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A MODELLING APPROACH FOR ASSET DEGRADATION: ADVANCING DIGITAL TWIN IN MAINTENANCE

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Abstract
Recently, a considerable literature has grown up around the theme of maintenance applications in Industry 4.0. Optimizing complex maintenance systems in particular poses a challenge as modern manufacturing systems involve numerous dependencies and interactions. Simulation has shown success in modelling comparable problems in other fields. This study introduces a novel discrete event simulation method for modelling stochastic asset degradation, which facilitates seamless integration into digital twin frameworks for maintenance systems. Rather than modelling the mean time between failures or predicting the remaining useful life, generating accurate and live asset degradation profiles enables the development of a digital twin that optimizes maintenance strategies in real time. However, assuming the asset health index does not improve without maintenance interventions makes these findings less generalizable. We apply the proposed methodology to a maintenance problem in a published study. Further research might explore the effectiveness of integrating real time optimization.
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Key Words: Simulation, Maintenance, Modelling, Stochastic, Degradation

1. INTRODUCTION

Recently, a considerable literature has grown up around the theme of maintenance applications in Industry 4.0. Smart maintenance systems can leverage the connectivity brought forth by Internet of Things (IoT) and Artificial Intelligence (AI) to self-adjust and self-optimize in real-time with minimum human intervention. This in turn might promise significant improvements in the performance of the maintenance system such as higher availability and lower costs.

A pre-requisite for realizing the full benefits of Industry 4.0 in maintenance is developing a valid digital version of the maintenance system. The digital twin will receive updates from the various sensors in the physical system in order to simulate possible scenarios and decide the optimum course of action. However, modelling current maintenance systems is challenging. This is partly due to the variable interaction of maintenance systems with other related systems such as operation and spare parts logistics and maintenance teams. Another contributing factor is the complexity of asset degradation as it involves structural, stochastic, economic and resource dependencies. This is particularly true for condition-based maintenance where the asset's health fluctuates dynamically.

Discrete Event Simulation (DES) is a promising modelling technique as it has been utilized successfully to simulate complex maintenance systems. In addition, it is widely used for modelling manufacturing operations including production, product-service systems and spare parts logistics. However, in terms of modelling asset degradation, research on the subject has been mostly restricted to modelling Preventive Maintenance. Therefore, researchers have not treated the modelling of dynamic asset degradation using DES in much detail.

This paper contributes to the field by:

1. Proposing a discrete event simulation approach for modelling stochastic asset degradation.
2. Demonstrating its compatibility with digital twin frameworks for maintenance systems.
3. Validating the approach through an industrial case study.

Generating accurate and live asset degradation profiles enables the development of a digital twin that optimizes maintenance strategies in real time. The use of DES enables the exploitation of success this particular approach had with complex maintenance systems in addition to other related systems such as production and spare parts inventory management.

The remaining part of the paper proceeds as follows: Section 2 presents a review of related work, highlighting the potential and challenges in applying digital twins in maintenance, existing methods for modelling asset degradation, current practices in modelling maintenance with DES and the main contribution of this paper. In section 3, we describe the research methodology and its limitations. In section 4, the details of the proposed approach is laid and explained. The results of applying the proposed approach on real-world data are presented and discussed in section 5. Finally, section 6 concludes the paper by summarizing key findings and suggesting directions for future research.

2. RELATED WORK

2.1 Digital twin in maintenance

The progression towards Industry 4.0 brought disruptive innovations that significantly changed the face of manufacturing. The advancements in IoT and sensor technology provided real-time data on maintenance systems and allowed the continuous streaming of asset conditions, operating environment and maintenance resources. This connectivity can be integrated to Intelligent systems that analyse Big Data, simulate possible scenarios and optimize dynamically in real time [1-6].

Developing a smart and self-configurating maintenance system holds the potential to drastically enhance key performance metrics. Essentially, the purpose of maintenance modelling is to reflect on the bottom line. This means making maintenance planning more efficient resulting in the maximization of asset availability and minimization of all associated costs [7-9].

One of the main challenges in fully realizing the benefits of Industry 4.0 lies in developing a representative digital model of the maintenance system. The high-fidelity digital model needs to ingest online data and adjust the prediction of the asset condition in an efficient manner reflected in short time and low computation costs. This might be one of the reasons for the reported low level of Digital Twin adoption in maintenance [10-12].

2.2 Asset degradation modelling

To date, several studies have reviewed the published research on modelling asset degradation [13-18]. In general, degradation models can be categorized into physics-based models and data-driven models. Physics-based models analyse the failure mechanism for the asset based on physics laws to develop a specific degradation model. By contrast, data-driven models rely on statistical analysis and data fitting without necessarily evaluating the mechanical or electrical failure initiation and progression processes.

Research in data-driven models have received more attention over the years due its applicability to a wide range of engineering problems, its ability to better reflect the inherited stochastic nature of asset degradation and due to the large volume of data available in today's maintenance systems.

Much of the literature on data-driven approach seems to have been based on developing regression models. This allows the fitting the degradation data over time through a line or a curve. Random coefficients can be added to reflect the variations in the asset degradation profile. Brownian motion error and its various extensions such as the Wiener process or Brownian motion with a drift is considered popular due to its ability to capture uncertainty as well as its mathematical properties. Although the inclusion of variability enhanced the model accuracy, it increased the model complexity and required computations. In addition, such models are not suitable for modelling monotonic degradation.

Other researchers attempted to model assets profiles by fitting degradation data into stochastic distributions such as Gamma and Inverse Gaussian processes. Such models are more suitable for characterizing monotonic degradation processes. However, they are applicable to special cases since strict requirements for the degradation must be met.

2.3 Discrete event simulation in reliability and maintenance

Discrete Event Simulation is one of the most popular approaches in modelling and optimizing maintenance systems [19]. Using this approach, researchers have been able to model complex maintenance systems [20] and various types of dependencies found in non-identical components [21]. This has shown that it can capture the variable and dynamic nature of modern maintenance systems.

The Discrete Event Simulation model can act as a cyber twin that connects with the physical assets to update the inputs and evaluate future scenarios to produce real-time decision making [22]. In addition, DES have been proved successful in simulating and optimizing systems that are integrated with maintenance such as production and inventory operations [23]. This can enhance the outcome of the analysis since a wider perspective of the system is taken into consideration as opposed to conducting analysis separately on a sub-system level.

Most studies that utilize DES tend to focus on preventive maintenance as the prime strategy [19]. In addition, the use of DES has been mainly used as an offline scheduling tool [22]. Therefore, asset failure or degradation is simulated using either regression models or reliability indices such as mean time between failures. However, the application of digital twin in condition-based maintenance requires the dynamic description of the asset degradation.

2.4 Contribution of this research

The evidence reviewed here seems to suggest a pertinent role for DES in developing maintenance digital twins. However, little attention has been paid to using this approach to describe the dynamic asset degradation. This paper proposes a methodology for modelling stochastic asset degradation using discrete event simulation. Generating accurate and live asset degradation profiles enables the development of a digital twin that optimizes maintenance systems in real time.

3. RESEARCH METHODOLOGY

The present study utilises Discrete Event Simulation (DES) to model the stochastic degradation patterns of assets. DES is a modelling technique that models the behaviour of systems as it evolves over time when certain events occur. DES has been used to model and analyse complex behaviours and variable processes. Application areas include manufacturing, logistics and maintenance [24].

The degradation profile of an asset typically experiences changes at discrete points in time. For example, at breakdowns and after maintenance interventions. The continuous change in the asset condition can be modelled in discrete times depending on the condition monitoring frequency.

The generic approach for modelling unpredictable variability through statistical distributions was customized to represent the degradation process (see Fig. 1). It is widely established for arrival and service times. The approach is an iterative process which includes analysing the input data with the aim of finding the most appropriate statistical distribution [25, 26].

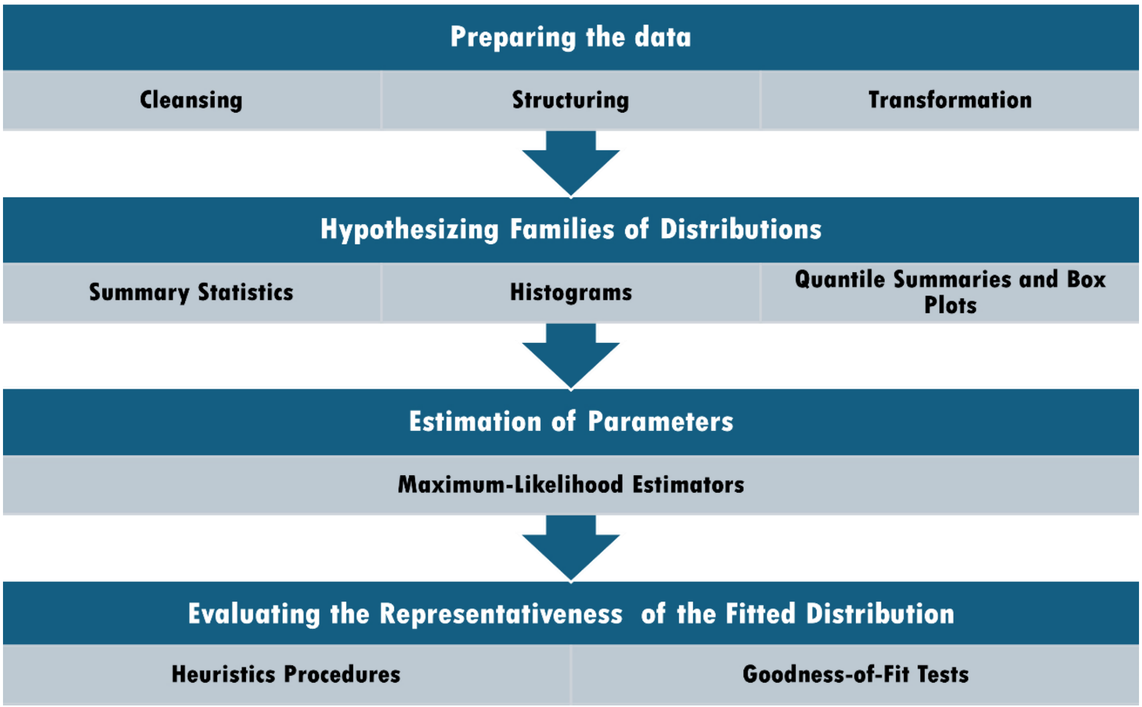

Figure 1: A generic input modelling approach. Adapted from [24].

In this study, we assume that the asset condition only improves following a maintenance intervention. This implies that any improvement in the condition without a maintenance intervention will be overlooked. It is a common assumption in maintenance literature [27].

4. PROPOSED APPROACH

Nomenclature:

X_t – degradation state of the asset at time *t*,
ΔX_t – increase in in the degradation state of the asset for one time unit,
R – uniformly distributed random number [0, 1],
P – the probability of positive changes in the asset degradation.

The proposed approach to model stochastic asset degradation consists of six steps as shown in Fig. 2. It starts with the asset's health data and concludes with the ability to generate accurate degradation profiles. Each step is explained in detail below.

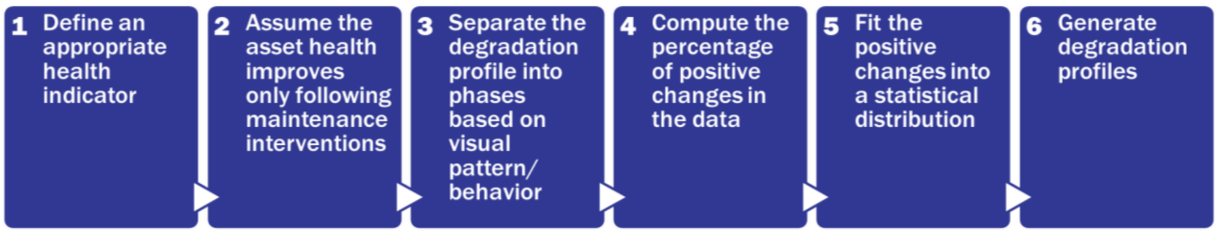

Figure 2: Main steps in the proposed approach.

- **Define an appropriate health indicator**

An appropriate health indicator can be chosen based on the asset nature, critical functions, operation environment and available sensors and inspection devices. it could be a single reading or a health index aggregating several different readings. The indicator should reflect the asset's health and assist in detecting and predicting failures to enable timely interventions. It is inevitable to obtain sufficient data that covers both normal and abnormal conditions.

- **Assume the asset health improves only following maintenance interventions**

This assumption implies that the asset either deteriorates or remains in the same condition if it was not maintained. Therefore, if the health data showed unexplained improvements in the condition, it will be overlooked.

- **Separate the degradation profile into phases based on visual pattern/ behaviour**

The asset's condition can be classified into various stages based on degradation and failure progression. Each stage is analysed and modelled individually. the simplest form can include: normal operation, failure progression and failure. Other stages can be added if required to reflect the actual degradation profile.

- **Compute the percentage of positive changes in the data**

The health data of the selected stage will consist of individual readings that are either increasing or remaining constant. The objective of this step is quantifying the chance of increase in degradation by computing its probability. This can be calculated based on one data set or preferably multiple data sets for the same stage.

- **Fit the positive changes into a statistical distribution**

The increase in degradation is analysed in this step to find the most suitable statistical distribution. Here, we follow the established distribution fitting methods in simulation literature [24, 25]. It consists of performing basic statistics analysis and data visualization, selecting a set of candidate statistical distributions, determining the best fitted distribution and assessing the quality of the best distribution.

- **Generate degradation profiles**

The degradation profile can be generated by simulating the deterioration behaviour. For each stage, the health condition will increase depending on the computed probability according to selected statistical distribution and its parameters.

Fig. 3 presents a flowchart of the simulation procedure for modelling a single degradation phase of a given asset. For each time unit, a uniformly distributed random number is generated between 0 and 1. The asset degradation will increase according to the suitable statistical distribution if the generated number is less than the probability of positive changes in the asset degradation. The simulation will continue in iteration until the failure threshold is reached. The simulation can be further expanded to accommodate multiple degradation phases and/or multiple assets.

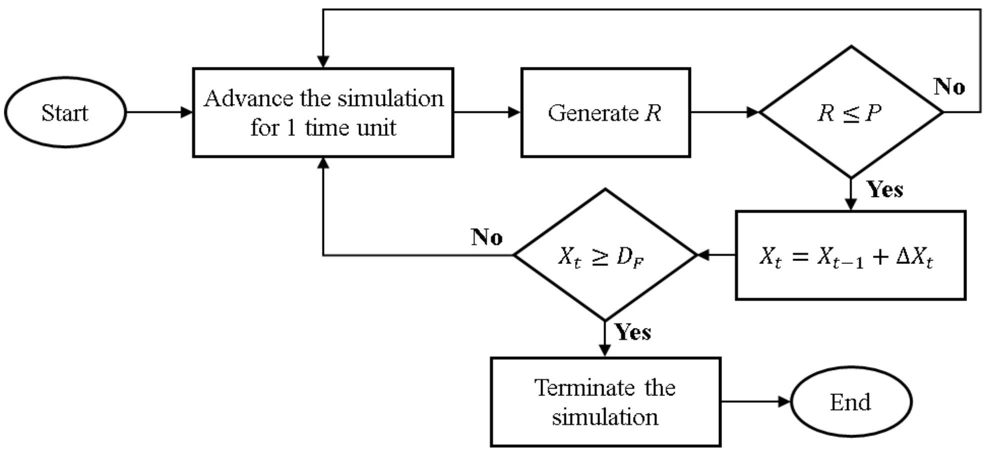

Figure 3: Basic flowchart of the simulation model.

The simulation model can act as the digital representation of the asset. Common DES software packages support data exchange with the physical system including direct integration with Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), Supply Chain Planning (SCP), and Internet of Things systems (IoT).

5. CASE STUDY

In this section, the proposed approach is demonstrated through an industrial case study. The data is acquired from The Prognostics Data Repository at NASA [28, 29]. Run to failure experiments were conducted on bearings on a shaft while continuously monitoring its condition through accelerometers. In order to model the degradation profile of the bearing, the steps in approach will be followed.

Step 1: Define an appropriate health indicator

The bearing health will be inferred from the accelerometers placed on the bearing housing. The Root Mean Squared (*rms*) reflects the average power of the vibration signal as shown in Fig. 4. The breakdown threshold is assumed to be 0.15.

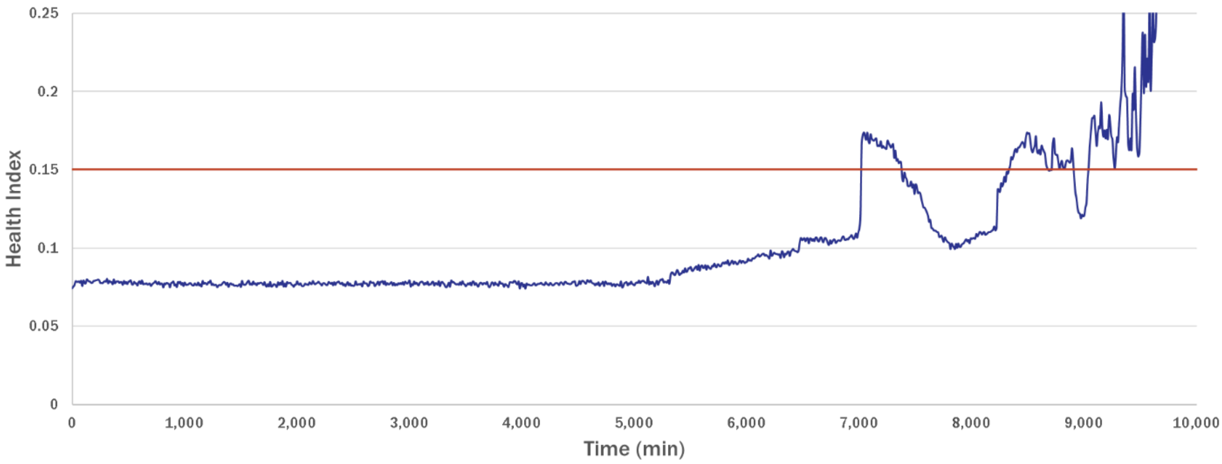

Figure 4: Bearing health data [28].

Step 2: Assume the asset health improves only following maintenance interventions

As this was a run-to-failure experiments, all improvements in the health index will be disregarded and presumed originated from noise. The modified data is shown in Fig. 5.

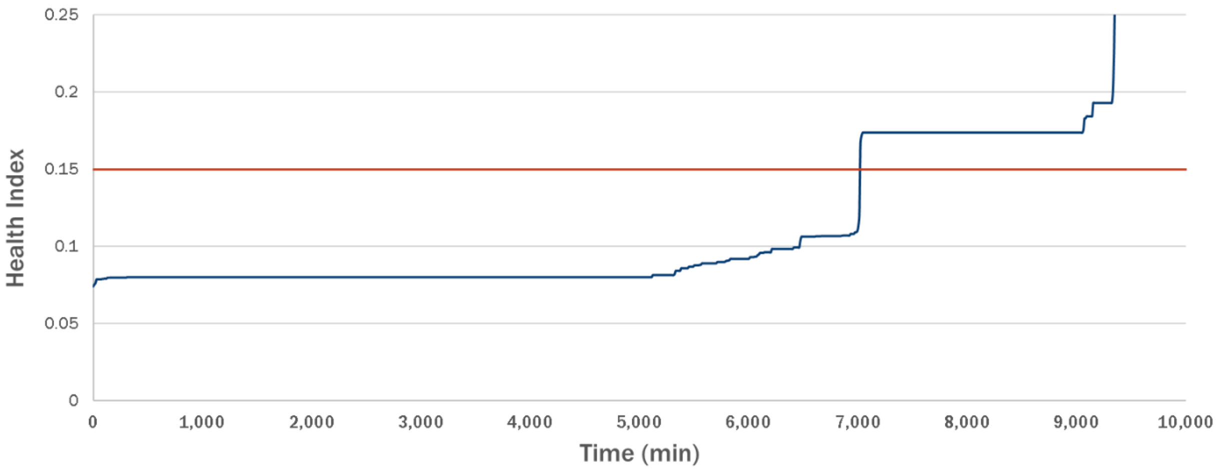

Figure 5: Bearing health data assuming it improves only following maintenance interventions.

Step 3: Separate the degradation profile into phases based on visual pattern/ behaviour

The degradation profile in Fig. 5 can be categorized into three phases based on the behaviour analysis of the health index. As Fig. 6 illustrates, the asset seems to be under normal operating conditions in the first phase starting from the beginning of the test up to 5110 minutes. Fault begins to propagate in the second phase leading to failure in the third phase (7020 minutes). The phase in interest in this case is the second one where failure is propagating.

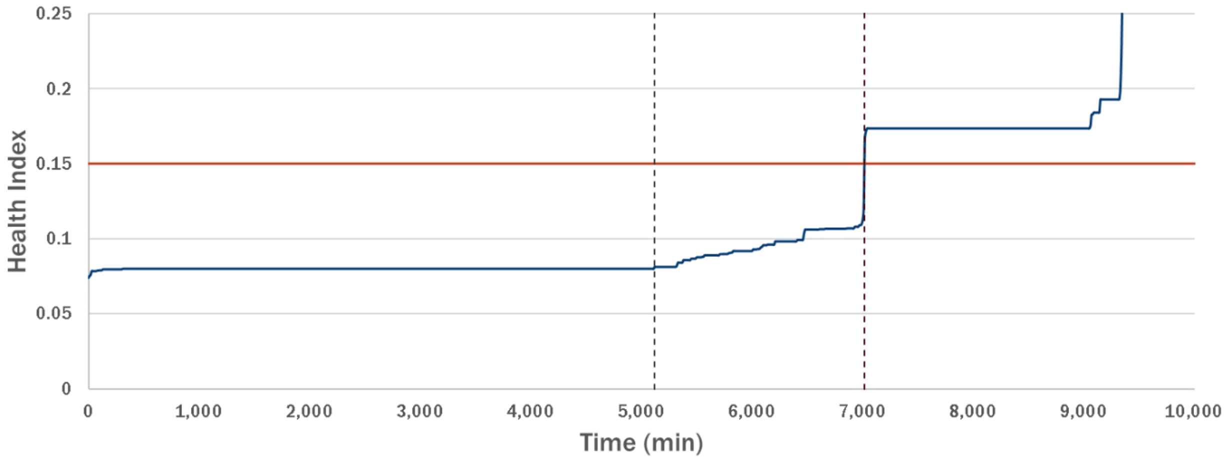

Figure 6: Phases of the bearing degradation profile.

Step 4: Compute the percentage of positive changes in the data

There are 191 data points in the second phase. Only 37 constituted a positive change which indicates that the probability of asset deterioration in the phase is 19.4 %. In the remaining instances, the asset condition remains constant.

Step 5: Fit the positive changes into a statistical distribution

The data was fitted to a statistical distribution. The process involves analysing the data statistically and graphically to nominate a number of candidate distributions and estimate their parameters. The most suitable candidate distribution is selected based on goodness of fit tests such as Anderson-Darling and Kolmogorov-Smirnov tests (see Table I). In addition, visual checks are conducted of various graphs of the fitted distribution vs. empirical data such as the cumulative distribution function, probability-probability plot and quantile-quantile plot (see Figs. 7 and 8). In this case, the Lognormal distribution with a minimum of 0, a mean of -7.44 and a standard deviation of 1.63 emerged as the top ranked distribution.

Table I: Goodness of fit results.

Data points	37
Estimates	Maximum likelihood estimates
Accuracy of fit	0.0003
Level of significance	0.05
Kolmogorov-Smirnov test	
ks stat	0.121
alpha	0.05
ks stat (37, 0.05)	0.218
p-value	0.609
result	DO NOT REJECT
Anderson-Darling test	
ad stat	1.06
alpha	0.05
ad stat (37, 0.05)	2.49
p-value	0.329
result	DO NOT REJECT

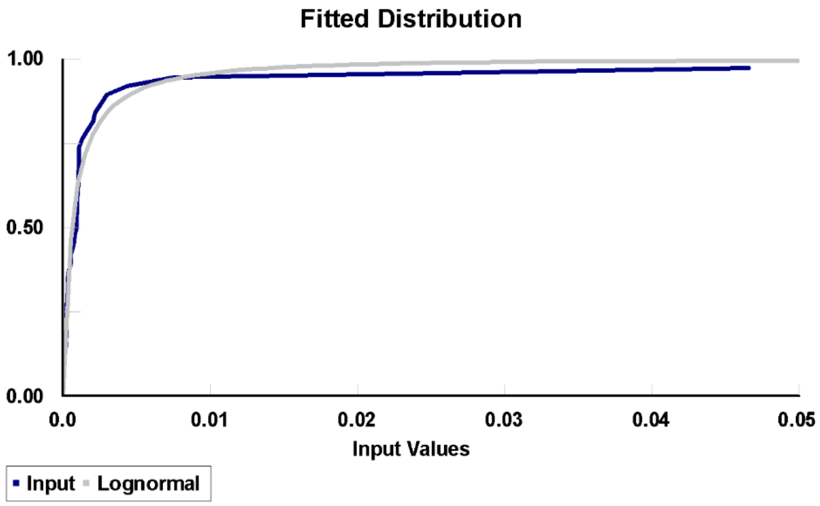

Figure 7: Fitted cumulative distribution functions of empirical data vs. fitted distribution.

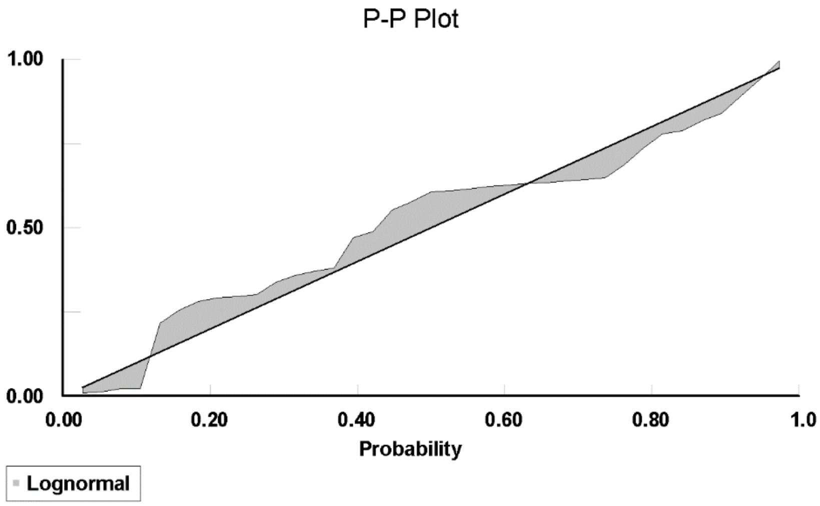

Figure 8: Probability-probability plot of empirical data vs. fitted distribution.

Step 6:Generate degradation profiles

The asset degradation profile can be generated by simulating its behaviour based on the probability of increase in deterioration at each instance. In instances where deterioration occurs, random variates are generated from the fitted distribution to quantify the volume of increase at that instance. Fig. 9 shows three different degradation profiles that were generated for the bearing.

As can be seen from Fig. 9, the generated degradation profiles resemble the general pattern of the original degradation profile. This is reflected in the stability of the health index, the gradual increase and the occasional dramatic increase. The variability across the generated profiles is expected since it represents the inherited randomness in the real world. In fact, we expect to find variability in the degradation profiles of two identical assets operating in the same environment.

The model's results can be used to predict the remaining useful life (*RUL*) of the asset. The empirical data indicated a breakdown at 7020 minutes, while the generated profiles predicted a breakdown at 7810, 6680 and 6810 minutes respectively. Interestingly, the average expected *RUL* across all three degradation profiles was 7100 minutes, which closely is aligned with the observed value. This might indicate that generating multiple profiles and using average values for the asset condition and the expected *RUL* can enhance the effectiveness and accuracy of the model.

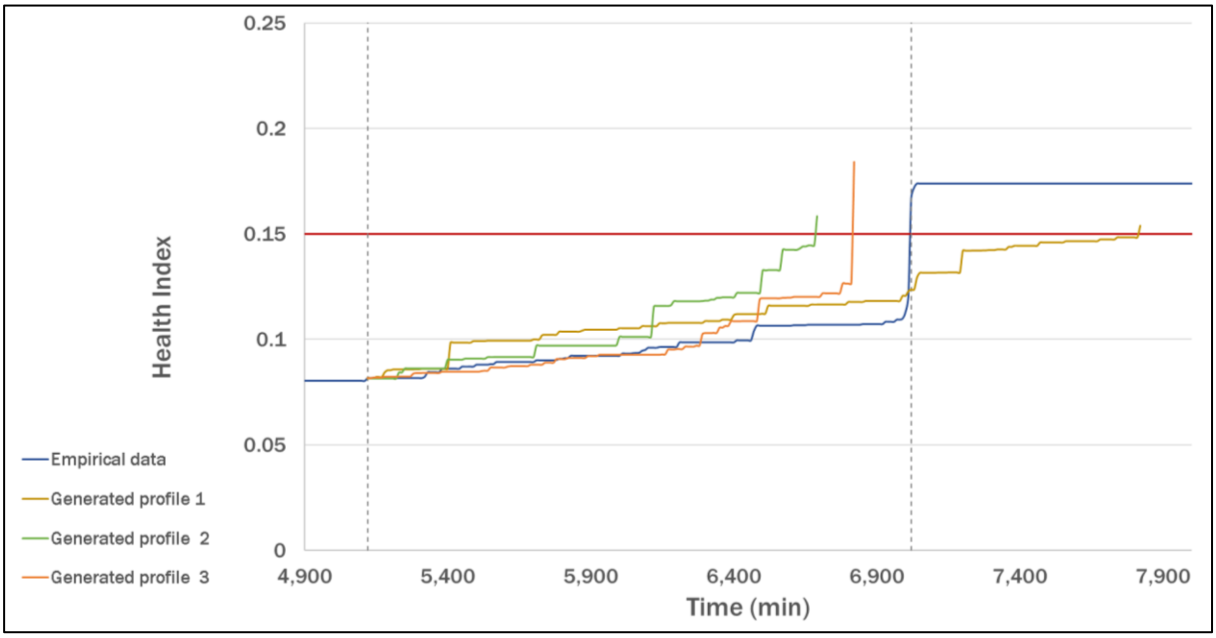

Figure 9: Generated degradation profile for the bearing.

It is worth noting that the current simulation study was conducted offline. Therefore, both asset degradation path and *RUL* were estimated once at the beginning of the simulation run. Updating the model with actual readings either in real time or periodically is likely to enhance the predictions.

Taken together, these findings contribute to the field of maintenance digital twins by proposing an approach for modelling of asset degradation in DES. Generating accurate and live asset degradation profiles enables the development of a cyber version of the maintenance system. This will complement the current growing body of research in modelling and optimizing maintenance systems using DES including optimization of maintenance strategies in real time, joint optimization of maintenance and production, joint optimization of maintenance and spare parts and the joint optimization of all three systems together.

The generalisability of these results is subject to certain limitations. For instance, sufficient historical data must be available on the asset of interest to enable the required statistical analysis. Common data challenges include incomplete or noisy data, lack of data format standardization and limit access to real-time data. Also, it is assumed that either a statistical or an empirical distribution can describe the asset degradation profile. In addition, the approach assumes that the asset health index does not improve without maintenance interventions which may not be true for all assets.

6. CONCLUSIONS

We are seeing a growing interest from both academics and practitioners in maintenance applications of Industry 4.0. Modelling and simulation are central to the concept of a digital twin. However, modelling and optimizing complex maintenance systems in particular poses a challenge as modern manufacturing systems involve variability, numerous dependencies and interactions with related systems such as production and spare parts.

This paper proposes a methodology for modelling stochastic asset degradation dynamically using DES. Generating accurate and live asset degradation profiles enables the development of a digital twin that optimizes maintenance strategies in real time. In addition, the use of DES enables the exploitation of success this particular approach had with systems that are closely related to maintenance. Finally, the proposed approach is demonstrated through an industrial case study.

The findings should be interpreted with caution and may not generalize to all scenarios, as they are limited by several assumptions. This study was limited as it assumes that sufficient historical data is available on the asset degradation. Additionally, assuming the asset health index does not improve without maintenance interventions makes these findings less generalizable.

A natural progression of this work is to explore the validity of the suggested approach across a wider set of assets with distinct degradation behaviours. Further research might explore the effectiveness of real time optimization of both maintenance and spare parts inventory management. Future research might also explore the integration of advanced machine learning techniques to enhance predictive capabilities within the digital twin.

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REFERENCES

[1] Alrabghi, A. (2018). Simulation based optimization frameworks as key enablers for the transformation to Industry 4.0, *The 48th International Conference on Computers and Industrial Engineering (CIE 48)*, 201.1-201.6

[2] Gupta, S.; Kumar, A.; Maiti, J. (2024). A critical review on system architecture, techniques, trends and challenges in intelligent predictive maintenance, *Safety Science*, Vol. 177, Paper 106590, 29 pages, doi:10.1016/j.ssci.2024.106590

[3] Pang, J. L. (2023). Adaptive fault prediction and maintenance in production lines using deep learning, *International Journal of Simulation Modelling*, Vol. 22, No. 4, 734-745, doi:10.2507/IJSIMM22-4-CO20

[4] Nota, G.; Nota, F. D.; Toro, A.; Nastasia, M. (2024). A framework for unsupervised learning and predictive maintenance in Industry 4.0, *International Journal of Industrial Engineering and Management*, Vol. 15, No. 4, 304-319, doi:10.24867/IJIEM-2024-4-365

[5] Putnik, G. D.; Varela, L.; Pinheiro, P.; Maia, S.; Alves, C. (2024). Identification of the major trends in current maintenance policies using LDA methodology for semantic analysis of the published research results, *International Journal for Quality Research*, Vol. 18, No. 2, 587-602, doi:10.24874/IJQR18.02-17

[6] Patalas-Maliszewska, J.; Losyk, H. (2022). An approach to maintenance sustainability level assessment integrated with Industry 4.0 technologies using Fuzzy-TOPSIS: a real case study, *Advances in Production Engineering & Management*, Vol. 17, No. 4, 455-468, doi:10.14743/apem2022.4.448

[7] Werbińska-Wojciechowska, S.; Winiarska, K. (2023). Maintenance performance in the age of Industry 4.0: a bibliometric performance analysis and a systematic literature review, *Sensors*, Vol. 23, No. 3, Paper 1409, 55 pages, doi:10.3390/s23031409

[8] Kang, B. G.; Kim, B. S. (2024). Attachable IOT-based digital twin framework specialized for SME production lines, *International Journal of Simulation Modelling*, Vol. 23, No. 3, 471-482, doi:10.2507/IJSIMM23-3-694

[9] Banyai, A. (2023). Impact of agile, condition-based maintenance strategy on cost efficiency of production systems, *Advances in Production Engineering & Management*, Vol. 18, No. 3, 317-326, doi:10.14743/apem2023.3.475

[10] You, Y.; Chen, C.; Hu, F.; Liu, Y.; Ji, Z. (2022). Advances of digital twins for predictive maintenance, *Procedia Computer Science*, Vol. 200, 1471-1480, doi:10.1016/j.procs.2022.01.348

[11] Van Dinter, R.; Tekinerdogan, B.; Catal, C. (2022). Predictive maintenance using digital twins: a systematic literature review, *Information and Software Technology*, Vol. 151, Paper 107008, 20 pages, doi:10.1016/j.infsof.2022.107008

[12] Ma, S.; Flanigan, K. A.; Bergés, M. (2024). State-of-the-art review and synthesis: a requirement-based roadmap for standardized predictive maintenance automation using digital twin technologies, *Advanced Engineering Informatics*, Vol. 62, Part C, Paper 102800, 22 pages, doi:10.1016/j.aei.2024.102800
[13] Gorjian, N.; Ma, L.; Mittinty, M.; Yarlagadda, P.; Sun, Y. (2010). A review on degradation models in reliability analysis, Kiritsis, D.; Emmanouilidis, C.; Koronios, A.; Mathew, J. (Eds.), *Engineering Asset Lifecycle Management (WCEAM 2009)*, Springer, London, 369-384, doi:10.1007/978-0-85729-320-6_42
[14] Shahraki, A. F.; Yadav, O. P.; Liao, H. (2017). A review on degradation modelling and its engineering applications, *International Journal of Performability Engineering*, Vol. 13, No. 3, 299-314, doi:10.23940/ijpe.17.03.p6.299314
[15] Kang, R.; Gong, W.; Chen, Y. (2020). Model-driven degradation modeling approaches: investigation and review, *Chinese Journal of Aeronautics*, Vol. 33, No. 4, 1137-1153, doi:10.1016/j.cja.2019.12.006
[16] Li, S.; Chen, Z.; Liu, Q.; Shi, W.; Li, K. (2020). Modeling and analysis of performance degradation data for reliability assessment: a review, *IEEE Access*, Vol. 8, 74648-74678, doi:10.1109/ACCESS.2020.2987332
[17] Alaswad, S.; Xiang, Y. (2017). A review on condition-based maintenance optimization models for stochastically deteriorating system, *Reliability Engineering & System Safety*, Vol. 157, 54-63, doi:10.1016/j.ress.2016.08.009
[18] Elasha, F.; Shanbr, S.; Li, X.; Mba, D. (2019). Prognosis of a wind turbine gearbox bearing using supervised machine learning, *Sensors*, Vol. 19, No. 14, Paper 3092, 17 pages, doi:10.3390/s19143092
[19] Alrabghi, A.; Tiwari, A. (2015). State of the art in simulation-based optimisation for maintenance systems, *Computers & Industrial Engineering*, Vol. 82, 167-182, doi:10.1016/j.cie.2014.12.022
[20] Alrabghi, A.; Tiwari, A. (2016). A novel approach for modelling complex maintenance systems using discrete event simulation, *Reliability Engineering & System Safety*, Vol. 154, 160-170, doi:10.1016/j.ress.2016.06.003
[21] Alrabghi, A. (2021). Modelling condition-based maintenance for nonidentical two-component systems considering four types of dependencies, *Journal of Quality in Maintenance Engineering*, Vol. 27, No. 1, 169-186, doi:10.1108/JQME-09-2019-0091
[22] Agalianos, K.; Ponis, S. T.; Aretoulaki, E.; Plakas, G.; Efthymiou, O. (2020). Discrete event simulation and digital twins: review and challenges for logistics, *Procedia Manufacturing*, Vol. 51, 1636-1641, doi:10.1016/j.promfg.2020.10.228
[23] Alrabghi, A.; Tiwari, A.; Savill, M. (2017). Simulation-based optimisation of maintenance systems: industrial case studies, *Journal of Manufacturing Systems*, Vol. 44, Part 1, 191-206, doi:10.1016/j.jmsy.2017.05.008
[24] Law, A. M. (2007). *Simulation Modeling and Analysis*, 4th edition, McGraw-Hill, Boston
[25] Robinson, S. (2004). *Simulation : The Practice of Model Development and Use*, John Wiley & Sons, Chichester
[26] Leemis, L. (2001). Input modeling techniques for discrete-event simulations, *Proceeding of the 2001 Winter Simulation Conference (Cat. No.01CH37304)*, Vol. 1, 62-73, doi:10.1109/WSC.2001.977247
[27] Kobbacy, K. A. H.; Murthy, D. N. P. (2008). *Complex System Maintenance Handbook*, Springer, London, doi:10.1007/978-1-84800-011-7
[28] Lee, J.; Qiu, H.; Yu, G.; Lin, J. and Rexnord Technical Services (2007). *Bearing Data Set*, IMS, University of Cincinnati, NASA Prognostics Data Repository, NASA Ames Research Center, Moffett Field
[29] Qiu, H.; Lee, J.; Lin, J.; Yu, G. (2006). Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics, *Journal of Sound and Vibration*, Vol. 289, Nos. 4-5, 1066-1090, doi:10.1016/j.jsv.2005.03.007