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An End-To-End Maintenance Model For Systems Under Different Working Conditions

Guo Shi, Bin Liu, Lesley Walls

Department of Management Science, University of Strathclyde, Glasgow, United Kingdom

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Decision-making in maintenance during the aging process plays a crucial role in reducing unexpected failures and economic losses across diverse sectors, including manufacturing, national infrastructure, and the automobile industry (Elwany et al., 2011). The aging of a system is affected by its working condition, encompassing both environmental and operating factors like temperature, humidity, and operating speed. For instance, the lifespan of lithium-ion batteries significantly diminishes when operating in lower temperatures. Furthermore, it has been confirmed that a higher charge/discharge rate accelerates capacity loss due to mechanically induced damage to active particles (Kong et al., 2021). The varied working conditions impacts degradation mechanisms, underscoring the necessity for the formulation of maintenance policies that account for various working conditions. With the pervasive adoption of the Internet of Things, a wealth of data on failure events occurring under various working conditions becomes accessible. In this context, the primary challenge lies in identifying the optimal or near-optimal maintenance decisions by leveraging big data patterns containing pertinent information.

Categorised based on the available data, maintenance policies can be broadly divided into two groups: Time-Based Maintenance (TBM) and condition-based maintenance (Ahmad and Kamaruddin, 2012). Both policies share the common goal of making decisions related to the appropriate maintenance plan, encompassing factors like maintenance timing and the type of maintenance action. The key distinction lies in the fact that TBM primarily relies on time-to-failure data for the research object, whereas condition-based maintenance is contingent upon degradation behavior and monitoring data (de Jonge et al., 2017). In practical applications, many organisations predominantly favor the adoption of TBM policies due to their effectiveness in organising and implementing maintenance actions based on recorded failure events (de Jonge et al., 2015). The primary focus of TBM policy is to determine the optimal Preventive Maintenance (PM) time by minimising key objectives, such as expected maintenance cost, cost per unit time, or availability.

The conventional TBM approach involves two key steps: initially estimating the hazard rate parameter for non-repairable systems or the rate of occurrence of failure for repairable systems, and subsequently determining the optimal PM time. This methodology is commonly known as the "estimation-then-optimisation" method. In the estimation phase, much of the research assumes a specific distribution for the time of failure, such as the Weibull distribution or Gamma distribution. For non-repairable systems, the Cox proportional hazard model employs regression techniques to establish the relationship between covariates and the hazard rate (Thijssens and Verhagen, 2020). Similarly, the Cox proportional intensity function extends the Cox proportional hazard model to accommodate recurrent failure events in repairable systems. Once the parameters in the distribution or function are estimated, the prediction results are incorporated into the optimisation model for maintenance decision-making. However, this widely utilised two-step method has several drawbacks. Firstly, it separates prediction and optimisation, resulting in loss of initial information during the optimisation stage (Qi et al., 2023). Secondly, the criteria in the estimation stage may differ from the ultimate criteria in the optimisation stage, potentially leading to sub-optimal decision-making (Donti and Kolter, 2017). Lastly, the error between the decision result and the optimal one can be substantial, particularly when the decision maker lacks knowledge of the underlying distribution (Ban and Rudin, 2019).

In this paper, we explore a data-driven End-to-End (E2E) supervised learning framework designed for the maintenance decision, specifically addressing the management of high-dimensional features without relying on the knowledge of underlying distribution. Here, the term "features" is used interchangeably with covariates, representing working conditions quantitatively. The E2E method functions is a one-step approach, seeking to determine the near-optimal maintenance time for the PM based on input features. However, labeling the optimal PM time proves to be a substantial challenge, especially in a data-driven context where the underlying failure distribution is unknown. Nevertheless, past run-to-failure data and feature values can be collected. In the raw historical data, multiple systems operate under the same conditions, resulting in identical feature values for these systems. To address this, for each running condition, we employ supervised learning algorithms to establish the mapping between the features of working conditions and maintenance decisions.

The E2E decision-making model, depicted in Figure 1, utilises a historical dataset for deriving maintenance decisions. It begins by categorising systems as repairable or non-repairable, influencing subsequent objective function formulations. In the second stage, historical failure times tested under same conditions inform an approximated maintenance cost rate function, guiding data-driven decisions. A supervised algorithm, trained on paired features and maintenance decisions from the second stage, learns patterns and relationships. This trained model then facilitates obtaining maintenance decisions for new working conditions.

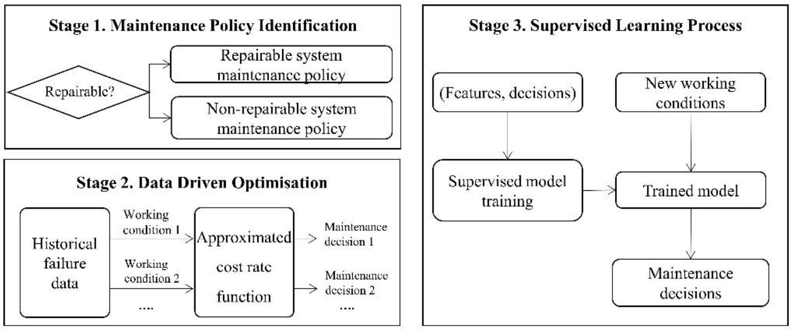

Fig 1. Overall framework of E2E maintenance policy

The contribution of our work can be summarised as follows. First, we propose approximated cost rate functions for repairable systems and non-repairable systems, enabling us to label near-optimal PM time without relying on the underlying time-to-failure distribution. In addition, we develop an E2E method for maintenance decisions. The optimal maintenance decisions are provided directly from the data, without estimating the underlying failure distributions and thus avoiding error propagation in the optimisation stage. Furthermore, we theoretically establish the bound between the approximated cost rate and the underlying cost rate function, providing a theoretical guarantee of the accuracy of the approximation objective function. Numerical experiments illustrate the superiority of the proposed E2E framework over the traditional approaches by comparing the maintenance cost.

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Deep Learning For Fault Classification Using Digital Twin Centrifugal Pump

Davi Souza, Eduardo Menezes, Isis Lins, Márcio Moura

Universidade Federal de Pernambuco, Recife, Brazil

Keywords: autoencoder, simulation data, bearing fault, reliability

Rolling bearing are a common component in rotating systems, especially ones with centrifugal pumps used in Oil & Gas refineries. Its failure can cause massive damage or even stop production, and therefore its safety operation and reliability is very important. There are many ways to perform fault diagnosis on systems with rotating machinery, in specific rolling bearings (Haidong et al., 2018) using artificial intelligence models such as artificial and convolution neural network (ANN / CNN), support vector machine (SVM), autoencoders (AE) with deep or ensemble or even sparse methodologies.

All of these approaches work with big enough data sets so the algorithm can be trained with, using a major part of the set, and also have some remaining data to validate the procedure. For the particular case of rolling bearings, there is enough datasets available for some configurations. Another technology that's been used is the virtual representation of a physical model, called Digital Twin – DT (Rathore et al., 2021). By using a DT one can generate a dataset with faulty operations for a specific case like a O&G Naphtha Refinery, with the goal of evaluating reliability of the centrifugal pumps for the compound (Elbar et al., 2023).

In the present work the goal is to use a previous validated centrifugal pump DT (Souza et al., 2023) to generate data that can be used in a further analysis for fault detection and classification. The methodology accounts initially for a bearing fault mechanism via time series that after a Fast Fourier Transformation (FFT) will show in the frequency domain some characteristic frequencies that could be associated with either roller, inner race or outer race faults.

With the validated DT it is possible to generate fault datasets by varying specific parameters. A way to generate fault modes that will resemble a bearing fault is to add disturbances in specific frequency ranges around values that can be theoretically evaluated, using the bearing information (Hou et al., 2023). This was done and also a small random variation was applied to specific parameters that are related to the bearing and also impeller to replicate a physical degradation of the parts.

The dataset was generated composed of 70% healthy generated data that contains frequencies only on the rotor 34 Hz frequency and sub harmonics, and 10 % of the other 3 frequencies related to roller, inner race and outer race faults. The model was assembled in Simulink® within Matlab® coding. After the generation of the dataset, an Auto Encoder was used with 90% of the samples for training and the remaining for validation. An Adam solver was used in the AE. Some random samples from the original dataset were used in the AE and reconstructed. A random sample of this reconstructed data indicates a healthy condition and can be used for comparison with fault data where the different areas would indicate frequency values that can be traced to a specific fault, see Figure 1.

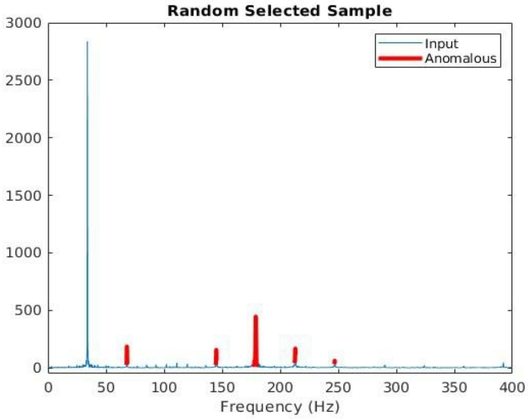

Fig. 1. Random sample anomaly detection using one AE.

Since the AE already captured the fault sample without categorizing it, a deep auto-encoder is used as a tool for this diagnostic (Haidong et al., 2018). For this case, a second AE will be used inside the hidden feature from the first AE and a third AE is used inside the hidden feature from the second AE. Also, different activation functions are used due to instability for some cases. For each tested activation function is calculated an acceptance threshold that will be used both as a criterion to use or not such function, and in the calculation of the weights. The weights are used in the predicted DAE as a combination for the ensemble. Another option is to use the generated data and use a Convolution Neural Network (CNN) for fault classification, which is well known for its accuracy in many tests (Sobie et al., 2018). The CNN is used here as complementary of the DEA formulation for performance comparison.

The result of the ensemble procedure is then used for the feature extraction and fault identification using trained samples. The validation is done with the test data set using all the different DAE combinations. After that the accuracy of each combination is evaluated and compared against each other in order to choose the rout within activation function, weights and DAEs. This rout is then used for fault diagnosis and applied to a random fault sample to see if the procedure identification corresponds to the correct fault. The fault classification from the CNN achieves more than 96% accuracy for the generated data and the confusion map shows no misclassification.

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