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Selecting optimal preventive maintenance periods for one-shot devices: a new fuzzy decision approach

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Abstract

Purpose: A one-shot device is defined as a unit that can be used only once, and hence the device cannot be used for testing more than once. This paper proposes a new simulation method conducive toward choosing optimum preventive maintenance periods (PMPs) with the assumption that, to data, there is no data available in the meantime to failure of one-shot devices.

Design/methodology/approach: In this study, an expert team is selected to determine optimum PMPs for the one-shot devices using ARENA simulation as well as fuzzy TOPSIS. Also, to comparatively evaluate the performance of the proposed approach, composite overwrapped pressure vessels (COPVs) for storing oxygen under high pressure are used as real case studies.

Findings: The results particularly underscore the point that the proposed integrated model works most effectively for one-shot devices. This approach can therefore be used by considering fuzzy mean time to failure as well as making and selecting scenarios. Also, for COPVs, the best PMPs are obtained annually.

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Research limitations/implications: It is worth mentioning that, results are referred to the current case study. Also, results are limited to indices identified and evaluations related to the ARENA simulation approach for the considered time interval.

Practical implications: One of the most important management challenges in industrial organizations is the selection of the best PMPs with minimum costs. PMP Analysis in maintenance engineering is a strategy that helps managers for selecting, support, and manage a set of devices.

Originality/value: Although numerous studies have been carried out, to the best of our knowledge, no attempt has been made in taking into account fuzzy discrete-event simulation to evaluate PMPs, especially, for one-shot devices. So, this paper can be regarded as the first attempt in this direction.

Keywords: Composite Overwrapped Pressure Vessel, One-shot devices; Preventive Maintenance Period (PMP); Discrete-event simulation; Multi-Attribute Decision Making; Fuzzy TOPSIS

1. Introduction

Today, one of the most important issues related to improving the performance level of equipment and assets of an organization is to follow maintenance procedures with minimum inspection and repairs (Zhang et al., 2020). This, in turn, can improve the efficiency of the organization through proper use of its resources (Azimian et al., 2012). Maintenance measures also improve the useful life of devices (Zio & Di Maio, 2010) and can be implemented not only for equipment with a continuous operation (Li et al., 2019) or equipment with periodic use (Jianxing et al., 2019) but also for one-shot devices (Kitagaw et al., 2016). One-shot equipment is a term invented to refer to devices that are ready for use and which are discarded as soon as they are consumed; alternatively, there might be a need to overhaul or replace parts and subsystems completely (Azimian et al., 2021). Examples of one-shot devices can be found in diverse places such as space shuttles, missiles, automobile airbags, thermal batteries, magneto-rheological fluids, and some electronic standby systems (Azimian et al., 2021). Hence, the proper operation of one-shot devices at designated times has become an important challenge to industries (Petrovic et al., 2018). Therefore, measures to maintain the reliability of this type of equipment are crucially important. These activities are generally termed reliability maintenance measures (Nakagawa, 2006).

Generally, the published studies on monitoring the status and storing procedures regarding the reliability of one-shot issues can be branched into three general groupings: i) some researches including (Dunson & Dinse, 2002; Yates & Mosleh, 2006; Vinter & Valis, 2008; Fan, Balakrishnam, & Chang, 2009; Guo et al., 2010; Ling & Hu, 2020; Wu, Li, & Bérenguer, 2020) have concentrated on the optimal volume of samples for ascertaining the reliability of equipment. In this approach, the focus is on determining the sample size; ii) some another such as (Kaio Dohi, & Osaki, 1994; Hariga, 1996; Ito & Nakagawa, 2000; Grall, Bérenguer, & Dieulle, 2002; Li & Pham, 2005; Newby, 2008; Yun, Kim, & Han, 2012;

Yun, Han, & Kim, 2014; Kitagaw et al., 2016) directed their attention on determining optimal inspection and replacement of the device at different periods using reliability relations; and iii) to estimate the parameters related to failure distribution of one-shot equipment, several pieces of research such as (Morris, 1987; Kaio Dohi, & Osaki, 1994; Fan, Balakrishnam, & Chang, 2009; Guo et al., 2010; Ling & Hu, 2020) focused on accelerating the life test.

All the above three groups of literature assumed that the necessary data for estimating the parameters related to probable failure rate is available. But the available data is not adequate when it comes to one-shot systems. Hence, it is best to periodically carry out preventive maintenance periods (PMPs) to maintain the reliability of such systems using fuzzy sets.

The most important maintenance strategies can be divided into scheduled preventive maintenance (SPM), corrective maintenance (CM), condition-based maintenance (CBM), and breakdown maintenance (BM) (Felecia, 2014). Also, determining the optimal PMPs for a piece of equipment of time-based strategies is crucial for reducing maintenance and repair costs (Nourelfath, Nahas, & Ben Doya, 2016). Therefore, since equipment maintenance plays a very critical role in organizations and the process is a costly one, its optimization has reached such a level of importance that several studies have concentrated on optimizing maintenance activities (Yang et al., 2017), and so resorting to simulation and control results could prove beneficial in this regard (Alrabghi & Tiwari, 2016).

Moreover, simulation is an imitation of how a process or system works in the real world, given that simulation can not only be used to create an artificial history for the system but also exploited to conclude regards how the system works in real-life situations (Banks et al., 2009). The purpose of the simulation is to design a model that enables users to observe the approximate behavior of the real system. Simulation can also identify system bottlenecks helping to improve future endeavors by optimizing relevant inputs and outputs (Daneshkhah, Stocks & Jeffrey, 2017).

Simulations also enable the individual to consider uncertainties and complexities using fuzzy theory (Azadeh, Seifoory & Abbasi, 2010). Fuzzy logic is used as a suitable strategy for analyzing systems that lack previous records (Safarianzengir et al., 2021). In fuzzy theory, the members of a set are not precisely the members of the set (Saffari et al., 2019), but a membership function is defined for each member (Alimohammadlou & Khoshsepehr, 2021).

Also, in light of multiple indices obtained through simulation models, best scenario selection should be accomplished using Multiple Criteria Decision Making (MADM) models (Saeedpoor & Vafadarnikjoo, 2015). This usually involves going through a variety of conflicting and incompatible criteria whereby one scenario is chosen from among available options (Azimian et al., 2017).

Few studies, however, have considered using the fuzzy simulation approach as an option for selecting the best PMP, particularly, for one-shot devices. To bridge the gap, this paper seeks to create a fuzzy simulation network that can identify the best period for one-shot devices.

In this regard, this research addresses the following questions:

(a) How are the input and output indices determined for the preventive maintenance periods (PMPs) of one-shot devices?

(b) How is the simulation model developed for selecting the best PMPs in one-shot devices using fuzzy sets?

The remaining part of the present study is structured as follows: Section 2 provides a brief overview of the previous works on the design of the fuzzy simulation and its application; Section 3 deals with the research methodology and introduces the proposed framework; Section 4 presents a case study furnishing an analysis of the proposed framework; Section 5 brings up a discussion on the findings; and finally, a conclusion in Section 6 brings the paper to an end.

2. Literature review

As mentioned in the introduction section, the literature on one-shot device/system reliability may be classified into three general categories: i) those focusing on sampling as a means to assure equipment reliability; ii) those employing reliability relations containing parameters related to failure probability distributions; and iii) those based on accelerated life test or maximum likelihood estimation (MLE) used to determine the parameters related to failure distribution of one-shot equipment. All the above categories of studies are similar in that they base their one-shot device reliability evaluation on the determination of parameters related to probable failure rates. Moreover, the failure rate in these studies is commonly estimated using conventional accelerated life testing and maximum likelihood estimation.

Nevertheless, maintenance strategies are designed for other devices to ensure that maintenance operations are performed only when there is evidence of an imminent failure (Felecia, 2014) and discrete events simulation was a useful tool for this issue (Azadeh, Seifoory & Abbasi, 2010).

As regards using discrete events simulation for maintenance issues, it should be noted that this type of simulation is mostly focused on determining appropriate maintenance strategies for optimizing maintenance costs. For example, Petrovic et al. (2018) proposed a combined approach to statistical process control and discrete events simulation to enable rapid evaluation of military equipment repairs. They considered two key performance indicators; namely, the number of corrective and preventive maintenance activities and the total time of corrective and preventive maintenance on three types of military equipment using statistical process control charts. Then, they established a discrete events simulation in the ARENA software by creating a parallel structure for corrective and preventive repairs according to the probability distribution of activities, repairs, and forces. Finally, the best maintenance strategy for such equipment was predicted. Alrabghi & Tiwari (2016) examined the repair strategies on the assets of a production system using discrete events simulation. These researches compared corrective maintenance strategy with preventive, opportunistic, and condition-based maintenance strategies through defining the production process and available assets. In their study, evaluation indices for corrective repairs included the following: Mean Time Between Failure (MTBF), repair time, and costs. For preventive maintenance, it contained the number of preventive repairs, repair times, and costs, and for the two other strategies, this included repair times and costs. Boukhtouta & Ghanmi (2014) evaluated the operational availability of military ground equipment using discrete events simulation and the ARENA software. This study investigates accessibility by allowing equipment to break down under possible distributions of different maintenance strategies. Based on the final results, the condition-based maintenance policy proved more efficient than others. According to another reported research study, preventive maintenance was made more accessible than condition-based maintenance. Eslami et al. (2014) examined three time-based maintenance strategies i.e., the value-based maintenance order, reliability-based maintenance order, and the global-based maintenance order. This study also exploited AHP (Analytical Hierarchy Process) and TOPSIS methods to compare the strategies while considering multi-attribute decision-making procedures. Azadeh, Seifoory & Abbasi (2010) used fuzzy simulation and fuzzy multi-attribute decision-making methods for determining the best preventive maintenance period. In fact, in their study, a solution was proposed to determine the fuzzy outputs based on the fuzzy inputs through simulations. Finally, different scenarios with fuzzy outputs were compared with those of fuzzy multi-attribute decision-making procedures. Despite previous research works on optimizing maintenance activities with fuzzy discrete event simulations through ARENA software, the issue has not been dealt with as far as one-shot electronic equipment and systems are concerned. Accordingly, the model presented in this paper provides a new fuzzy simulation model for such systems by defining the indices which can be used to check the preventive maintenance periods of one-shot electronic devices with time-based repair strategies.

3. Proposed methodology

From a functional point of view, the method employed in the study is a practical development one. The data is fuzzy and the data collection is cross-sectional and a correlational one from the research point of view. Data collection is performed via a questionnaire administrated among a group of elite experts. The dependent variables are final ranks of PMP scenarios for one-shot equipment, the input variables are periods of PMPs, the interfering variables are also mean time to failure (MTTF) in one-shot equipment for each scenario, and the moderator variables comprise values of triangular fuzzy numbers which are derived from the ARENA software simulation for each scenario.

Since in this study, making decisions of management to the identification of periods of PMPs and also assessment indicators were required, a decision-making team was established in the early stage. They were seven experts including senior managers, research assistants, leaders of research groups, and faculty members of Malek-Ashtar university of technology (MUT). To obtain assessment indicators, by meeting with decision-making group individuals and using brainstorming, the major indexes were identified.

An overview of the framework is illustrated in Figure 1.

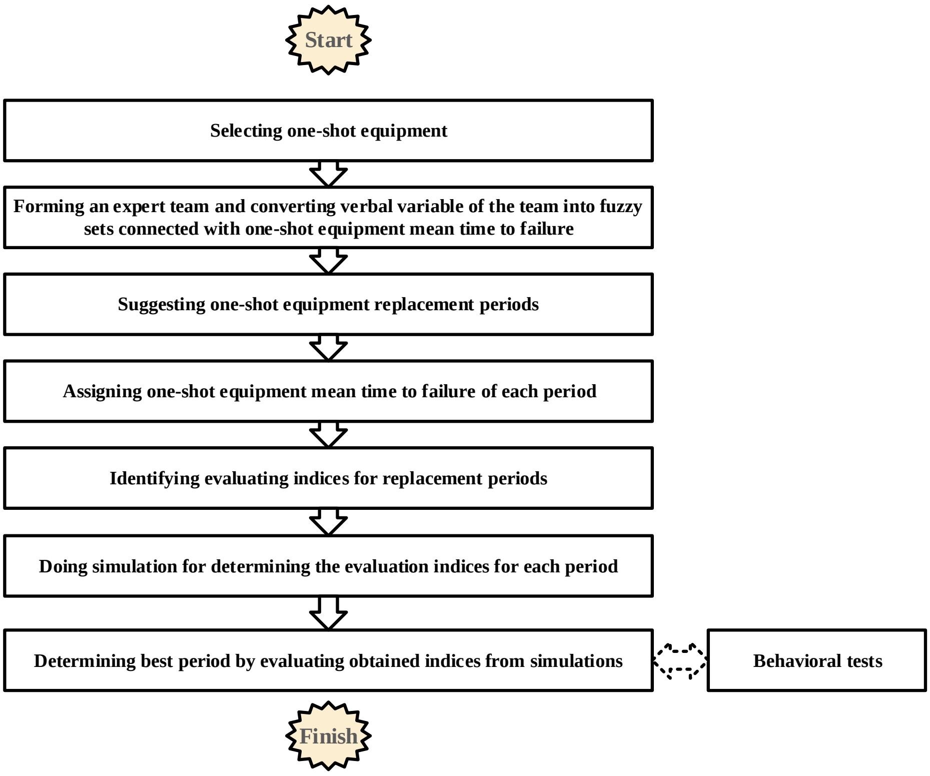

Fig. 1. The proposed framework

In this study, to simulate and determine suitable equipment PMPs in one-shot devices, two inputs variables designated as PMPs and MTTF are considered. Essentially, by examining different PMPs and their impacts on the MTTF, it is possible to determine the best scenario through evaluating indices. The input variables in the simulation framework are triangular fuzzy numbers for MTTF and crisp data for PMPs in each scenario. Also, assessment indicators are averages of total waiting time, queue waiting time, schedule utilization, success utilization number, and equipment replacement number, (See Table1).

Table 1. Input and output variables

Type	Name	Abbreviation	Fuzzy	Crisp
Input	PMPs	(PMT)		×
	Meantime to failure	$(\widetilde{FR})$	×	
Output	Waiting time average	$(\widetilde{WT})$	×	
	Queue waiting time average	$(\widetilde{QWT})$	×	
	Schedule utilization average	$(\widetilde{SU})$	×	
	Success utilization number average	$(\widetilde{UNO})$	×	
	Equipment replacement number average	$(\widetilde{PNO})$	×	

3.1 ARENA software: fuzzy simulation

ARENA is a discrete event simulation and automation software developed by systems modeling and acquired by Rockwell Automation in 2000. In ARENA, the user builds an experiment model by placing modules (boxes of different shapes) representing processes or logic. Also, connector lines are used to join these modules together and specify the flow of entities. While modules have specific actions relative to entities, flow, and timing; the precise representation of each module and entity relative to real-life objects is subject to the modeler. It includes Visual Basic for applications so models can be further automated if specific algorithms are needed. The software also supports importing Microsoft Visio flowcharts, as well as leading from or sending output to Excel spreadsheets and Access databases. Hosting ActiveX controls is also supported (Banks et al., 2009). To determine the best scenario for preventive maintenance periods using ARENA simulation, it is required that a simulation network is plotted. To achieve this, the following parameters are required:

- Period the equipment is used
- PMPs in each scenario
- Operation duration for each piece of equipment used
- Duration of PM for each equipment
- MTTF for each piece of equipment in each scenario
- Downtime in case of emergency breakdown

Based on the framework presented in this study, to simulate in the ARENA environment, each of the three top triangular fuzzy numbers related to MTTFs in each scenario, network simulation runs, and assessment indices are determined. So, the triangular fuzzy numbers of evaluation indices with three network implementations must be ascertained. Figure 2 presents the way a triangular fuzzy number is formed. Naturally, by using the α-cut method, more points can be investigated (Azadeh, Seifoory & Abbasi, 2010). In this method, several scenarios for PMPs are produced and for each scenario, the MTTF for each piece of equipment is assigned based on experts' opinions. Then, for each scenario, three simulation runs are executed based on triangular fuzzy numbers for each equipment MTTF. In this way, the triangular fuzzy numbers for all output indexes can be obtained using three simulations.

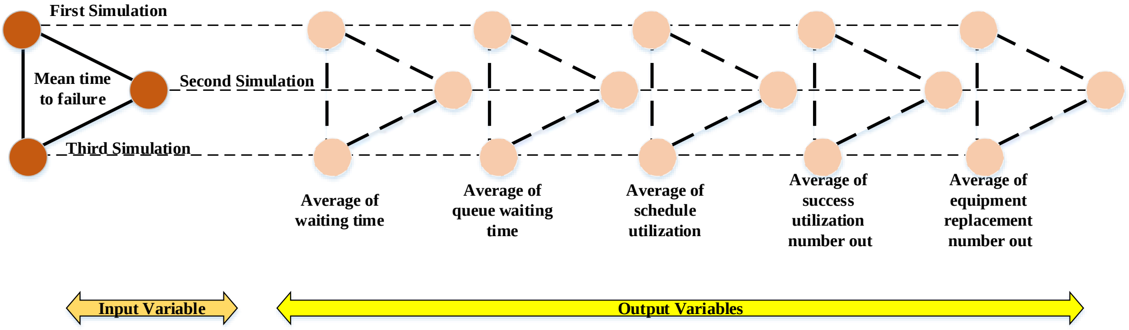

Fig. 2. Triangular fuzzy making for evaluating indices

In this study, we have employed the fuzzy TOPSIS method to determine the best scenario, because the assessment indicators are obtained through the ARENA fuzzy simulations.

4. Case study and behavioral tests to validate the proposed framework

In this section, to investigate the potential capability of the proposed model, we have exploited composite overwrapped pressure vessels (COPVs). COPVs are storage equipment kept in a warehouse under pressure (Xiaoqiang et al., 2021). They are used only once in their lifetime, which point becomes of such crucial importance that they should not experience any decline in pressure in their lifetime. These vessels are composed of such parts as O-ring whose function is to stop air leakage; air-tight layer functioning as a chamber for compressed air; composite layer which burdens the task of withstanding pressure; nipple which is made of AL7075; and some other ancillary gears. The three important and critical components of such vessels are air-tight layers, nipple, and O-ring, which in the order mentioned, are subjected to conditions of material creep, corrosion, and pressure sustainability, which factors bring about a reduction in the expected lifetime of such vessels (McLaughlan, Forth, & Grimes-Ledesma, 2011).

Creep refers to a situation where constant pressure applies to plastic gradually causing changes in size and dimensions (Crawford & Martin, 2020). Corrosion is defined as the damage and destruction to the material as a result of interaction with ambient elements (Stansbury & Buchanan, 2000).

Hence, thermodynamic loads-fatigue and age- are considered among threats to pressure vessels. For this reason, these tanks should undergo periodic inspections at regular intervals. At the moment, the inspections are performed by relevant technicians by doing hydraulic pressure testing as well as naked eye inspections of the internal and external surfaces of the vessels. These surveys which are usually conducted manually by human individuals are time-consuming and costly processes. That is, the filling and emptying of the tanks by water and gas and drying them out should take place on several occasions. Nevertheless, despite these inspections, it is still possible that dangers are threatening the COPVs due to severe impacts and accidents. For this reason, using AE (Acoustic Emission) testing is usually regarded as an appropriate substitution for conventional inspection methods especially when the vessel is filled with hydrogen. Furthermore, the AE inspections can pinpoint weak and dangerous spots in COPVs. These inspection procedures can be used for less dangerous applications. There are different failure modes impacting COPVs and all other metal tanks, however, recognizing failure modes of COPVs is a harder task than determining those of metal tasks (McLaughlan, Forth, & Grimes-Ledesma, 2011).

The case study goes through the following procedure: forming an expert group, converting the verbal variables of the expert group into fuzzy sets, creating a fuzzy simulation through ARENA software, selecting the best scenario by fuzzy TOPSIS; and finally testing the model behavior.

4.1 Forming an expert team

An expert group consisting of repair and maintenance specialists of an Iranian PIHO was set up to determine the inputs and also to evaluate the relevant indices for suitable PMPs of one-shot systems in an ARENA simulation. The criteria adopted for selecting these individuals included their expertise and experience in the repair and maintenance of medical one-shot equipment and systems.

4.2 Converting the verbal variables of the expert group into fuzzy sets

To convert the expert team linguistic variables to fuzzy sets via summing up the opinions of all the experts, a triangular fuzzy set, according to Table 2, was assigned to each number that represented the MTTFs of each equipment replacement period in a medical one-shot gear. The time units used in this section indicate the MTTF.

In our research, the verbal variables of the expert team were converted into fuzzy sets using the data gathered through the administered questionnaires. To explain more, by allocating a membership rate in each day for each three fuzzy MTTF sets (low, medium, high), the averages of the expert team's opinion were summed up, (see Table 3). It is to be mentioned that in this study, very low and very high fuzzy MTTF sets have been ignored.

Table 2. Converting MTTFs of the expert team into triangular fuzzy sets

One-shot Equip MTTF		
Low	Medium	High
(90,120,150)	(60,80,100)	(20,40,70)

Table 3. Summing up the expert team's opinions on the degree of membership

Day	Average of Membership Rate for Fuzzy MTTF Sets (Low, Medium, high) Based on Expert Team's Opinion		
	Low	Medium	High
20	0	0	0
30	0	0	0.5
40	0	0	1
50	0	0	0.2
60	0	0.2	0.2
70	0	0.2	0
80	0	1	0
90	0	0.2	0
100	0.2	0.2	0
110	0.2	0	0
120	1	0	0
130	0.2	0	0
140	0.2	0	0
150	0	0	0

4.3 Fuzzy simulations using ARENA

Table 4 sums up the experts' operations on each scenario representing the MTTFs related to each equipment in the one-shot system under study considering the PMPs.

Table 4. Making scenarios

Scenario Number	Period (Days)	MTTF				
		Equip 1	Equip 2	Equip 3	Equip 4	Equip 5
One	30	Low	Low	Low	Low	Low
Two	90	Low	Medium	Medium	Medium	Medium
Three	180	Medium	Medium	High	High	Medium
Four	360	Medium	High	High	High	High

The model assumptions are as follows:

i) There are five pieces of equipment in the one-shot system under study with a time-based repair strategy.

ii) The period each equipment is used as a normal distribution with a mean of 360 and a standard deviation of 100 days.

iii) The operational duration in each use of the equipment follows a normal distribution with a mean of 20 and a standard deviation of 5 days.

iv) The PM duration in each piece of equipment also follows a normal distribution curve with a mean of 14 and a standard deviation of 5 days.

v) MTTFs are defined in the failure module of ARENA software.

vi) MTTFs are allocated by the resource module to each equipment as to each scenario.

vii) In the simulation model, 360 days are allocated for the warm-up period, and 10 years (3600 days) allocated for replication lengths. Also, 30 counts of replications are considered.

Figure 3 illustrates the network simulation.

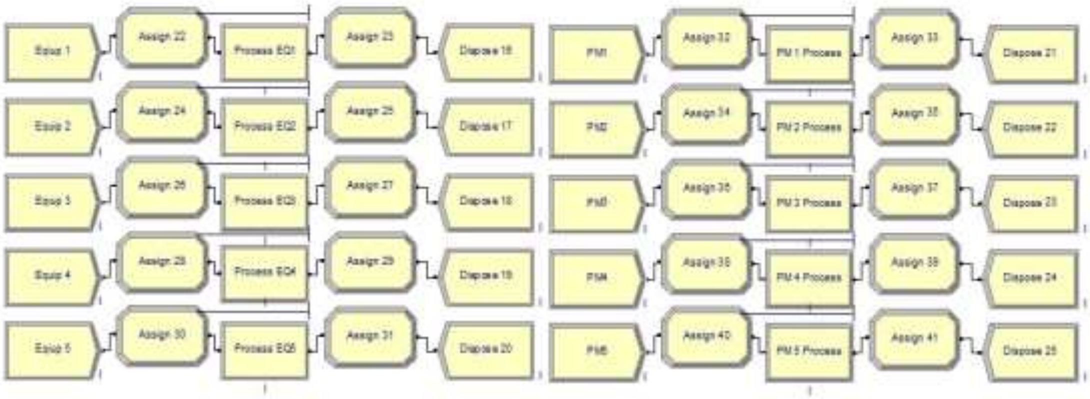

Fig. 3. ARENA network simulation

The results of the 12-simulation run (4 scenarios and three triangular fuzzy numbers for each scenario) are summarized in Table 5.

Table 5. ARENA fuzzy simulation results

Scenario	Period (Days)	Evaluation Indices				
		$(\widetilde{WT})^-$	$(\widetilde{QWT})^-$	$(\widetilde{SU})^-$	$(\widetilde{UNO})^+$	$(\widetilde{PNO})^-$
1	30	(2.328,2.23,2.189)	(2.33,2.226,2.206)	(0.523,0.521,0.52)	(10.56,10.41,10.51)	(119.98,119.96,119.96)
2	90	(0.946,0.992,0.97)	(0.95,1.06,0.974)	(0.211,0.211,0.211)	(10.478,10.484,10.468)	(40,40,40)
3	180	(0.573,0.598,0.555)	(0.565,0.593,0.548)	(0.134,0.134,0.134)	(10.51,10.51,10.51)	(20,20,20)
4	360	(0.56,0.553,0.537)	(0.535,0.529,0.507)	(0.095,0.095,0.095)	(10.52,10.55,10.55)	(10,10,10)

4.4 Selecting the best scenario with help of Fuzzy TOPSIS

To determine the best scenario, Table 4 is considered a decision matrix, assuming that all other indices have the same weights. The linear scale transformation is then used to convert various criteria into proportionate scales. Following this procedure, the fuzzy numbers in the decision matrix for positive indices are calculated through Equation (1), where C_j is obtained through equation (2). Also, for negative indices, Equations (3) and (4) are used. Therefore, all the criteria are converted into positive ones (Ploskas & Papathanasiou, 2019).

$$r_{ij} = \left(\frac{a_{ij}}{c_j} . \frac{b_{ij}}{c_j} . \frac{\mathrm{c_{ij}}}{\mathrm{c_j}}\right) \tag{1}$$

$$\mathrm{C_j} = \max \mathrm{C_{ij}} \tag{2}$$

$$\mathrm{r_{ij}} = \left(\frac{\mathrm{a_j}}{\mathrm{c_{ij}}} . \frac{\mathrm{a_j}}{\mathrm{b_{ij}}} . \frac{\mathrm{a_j}}{\mathrm{a_{ij}}}\right) \tag{3}$$

$$\mathrm{a_j} = \min \mathrm{a_{ij}} \tag{4}$$

Where $r_{ij}$is de-scaled triangular fuzzy number in decision-matrix, a_{ij} is the lower limit of the triangular fuzzy number of i^{th} option in $the\ j^{th}$ index in decision-matrix, b_{ij} is the upper limit of the triangular fuzzy number of i^{th} option in $the\ j^{th}$ index in decision-matrix, c_{ij} is the middle limit of the triangular fuzzy number of i^{th} option in $the\ j^{th}$ index in decision-matrix, c_j is the maximum upper limit of triangular fuzzy number in decision-matrix used for de-scaling numbers, and a_j is the minimum lower limit of triangular fuzzy number in decision-matrix used for de-scaling numbers.

Table 6 shows the obtained scaled-up fuzzy decision matrix.

Table 6. Scaled up a fuzzy decision matrix

Scenario	Period (Days)	Evaluation Indices				
		$(\widetilde{WT})^+$	$(\widetilde{QWT})^+$	$(\widetilde{SU})^+$	$(\widetilde{UNO})^+$	$(\widetilde{PNO})^+$
1	30	(0.255,0.251,0.240)	(0.242,0.240,0.229)	(0.182,0.182,0.182)	(1,0.986,0.996)	(0.083,0.083, 0.083)
2	90	(0.577,0.564,0.592)	(0.549,0.504,0.563)	(0.451,0.451,0.451)	(0.992,0.993,0.991)	(0.25,0.25,0.25)
3	180	(1.01,0.936,0.978)	(0.976,0.903,0.947)	(0.710,0.710,0.709)	(0.995,0.995,0.996)	(0.5,0.5,0.5)
4	360	(1.043,1.012,1)	(1.055,1.012,1)	(0.995,0.997,1)	(0.997,1,1)	(1,1,1)

The acquired Fuzzy Positive Ideal Solutions (FPIS) and Fuzzy Negative Ideal Solutions (FNIS) are addressed in Table 7.

Table 7. FPIS and FNIS

	Evaluation Indices				
	$(\widetilde{WT})^+$	$(\widetilde{QWT})^+$	$(\widetilde{SU})^+$	$(\widetilde{UNO})^+$	$(\widetilde{PNO})^+$
FPIS	(1.043,1.012,1)	(1.055,1.012,1)	(0.995,0.997,1)	(1,1,1)	(1,1,1)
FNIS	(0.255,0.251,0.240)	(0.242,0.240,0.229)	(0.182,0.182, 0.182)	(0.992,0.993,0.991)	(0.083,0.083,0.083)

Tables 8 and 9 show the distances between each scenario and FPIS and FNIS via Equation (5).

$$d(M_1.M_2) = \sqrt{\frac{(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2}{3}} \tag{5}$$

Where $\mathrm{d}(\mathrm{M}_1.\mathrm{M}_2)$ is the mathematical relation of the distance between different options and ideal options in the TOPSIS method.

Table 8. Distances between each scenario and FPIS

Scenario	Period (Days)	Evaluation Indices					S_i^+
		$(\widetilde{WT})^+$	$(\widetilde{QWT})^+$	$(\widetilde{SU})^+$	$(\widetilde{UNO})^+$	$(\widetilde{PNO})^+$	
1	30	0.77	0.785	0.815	0.008	0.917	3.295
2	90	0.441	0.484	0.546	0.008	0.750	2.230
3	180	0.049	0.083	0.288	0.004	0.5	0.925
4	360	0	0	0	0.002	0	0.002

Table 9. Distances between each scenario and FNIS

Scenario	Period (Days)	Evaluation Indices					S_i^-
		$(\widetilde{WT})^+$	$(\widetilde{QWT})^+$	$(\widetilde{SU})^+$	$(\widetilde{UNO})^+$	$(\widetilde{PNO})^+$	
1	30	0	0	0	0.007	0	0.007
2	90	0.329	0.303	0.269	0	0.167	1.068
3	180	0.727	0.706	0.527	0.004	0.417	2.380
4	360	0.770	0.785	0.815	0.007	0.917	3.294

Finally, similarity indices for each option (Scenario) are worked out in Table 10 via Equation (6).]

$$CC_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{6}$$

Where CC_i is the similarity index in the TOPSIS method, S_i^+ is a distance of i^{th} option from positive ideal option, and $S_i^-$is distance of i^{th} option from negative ideal option.

Table 10. Similarity indices

Scenario	Period (Days)	CC_i	Rank
1	30	0.001	4
2	90	0.323	3
3	180	0.720	2
4	360	0.999	1

The final results obtained indicate that annual PMP can be selected as the best option. The developed framework can be used as a fast and reliable reference for determining appropriate PMPs of one-shot systems by considering fuzzy sets for MTTF. when it comes to one-shot systems, the available data is not adequate. Providing resilient and expedient one-shot devices, however, reduces the general faults in such systems.

4.5 The behavioral tests of the proposed framework

To test the behavior of the models, the logical changes in the output can be validated based on variations in the input variables (Azimian et al., 2013). The obtained results indicate that the proposed framework is of great capacity for selecting appropriate PMPs for one-shot gears. That is to say, by reducing the period each equipment is used and keeping the meantime to failures unchanged, the trend moves toward shorter PMPs. Also, by increasing the period each piece of equipment is used and keeping the meantime to failures unchanged, the annual time interval is still the best option. Also, by reducing the meantime to failure, the trend moves toward longer PMPs and vice versa. Figure 4 presents the obtained results in this regard.

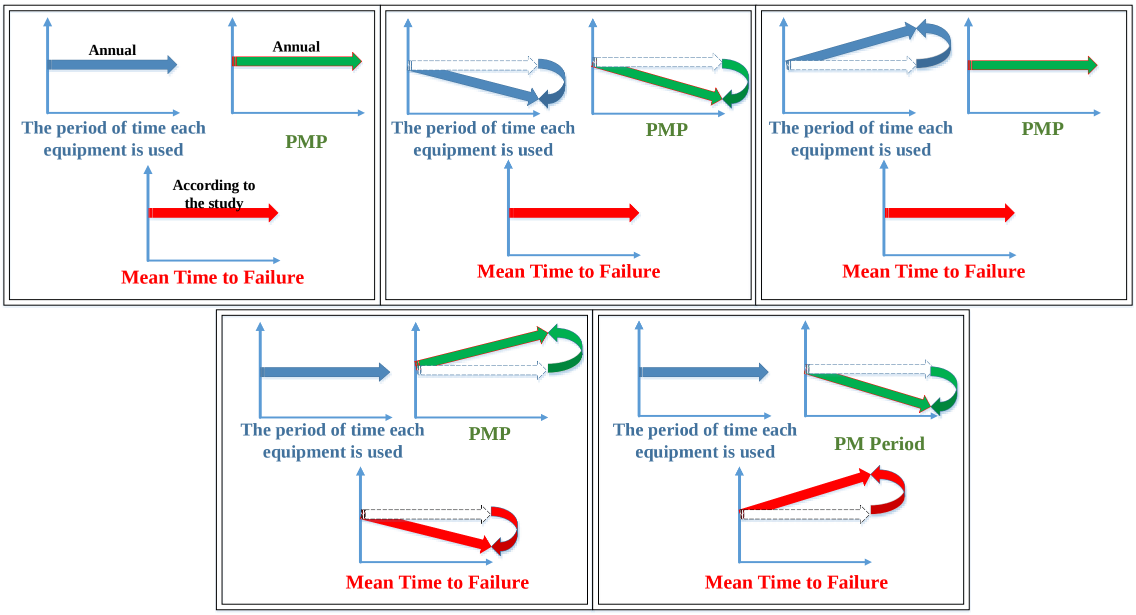

Fig. 4. The behavioral tests of the proposed framework

5. Discussion

One-shot equipment or devices are kept in stand-by mode until called for duty. What is important in this regard related to life-cycle management is determining an appropriate time for their service and maintenance – such that the maintenance costs are reduced. The point worthy of attention in determining the latter times is the existence of adequate data for ascertaining the meantime to failures. But the available data is not adequate in one-shot systems. Hence, it is best to periodically carry out PMPs using fuzzy sets.

Therefore, our main objective in this research is to present a new approach towards determining optimal time intervals for PMPs of one-shot equipment using fuzzy sets as well as ARENA simulation.

Also, the maintenance strategy evaluations obtained with the help of ARENA simulations are in line with numerous other research studies conducted in the field (Petrovic et al., 2018; Alrabghi & Tiwari, 2016; Boukhtouta & Ghanmi, 2014; Eslami et al., 2014). In many cases, however, definitive inputs cannot be defined, so we resorted to a fuzzy analysis of the issue. The procedure adopted agrees with a previous study in the field (Azadeh, Seifoory & Abbasi, 2010).

In the present study, however, PMPs are evaluated based on a one-shot system accomplished by designing a fuzzy simulation system in the ARENA environment. The obtained results demonstrate that fuzzy ARENA simulations serve as useful tools for managers especially when they intend to estimate the PMPs in one-shot devices.

Table 11 summarizes the similarities and innovations of the current research compared with those of other research works referred to above.

Table11. Methods used in this research for analyzing the maintenance of one-shot devices

References	One-Shot		Data		Arena Simulation		Other Methods
	Yes	No	Crisp	Fuzzy	Maintenance Strategy	Maintenance Period	
(Mehrvars et al., 2018)	×		×				×
(Guo et al., 2010)	×		×				×
(Fan et al., 2009)	×		×				×
(Petrovic et al., 2018)	×		×		×		
(Alrabghi & Tiwari, 2016)		×	×		×		
(Boukhtouta & Ghanmi, 2014)	×		×		×		
(Eslami et al., 2014)		×	×		×		
(Azadeh et al., 2010)		×		×		×	
This study	×			×		×	

On the whole, the developed framework can be used as a fast and reliable reference for determining appropriate PMPs of one-shot gears. In other words, the results can be relied upon with a suitable approximation bearing in mind the behavioral tests. To derive maximum benefits/results out of the analyses, it is recommended that responders get themselves familiar with the concepts prevalent in PMP monitoring. Top managers are strongly advised to employ various teaching methods and introduce their staff to relevant concepts.

6. Conclusions

This study was designed to determine appropriate preventive maintenance periods for one-shot devices with time-repaired strategies. This objective was accomplished by proposing a new fuzzy ARENA simulation framework using fuzzy TOPSIS. The reason why we adopted this approach was the lack of requisite records on such type of equipment. This naturally conduced us toward selecting a resilient and expedient approach that would decrease the overall faults in such types of systems. Hence, using the fuzzy method for determining the best preventive maintenance periods seems to be an appropriate choice for preserving the reliability of one-shot devices.

6.1 Research limitations and future study agenda

The limitation of the current study is the possibility of defining the effective indices for choosing appropriate PMPs in one-shot systems following the recommendations made by the expert group; that is to say, the results can be changed or modified by changing the latter group. It is also possible to change the fuzzy sets associated. It should be mentioned that there are major strategies discussed in the literature with such designations as time changed, time repaired, calibration, failure detection, and run to failure for maintaining the reliability of one-shot devices. In this study, however, our focus was on time-repaired strategies. So, calibration profiles can be used to establish the calibration status of the intended device. Alternatively, in case of fault-detecting failures arising from the impossibility of estimating the initial parameters which in turn stem from a lack of required repair data, it is possible to use a self-starting profile for determining the status of the equipment. As a final word, the researchers are strongly encouraged to expand on the presented framework and apply it to other one-shot equipment or systems.

References

Alimohammadlou, M., & Khoshsepehr, Z. (2021). Investigating Organizational Sustainable Development through an Integrated Method of Interval-Valued Intuitionistic Fuzzy AHP and WASPAS. *Environment, Development, and Sustainability*, 24(1), 2193-2224. doi:https://doi.org/10.1007/s10668-021-01525-7

Alrabghi, A., & Tiwari, A. (2016). A Novel Approach for Modelling Complex Maintenance System Using Discrete Event Simulation. *Reliability Engineering and System Safety*, 154, 160-170.

Azadeh, A., Seifoory, M., & Abbasi, M. (2010). Integration of Simulation and Fuzzy Multi-Attribute Decision Making for Modelling and Assessment of Fuzzy Parameters. *International Journal of Industrial and Systems Engineering*, 6(4), 483-501.

Azimian, M., Bardi, M., & Javadi, H. (2013). Sensitivity Analysis of Project Efficiency in a Multi-Project Environment Based on Data Envelopment Analysis. *International of Engineering Sciences*, 2(7), 259-265.

Azimian, M., Javadi, H., Farshchiha, A., & Nosohi, I. (2017). Selection of the Optimum Suppliers Compound Using a Mixed Model of MADM and Fault Tree Analysis. *Production and Operation Management,* 8(1), 45-64 (In Persian).

Azimian, M., Karbasian, M., Atashgar, K., & Kabir, G. (2021). A New Approach to Select the Reliable Suppliers for One-shot Devices. *Production Engineering,* 15, 371-382. doi:https://doi.org/10.1007/s11740-021-01032-8

Azimian, M., Karbasian, M., Atashgar, K., & Kabir, G. (2021). Appropriate Strategy Selection for Reliability-Centered Maintenance of One-Shot Systems using Fuzzy Model. *Journal of Quality in Maintenence Engineering*, ahead-of-print, 1355-2511. doi:10.1108/JQME-06-2020-0050

Azimian, M., Shahin, A., Alinaghiyan, M., & Badri, M. (2012). Development of Integration Approach of DEA and Malmquist for Evaluation of Proiect Efficiency - Case Study. *Industrial Management,* 5(1), 43-62 [In Persian].

Banks, J., Carson, J., Nelson, B., & Nicol, D. (2009). *Discrete-Event System Simulation.5rd ed.* New Jersey: Prentice-Hall, Inc.

Boukhtouta, A., & Ghanmi, A. (2014). A Simulation Study of Operational Availability of Canadian Armed Forces Equipment under Different Maintenance Regimes. *International Conference on Analytics Driven Solutions-ICAS 2014, Ottawa-Ontario-Canda* (p. 183).

Crawford, R., & Martin, P. (2020). *Plastics Engineering 4th Edition.* USA: Butterworth-Heinemann . DOI: eBook ISBN: 9780081007105.

Daneshkhah, A., Stocks, N., & Jeffrey, P. (2017). Probabilistic Sensitivity Analysis of Optimised Preventive Maintenence Strategies for Deteriorating Infrastructure Assets. *Reliability Engineering and System Safety,* 163, 33-45.

Dunson, D., & Dinse, G. (2002). Bayesian Models for Multivariate Current Status Data with Informative Censoring. *Biometrics,* 58, 79-88.

Eslami, S., Sajadi, S., & Hosseinzadeh Kashan, A. (2014). Selecting a Preventive Maintenance Scheduling Method by Using Simulation and Multi-Criteria Decision Making. *International Journal of Logistics Systems and Management, 18*(2), 250-269.

Fan, T., Balakrishnam, N., & Chang, C. (2009). The Bayesian Approach for Highly Reliable Electro-Explosive Devices Using One-Shot Device Testing. *Journal of Statistical Computation and Simulation,* 79(9), 1143-1154.

Felecia, Ong (2014). Fuzzy Logic Reliability Centered Maintenance. *Jurnal Teknik Industri,* 16(2), 121-126.

Grall, A., Bérenguer, C., & Dieulle, L. (2002). A Condition-Based Maintenance Policy for Stochastically Deteriorating Systems. *Reliability Engineering & System Safety,* 76, 167-180.

Guo, H., Honecker, S., Mettes, A., & Ogden, D. (2010). Reliability Estimation for One-Shot Systems with Zero Component Test Failures. *Annual Reliability and Maintain Ability Symposium, IEEE,* (pp. 1-7).

Hariga, M. (1996). A Maintenance Inspection Model for a Single Machine with General Failure Distribution. *Microelectronics Reliability,* 36, 353-358.

Ito, K., & Nakagawa, T. (2000). Optimal Inspection Policies for a Storage System with Degradation at Periodic Tests. *Mathematical and Computer Modelling,* 31, 191-195.

Jianxing, Y., Haicheng, C., Yang, Y., & Zhenglong, Y. (2019). A Weakest T-norm-Based Fuzzy Fault Tree Approach for Leakage Risk Assessment of Submarine Pipeline. *Journal of Loss Prevention in the Process Industries*, 62, 103968.

Kaio, N., Dohi, T., & Osaki, S. (1994). Inspection Policy with Failure due to Inspection. *Microelectronics Reliability,* 34, 599-602.

Kitagaw, T., Yuge, T., & Yanagi, S. (2016). Periodic and Non-Periodic Inspection Policies for a One-Shot System with Minimal Repair. *Journal of Japan Industrial Management Association,* 66(4), 387-395. doi:10.11221/jima.66.387

Li, W., & Pham, H. (2005). An Inspection-Maintenance Model for Systems with Multiple Competing Processes. *IEEE Transactions on Reliability,* 54, 318-327.

Li, W., He, M., Sun, Y., & Cao, Q. (2019). A Novel Layered Fuzzy Petri Nets Modeling and Reasoning Method for Process Equipment Failure Risk Assessment. *Journal of Loss Prevention in the Process Industries*, 62, 103953.

Ling, M., & Hu, X. (2020). Optimal Design of Simple Step-stress Accelerated Life Tests for One-shot Devices Under Weibull Distributions. *Reliability Engineering and System Safety,* 193, 106630.

McLaughlan, P., Forth, S., & Grimes-Ledesma, L. (2011). *Composite Overwrapped Pressure Vessels: A Primer.* NASA. doi:Doc ID: NASA/SPe2011e573

Mehrvars, A., Sanei Monfared, M., Farsi, M., & Shafiei, M. (2018). Monitoring the States and Maintaining the Reliability of the One-Shot Systems. *Journal of Sharif Industrial Engineering and Management,* 34-1(1/1), 73-85 [In Persian].

Morris, M. (1987). A Sequential Experimental Design for Estimating a Scale Parameter from Quantal Life Testing Data. *Technometrics,* 29, 173-181.

Nakagawa, T. (2006). *Maintenance Theory of Reliability.* Springer Science and Business Media.

Newby, M. (2008). Monitoring and Maintenance of Spares and One-Shot Devices. *Reliability Engineering & System Safety,* 93, 588-594.

Nourelfath, M., Nahas, N., & Ben Doya, M. (2016). Integrated Preventive Maintenance and Production Decisions for Imperfect Processes. *Reliability Engineering and System Safety,* 148, 21-31.

Petrovic, S., Milosavljevic, P., & Lozanovic Sajic, J. (2018). Rapid Evaluation of Maintenance Process Using Statistical Process Control and Simulation. *International Journal of Simulation Model,* 17, 119-132.

Ploskas, N., & Papathanasiou, J. (2019). A Decision Support System for Multiple Criteria Alternative Ranking Using TOPSIS and VIKOR in Fuzzy and Nonfuzzy Environment. *Fuzzy Sets and Systems,* 377, 1-30.

Saeedpoor, M., & Vafadarnikjoo, A. (2015). A Comparison Between Fuzzy AHP and Fuzzy TOPSIS Methods to Supplier Selection. *Applied Soft Computing,* 26, 545.

Safarianzengir, V., Sobhani, B., Madadi, A., & Yazdani, M. (2021). Monitoring, Analyzing and Estimation of Drought Rate Using New Fuzzy Index in Cities of West and Southwest of Iran, Located in the North of the Persian Gulf. *Environment, Development and Sustainability,* 23, 7454–7468. doi:https://doi.org/10.1007/s10668-020-00925-5

Saffari, A., Ataei, M., Sereshki, F., & Naderi, M. (2019). Environmental Impact Assessment (EIA) by Using the Fuzzy Delphi Folchi (FDF) Method (Case Study: Shahrood Cement Plant, Iran). *Environment, Development, and Sustainability, 21,* 817–860. doi:https://doi.org/10.1007/s10668-017-0063-1.

Stansbury, E., & Buchanan, R. (2000). *Fundamentals of electrochemical corrosion.* ASM international.

Vinter, Z., & Valis, D. (2008). Reliability Modelling Of Automatic Gun With Pyrotechnic Charging. *Advances In Military Technology,* 3(1), 33.

Wu, H., Li, Y.-F., & Bérenguer, C. (2020). Optimal Inspection and Maintenance for a Repairable k-out-of-n: G Warm Standby System. *Reliability Engineering and System Safety,* 193, 106669.

Xiaoqiang, W., Lunyang, L., Shaowei, L., & Bohan, L. (2021). Condition Monitoring of Composite Overwrap Pressure Vessels using MXene Sensor. *International Journal of Pressure Vessels and Piping,* 191, 104349.

Yang, L., Ma, X., Peng, R., Zhai, Q., & Zhao, Y. (2017). A Preventive Maintenence Policy Based on Dependent Two-Stage Deterioration and External Shocks. *Reliability Engineering and System Safety,* 160, 201-211.

Yates, S., & Mosleh, A. (2006). A Bayesian Approach to Reliability Demonstration for Aerospace Systems. *Reliability and Maintainability Symposium. Annual.* Newport Beach, CA, USA.

Yun, W., Kim, H., & Han, Y. (2012). Simulation-Based Inspection Policies for a One-Shot System in Storage. *5th Asia-Pacific Int. Symp. Advanced Reliability and Maintenance Modeling (APARM 2012),* (pp. 621-628).

Yun, W.-Y., Han, Y., & Kim, H.-W. (2014). Simulation-Based Inspection Policies for a One-Shot System in Storage Over a Finite TimeSpan. *Communications in Statistics-Simulation and Computation,* 43, 1979-2003.

Zhang, C., Qian, Y., Dui, H., Wang, S., & Shi, J. (2020). Component Failure Recognition and Maintenance Optimization for Offshore Heave Compensation Systems Based on Importance Measures. *Journal of Loss Prevention in the Process Industries,* 63, 103996.

Zio, E., & Di Maio, F. (2010). A Data-Driven Fuzzy Approach for Predicting the Remaining Useful Life in Dynamic Failure Scenarios of a Nuclear System. *Reliability Engineering and System Safety,* 95, 49-57.