated with a prescriptive maintenance model to enable the evaluation of monetary and non-monetary performance indicators. A comparative study revealed that perfect maintenance approaches tend to vastly underestimate the maintenance-related cost aspects. Moreover, the study showed that a technician's lack of experience cannot be compensated by an improved working environment. Only the use of an automated monitoring system to replace error-prone inspection tasks resulted in an overall cost reduction. The developed model allows the individual evaluation of the technician's expected performance to enable a more targeted deployment of the available workforce and to improve the effectiveness of maintenance.

Keywords: Imperfect Maintenance, Imperfect Inspection, Human Factor, Human Reliability Analysis, HEART.

1. Introduction

In order to predict upcoming maintenance events, optimize maintenance resources, and estimate maintenance costs reliably, a system's state of degradation needs to be diagnosed as accurately as possible during operation. In reality, the accuracy of the obtained system condition and the quality of executed maintenance tasks is subject to different ambient conditions. This effect is described as Imperfect Maintenance (IM). However, when modeling maintenance, the system state after maintenance is often assumed As Good As New (AGAN) - also referred to as perfect maintenance. Another frequently used assumption is that the system's state after maintenance is As Bad As Old (ABAO), i.e. the repair scope has been limited to its absolute minimum.

Do et al. (2015) pointed out that IM can be related to two main causes. One is the bad realization of an intended perfect maintenance, e.g. due to Human Factor (HF) such as lack of attention, stress or limited repair time. The other cause is a cost-saving maintenance policy that for instance may result in low-quality spare parts or logistics. Carlo and Arleo (2017) defined three practical cases of IM, namely conscious IM (e.g. use of unsuitable spare parts), unconscious IM (e.g. low skills), and the replacement of one component within a complex system. A more general definition of the effect of IM is given by Lie and Chun (1986) who assumed that the effectiveness of a conducted maintenance task can be related to the resources spent and the relative age of the system. Other researches defined that IM can be classified by the respective task conducted, i.e. doing nothing corresponds to minimal repair while replacing the system is assumed to fully restore the system condition and intermediate levels of maintenance would correspond to IM (Wang et al., 2019).

In this paper, IM is defined as the incapability

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of a technician to restore the system to its best condition due to the negative effect of HFs. We propose an IM model that integrates the effect of HFs to determine the resulting system condition. The effect of imperfection is considered individually for restoration tasks and inspection actions.
The structure of the paper is as follows. First, a literature review is conducted to identify research gaps. Next, the IM model based on a Human Reliability Assessment Technique (HRAT) and fuzzy logic is introduced. Finally, a comparative study between the deployment of experienced and inexperienced technicians is presented to demonstrate the effect of varying HFs on the resulting degree of system restoration.

2. Literature Review

This literature review examines IM models for binary systems, Multi-State Systems (MSSs) and models considering the effect of HFs.

2.1. *Imperfect Maintenance*

The majority of IM models deal with binary systems, that only allow the consideration of a fully functioning state and a complete failure state. These models are extensively reviewed by Pham and Wang (1996). One frequently used model due to its ease in application is the imperfect repair model by Brown and Proschan (1983) where a repair action leads either to an AGAN condition with probability p or to an ABAO condition with probability $1 - p$. Another important IM model is the virtual age model developed by Kijima (1989). In his work, he described the system's state through a virtual age where IM reduces that age between AGAN and ABAO. Another probabilistic approach to implement IM is given by Wang and Pham (1996) with the introduction of a quasi renewal process. They assumed that after each repair, the system's lifetime is reduced by a fraction α, with $0 < \alpha < 1$, while repair times are increased by the multiplier β, with $\beta > 1$.
More recent IM models are developed for MSSs. Liu and Huang (2010) defined a MSS as a system possessing varying performance levels ranging from properly functioning to total failure. The system's failure is determined by a comparison of the currently available performance with a user-defined threshold. They considered IM as follows: After a repair, all elements are restored to their best state; however, the element's state transition accelerates with each repair cycle. Pandey et al. (2013) considered a MSS with multi-state components and define IM between the options of doing nothing and replacement. In their model, the quality of maintenance for each component depended on the allocation of maintenance resources in order to achieve the maximum system reliability for the subsequent mission. A similar approach was pursued by Khatab et al. (2017) who defined a list of different maintenance activities ranging from minimal repair to overhaul. They defined IM actions according to the age reduction coefficient θ, i.e after repair, a component's age t is reduced to $t * \theta$, with $0 \leq \theta \leq 1$.

2.2. *Effect of Human Factors*

An early attempt to deal with IM due to HFs is done by Helvik (1980) who defined IM as insufficient maintenance task execution. In his work, imperfectness is defined as the probability that a maintenance action does not result in a system condition improvement due to the personnel's skill, procedure quality, and system's maintainability. Bao et al. (2016) defined three operational scenarios for power system operations and proposed for each scenario a respective HRAT. IM is considered by the probability that a human error occurs and leads to a system failure. Zhao et al. (2019) considered the effect of HFs on multi-state components by different reliability levels of workers defined through their human error probabilities. In contrast to binary systems, human error does not lead to the component's failure, but rather to a lower component state than the targeted one. Okumura et al. (1996) evaluated the effect of imperfect inspection where two types of probabilities are considered: probability of a wrong diagnosis of a system being in an acceptable state when actually the system is in risky state and probability of a wrong diagnosis for vice versa. Hennequin et al. (2009) suggested that the quality of maintenance depends on the technician's skills and the time spent on completing the task. They used a fuzzy logic approach to determine the quality of maintenance. Based on this work, Segura et al. (2016) refined the analysis of HFs by consideration of the human skill's effect, depending on the factors knowledge, know-how, and behavior. Two fuzzy inference systems (FISs) are used in their framework to determine the technician's skill and subsequently assess the maintenance quality, depending on the task complexity, task duration, and the technician's skill.

2.3. *Research Gap*

In conclusion, it has been identified that most IM models are defined for binary systems which solely represent the states of failure and functionality. Since the effect of HFs does not necessarily lead to the system's failure, but can cause a lower degree of restoration, these models are insufficient for the scope of this paper. The majority of IM models for MSS assume that the quality of maintenance depends on the respective maintenance task. However, the system's restoration degree can also vary for identical tasks with the worker's efficacy. IM models considering the effect of HFs on the system condition are limited. One precise classification of the effect of technician skill on a system's restoration level is given by Hennequin et al. (2009). Nevertheless, important HFs such as fatigue, environmental conditions, and the quality of maintenance procedures are not considered. Furthermore, the effect of HFs on an inspection task receives low attention. In respect to the highlighted research gaps, the subject of this paper is to develop an IM model which assesses the system condition after imperfect restorations and imperfect inspections considering HFs. Additionally, the impact of a fully automated condition monitoring system towards the avoidance of adversarial HFs within the maintenance process will be analyzed.

3. Model Description

We assume a system in operation, which is inspected periodically at $T, 2T, ..., kT$ time intervals. The system of interest possesses a finite number of health levels defined as

$$HL = [HL_1, HL_2, ..., HL_n] \tag{1}$$

with HL_1 corresponding to a perfect AGAN condition and HL_n to a complete failure. According to the measured condition HL_x, the technician has to decide whether the system can continue operation $HL_x > HL_{min}$ (maintenance threshold) or needs to be maintained $HL_x \leq HL_{min}$. Hence, the system is maintained aperiodically with respect to its measured states. If the system is repaired to its initial nominal new condition, the maintenance action is defined as perfect maintenance. Exemplary, this will always be the case when replacing a system completely. If a system is minimally maintained, meaning no major restoration task has been performed, it is assumed to have the condition as it had before maintenance. In this paper, IM is defined as the incapability of the technician to restore a system to its first into service condition due to unfavorable HF effects. The quality of maintenance can therefore vary between the best state (HL_1) and the condition before maintenance (HL_x). In most practical engineering tasks, the maintained system has to fulfill a minimum quality level to be able to continue performing its intended function, otherwise the maintenance task would be repeated obligatorily. Hence, it is assumed that the system condition has to be restored to a minimum required level to pass a mandatory quality test.

The inspection task itself, on the other hand, does not include any restorative action that may improve the system's health level. In reality, inspection activities and restoration tasks can cause the effect of worse or worst maintenance, for instance by intending to inspect or repair a component, the technician may damage another. This effect is assumed rare, therefore having a minimal effect on the system state and will be neglected. Nevertheless, the inspection task has an impact on the decision, when and which aperiodic maintenance task has to follow. An incorrect condition assessment may lead to incorrect aperiodic maintenance action decisions such as unintended premature replacements or unnecessary extensive maintenance events increasing the system's downtime. Hence, imperfect inspection is defined as the incapability of a technician to assess the real system condition due to unfavorable effect of HFs.

A technician's performance is subject to variations of HFs, e.g. the performance of a technician can increase with a more favorable working environment, more experience or training. On the other hand, the technicians performance may decrease with rush working conditions, fatigue, or when performing under stress. The assessment of the technician's performance level is conducted with the Human Error Assessment and Reduction Technique (HEART) (Williams, 1988). This method enables the identification of major influences on human errors and human performance. HEART belongs to the first generation of HRATs and can be applied to any industry that aims to evaluate the effect of HF on the Human Reliability (HR) (Smith, 2011). For the HEART application, nine generic task types with basic failure probabilities defined as Nominal Human Unreliability (NHU), are provided (Williams, 1988). Additionally, there are 40 Error Producing Conditions (EPCs), i.e. performance shaping factors that represent the impact of HF on the human reliability (Bell and Williams, 2017). In HEART, each EPC is given by a maximum multiplier that depicts the maximum impact of the respective HF. The maximum multiplier can be adjusted by the Proportion of Effect (PE) parameter, ranging from zero to one, to scale the intensity of the effect (Smith, 2011). The Assessed Impact (AI) of each EPC is defined as:

$$AI = ((EPC - 1) \cdot PE) + 1 \tag{2}$$

The Human Error Probability (HEP) of one specific maintenance task can be assessed with:

$$HEP = NHU \cdot \prod_{i=1}^{k} AI_i \tag{3}$$

Taking Eq. (3) into consideration, the HR can be calculated as follows:

$$HP = HR = 1 - HEP \tag{4}$$

where Human Performance (HP) describes the performance efficacy. For the evaluation of HP the required PEs of each EPC have to be defined. PEs are generally defined by experts or adopted with the best endeavors of the applicant (Smith, 2011). In this paper, the respective PEs will be defined with appropriate HF studies from literature or through logical correlations. The respective PEs are divided into discrete steps, between zero and one, to model different ambient condition categories.

3.1. *Human Factors in Aviation*

HFs can be classified into four major categories: organization, supervision, immediate environment, and technician (Allen and Rankin, 1997). This paper will focus on HFs of the latter two categories. From these, HF parameters for the IM model are selected (ref. Fig. 1).
Knowledge, Skills, and Experience: This category consist of the parameters age, training, certifications, and experience. According to the HEART method, after a peak at the age of 25, the HR steadily decreases up to the age of 85 due to a continuous deterioration of cognitive abilities (Bell and Williams, 2017). This relation is used for the PE discretization of the age parameter. For the remaining parameters, the PE discretizations are done according to the conducted performance study by Seong-O Bae et al. (2013). They showed the relationship between different levels of training, experience, and certification on one hand and the resulting human performance on the other. Although, their study has been performed outside the aviation industry context and a transfer of the obtained results will need to be further examined, their identified relationships will be applied for the use case demonstration in this paper.
As aviation technicians and engineers need to be properly trained and licensed to be able to perform aviation maintenance, the number of certifications is represented by type ratings in the case of B1, B2, and C holders and by the number of tasks specified on the task list in the case of CAT A holders. Moreover, the training level is defined by the number of practical and formal training sessions completed by the aircraft technician. For more information regarding aircraft technicians license categories and training requirements, the reader is referred to Hinsch (2019).
Fatigue: The HF fatigue will be expressed by

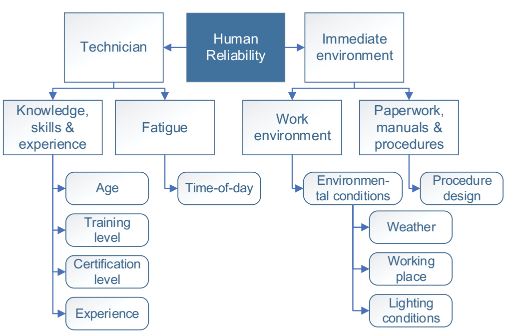

Fig. 1. Human Factor parameters of the IM model

the parameter time-of-day. An increase in fatigue level - equivalent to a reduction in alertness level - results in a decline in performance (Maddox, 2006). His examination of the alertness level over the day is used to proportionate PE for different day times (see Tab. 1). The HEART method proposes, that the lowest reliability is around 3am, translating to the maximum multiplier of 2.4. Peak alertness is assumed with the minimum multiplier of zero. The PE parameter for all other times of the day have been calculated through interpolation and - wherever given - through conversion of the corresponding EPC.

Table 1. Alertness levels with respect to time-of-day

Time	Alertness Type	EPC	PE
$[0...3am]$	Dangerously drowsy	2.4	1.00
$[3...6am]$	Dangerously drowsy	2.4	1.00
$[6...9am]$	Reduced alertness	1.85	0.77
$[9...12pm]$	Peak alertness	0	0.00
$[12...3pm]$	Slightly impaired	1.3	0.54
$[3...6pm]$	Slightly impaired	1.3	0.54
$[6...9pm]$	Peak alertness	0	0.00
$[9...12am]$	Slightly impaired	1.3	0.54

Work Environment: Aircraft maintenance is performed under three different environments: workshops, hangars, and open-air (apron or ramp). Within this paper, the HF for various environmental conditions is considered via different working environments with regard to weather, working place, and lighting conditions. The parameter environmental conditions can take the states given in Tab. 2. The term "Outside" (line maintenance) is defined as working at open-air (apron or ramp) and "Inside" (shop or base maintenance) is defined as working within a facility. It is assumed that working outside is connected to higher noise levels and a busier working environment. Comfortable weather is given by the "zone" of relative humidity and temperature that a human feels comfortable working in. This is assumed with an ambient temperature between 20 to 25 degrees Celsius and a relative humidity between 29 percent to 60 percent (Maddox, 2006). Outside this zone, it is assumed that the technician works

Table 2. Environmental conditions

Environmental condition	PE
Outside, faint light, uncomfortable weather (OFUW)	1
Outside, faint light, comfortable weather (OFCW)	0.8
Outside, bright light, uncomfortable weather (OBUW)	0.6
Outside, bright light, comfortable weather (OBCW)	0.4
Inside, faint light (IF)	0.2
Inside, bright light (IB)	0.0

Table 3. Procedure designs

Proc. design	Description	PE
Individual	Procedure that is individually optimized for the applicant. This assumes a procedure form especially designed from the technician supported by a qualified engineer.	0
Standard	Procedure provided by aircraft manufacturer without any modifications done by the maintenance provider.	0.5
Poor	A procedure which has been modified or expanded by a prior technician and passed to another technician to follow the subsequent steps.	1

under uncomfortable weather conditions. Bright lighting conditions include facility lighting such as a common lighting system, including windows and fixtures, as well as natural lighting given by daylight. If additional task lighting, such as drop lights, interior aircraft lights, flashlights, or portable light stands are required, it is assumed to work under faint lighting conditions. To represent each different environmental condition, the PE is divided into six equidistant fractions.

Paperwork, Manuals, and Procedures: In the aviation sector, many human errors can be related to poorly designed procedures (Drury, 2006). To capture this effect, the parameter procedure design is introduced. Three possible procedure designs are considered in the IM model which result in equidistant PEs (ref. Tab. 3).

3.2. *Effect of Imperfection*

Since HF data are inherently vague, a method is needed to describe and quantify them at a higher detail level. Hennequin et al. (2009) first applied fuzzy logic to deal with HFs in IM. While they only assessed the technician's skill, this paper intends to consider seven different HFs. As the complexity of fuzzy logic systems increases exponentially with an increase of input parameters, we propose to model HFs differently. First, the effect of the given HFs on the technician's HR will be assessed through the HEART methodology. Next, the determined HR is considered as an input parameter in the intended Fuzzy Inference System (FIS). Due to its adaptability and ease of application, the Mamdani FIS is used in this context to apply fuzzy logic. The chosen FIS is a rule-based fuzzy logic following the steps of fuzzification, rule evaluation, and defuzzification (Sudiarso and Labib, 2002; Zimmermann, 2001). Input and output parameters are expressed by membership functions (MF), which divide the parameters into different subsets. Within the developed fuzzy system, all MF are represented either through trapezoid or triangular fuzzy sets due to their computational efficiency (Zimmermann, 2001).

For IM, it is assumed that the quality of maintenance, given in terms of a Restoration Degree (RD), depends on the input parameters Degradation Progress (DP) and HR. With advancing DP, the system is assumed to be maintained with an higher quality, because at the time of inspection, the system's state of degradation can vary between $DP = 0$, representing the nominal, new condition, and $DP = 1$, representing a complete system failure. After maintenance, the system can be restored between HL_{min} and HL_1.

Furthermore, based on the fuzzy logic, the Inspection Error (IE), which indicates the difference between a measured and the true system condition, is assessed. The IE is assumed to depend on the input parameters HR and the Inspection Interval (II). An increasing inspection frequency is presumed with a lower IE because more previous measurement data can lead the technician on a more accurate track. The IE is then randomly generated as a positive or negative deviation from the true value with a 50 percent probability in each case.

4. Use Case Scenario

To demonstrate the IM model's capability, it is applied to the use case of the tire pressure maintenance task of an Airbus A320. The effect of HFs is less intensive here, nevertheless, the use case has a high implication on operations due to its high frequency in aircraft maintenance. The aircraft maintenance eco-system is simulated via a prescriptive simulation framework (PreMaDe), allowing to assess monetary and non-monetary performance indicators. The reader is referred to Meissner et al. (2021) for specifications of PreMaDe. The prescriptive simulation framework is able to optimize the time for maintenance when using a condition monitoring technology, i.e. based on the given operational conditions (e.g. available technicians) and the system's remaining useful lifetime, PreMaDe selects the optimal point for maintenance. This is to be understood as a prescriptive maintenance strategy. However, this feature is omitted in the following study in order to obtain comparable results.

The conventional tire pressure check occurs periodically at three-day intervals. In contrast, the pressure check can be omitted when assuming the automatic continuous transmission of tire pressure data measured via a Tire Pressure Indication System (TPIS). Perfect inspection is assumed when such a system is integrated into the aircraft. Note, that reading errors are neglected in this case.

Depending on the tire's condition, different aperiodic maintenance tasks can follow. The input DP contains the three possible aperiodic maintenance tasks, i.e. inflate, inflate plus re-check and replacement, as subsets. Here, the chosen subset

boundaries for each maintenance task are defined according to the manufacturer's recommendations (see for thresholds (Meissner et al., 2021)). The lower boundary of the output RD is defined closely above the threshold of inflation and the upper boundary marks a perfect restoration. The output IE contains the subsets precise, standard, and poor. While the precise subset results in an IE of zero percent, the poor subset, defined as six percent, always results in an undesirable maintenance task as there is a five percent incremental difference in health between each aperiodic task. Intermediate values via a triangular membership function is assumed for the standard IE.
The aircraft operation is simulated for a 30-days time span. During this time, the aircraft is operated continuously, the tire is inspected according to the defined inspection threshold, and subsequent maintenance tasks are performed according to the measured tire condition. Three technicians work during this period fulfilling their eight hours shift daily.
Under the given assumptions, it is investigated whether less complex systems such as the tire should rather be maintained by experienced or less experienced technicians. First, the study is investigated under the same working conditions. Second, it is investigated if improvements in working conditions (procedure design and work place) for the assignment of less experienced technicians yield economic advantages. Last, it is investigated if inexperienced staff with improved working conditions and TPIS application yield economic advantages.
For the short simulation time span of 30-days, it is assumed that the technicians are working in a season of comfortable weather conditions during day and night. Note, that the effect of fatigue is considered according to the time of day when maintenance is performed. In addition to the available simulation parameters (see Meissner et al. (2021)), PreMaDe was extended by the process parameters depicted in Tab. 4. It is assumed that an experienced technician performs maintenance tasks more quickly and receives a higher salary in return.

Table 4. Additional process parameters

Hangar fee per hour	$288[a]
Apron fee per hour	$84[a]
Man hour cost (experienced)	$80[b]
Man hour cost (inexperienced)	$60[b]
Time factor all tasks (experienced)	0.8[b]
Time factor all tasks (inexperienced)	1.0[b]

a: Based on information from "Price List Line Maintenance Services" found at [`https://www.lufthansa-technik.com/line-maintenance`]
b: Based on assumptions.

5. Simulation Results

In this section, the results of the presented use case scenarios will be discussed. First, the maintenance-related cost - calculated with PreMaDe - will be examined. This cost-share comprises of four different categories: Man Hour (MH), material, facility, and waste-of-life cost. MH cost is directly correlated to the time required for each task execution and depends on the technician's experience level which correlates in this case with the salary. Material cost incorporate all cost aspects of required tools or repair material for the tasks; thus, they depend on the extent of the necessary maintenance task. The facility cost incorporates all cost related to the usage of available facilities, i.e. the hangar or apron infrastructure, and is calculated based on the task duration. Ultimately, the waste-of–life cost is an artificial cost element that applies whenever maintenance will be conducted prematurely, i.e. the system's remaining useful lifetime will not be fully exploited. As depicted in Fig. 2, the individual cost elements will be aggregated for each use case and their respective cost shares as well as normalized by the total cost that would result with a perfect maintenance regime. This way, we can observe the relation between perfect and imperfect maintenance as well as the individual cost composition for each scenario. Comparing the height of each individual column, shows that by neglecting IM aspects within the simulation, the resulting cost will systematically be underestimated. Additionally, in terms of overall cost minimization, it seems beneficial to assign the maintenance tasks to more experienced technicians – unless an automated condition monitoring system is available (ref. IM experienced). Although the wage level increases with growing experience, the resulting shorter task execution times and higher tasks precision overcompensate these additional costs (ref. IM inexperienced). As the human performance can improve within a designated maintenance facility, it has further been examined whether this improvement can compensate for any inexperi-

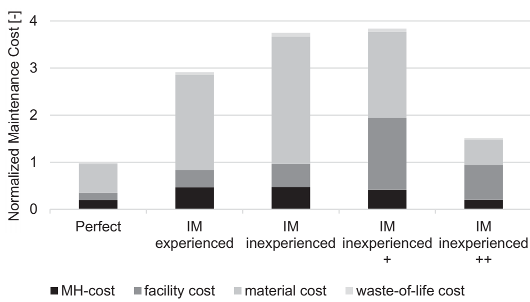

Fig. 2. Comparison of maintenance costs

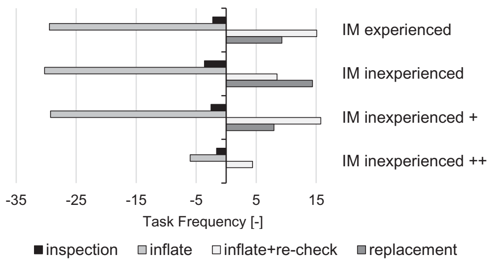

Fig. 3. Task frequency in relation to perfect maintenance

ence of the technicians (ref. IM inexperienced+). Although, the additional precision will result in a reduction of costly maintenance tasks, the adversarial effect of an increase in facility cost prevents any overall benefit. Thus, the mere adjustment of ambient conditions cannot compensate for a lack of experience under given assumptions. However, an automated condition monitoring technology – and the subsequent avoidance of the failure prone inspection task – will boost the (inexperienced) technician's performance well beyond their experienced counterparts (ref. IM inexperienced++). This effect can also be observed in Fig. 3, where the varying frequency for specific maintenance tasks is shown, compared to their equivalents under perfect maintenance assumptions. A lack of experience results in less accurate obtained tire pressure measurements and, ultimately, leading to a higher frequency of more extensive tasks, such as tire replacements. Notably, the task frequency hardly changes between the different experience levels, except of tire replacements and re-inflation tasks with an additional check. Only, with the utilization of an automated condition monitoring system, the task frequency will be significantly reduced, yielding the above-mentioned, overall cost advantage. Note, that a perfect inspection (ref. IM inexperienced++) ensures that the tire condition is determined accurately and restored early, avoiding unnecessary extensive maintenance such as replacements.

Finally, Tab. 5 shows the different human performances for equally experienced technicians throughout the day – subdivided for the different task types. Eliminating any differences in performance due to different levels of training and age, these values show the influence of different working conditions, i.e. the ambient lighting and the human performance as a result of the time-of-the-day. As can be seen, the technician operating throughout the night (9pm to 5am) provides the least performance, while during the day shift (1pm to 9pm) the resulting HR is the highest. As the performance difference is the highest for inspection tasks, these tasks should be either automated completely or not being conducted during night – at least from a human performance perspective.

Table 5. Normalized HR deviation compared to night shift technician for use case experienced staff

Task Type	Technician	
	Morning Shift	Day Shift
ΔHR inspection	13%	33%
ΔHR inflate + re-check	2%	4%
ΔHR inflate	1%	3%

6. Conclusion

This paper has presented a model for estimating the impact of IM in the aviation industry. It has been shown that there is a lack of comprehensive approaches that consider the effect of multiple human factors on maintenance activities. Subsequently, a model has been developed that determines a system's restoration degree under consideration of different human factors, using the HEART method. The resulting human reliability of the available technician has been used within a fuzzy logic to estimate the resulting system condition after maintenance. The capability of the developed IM model has been demonstrated on a tire pressure maintenance task. In particular, it has been examined how different levels of experience and maintenance assistance systems can influence the overall efficacy of maintenance.

The study revealed the following key findings. First, neglecting IM will result in a systematic underestimation of maintenance-related cost. Second, if no other augmentation systems are available, an increased experience level of the maintenance staff will yield favorable results, despite any subsequent increase of wages. Third, even under improved working conditions, a lack of technician's experience level cannot be compensated as the increased facility cost prevents any overall cost benefit. Fourth, only the utilization of an automated condition monitoring system resulted in a strong reduction of maintenance cost. Finally, tasks that are subject to a strong variation of HR, e.g. inspection tasks, should not be conducted during overnight stops in order to improve the maintenance's efficacy. For future studies, it should be examined how maintenance decision making should incorporate human reliability in order to allow a holistic optimization among all involved stakeholders.

References

Allen, J. P. and W. L. Rankin (1997). An Integrated Approach to Maintenance Human Factors. *SAE*

Transactions (106), 1185–1190.

Bao, Y., C. Guo, J. Zhang, J. W. S. Pang, and Z. Zhang (2016, dec). Impact analysis of human factors on power system operation reliability. *Journal of Modern Power Systems and Clean Energy 6*(1), 27–39.

Bell, J. L. and J. C. Williams (2017, jun). Evaluation and Consolidation of the HEART Human Reliability Assessment Principles. In *Advances in Human Error, Reliability, Resilience, and Performance*, pp. 3–12.

Brown, M. and F. Proschan (1983, dec). Imperfect repair. *Journal of Applied Probability 20*(4), 851–859.

Carlo, F. D. and M. A. Arleo (2017, dec). Imperfect maintenance models, from theory to practice. In *System Reliability*. InTech.

Do, P., A. Voisin, E. Levrat, and B. Iung (2015). A proactive condition-based maintenance strategy with both perfect and imperfect maintenance actions. *Reliability Engineering & System Safety 133*, 22–32.

Drury, C. G. (2006). The Human Factors Guide for Aviation Maintenance and Inspection: Chapter 6: Procedures and Technical Documentation. Technical report, Federal Aviation Administration. 2nd edition.

Helvik, B. E. (1980). Periodic maintenance, on the effect of imperfectness. In *10th International Symposium on Fault-Tolerant Computing*, pp. p.204–206.

Hennequin, S., G. Arango, and N. Rezg (2009, sep). Optimization of imperfect maintenance based on fuzzy logic for a single-stage single-product production system. *Journal of Quality in Maintenance Engineering 15*(4), 412–429.

Hinsch, M. (2019). *Industrial aviation management: A primer in European design, production and maintenance organisations*. Berlin, Germany: Springer.

Khatab, A., E. Aghezzaf, I. Djelloul, and Z. Sari (2017, apr). Selective maintenance optimization for systems operating missions and scheduled breaks with stochastic durations. *Journal of Manufacturing Systems 43*, 168–177.

Kijima, M. (1989, mar). Some results for repairable systems with general repair. *Journal of Applied Probability 26*(1), 89–102.

Lie, C. H. and Y. H. Chun (1986). An Algorithm for Preventive Maintenance Policy. *IEEE Transactions on Reliability 35*(1), 71–75.

Liu, Y. and H.-Z. Huang (2010, sep). Optimal Replacement Policy for Multi-State System Under Imperfect Maintenance. *IEEE Transactions on Reliability 59*(3), 483–495.

Maddox, M. (2006). The Human Factors Guide for Aviation Maintenance and Inspection: Chapter 3: Fatigue and Fitness for Duty & Chapter 4: Facility Design. Technical report, Federal Aviation Administration.

Meissner, R., H. Meyer, and K. Wicke (2021). Concept and Economic Evaluation of Prescriptive Maintenance Strategies for an Automated Condition Monitoring System. *International Journal of Prognostics and Health Management*.

Okumura, S., A. K. S. Jardine, and H. Yamashina (1996, sep). An inspection policy for a deteriorating single-unit system characterized by a delay-time model. *International Journal of Production Research 34*(9), 2441–2460.

Pandey, M., M. J. Zuo, and R. Moghaddass (2013, nov). Selective maintenance modeling for a multi-state system with multistate components under imperfect maintenance. *IIE Transactions 45*(11), 1221–1234.

Pham, H. and H. Wang (1996). Imperfect maintenance. *European Journal of Operational Research 94*(3), 425–438.

Segura, M. A., S. Hennequin, and B. Finel (2016). Human factor modelled by fuzzy logic in preventive maintenance actions. *International Journal of Operational Research 27*(1/2), 316.

Seong-O Bae, Samsung Economic Research Institute, Korea Louise Patterson, and Kyung Hee University Korea (2013). The effect of corporate investment in human capital on employee's performance: Major Korean financial corporation examined. In *Academy of strategic management Journal 2013*, Volume 12, pp. 55–76.

Smith, D. J. (2011). *Reliability, Maintainability and Risk 8e: Practical Methods for Engineers including Reliability Centred Maintenance and Safety-Related Systems*. Burlington, USA: Elsevier Science.

Sudiarso, A. and A. W. Labib (2002, jan). A fuzzy logic approach to an integrated maintenance/production scheduling algorithm. *International Journal of Production Research 40*(13), 3121–3138.

Wang, H. and H. Pham (1996, oct). A quasi renewal process and its applications in imperfect maintenance. *International Journal of Systems Science 27*(10), 1055–1062.

Wang, Y., E. Elahi, and L. Xu (2019). Selective Maintenance Optimization Modelling for Multi-State Deterioration Systems Considering Imperfect Maintenance. *IEEE Access 7*, 62759–62768.

Williams, J. (1988). A data-based method for assessing and reducing human error to improve operational performance. In *Conference Record for 1988 IEEE Fourth Conference on Human Factors and Power Plants*, 5-9 June 1988 , Monterey, USA. IEEE.

Zhao, Z., B. Xiao, N. Wang, X. Yan, and L. Ma (2019, may). Selective maintenance optimization for a multi-state system considering human reliability. *Symmetry 11*(5), 652.

Zimmermann, H.-J. (2001). *Fuzzy Set Theory—and Its Applications*. Springer Netherlands.