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RESEARCH ARTICLE

Incorporating Human Factors in Delay Time Modeling of Inspection Maintenance Using Fuzzy Logic

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ABSTRACT Human factors (HF) affecting maintenance performance are common in practice, but have never been considered in delay-time modelling (DTM). The objective of this study is to integrate HF affecting maintenance performance in DTM to obtain an accurate and realistic optimal inspection interval. First, a list of HF that affects maintenance performance is identified through a literature review. Then, a conceptual framework is proposed to illustrate the integration of HF in the maintenance system. Three significant HF are selected, based on experts' opinion to be incorporated into the DTM, namely operator experience level, operator fatigue level, and task seriousness. Fuzzy modeling is used to estimate a time allowance for human factors, which can be added to the inspection duration of the DTM. Two inspection models are developed based on the modified DTM with the objectives of minimizing expected downtime and total cost per unit of time. Both models are validated against a realistic case study. Sensitivity analysis is performed to study the effect of HF on determining the optimal inspection interval. The results show that failing to account for HF results in increasing the frequency of (unnecessary) inspections; hence interruptions of production by up to 45.5% based on expected downtime and 49% based on expected total cost. This also results in the allocation of 25% to 92% less inspection time, which may significantly affect operator performance and work quality. The developed models provide a mechanism for decision makers to set an accurate inspection duration that accounts for HF and hence determines a realistic optimal inspection interval. In addition, the proposed conceptual framework can help manufacturing firms in designing maintenance systems with superior long-term performance.

INDEX TERMS Human factors, inspection maintenance, delay-time model, fuzzy logic.

I. INTRODUCTION

Maintenance has been a major area of interest for researchers and practitioners as it contributes to a significant part of overall costs (up to 70% in manufacturing industries) [64]. Maintenance offers a potential source of cost savings and competitive advantage due to its role in maintaining and improving product quality, availability, performance efficiency, on-time delivery, safety and overall plant productivity [1], [50]. Making cost-effective maintenance decisions is necessary to achieve a company's strategic goals for higher profitability and better competitiveness [2].

Maintenance can be defined as those activities required to keep plant assets in a functioning state. It involves activities like inspection, repair, replacement, and modification of a component or a group of components of a system. Preventive maintenance (PM) is one of the most important maintenance policies where all actions are performed at a planned, periodic and specific schedule to prevent potential plant failures from occurring. Inspection is one of the key functions in PM, which is widely used in industry to identify the condition of the plant and make maintenance decisions [64], [67]. Maintenance problems of real systems, such as production plants, is

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complicated and requires sophisticated solution methods [38]. Therefore, the conventional reliability analysis of time-to-first failure or time-between failures becomes insufficient to capture the relationship between the performance of the equipment and maintenance intervention [20]. This relationship can be captured using the delay-time concept.

The delay-time concept divides the asset failure process into two stages: normal operating time (from new to the point of defect identification) and failure delay time (from the point of defect identification to failure occurrence). Failure delay time allows PM to be performed to identify and remove/rectify defects before failures [48]. Wang et al. [59] give an example of fine cracks that appear in the welding joint of a vessel. Cracks will grow over time and eventually lead to leakage, if not repaired.

Delay-time modelling (DTM) has been efficiently used to model a wide class of actual industrial maintenance problems in general and inspection problems in particular [61]. DTM provides a framework that can be readily applied to modelling the consequences of alternative maintenance and inspection practices until the best one is identified. DTM was initiated by Christer [18] in building maintenance and was first applied to an industrial maintenance problem in Christer and Waller [24]. Since then, research work has been carried out on the theory of DTM [6], [20], [21], [22], [43], [48], [52], [63] and applications of DTM along with other PM models [26], [32], [33], [47], [49]. Most PM policies aim at slowing down system (i.e., machine) degradation while it operates to increase its availability. The performance of maintenance policies depends on several factors, such as operator experience, availability of parts, type of industry, repair time and task complexity. In order to have a good model of the system, it is essential to take into account not only the industrial constraints but also the human issues. Human factors (HF) is a discipline devoted to optimizing the design variables that affect the human-machine interaction to improve both work performance and operator wellbeing [41].

The literature review revealed that none of the previous studies considered HF in DTM when applied to the optimization of inspection and maintenance. Given the high human involvement in various maintenance activities, the incorporation of HF into maintenance problems is essential to obtain more accurate and realistic results (e.g., cost-effective inspection policy) [34]. In addition, HF consideration can help to reduce human errors and accidents [54], maintenance time [27] and improve maintenance quality [34]. However, due to the difficulty of identifying and incorporating HF in mathematical modelling, the majority of inspection and maintenance models ignore them. Therefore, in this study, we integrate HF in basic DTM by using the fuzzy set theory [70]. This theory is one of the most competent artificial intelligence techniques that have shown effectiveness in handling uncertainties and modelling complex and ill-defined problems [53]. The contribution of this study lies in the development of realistic inspection models (based on modified DTM) that account for HF related to an operator's experience and fatigue level and seriousness of task. The concept of fuzzy logic is used to integrate HF into the basic inspection models. The inspection policy obtained by the developed inspection models are expected to be more accurate, realistic and attainable by maintenance operators. In addition, this study attempts to bridge the gap, in research and practice, between the fields of HF and maintenance system design that has not been previously discussed in the maintenance literature; this is achieved by presenting a conceptual framework that explains the relationship between both fields. This knowledge gap may be limiting manufacturing firms' ability to profit from application of HF principles in their maintenance system designs.

The primary objective of this study is to develop two delay-time based inspection models that incorporate HF (i.e., significant human-based risk factors of maintenance performance) into the existing basic inspection models. The two developed models determine the optimal inspection intervals that minimize the expected downtime and total cost per unit of time, respectively. To achieved this, we first identify a list of HF that affect maintenance performance through a literature review. Experts' opinion is used to determine the most significant HF affecting maintenance performance. Then, a fuzzy model is developed to estimate a time allowance for human factors, called human factors allowance (HFA), from the significant HF. In this case, inspection duration will be a function of HFA instead of being constant (as in the existing models).

The secondary objective is to propose a conceptual framework that addresses and explains the integration of HF in the maintenance system. A case study is used to illustrate the utility of the developed models. The rest of the paper is organized as follows: a literature review is provided in Section II, the problem statement is provided in Section III and the models developed for the problem are provided in Section IV. The utility of the developed models is demonstrated in a realistic case study in Section V.

A comparison between original inspection models and modified ones, as well as sensitivity analysis, is presented in Section VI. Section VII includes the conclusion and future research directions.

II. LITERATURE REVIEW

The research work on DTM has progressed considerably in two main streams. The first research stream focuses on DTM for single-unit systems (i.e., composed of a repairable component). The second research stream focuses on DTM for multi-unit (complex) systems, which comprise of many independent components that each of which can cause system breakdown. The method described in this paper is based on a single repairable component, which can be considered as a building block for the main cases of practical multi-unit systems. Therefore, this section reviews the literature on DTM for single-unit systems. More details about DTM for multi-unit systems can be found in [64].

The literature on DTM for single-unit systems can be divided into two main parts, those studies concerning systems with a two-stage failure process (under single or multiple failure modes) and those concerning systems with a three-stage failure process. Most studies related to a two-stage failure process assume a single dominant failure mode. Christer [19] developed the basic delay-time model of single-unit systems reliability subject to one type of inspectable defect and assuming perfect inspection. The basic model has been extended by many authors in different directions. Cerone [14] proposed a simplified approximation model for Christer's [19] basic delay-time model and provided some illustrative numerical examples. The author showed that a linear approximation of average reliability over an inspection period yields a relative error of the order of 10%. In 1993, Cerone extended the basic delay-time model by addressing what is called ''the converse problem''. This problem is concerned with determining the optimal inspection interval, for a given number of inspections, that will result in the maximum reliability at some point in the future. Attia [4] simplified the basic delay-time model by assuming exponential density functions for delay time and time to failure while using the other assumptions in Cerone [15]. The author provided a numerical example to illustrate the implementation of the simplified approximation model.

Jia and Christer [35] extended the basic delay-time model by using the availability function as an optimization criterion and by assuming periodic testing of a preparedness system. The authors investigated three variants of the basic model, including situations where a delay time period exists with no technology to detect defects, the delay time is zero (only failures are detected), and the system is regularly replaced without testing. Wang [60] extended the basic model by considering DTM in the context of risk analysis of maintenance problems. The author developed models for single-unit and multi-unit cases. The developed models aim to minimize the consequences and likelihood of risks associated with maintenance activities and failures. The author presented a prototype software that can help automate the DTM process. Aven and Castro [5] extended the basic delay-time model by assuming that failures are safety critical, therefore risk should be controlled. The authors considered two types of safety constraints: the probability of having at least one failure in a given time interval that should not exceed a fixed probability level and the fraction of time where the system is in a defective state that should not exceed a fixed limit. The developed model determines optimal inspection intervals that minimize expected discounted costs. Cavalcante et al. [13] considered the preparedness system maintenance optimization problem. They extended Jia and Christer's [35] model by implementing a two-phase inspection policy with frequent inspections in early component life and less frequent inspections in later component life. The authors developed cost and reliability models for finite- and infinite-horizon conditions. Wang et al. [59] improved the Jia and Christer [35] model by considering the impact of imperfect maintenance on the two-stage failure processes. The authors developed a long-term availability model for improved DTM and analyzed it using simulation. The results showed that imperfect maintenance decreases the expected values of cycle length and long-term availability. The study also discussed the use of the maximum likelihood estimation (MLE) method to estimate the parameters of improved DTM. Another approximation model is presented in Jiang [36] along with a simulation-based method to determine the timelines-based optimal inspection interval.

Zhang et al. [71] extended the basic delay-time model by assuming that the inspection span time and the failure renewal time are not negligible. The authors proposed a block-based inspection model to determine the optimal inspection interval. In addition, the authors studied the effect of possible overlap of inspection span with failure downtime on the optimal inspection interval. The proposed model was compared with the age-based inspection model and a numerical example was used to demonstrate its implementation. Jodejko-Pietruczuk et al. [37] developed a delay-time maintenance model for a single-unit system assuming that the working element is not defected at the point of inspection maintenance time. The authors determined the optimal time between inspections using two approaches. First, they used the basic delay-time model to define a constant time between inspections. Second, they defined the optimal time period based on the results obtained from the following performance of the inspection actions. In this case, the optimal time between inspections will not be constant, but rather will depend on the technical object achievement. This work was extended in Jodejko-Pietruczuk and Werbinska-Wojciechowska [39] by developing an analytical model for the expected system availability, instead of the cost model.

Most previous studies assume instant replacement of defects when detected during inspection. This assumption was relaxed in Van Oosterom et al. [56] to allow replacement to be postponed for an additional time period. The authors modeled the preventive replacement cost as a non-increasing function of the postponement interval. They derived the optimal policy under the modified assumption for a system with exponentially distributed defect arrival times. A case study was used to demonstrate the advantage of the modified model over the basic model. Yang et al. [66] extended the model in Van Oosterom et al. [56] by considering a single component system that successively executes missions with random durations. The authors assumed that inspections were performed periodically and immediately after the completion of each mission. They derived the expected long-term cost per unit of time and then investigated the optimal periodic inspection interval and postponement threshold. A numerical example was used to demonstrate the implementation of the maintenance policy developed. Berrade et al. [7] investigated further the postponed replacement problem. They focused on imperfect inspection performance and opportunity replacements that appear after a positive inspection.

All previous studies assume a single and specific type of inspection (failure mode). Few studies consider multiple failure modes [44], [45], [61]. Zhao et al. [73] presented a delay-time maintenance model for a component with multiple defects. The model assumes that defects undergo minimal repair after a perfect/imperfect inspection as they arrive in a nonhomogeneous Poisson process. Wang [61] developed a delay-time inspection model for a component with multiple failure modes (minor defect and major defect). The model assumes that the minor defect is handled by minor inspection and repair, whereas the major defect is handled by major inspection and repair. A numerical example was used to demonstrate the implementation of the model. Li et al. [44] analyzed the problem of imperfect inspection of single-unit systems with multiple failure modes. The authors proposed a new imperfect maintenance model using DTM and the accumulative age concept. The proposed model assumes that failure modes are independent of each other and all kinds of defects will be handled in each maintenance task. Ma et al. [45] considered the case of an imperfect maintenance model with two failure modes: the traditional 0-1 logic failure and another failure mode described by a two-stage failure process. They developed a delay-time maintenance model that optimizes the expected long-term cost per unit time.

Another extension in DTM for single-unit systems accounts for the implementation of a three-stage failure process [58], [62], [67], [68], [72]. In a latest study, Wang et al. [58] developed a two-phase inspection model for a single component system with three-stage degradation (normal, low-grade defective and critical defective). The authors assumed that if an item is identified as in a low-grade defective stage, preventive replacement can be delayed if the time to the age-based replacement does not exceed a threshold level. However, if it exceeds the threshold level, the item will be replaced immediately. Additionally, if the item is identified as in the critical defective stage, it will be replaced immediately. The authors developed a hybrid bee colony algorithm to determine the optimal solution for the proposed model.

The literature review reveals that no work has been done on incorporating the human factors affecting maintenance performance in DTM and studying their effect on determining the optimal inspection interval.

III. PROBLEM DEFINITION

Consider a repairable single-component equipment that processes a set of jobs. The equipment is subject to random failures due to factors, such as deterioration, initial design, maintenance activities and external factors. The equipment failure process can be described in two stages: the first stage where a defect becomes detectable and the second stage where this detectable defect ultimately leads to equipment failure. The period h between the time when the defect is detectable first and the time of equipment failure is called the delay time (see Figure 1). A repair is undertaken at any time during this period. The delay time of a defect is governed by a probability density function $f(h)$, which enables the modelling of the relationship between the inspection interval (T) and the expected downtime or the expected operating cost per unit of time.

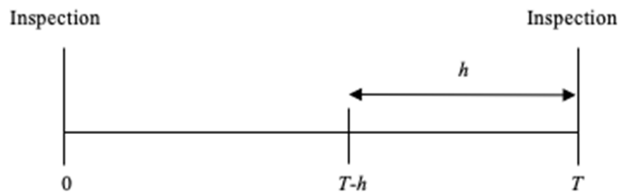

FIGURE 1. The delay time for a defect.

Assume that defects are fixed after inspection (as inspection repairs) or at failure (as breakdown repairs). Minimal repair is performed in the event of failure (assuming a mild shift in the production process). The equipment is inspected for early defect detection. A defect is characterized by the appearance of symptomatic malfunction of the equipment (e.g., excessive vibration, uncommon noise, extreme heat, surface staining, smell, reduced output or bad quality). At this instant of time, equipment failure is suspected and its delay time represents a window of opportunity to prevent the failure.

The delay time analysis is used to model the consequences of inspection policies on the inspection interval T, where the production downtime $D(T)$ and the total operating cost $C(T)$ can be expressed as functions of T. The probability of defects becoming failures (equipment breakdown) is $P(T)$ and increases as the inspection interval increases. As soon as a defect is detected, the equipment is inspected and minimal repairs are performed to ensure continuous operation (assuming a mild shift in the production process) until the PM action is performed and repair or replacement of defective parts are carried out. The inspection is performed every T units of time and requires a duration of d units of time, called the "inspection duration" or "inspection downtime". The classic problem is to determine the optimal inspection interval (T^*) such that the expected system downtime (or the expected total cost) is minimized.

The basic DTM assumes that the time required to perform inspection (d) is fixed. In reality, most inspection activities are performed by maintenance operators, therefore the current study assumes that inspection duration is not fixed, but depends on factors affecting the performance of the operator (i.e., HF). The problem addressed in this study is to determine a realistic optimal inspection interval that takes HF into consideration, so that the expected system downtime (or the expected total cost) is minimized.

IV. METHODS

The proposed methodology for developing inspection models that account for HF affecting maintenance quality consists of the following steps. First, human-related risk factors that impact the effectiveness of maintenance performance, called risk factors for maintenance performance (RFMP), were identified and classified based on literature review. A conceptual framework is proposed to illustrate the integration of HF in the maintenance system. The significant RFMP (i.e., significantly impacting inspection maintenance) were determined based on literature review and expert opinion. A fuzzy model was then constructed to estimate HFA from the significant RFMP. HFA will be used as an allowance to be added to inspection duration (d) of the delay-time model. Two inspection models were developed based on the modified delay-time model with the objective of minimizing the expected system downtime and the expected total cost.

A. RISK FACTORS FOR MAINTENANCE PERFORMANCE

The risk factors for maintenance performance (RFMP) are all the elements that could negatively affect the maintenance performance of a system causing errors, poor work quality, and accidents. Identifying the RFMP can help in understanding the HF that affect the system, determining the human reliability, and predicting human error. Reviewing the literature on HF that impact maintenance performance reveals three classification schemes [9], [28], [41], [54]. The first scheme classifies RFMP into direct and indirect factors. Direct factors are the factors that can be measured directly while performing a task (e.g., completion time of a task). On the other hand, indirect RFMP are the factors that can be measured through other means (e.g., using the level of worker fatigue to determine work fitness).

The second classification scheme, commonly used in industry, classifies RFMP into internal and external factors [9]. The internal factors are those inherent aspects that a person brings to the system (e.g., stress, mood, fitness, and morale). On the other hand, external factors are those related to the environment that influence the person's job or task, such as noise, temperature and illumination. The identified internal and external RFMPs were further grouped on the basis of similarity. The internal RFMPs were grouped into two categories (person and knowledge) and the external RFMPs were grouped into two categories (environment and system). The "knowledge" category is related to the internal influencing factors that affect the information needed to perform the maintenance action. It includes the non-physical resources of the personnel performing the maintenance actions, such as level of experience, skills and training. The "person" category is related to the internal influencing factors that affect the person performing the maintenance action. It includes the characteristics describing the physical and mental state, such as fatigue, stress and morale. The "system" category is related to the external influencing factors that affect the performance and the comfortability of performing the maintenance action. These factors are usually related to management, such as standards, procedures and facility layout. The "environment" category is related to the external influencing factors that affect the performance under certain conditions of maintenance actions. These factors include: noise, temperature and illumination at the workplace where maintenance activities are performed.

The third classification scheme which is adopted in this study, is based on a recent review of the literature by Kolus et al. [41]. The authors systematically examined available empirical evidence of the relationship between HF and the quality of work in the production system. The study identified 204 human-related risk factors for work quality. The risk factors were grouped based on similarity, into four categories: product, process, workstation and individual related risk factors. The authors developed a conceptual framework that illustrates the integration of HF into the production system. The product design category includes risk factors related to the design of the product, such as complexity, weight and posture. The process design category includes the risk factors related to the processes, methods and policies required to make the product, such as procedures, training programs and management support. The workstation design category includes the risk factors related to the work environment where the product is made, such as lighting, layout and tools.

In this study, the 204 risk factors in Kolus et al. [41] were reviewed. Then, the risk factors related to maintenance activities in manufacturing were identified. The identified factors were also compared to previous literature reviews [28], [29], [42], [54]. As a result, a total of 30 human-related risk factors for maintenance performance (RFMP) were identified. These risk factors were classified (according to the maintenance system perspective) into four categories: factors related to task design, factors related to process design, factors related to workplace design and factors related to maintenance personnel characteristics. Table 1 describes the list of identified human-related risk factors for maintenance performance.

A maintenance system can be considered part of a production system in an enterprise [3]. Taking this into account, we modified the conceptual framework [41] to illustrate the relationship between HF and the quality of work from a maintenance perspective. The proposed framework shown in Figure 2 illustrates how the consideration of HF in the design of maintenance operations affects human and system.

Task/component design - the design of the task/component will affect the type, duration, and frequency of maintenance activities performed. For example, the complexity of design configuration [51], [57], physical shape, weight, and required posture are key factors impacting human performance in maintenance [61]. Improper design of task/component may negatively impact human wellbeing (e.g. injuries) and system performance (e.g., human errors).

Process design – maintenance tasks (e.g., inspection, restoration and lubrication) varies in the amount of physical and cognitive demands required for their successful completion. Inadequate task design occurs when task demands exceed personnel capability, which can negatively impact human well-being and system performance. For example, factors such as task duration/frequency [41] and work/rest

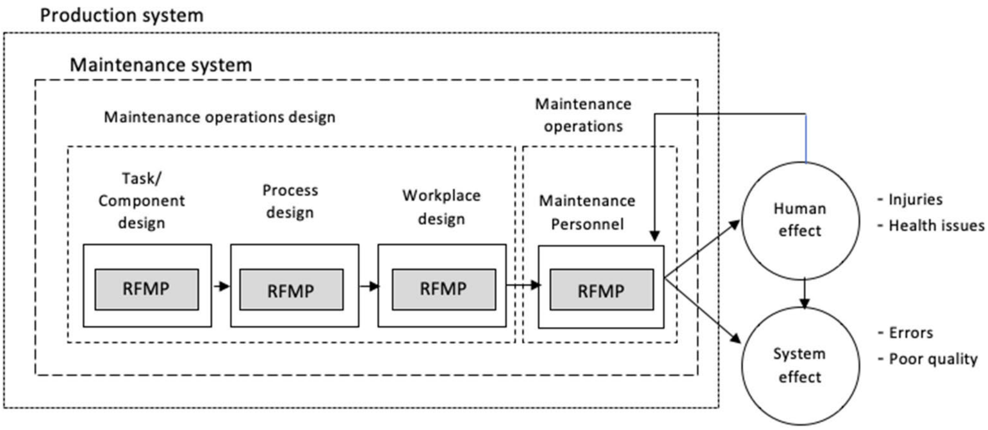

FIGURE 2. A conceptual framework illustrating the integration of HF into maintenance system [RFMP: human-related risk factors for maintenance performance].

TABLE 1. Descriptions of identified risk factors for maintenance performance (rfmp).

Type	Category	#	RFMP	Group	Description
External	Task/ Component	**1**	**Seriousness of task**	**Product**	**The risk level while performing maintenance activity and the failure consequences**
		2	Stress	Product	The physical and mental demands that are required by a maintenance activity
		3	Complexity	Product	The task-related complexity of maintenance activity
		4	Design of machine	Product	The design-related complexity of the machine on which maintenance is performed
	Process	**5**	**Fatigue**	**Process**	**The condition resulting from prolonged working hours with no sufficient rest**
		6	Training	Process	The training level and certificates offered by a company
		7	Working time	Process	The time spent in a maintenance activity
		8	Morale	Process	The amount of confidence felt by personnel while performing maintenance activity
		9	Fear	Process	The fear from performing the job incorrectly
		10	Satisfaction	Process	The emotional feeling of maintenance personnel toward their jobs
		11	Procedures	Process	The written procedures for the maintenance activity
		12	Standards	Process	The set rules and standards needed for performing the maintenance activity
		13	Peer Pressure	Process	The pressure of performing the task correctly from co-workers and management
		14	Team	Process	The chemistry and level of cooperation between team members
		15	Communication	Process	The feedback and communication with co-workers and managers
		16	Motivation	Process	The motivation, incentives, and appreciation received from superiors
	Workplace	17	Accessibility	Workstation	The ability to reach for the parts and equipment during maintenance activity
		18	Tools	Workstation	The tools and equipment used in the maintenance activity
		19	Layout	Workstation	The layout of the workplace and how easy is it to move around and reach to equipment
		20	Special tools	Workstation	The need of special tools in maintenance activities
		21	Noise	Workstation	The level of noise produced by maintenance activity
		22	Temperature	Workstation	The air temperature in the working area where maintenance is performed
		23	Illumination	Workstation	The lighting condition of the workplace where maintenance is performed
Internal	Person	**24**	**Experience**	**Individual**	**The number of years of experience or the experience level (low, medium, or high)**
		25	Knowledge	Individual	The knowledge of maintenance personnel in the specific maintenance action
		26	Skills	Individual	The skill set needed to perform the maintenance action
		27	Learning	Individual	The learning ability of maintenance personnel
		28	Distraction	Individual	The personal issues that distract maintenance personnel
		29	Complacency	Individual	The personnel being over confident and not following procedures
		30	Assertiveness	Individual	The ability for the personnel to express their feelings, opinions, and needs

time [17] can influence human performance and maintenance quality.

Workplace design – maintenance tasks are performed in a physical environment that has an impact on human performance. Workplace design is essential in defining postures and loads on maintenance personnel, which influence human performance and eventually maintenance quality. For example, poor lighting conditions may cause visual discomfort and headache and degrade inspection performance [11].

Maintenance personnel – the characteristics of maintenance personnel include personal (e.g., age, gender and health condition) and professional characteristics (e.g., experience, skills and adaptability). Studies showed that individual characteristics of maintenance personnel may cause excessive workload [16], errors [10] and poor quality of work [25].

Based on the literature review and the opinion of experts in the field of maintenance, RFMP with most significant effect on maintenance performance were selected as input to the proposed fuzzy model in the next section (see RFMP highlighted in bold in Table 1). These inputs are: experience level of the maintenance personnel (related to personal characteristics), fatigue level of the maintenance personnel resulting from having prolonged working hours and insufficient rest time (related to process design) and seriousness of the task (related to task/component design).

B. FUZZY MODEL DEVELOPMENT

The fuzzy model development can be divided into four steps, as shown in Figure 3. The first step is "fuzzification", which involves converting crisp (numeric) values into fuzzy values by determining the degree to which they belong to appropriate fuzzy sets using membership functions. The second step is the "knowledge base" development, which consists of two parts: data base and rule base. The third step is to select a "fuzzy inference system" that aggregates the fuzzy rules in order to obtain the output. The last step is "defuzzification" which involves converting fuzzy values to crisp values. These steps are discussed in detail in the following subsections.

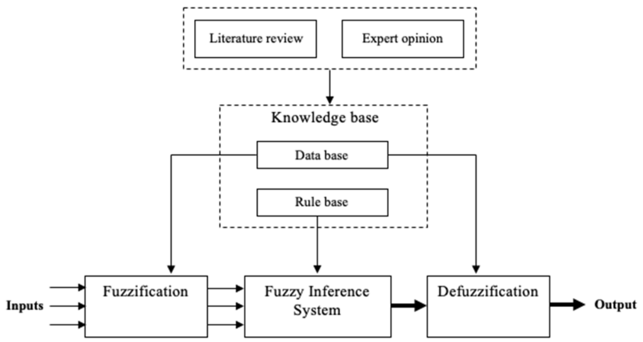

FIGURE 3. Fuzzy model (expert system) development.

1) FUZZIFICATION OF INPUT AND OUTPUT VARIABLES

Based on the literature review and the opinion of experts, three human-related RFMP were selected as input variables to the fuzzy model, namely experience level (EL), fatigue level (FL) and task severity level (SL). Each one of these input (linguistic) variables were divided into an appropriate number of fuzzy sets (linguistic values) that were characterized by appropriate membership functions (e.g., triangular, trapezoidal, rectangular and gamma). Triangular membership functions were found appropriate to be used in this study due simplicity, understandability and frequent use in the literature [55], [65].

In this study, the first input variable (experience level) was divided into three fuzzy sets: Low, Medium and High, as in Ung et al. [55]. These sets represent the number of years of experience of maintenance personnel. Triangular membership functions were selected to determine the association of the input to the fuzzy sets with a range from 0 to 5 years according to a previous study by Hennequin et al. [34]. The range and the values of the membership function parameters were determined based on the opinions of experts who have worked in the maintenance field in manufacturing, and from research done at different job hunting sites.

The second input variable (fatigue level) was divided into three fuzzy sets: Very Weak, Moderate and Very Heavy. These sets represent the level of fatigue in maintenance personnel just before performing the job. Fatigue level can be subjectively assessed using the Borg CR10 scale [8]. Triangular membership functions were incorporated to determine the association of input with fuzzy sets with a range of 0 to 10. The range and the values of the membership function parameters were determined based on the 0-10 score rubric of the Borg CR10 scale [8].

The third input variable (seriousness level of the task) represents the severity of loss or injury that might result from errors or accidents that occur during inspection. In this study, the level of seriousness of a task was divided into four fuzzy sets (Class 1, Class 2, Class 3 and Class 4), according to Goetsch [30]. These classes can be described as follows:

- Class 1 (least serious) is associated with accidents that are treated locally using a first aid kit. These accidents usually result in less than 8 hours of work loss or less than $100 in property damage.
- Class 2 is associated with minor injuries that do not require the intervention of a physician and usually result in more than $100 of property damage or 8 hours or more of work time.
- Class 3 is related to injuries that require the interference and treatment of a physician outside of the workplace.
- Class 4 (most serious) is related to accidents that include lost workdays, permanent partial disabilities and temporary total disabilities.

Triangular membership functions were incorporated to determine the association of the input to the fuzzy sets in a range of 1 to 4. The range and the values of the membership function parameters were determined based on the severity of the consequences of maintenance errors and equipment failure, as described in Goetsch [30] and experts' opinion.

The output variable of the fuzzy model is the linguistic variable (HFA) which represents the adjustment made (fraction added) to the duration of the inspection (downtime inspection) to incorporate the effect of human factors on the time required to perform the inspection. The output variable has a range of 0 to 1 and will be used as an input to the delay time model presented in the next section. HFA was divided into five fuzzy sets: Very Low, Low, Medium, High and Very High. Triangular membership functions were considered appropriate to determine the association of the output with the fuzzy sets. The values of the membership function parameters were determined based on experts' opinion.

TABLE 2. Fuzzy sets and associated triangular membership functions of input and output variables.

Type	Linguistic variable	Range	Fuzzy sets (linguistic values)	Parameters (minimum, mode, maximum)
Input	Experience level (EL)	[0, 5]	Low	[0, 0, 2.5]
			Medium	[0, 2.5, 5]
			High	[2.5, 5, 5]
	Fatigue level (FL)	[0, 10]	Very Weak	[0, 0, 3]
			Moderate	[0, 3, 7]
			Very Heavy	[3, 7, 10]
	Seriousness level (SL)	[1, 4]	Class 1	[1, 1, 2]
			Class 2	[1, 2, 3]
			Class 3	[2, 3, 4]
			Class 4	[3, 4, 4]
Output	Human factors allowance (HFA)	[0, 1]	Very Low	[0, 0, 0.25]
			Low	[0, 0.25, 0.5]
			Medium	[0.25, 0.5, 0.75]
			High	[[0.5, 0.75, 1]
			Very High	[0.75, 1, 1]

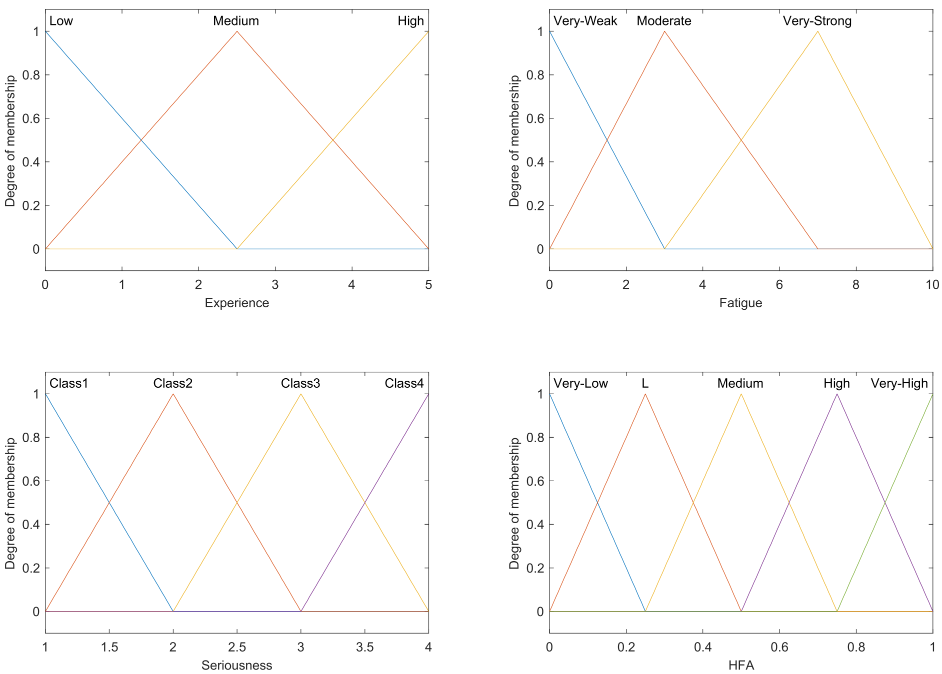

FIGURE 4. Triangular membership functions associated with: (a) Experience level, (b) Fatigue level, (c) Seriousness level and (d) Human factors allowance (HFA).

The triangular membership functions of the fuzzy sets associated with input and output variables are described by the following equation [65]:

$$\mu_A(x) = max\left[min\left[\frac{x-a}{b-a}, \frac{c-x}{c-b}\right], 0\right]$$

where $\mu_A(x)$ is a membership function of a fuzzy set and it represents the grade of membership of element x in a fuzzy set A. a, b, c and d are constant parameters. The parameters of the triangular membership functions associated with input and output variables are summarized in Table 2. Figure 4 shows the triangular membership functions associated with the input and output variables.

2) FUZZY RULE BASE, INFERENCE SYSTEM AND DEFUZZIFICATION

The knowledge base consists of two parts. The first part is the "data base" to determine the membership functions of inputs and output (based on historical data or expert opinion). The second part is the "rule base", in which fuzzy propositions are used to construct fuzzy conditional rules that describe the relationship between inputs and output. A fuzzy conditional rule is composed of a premise and a consequent in the form of: "IF *premise*, THEN *consequent*", for example "IF *a is low*, THEN *b is high*". The terms *low* and *high* can be represented by fuzzy sets or, more precisely, by membership functions.

A total of 36 fuzzy if-then rules were constructed based on the knowledge and reasoning of experts, see Figure 9 (in Appendix A). All fuzzy rules had equal weights. The IF-part (premise) describes the input variables (experience level, fatigue level and seriousness level of task) using linguistic values, whereas the THEN-part (consequent) uses linguistic values to describe the output (human factors allowance). For example, if operator's experience is high, operator's fatigue level is low and the seriousness of the task belongs to Class1 then the human factors allowance (HFA) is expected to be very low (Rule#25, Figure 9 in Appendix A). In order to aggregate all fuzzy rules, the Mamdani fuzzy inference system was used in this study [46]. In the Mamdani inference method, output membership functions are presented in the form of fuzzy sets that need to be defuzzified (i.e., converted to crisp numeric values). Among the various defuzzification methods, the centroid of area method was implemented in this study [31]. Accordingly, the crisp value can be obtained using the following equation:

$$z^*_{COA} = \frac{\int_z \mu_A(z)\, z dz}{\int_z \mu_A(z)\, dz}$$

where z^*_{COA} is the crisp value for "z" output and $\mu_A(z)$ is the aggregated output membership function. Finally, the results of the FIS, i.e. estimated human factors allowance (HFA), were validated against actual field data (i.e., actual inspection duration) as well as expert opinions.

C. EXPECTED DOWNTIME MODEL DEVELOPMENT

In the previous section, a list of 30 risk factors for maintenance performance *or*(RFMP), that can affect maintenance activities is identified through the literature review. Among the identified list, three common human factors with significant impact on inspection are selected based on experts' opinion, namely operator's experience level, operator's fatigue level and seriousness of task. A fuzzy model was developed to estimate the human factors allowance (HFA) – time allowance to be added to inspection duration – from the three commonly identified human factors. The assumption that inspection duration (d) is constant (as in basic inspection models) is now relaxed and replaced by the more realistic assumption that inspection duration depends on HF.

In this section, a modified delay time model is developed by incorporating the crisp output (HFA) of the fuzzy system obtained from the previous section. HFA is added to the inspection duration (d) in the delay-time model to account for HF. The modified delay-time model considers the impact of HF in determining the optimal inspection interval T that minimizes the expected downtime over an infinite time horizon.

In this case, the inspection duration can be expressed as a function of HF, i.e. (1+HFA)d instead of a constant d. The inspection duration can be defined as the minimum time required to perform the inspection (under ideal conditions: high experience level, low fatigue level and Class 1 task seriousness). The notations used in the expected downtime model development are presented below:

T	Inspection interval
$P(T)$	Probability of a defect arising as a breakdown
$D(T)$	Expected downtime of system per unit time
k	Arrival rate of defects per unit time
d	Minimum time required to perform inspection
HFA	Human factors allowance
h	Delay time (time between fault arise and time of failure)
$f(h)$	Probability density function of delay time
d_b	Average downtime for breakdown repair

The following assumptions are made to develop the expected downtime model:

1. An inspection takes place every T time units and requires (1+HFA)d time units, where $d \ll T$ *and* HFA is between 0-1.
2. Inspections are perfect in that all defects are identified in the inspection.
3. Defects are identified and repaired within the inspection period.
4. Defects arrivals follow a homogeneous Poisson process and they arise at a rate of k per unit time.
5. The delay time h is independent from the defect arrival time and its density function $f(h)$ is known.
6. A failure is repaired immediately at average downtime of d_b.
7. Failures and defects arise only while the plant is operating.

According to Assumption 1, inspection duration is not fixed as in a classical delay-time model, but depends on human factors, namely the experience of the operator, the fatigue level of the operator and the seriousness level of the task. HFA represents the allowance for HF that is added to the minimum time required to perform inspection (d). This assumption makes the delay-time model more realistic since inspection activities are carried out by human operators. Assumption 3 requires that all inspection repairs can be completed within (1+HFA)d time units regardless of the number of repairs. This assumption is reasonable when sufficient maintenance personnel is available to work in parallel.

According to Assumption 4, the expected number of defects that arise in the inspection interval T is equal to kT. In this case, the downtime due to breakdowns is not taken into account since no defects would arise when the machine is idle. If the downtime of the breakdown is small compared to T, the error will also be small. Consider Figure 1 where inspection occurs every T time units. An arising defect in the interval $(0, T)$ has a delay time in the interval $(h, h+dh)$ with a probability of $f(h)dh$. The defect is repaired as a breakdown repair if it occurs in the interval $(0, T\text{-}h)$ and as an inspection repair if it occurs in the interval $(T-h, T)$. The probability that a defect arises before $(T-h)$ is $(T-h)/T$. The probability that the defect is repaired as a breakdown and has delay time in the interval $(h, h+dh)$ is given by:

$$\left(\frac{T-h}{T}\right) f\left(h\right) dh \tag{1}$$

Considering the probability for all values of h yields the probability of a defect arising as a breakdown [12]:

$$P\left(T\right) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) f\left(h\right) dh \tag{2}$$

The expected downtime for breakdowns and inspection is given as:

$$kTd_b P\left(T\right) + \left(1 + \text{HFA}\right) d \tag{3}$$

Then the expected downtime per unit of time to be incurred in period T is given by:

$$D\left(T\right) = \frac{kTd_b P\left(T\right) + \left(1 + \text{HFA}\right) d}{T + \left(1 + \text{HFA}\right) d} \tag{4}$$

Equation (4) represents the modified expected downtime model that accounts for HF. The objective is to determine the optimal inspection interval T that minimizes the expected downtime per unit of time.

D. EXPECTED TOTAL COST MODEL DEVELOPMENT

In this section, a modified delay-time model (that incorporates HF) is developed to determine the optimal inspection interval T with the objective of minimizing the expected total cost over an infinite time horizon. The expected cost consists of the expected costs of: breakdown repair, preventive maintenance and inspection. In the classical delay-time model, the inspection cost is defined as the cost needed to perform the inspection assuming that the inspection is carried out under ideal conditions (experienced operator with no fatigue and low level of seriousness of work) at duration d. However, in the modified model, it is assumed that the inspection cost is proportional to the inspection duration. That is, a percentage increase in inspection duration d (due HF) results in an equal percentage increase in inspection cost C_i. The notations used to develop the expected total cost model are presented below:

T	Inspection interval
$P(T)$	Probability of a defect arising as a breakdown
k	Arrival rate of defects per unit time
d	Minimum time needed to perform the inspection
HFA	Human factors allowance
h	Delay time (time between fault arise and time of failure)
$f(h)$	Probability density function of delay time
C_f	Cost of breakdown repair
$C_f(T)$	Expected cost of breakdown repair
C_{pm}	Preventive maintenance action cost
$C_{pm}(T)$	Expected preventive maintenance cost
C_i	Maximum cost that is needed to perform the inspection
$C(T)$	Expected total cost per unit time

The assumptions used to develop the expected cost model are similar to those presented in the previous section. An additional assumption was made that the cost of breakdown is higher than the cost of preventive maintenance. The expected total cost can be written as [61]:

$$\begin{aligned}&\text{Expected total cost}\\&\quad = \text{Expected costs of breakdown repair}\\&\qquad + \text{Expected cost of preventive maintenance}\\&\qquad + \text{Inspection cost}\end{aligned}$$

The expected cost of breakdown repair, $C_f(T)$, can be calculated by multiplying the breakdown repair cost by the expected number of breakdowns in the inspection interval T, that is:

$$C_f\left(T\right) = C_f kTP\left(T\right) \tag{5}$$

Similarly, the expected cost of preventive maintenance, $C_{pm}(T)$, can be calculated by multiplying the cost of PM repair by the expected number of PM repairs, that is:

$$C_{pm}(T) = C_{pm}kT\left[1 - P\left(T\right)\right] \tag{6}$$

The last element of the total cost is the inspection cost (C_i), which is assumed to be proportional to the inspection duration (d). A percentage increase in inspection duration results in an equal percentage increase in inspection cost. Summing up all cost components yields the following expected total cost model:

$$C\left(T\right) = \frac{C_f kTP\left(T\right) + C_{pm}kT\left[1 - P\left(T\right)\right] + \left(1 + \text{HFA}\right) C_i}{T + \left(1 + \text{HFA}\right) d} \tag{7}$$

Equation (7) represents the modified expected total cost model that accounts for HF. The objective is to determine the optimal inspection interval T that minimizes the expected total cost per unit time.

V. CASE STUDY

In this section, a realistic case study is presented to illustrate the use of the modified delay-time model in determining the optimal inspection interval and to compare its performance with the classical delay-time model. This case study is adapted from [12] and can be described as follows: consider a manufacturing system with a single machine that is subject to breakdowns. The downtime due to machine breakdown and inspection is estimated to be 30 minutes and 21 minutes, respectively. The probability density function of the delay time is defined as negative exponential with a failure rate of 0.05 and an average delay time of 20 hours, given as:

$$f(h) = \lambda e^{-\lambda h}$$

The average arrival rate of defects during production is taken as one defect every 10 hours. The costs of repair and preventive maintenance for the breakdown are estimated at \$5,000 and \$2,000, respectively. The maximum cost required to perform the inspection is \$2,500. The maintenance operator performing maintenance activities has 3 years of work experience. Management classifies the task seriousness of this machine as Class 3. Given that the operator reported the pre-inspection score as 2 on the Borg CR10 scale, the manufacturing company was interested in determining the optimal inspection interval that would minimize the expected total downtime and cost.

The first step is to determine the human factor allowance HFA using the fuzzy model developed in Section IV-B2. The inputs to the fuzzy model are: experience level (EL=3 years), fatigue level (FL=2) and task seriousness (TS=Class3). Running the fuzzy model using Fuzzy Logic Toolbox in MATLAB R2018a, yields an HFA of 0.569.

The next step is to substitute the obtained value of HFA in the developed expected downtime model (Equation 4).

$$D(T) = \frac{0.05 \times T \times P(T) + 0.5492}{T + 0.5492}$$

The probability of a defect arising as a breakdown can be calculated using (Equation 2).

$$P(T) = \int_{h=0}^{T} \left(\frac{T-h}{T}\right) 0.05e^{-0.05h} dh$$

Table 4 (in Appendix B) shows the calculated values of $P(T)$ and $D(T)$ for different values of the inspection interval T. Figure 5 shows the expected downtime of the system with respect to different values of the inspection interval T. The results of the numerical analysis show that the minimum expected downtime of the system ($D(T) = 0.04143$ hours) can be obtained when the inspection is performed every 35 hours ($T^* = 35$).

With respect to the expected total cost function, the optimal inspection interval can be determined using (Equation 7).

$$C(T) = \frac{500 \times T \times P(T) + 200 \times T \times (1 - P(T)) + 3922.5}{T + 0.5492}$$

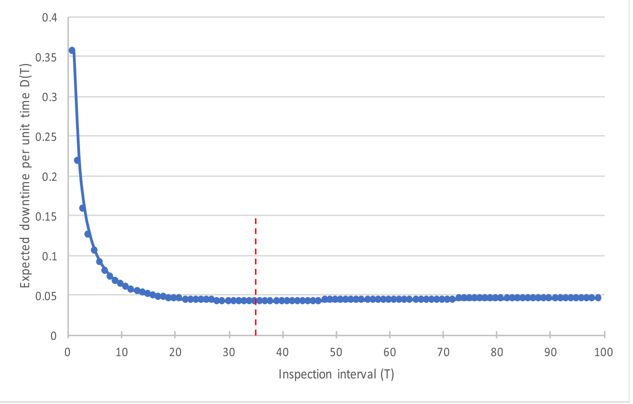

FIGURE 5. Expected downtime $D(T)$ versus inspection interval T.

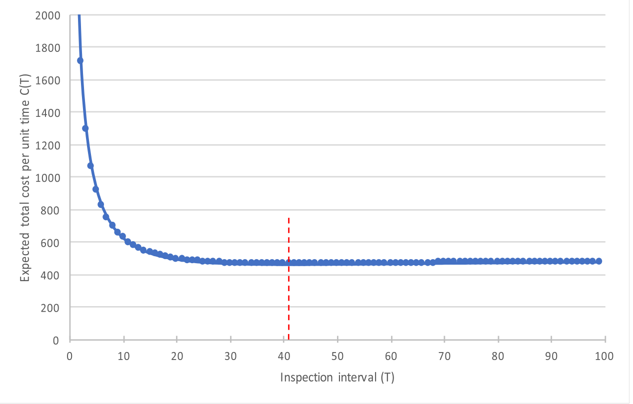

FIGURE 6. Expected total cost per unit time $C(T)$ against inspection interval T.

Table 5 (in Appendix B) shows the calculated values of $P(T)$ and $C(T)$ for different values of the inspection interval T. Figure 6 shows the expected total cost with respect to different values of the inspection interval T. The results of the numerical analysis show that the minimum expected total cost ($C(T) = 461.9809$ \$/hour) is obtained when the inspection is carried out every 41 hours ($T^* = 41$).

VI. VALIDATION AND SENSITIVITY ANALYSIS

In this section, the developed modified models are validated against the classical delay-time models (original models). This is done by solving the case study by both models (modified model vs. original model) and comparing their results. Furthermore, a sensitivity analysis is conducted to validate the modified models and understand how changes in variables influence the behavior of the models.

A. COMPARISON BETWEEN MODIFIED AND ORIGINAL INSPECTION MODELS

The case study was solved by Carr and Christer [12] using the original delay-time models (i.e., expected downtime and total cost models). In their study, the expected downtime *values* $D(T)$ were calculated for different values of the inspection intervals T. These values are drawn against the corresponding values obtained from the modified expected downtime model (based on the modified delay-time model) in Section V. Figure 7 shows a comparison between the results obtained by the modified and original expected downtime models.

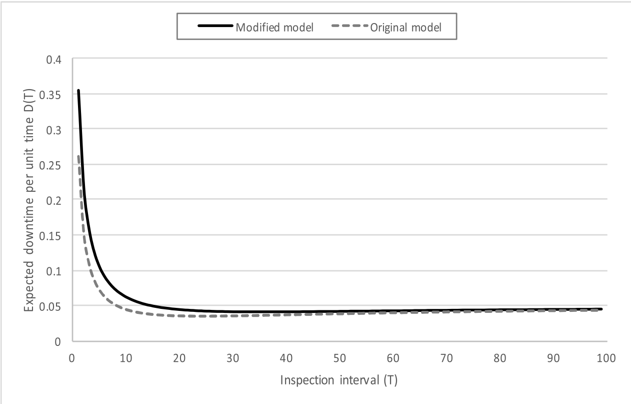

FIGURE 7. A comparison between modified and original expected downtime models.

In general, the results obtained by the modified expected downtime model are comparable to those obtained by the original expected downtime model. The original model yielded an optimal inspection interval of ($T^* = 24$) with a corresponding expected downtime of 0.035. On the other hand, as shown in Section V, the modified model yielded an optimal inspection interval of ($T^* = 35$) with corresponding expected downtime of 0.0414. The consideration of HF in the modified model resulted in an increase (about 18%) in expected downtime. This result is expected since, in order to account for HF, HFA was added to the inspection duration, which as a result led to an increase in the expected downtime of the system. The results also show that the modified model yields less frequent inspections (every 35 hours) than the original model (every 24 hours), which means about 46% less interruptions of production. These results are also comparable to those obtained in Carr and Christer [12], where human error was incorporated in DTM in the form of fault injection with associated probability. In their study, the expected downtime was underestimated by a range of 17.6–20% when human error was not considered in DTM.

Similarly, the results obtained by the modified expected total cost model are comparable to those obtained by the original model. The original model produced an optimal inspection interval of ($T^* = 27$) with a corresponding expected total cost of 422.5024 \$/hour. The modified model, on the other hand, produced an optimal inspection interval of ($T^* = 41$) with a corresponding expected total cost of 461.9809 \$/hour. The modified model yielded a less frequent inspection interval (every 41 hours) than the original model (every 27 hours). In addition, the solution obtained by the modified model results in a higher expected total cost (9.3%) than in the case of the original model. This result is expected since considering HF (by adding HFA) will increase the time

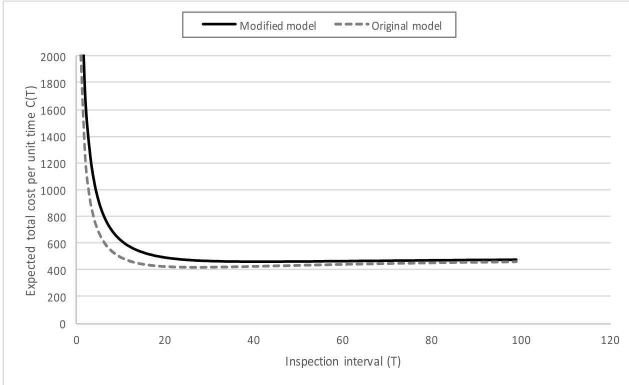

FIGURE 8. A comparison between modified and original expected total cost models.

required to perform the inspection, and hence the cost of the inspection. Figure 8 shows a comparison between the modified and original expected total models.

B. THE EFFECT OF HUMAN FACTORS ON EXPECTED DOWNTIME AND TOTAL COST

In this section, numerical experiments are conducted to investigate the effect of individual as well as combination of RFMP (human factors) on optimal inspection policy from the perspectives of both system downtime and total cost. For this reason, the analysis of four scenarios were considered. The first scenario assumes a low-experience operator with very weak fatigue level and Class 1 task seriousness. The second scenario assumes a high-experience operator with a very high fatigue level and a Class 1 task seriousness. The third scenario assumes a high-experience operator with very weak fatigue level and Class 4 task seriousness. The fourth case assumes worst case scenario where maintenance operator has low experience with very high fatigue level and task seriousness belonging to Class 4. All scenarios were also compared with the original model assuming perfect conditions. A summary of the results obtained are shown in Table 3.

The results showed that the inspection duration d should increase by 25% to account for the lack of experience in maintenance activities. This increase will result in a reduction in the optimal inspection frequency by 20.8% from the downtime perspective ($T^* = 29$ instead of 24) and by 22.2% from the total cost perspective ($T^* = 33$ instead of 27). However, the increase in inspection duration due to the addition of HFA increases the expected downtime (by 8.9%) and the expected total cost (by 4.6%). Failing to account for the low level of operator experience leads to 25% less time allocated for inspection (i.e., inappropriate task duration) – a common risk factor of human wellbeing and system performance [41]. Allocating inappropriate inspection duration may result in an increase in the standard work pace causing operator fatigue, human errors and poor work quality, as reported in Kolus et al. [41].

TABLE 3. The individual and combination effect of human factors on optimal inspection interval.

		Original model (perfect conditions)	Scenarios of modified model			
			Inexpert operator	Fatigued operator	Serious task	Worst case scenario
Human factors (Input variables)	Experience	High (EL=5)	Low (EL=0)	High (EL=5)	High (EL=5)	Low (EL=0)
	Fatigue	Very weak (FL=0)	Very weak (FL=0)	Very heavy (FL=10)	Very weak (FL=0)	Very heavy (FL=10)
	Seriousness	Class 1 (SL=1)	Class 1 (SL=1)	Class 1 (SL=1)	Class 4 (SL=4)	Class 4 (SL=4)
Output	HFA	0.08	0.25	0.5	0.5	0.92
Optimal solution based on downtime	T^*	24	29	34	34	44
	$D(T)$	0.035	0.0381	0.0408	0.0408	0.0444
Optimal solution based on cost	T^*	27	33	41	41	53
	$C(T)$	422.5024	441.9378	460.9114	460.9114	479.2797
% increase	$\Delta\, D(T)$	-	8.8571	16.5714	16.5714	26.8571
	$\Delta\, C(T)$	-	4.6	9.0908	9.0908	13.4383

In addition, the results showed that the inspection duration should increase by 50% in order to account for the very high fatigue level of maintenance operators. This increase in d results in a reduction of the optimal inspection frequency by 41.7% based on the system downtime ($T^* = 34$ instead of 24) and 51.9% based on total cost ($T^* = 41$ instead of 27). The increase in inspection duration due to the addition of HFA increases expected downtime by 16.6% and expected total cost by 9.1%. Failing to consider very heavy fatigue level of the operator results in 50% less time allocated for inspection, which can negatively impact operator's wellbeing and inspection quality. Similar results were obtained when the seriousness of task is at the highest level (belonging to Class 4).

Results associated with the worst case scenario (low experience, very heavy fatigue and Class 4 task seriousness) indicated the need to increase inspection duration by 92%. This leads to a reduction in optimal inspection frequency by 83.3% according to system downtime ($T^* = 44$ instead of 24) and by 96.3% according to total cost ($T^* = 53$ instead of 27). As a result, the expected downtime and expected total cost values increase by 26.9% and 13.4%, respectively. Failing to account for the combined effect of human factors (low experience, very heavy fatigue and Class 4 task seriousness) leads to 92% less time allocated for inspection, which can jeopardize the operator's wellbeing and inspection quality.

VII. CONCLUSION

The majority of maintenance activities are human intensive; therefore, HF must be considered when optimizing maintenance decisions. This study aims to modify the basic delay-time model to account for HF that can affect inspection performance. First, a list of HF that can affect the performance of various maintenance activities were identified through literature review. Then, a conceptual framework was proposed to illustrate the integration of HF into the maintenance system. In this study, two inspection models were developed based on the modified delay-time concept. Both models use fuzzy logic to estimate human factors allowance (HFA) that accounts for HF, namely, experience level of operator, fatigue level of operator, and seriousness level of task. The objective of the first model is to minimize expected production downtime, while the objective of the second model is to minimize the expected total production cost.

A case study was used to illustrate the implementation of the modified models. In addition, it was used to compare the modified models with the original ones that depend on the basic delay-time concept. Sensitivity analysis was performed to investigate the individual and combined effects of the three human factors considered in the modified models. The results show that the failure to account for HF results in an inaccurate determination of the optimal inspection interval. In particular, this will result in increasing the frequency of (unnecessary) inspections; hence interruptions to production by up to 45.5% based on expected downtime and 49% based on expected total cost. In addition, between 25% to 92% less time will be allocated for inspection, which can significantly impact operator performance and quality of work.

The generalizability of the results is often a drawback in case study-based research (i.e., research that uses the results to develop a theory). This is not an issue in this paper since we modify existing inspection models by incorporating a component that accounts for HF and then we use the case study as an example to illustrate the use of the developed model. Moreover, the modified inspection models incorporate three human-related risk factors, namely operator's experience level, operator's fatigue level and seriousness level of task. These three factors were selected from a list of 30 human factors that affect maintenance performance. The case study that was used to illustrate the modified models was taken from

```
'1. If (Experience is Low) and (Fatigue is Very-Weak) and (Seriousness is Class1) then (HFA is L) (1)                  '
'2. If (Experience is Low) and (Fatigue is Very-Weak) and (Seriousness is Class2) then (HFA is L) (1)                  '
'3. If (Experience is Low) and (Fatigue is Very-Weak) and (Seriousness is Class3) then (HFA is Medium) (1)             '
'4. If (Experience is Low) and (Fatigue is Very-Weak) and (Seriousness is Class4) then (HFA is High) (1)               '
'5. If (Experience is Low) and (Fatigue is Moderate) and (Seriousness is Class1) then (HFA is L) (1)                   '
'6. If (Experience is Low) and (Fatigue is Moderate) and (Seriousness is Class2) then (HFA is Medium) (1)              '
'7. If (Experience is Low) and (Fatigue is Moderate) and (Seriousness is Class3) then (HFA is High) (1)                '
'8. If (Experience is Low) and (Fatigue is Moderate) and (Seriousness is Class4) then (HFA is Very-High) (1)           '
'9. If (Experience is Low) and (Fatigue is Very-Strong) and (Seriousness is Class1) then (HFA is Medium) (1)           '
'10. If (Experience is Low) and (Fatigue is Very-Strong) and (Seriousness is Class2) then (HFA is High) (1)            '
'11. If (Experience is Low) and (Fatigue is Very-Strong) and (Seriousness is Class3) then (HFA is Very-High) (1)       '
'12. If (Experience is Low) and (Fatigue is Very-Strong) and (Seriousness is Class4) then (HFA is Very-High) (1)       '
'13. If (Experience is Medium) and (Fatigue is Very-Weak) and (Seriousness is Class1) then (HFA is Very-Low) (1)       '
'14. If (Experience is Medium) and (Fatigue is Very-Weak) and (Seriousness is Class2) then (HFA is L) (1)              '
'15. If (Experience is Medium) and (Fatigue is Very-Weak) and (Seriousness is Class3) then (HFA is Medium) (1)         '
'16. If (Experience is Medium) and (Fatigue is Very-Weak) and (Seriousness is Class4) then (HFA is High) (1)           '
'17. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class1) then (HFA is L) (1)               '
'18. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class2) then (HFA is Medium) (1)          '
'19. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class3) then (HFA is Medium) (1)          '
'20. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class4) then (HFA is High) (1)            '
'21. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class1) then (HFA is L) (1)               '
'22. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class2) then (HFA is Medium) (1)          '
'23. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class3) then (HFA is High) (1)            '
'24. If (Experience is Medium) and (Fatigue is Moderate) and (Seriousness is Class4) then (HFA is Very-High) (1)       '
'25. If (Experience is High) and (Fatigue is Very-Weak) and (Seriousness is Class1) then (HFA is Very-Low) (1)         '
'26. If (Experience is High) and (Fatigue is Very-Weak) and (Seriousness is Class2) then (HFA is Very-Low) (1)         '
'27. If (Experience is High) and (Fatigue is Very-Weak) and (Seriousness is Class3) then (HFA is L) (1)                '
'28. If (Experience is High) and (Fatigue is Very-Weak) and (Seriousness is Class4) then (HFA is Medium) (1)           '
'29. If (Experience is High) and (Fatigue is Moderate) and (Seriousness is Class1) then (HFA is Very-Low) (1)          '
'30. If (Experience is High) and (Fatigue is Moderate) and (Seriousness is Class2) then (HFA is L) (1)                 '
'31. If (Experience is High) and (Fatigue is Moderate) and (Seriousness is Class3) then (HFA is Medium) (1)            '
'32. If (Experience is High) and (Fatigue is Moderate) and (Seriousness is Class4) then (HFA is Medium) (1)            '
'33. If (Experience is High) and (Fatigue is Very-Strong) and (Seriousness is Class1) then (HFA is Medium) (1)         '
'34. If (Experience is High) and (Fatigue is Very-Strong) and (Seriousness is Class2) then (HFA is High) (1)           '
'35. If (Experience is High) and (Fatigue is Very-Strong) and (Seriousness is Class3) then (HFA is Very-High) (1)'
'36. If (Experience is High) and (Fatigue is Very-Strong) and (Seriousness is Class4) then (HFA is Very-High) (1)'
```

FIGURE 9. The rule base of the fuzzy model consisting of 36 fuzzy if-then rules.

manufacturing industry, however since these 30 factors are related to maintenance performance in general, the modified models can be implemented in other industries as well, such as construction and healthcare.

One of the limitations of this study is its reliance on experts' subjective opinion in the development and validation of the fuzzy model. The experts however, have extensive practical experience in the fields of maintenance and human factors. Engineer Mutaz Izmirly is a General Manager at Al Yamamah Steel Industries Co. with more than 20 years of practical experience in maintenance and quality control. Engineer Osman Gokhan Sahin is a Senior Manager at Procter & Gamble with more than 14 years of knowledge in maintenance and repair operations. Dr. Kolus has about 10 years of research experience with background in human factors and production quality. Further research could extend this paper to include the opinion of a broader audience. However, this extra precision is unlikely to change the general findings of this paper: integrating human factors in inspection models can help to determine realistic optimal inspection intervals that improves operator's wellbeing and system performance. Another limitation is related to the fact that different HF (other than the three selected in this study) may show significant association with maintenance performance in different industries (e.g. construction, mining and healthcare). These factors and their impacts on maintenance performance need to be further investigated. Additional limitation is related to the fuzzy model development where different types of membership functions and associated parameters can be further explored.

Although the developed inspection models include one new single component, (i.e., human factors allowance), this single component represents the integration of three commonly identified human factors in maintenance, namely operator's experience level, operator's fatigue level and task seriousness. The estimation of HFA using conventional mathematical modelling may not be possible due to the ambiguity and uncertainty associated with HF. Therefore, fuzzy modelling is used in this study since it has the ability to deal with HF as linguistic variables, which can be described using linguistic values. The proposed inspection models are original, based on a simple idea and open the door for further research on integrating HF in maintenance and inspection models. In practice, the developed models provide a mechanism for managers and decision makers to set a realistic inspection duration that accounts for HF and hence determine the optimal inspection interval that improves operator's wellbeing and performance. Future work can go in several important directions; one direction can be to extend our developed models to a multi-component system where it is impractical to

TABLE 4. Calculated *P*(*T*) and *D*(*T*) for different values of inspection interval (*T*).

T	P(T)	D(T)	T	P(T)	D(T)	T	P(T)	D(T)
1	0.024588	0.355278	34	0.519226	0.041443379	67	0.711965	0.043439
2	0.048374	0.217322	35	0.527871	0.04143345	68	0.715698	0.043509
3	0.071387	0.157744	36	0.536277	0.041435954	69	0.719347	0.043579
4	0.093654	0.124832	37	0.544453	0.041449332	70	0.722914	0.043648
5	0.115203	0.104151	38	0.552405	0.041472215	71	0.726401	0.043716
6	0.136061	0.090083	39	0.560141	0.041503397	72	0.729812	0.043784
7	0.156252	0.079988	40	0.567668	0.041541815	73	0.733148	0.04385
8	0.1758	0.07246	41	0.574993	0.041586528	74	0.736412	0.043916
9	0.194729	0.066684	42	0.582122	0.041636706	75	0.739605	0.04398
10	0.213061	0.062155	43	0.589062	0.04169161	76	0.742729	0.044044
11	0.230818	0.058541	44	0.59582	0.041750587	77	0.745787	0.044107
12	0.248019	0.055618	45	0.6024	0.041813057	78	0.74878	0.044168
13	0.264686	0.053228	46	0.608808	0.041878506	79	0.75171	0.044229
14	0.280836	0.051256	47	0.615051	0.041946474	80	0.754579	0.044289
15	0.296489	0.049618	48	0.621132	0.042016553	81	0.757388	0.044348
16	0.311661	0.048249	49	0.627059	0.042088383	82	0.76014	0.044407
17	0.326371	0.0471	50	0.632834	0.042161639	83	0.762835	0.044464
18	0.340633	0.046133	51	0.638463	0.042236034	84	0.765475	0.04452
19	0.354464	0.045316	52	0.643951	0.042311314	85	0.768062	0.044576
20	0.367879	0.044626	53	0.649302	0.04238725	86	0.770597	0.04463
21	0.380893	0.044043	54	0.654521	0.042463641	87	0.773082	0.044684
22	0.393519	0.04355	55	0.65961	0.042540306	88	0.775518	0.044737
23	0.405771	0.043135	56	0.664575	0.042617087	89	0.777905	0.044789
24	0.417662	0.042785	57	0.669419	0.042693842	90	0.780246	0.04484
25	0.429204	0.042493	58	0.674146	0.042770445	91	0.782542	0.044891
26	0.440409	0.042249	59	0.678759	0.042846786	92	0.784794	0.04494
27	0.451289	0.042048	60	0.683262	0.042922767	93	0.787002	0.044989
28	0.461855	0.041884	61	0.687659	0.042998302	94	0.789169	0.045037
29	0.472117	0.041751	62	0.691951	0.043073314	95	0.791295	0.045085
30	0.482087	0.041647	63	0.696144	0.043147739	96	0.793381	0.045131
31	0.491773	0.041567	64	0.700238	0.043221517	97	0.795429	0.045177
32	0.501185	0.041508	65	0.704238	0.0432946	98	0.797438	0.045222
33	0.510333	0.041468	66	0.708146	0.043366943	99	0.799411	0.045266

TABLE 5. Calculated *P*(*T*) and *C*(*T*) for different values of inspection interval (*T*).

T	P(T)	C(T)	T	P(T)	C(T)	T	P(T)	C(T)
1	0.024588	861.4411	34	0.519226	382.7366562	67	0.711965	426.9133
2	0.048374	610.4582	35	0.527871	384.5315193	68	0.715698	427.8297
3	0.071387	504.7329	36	0.536277	386.2994989	69	0.719347	428.727
4	0.093654	448.3276	37	0.544453	388.0393564	70	0.722914	429.6056
5	0.115203	414.4652	38	0.552405	389.7501427	71	0.726401	430.466
6	0.136061	392.728	39	0.560141	391.4311541	72	0.729812	431.3085
7	0.156252	378.2219	40	0.567668	393.0818944	73	0.733148	432.1338
8	0.1758	368.346	41	0.574993	394.7020438	74	0.736412	432.9421
9	0.194729	361.5918	42	0.582122	396.2914317	75	0.739605	433.734
10	0.213061	357.0249	43	0.589062	397.8500142	76	0.742729	434.5097
11	0.230818	354.0368	44	0.59582	399.3778546	77	0.745787	435.2698
12	0.248019	352.2147	45	0.6024	400.8751063	78	0.74878	436.0146
13	0.264686	351.2692	46	0.608808	402.341999	79	0.75171	436.7445
14	0.280836	350.9921	47	0.615051	403.7788262	80	0.754579	437.4598
15	0.296489	351.2298	48	0.621132	405.1859347	81	0.757388	438.161
16	0.311661	351.8669	49	0.627059	406.5637154	82	0.76014	438.8484
17	0.326371	352.8156	50	0.632834	407.9125958	83	0.762835	439.5223
18	0.340633	354.0078	51	0.638463	409.2330329	84	0.765475	440.183
19	0.354464	355.3899	52	0.643951	410.5255074	85	0.768062	440.8309
20	0.367879	356.92	53	0.649302	411.7905191	86	0.770597	441.4663
21	0.380893	358.5641	54	0.654521	413.028582	87	0.773082	442.0896
22	0.393519	360.2952	55	0.65961	414.2402209	88	0.775518	442.7009
23	0.405771	362.0914	56	0.664575	415.425968	89	0.777905	443.3006
24	0.417662	363.9348	57	0.669419	416.5863601	90	0.780246	443.8891
25	0.429204	365.8108	58	0.674146	417.7219365	91	0.782542	444.4665
26	0.440409	367.7073	59	0.678759	418.8332367	92	0.784794	445.0331
27	0.451289	369.6145	60	0.683262	419.9207984	93	0.787002	445.5892
28	0.461855	371.5244	61	0.687659	420.9851565	94	0.789169	446.1351
29	0.472117	373.4303	62	0.691951	422.0268415	95	0.791295	446.671
30	0.482087	375.3265	63	0.696144	423.0463785	96	0.793381	447.1971
31	0.491773	377.2087	64	0.700238	424.044286	97	0.795429	447.7137
32	0.501185	379.073	65	0.704238	425.0210757	98	0.797438	448.2211
33	0.510333	380.9165	66	0.708146	425.9772515	99	0.799411	448.7193

model each component individually. Another direction can be to assume imperfect maintenance at inspection where some defects will be repaired imperfectly or cannot be repaired due to limitations of labor force, time or material. In addition, more human-related risk factors can be involved to estimate HFA, such as adequate training, job satisfaction, facility layout and availability of tools. The proposed conceptual framework can help managers and researchers understand the ongoing influence of HF in maintenance system performance. Further research into maintenance system design alternatives should involve human factors aspects as well as both system and human effects. Stronger research collaboration between HF and maintenance researchers can help to bridge the gap between HF and maintenance system design.

APPENDIX A
FUZZY MODEL DEVELOPMENT

See Figure 9.

APPENDIX B
SOLUTION OF THE CASE STUDY

See Tables 4 and 5.

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