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Multi-Model Predictive Maintenance: Overview and A Linear System Perspective

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ABSTRACT

Multi-model predictive maintenance is a recently trending approach where information from different inputs and models are processed in a unified fashion in order to provide better failure prognostics. Multi-model systems aim to make clever use of labeled or unlabeled sensor observations, knowledge bases and device specific constraints. In this paper we present an overview for both single and multi-model approaches and provide a linear system perspective. The proposed system leverages linear classification and prediction methods such that the measurement space is partitioned via linear boundaries into nominal and failure operation regions and the distances from boundaries are tracked for providing remaining useful life calculations. The adopted linear approach simplifies the design process and it can efficiently incorporate different modalities in order to enhance the prediction performance. Also, the proposed method is simulated in generated dataset.

Çok Modelli Kestirimci Bakım: Genel Bakış ve Doğrusal Sistem Perspektifi

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Anahtar Kelimeler
Bakım tahmini
Lineer sınıflandırma
Çoklu-model yaklaşımı
Kalan faydalı ömür

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ÖZ

Çok modelli bakım tahmini, daha iyi arıza öngörüleri sağlamak amacıyla farklı girdilerden ve modellerden gelen bilgilerin birleşik bir şekilde işlendiği, son zamanlarda trend olan bir yaklaşımdır. Çok modelli sistemler, etiketli veya etiketsiz sensör gözlemlerinden, bilgi tabanlarından ve cihaza özgü kısıtlamalardan akıllıca yararlanmayı amaçlamaktadır. Bu yazıda hem tek hem de çoklu model yaklaşımlarına genel bir bakış sunuyoruz ve doğrusal bir sistem perspektifi sunuyoruz. Önerilen sistem, ölçüm alanının doğrusal sınırlar aracılığıyla nominal ve arıza operasyon bölgelerine bölünmesini ve kalan faydalı ömür hesaplamalarını sağlamak için sınırlardan uzaklıkların takip edilmesini sağlayacak şekilde doğrusal sınıflandırma ve tahmin yöntemlerinden yararlanır. Benimsenen doğrusal yaklaşım, tasarım sürecini basitleştirir ve tahmin performansını artırmak için farklı yöntemleri verimli bir şekilde birleştirebilir. Ayrıca, sunulan metot üretilmiş bir veri setinde simüle edildi.

1. INTRODUCTION

Technological progress has initiated the onset of the Fourth Industrial Revolution, often denoted as Industry 4.0, distinguished by the smooth fusion of physical and digital manufacturing systems. [1]. This transformation has given rise to a new era of industrial operations, marked by increased connectivity, data abundance, efficient inventory management, customization, and precision-controlled production processes [2-4]. Industry 4.0, initially coined as "the fourth industrial revolution" in Germany, has fundamentally altered the landscape of industrial processes [5]. It comprises three main dimensions: self-awareness, self-predictive for components; self-prediction, self-comparison for machines; self-configuration, self-maintenance, and self-organization for productive systems [5-6]. A key aspect of Industry 4.0 is the availability of vast amounts of data, which empower humans and machines to make informed, predictive decisions [7].

Effective maintenance practices minimize costs, prevent unplanned production stoppages, and sometimes extend the useful lifetime of industrial devices. As a result of the concerns and efforts of researchers, engineers, technicians, and specialists, maintenance procedures have changed. Figure 1 shows how this development has changed over time. Corrective maintenance (CM), often known as "run-to-failure," is the most basic method and entails only replacing or fixing a part when it is broken. Machinery cannot function without assistance [8].

The substantial expenses associated with unanticipated production pauses led CM to develop proactive strategies. Preventive maintenance (PM), which entails routine inspections by trained experts and replacement of parts before a severe breakdown occurs, was the first to arise. Equipment's manufacturers often offer this replacement at regular intervals or after a certain number of operating cycles. This can force the replacement of the components sooner or later. Whereas the first scenario results in greater maintenance costs by replacing parts that may perform a significantly higher number of operating cycles, the second scenario could have more severe repercussions because CM action is required [9,10].

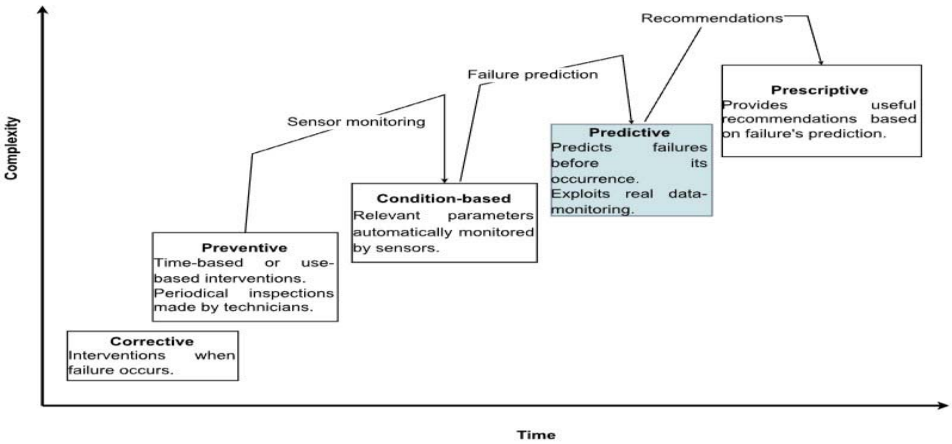

Figure 1. Development of maintenance techniques over time [8]

Condition-based maintenance (CBM) method has evolved with technical advancements within the realm of Industry 4.0, and the evolution of the IoT [11]. By using sensors and devices that can measure, monitor, and process signals that indicate the physical characteristics of industrial equipment, such as acoustic signals, current, voltage, temperatures, forces, vibrations, etc., inspections conducted by technicians and specialists have been automated. With this approach, interventions can be based on sensor values, and when a value deviates from the set bounds, actions can be initiated. Predictive maintenance (PdM) is an advanced and highly effective strategy that has evolved from CBM, seamlessly blending IoT and Cyber-Physical Systems (CPS) principles with expertise spanning automation, engineering, information technology, and data analytics. This integration allows PdM to accurately forecast failures, estimate the remaining useful life (RUL) of industrial assets, and efficiently plan maintenance activities. [12,13]. Conversely, prescriptive maintenance takes things a step further because it uses predictions to provide pertinent recommendations for addressing the failure mode and increasing the RUL [14,15].

This paradigm shift underscores the pivotal role of predictive maintenance (PdM) in optimizing industrial operations. PdM harnesses historical data, models, and domain knowledge to forecast trends, behavior patterns, and correlations. Utilizing statistical or machine learning models, PdM anticipates impending equipment failures, enhances maintenance decision-making, and minimizes downtime [16]. As Industry 4.0 continues to evolve, new concepts such as the Industrial IoT and CPS have emerged. IoT leverages IoT technologies within industrial settings, incorporating Machine Learning (ML) and Big Data to efficiently manage data and enhance decision making [12]. CPS, introduced by the National Science Foundation (NSF) in the United States, focuses on the next generation of engineered systems and relies on detailed information regarding machinery and physical processes [7]. The integration of these concepts forms the foundation of the burgeoning field of PdM, which remains a critical focus of Industry 4.0. PdM is instrumental in identifying equipment faults, reducing maintenance costs, and avoiding production disruptions. However, implementing PdM presents challenges, such as erroneous data measurements, the need for real-time processing of immense data volumes, and adaptation to diverse industrial environments [5,17-19].

2. SINGLE-MODEL APPROACHES TO PREDICTIVE MAINTENANCE

2.1. Physics-Based Methods

In physics-based methods, degradation of the system is observed based on the laws of physics. The closer the physics-based method is to the real-life model, the more accurate the performance of the method. However, it is quite difficult to achieve this goal. In the gyroscope sensor drift problem [20], the physics-based method is more accurate than the data-driven algorithm as a prognostic method. The majority of physics-based methods aim to perform prognostic modelling. The remaining useful life of lithium-ion batteries [21], filter clogging [22], damaged rotor cages [23], industrial robot health [24], solenoid valves [25] and boiler heat exchanger tubes [26] have been prognosticated to date.

2.2. Knowledge-Based Methods

In the context of predictive maintenance, knowledge-based models are related to computer systems that generate diagnoses and forecasts based on a body of experience. These models are derived from guidelines, data, or examples gathered several years of use and preservation of the technical system. Experiences can be shown in a variety of ways, including guidelines, data, or examples that demonstrate the skills and understanding of the maintenance staff. Experiences gathered over time are utilized to pinpoint errors, explain how parts or systems deteriorate, and forecast future problems. Knowledge-based models can estimate the system's present state of health and forecast future maintenance requirements by examining historical data and trends [27,28].

To facilitate care, the inference process in diagnostics and prognostics is automated using computational intelligence approaches. These methods use experience and knowledge stored in knowledge-based models to provide precise forecasts and diagnoses. Computational intelligence can be used to streamline and improve the efficiency of the maintenance process, which will improve system performance and minimize downtime. Research on knowledge-based models is crucial in the care context [27,28]. SCADA (Supervisory Control and Data Acquisition) systems are good examples of such models.

SCADA systems are important technologies used to monitor and control industrial processes and to collect data. These systems generally identify important situations in the processes that use alarm and trip values. Alarm values warn operators if a certain parameter goes out of bounds, whereas trip values automatically shut down the system in cases of danger. This information is critical to the safety and efficiency of these processes. Therefore, the correct setting and use of alarm and trip values in SCADA systems are vital for the safety and performance of industrial facilities. It is widely used in knowledge-based models of alarm and trip values of SCADA systems.

Maintenance decision systems are increasingly used in industrial and healthcare fields. These systems utilize artificial intelligence techniques to maintain and troubleshoot complex equipment. Rule-based reasoning (RBR) and case-based reasoning (CBR) are two of the AI approaches commonly used in this field. While RBR uses rules to determine actions based on specific circumstances, CBR aims to solve new problems by finding similar situations and learning from past cases [29].

The RBR can handle unknown errors by specifying general rules to determine appropriate actions based on specific circumstances. In contrast, CBR identifies similar situations and generates solutions using tacit knowledge from previous experiences [29]. Both methods have advantages: RBR provides a strong structure with easily understandable and independent rules, whereas CBR provides flexibility in problem-solving by contributing to the incremental learning process of previous experiences [30].

These two approaches can be used to improve the effectiveness of maintenance decision systems. The explainability and high efficiency of RBR with specific rules, and the ability of CBR to solve problems with tacit knowledge from previous experience, make systems more intelligent and adaptive. This integration can be applied to a wide range of applications, from predicting equipment failures in industrial plants to disease diagnosis in healthcare organizations [29,30]. An example of a rule-based method is the intelligent fault diagnosis model for power equipment based on case-based reasoning (IFDCBR), which builds a case base of the equipment and uses support vector machine (SVM) regression analysis to generate the equipment condition fingerprint [31]. An example of a case-based method is the integration of case-based reasoning with rule-based reasoning in the design of a care decision system that proposes a care decision intelligent reasoning method based on the health status [29].

2.3. Data-Driven Methods

Owing to technological advances in computational power and enormous amounts of available data from technical systems, data-driven methods have been used for various motives. RUL of components, degradation analysis, the current health state are the examples of some purposes.

Statistical, stochastic, and machine learning methods are the three main data-driven methods classes. Statistical methods investigate the manner in which random variables are based on datasets using the probability theory. Similar to statistical methods, stochastic methods also use the probability theory and investigate the evolution of random variables over time. Machine-learning methods are built models that capture complex relationships from data.

In the area of predictive maintenance, statistical methods are mostly used for prognostic applications. The duties of these methods are degradation analyses and RUL of the components. The first statistical method is regression analysis, which is used to determine the decrease in the observations. Berecibar et al. estimated the health of Graphite/Nickel Manganese Cobalt Oxide cells by using supervised learning and regression [32]. The remaining useful life of aluminium plates was analyzed using the autoregression method, based on its crack growth [33]. Wan-Jui Lee detects air leakage anomaly of breaking pipes on train and calculates the remaining life of pipes with the help of regression analyze [34]. Downey et al. combined regression with physic-based method for prognostics of lithium-ion battery [21]. Xu et al. expanded the use of regression analysis to multi-component systems [35]. Coble and Hines combined regression with a Bayesian model for the degradation of jet engines [36]. As a second statistical method, autoregressive-moving average method (ARMA) forecasts the future values of a data series. ARMA methods are only used for calculating the remaining life of components such as semiconductor switches [37], gear vibration signals [38,39], bearings [40]. The last statistical method is the Bayesian methods, which mostly used as an auxiliary tool along with other data-driven methods to manage uncertainty. Bayesian statistical methods estimate the conditional probabilities of hypothesis-based probabilities. Zhang et al. used Bayesian analysis as a degradation process in a semiconductor manufacturing facility [41]. Fault diagnosis for nonlinear gas turbine engines [42], prognosis of high-voltage circuit breaker failure [43] and remaining useful life of circuit boards [44] are some examples of Bayesian statistical methods. In addition, the Bayesian method can be used to update model coefficients using the autoregressive method [45].

The aim of application of the stochastic methods are diagnostics and prognostics. In predictive maintenance, stochastic methods provide convenient regression capabilities for degradation modelling and RUL estimation. However, these methods have many disadvantages, such as high computational power requirements and uncertainty management. Gaussian processes are a part of stochastic methods that are simple to implement in small or large-dimensional datasets. The fault diagnosis of wind turbines [46] and RUL prediction of slow-speed bearings [47] are two examples of Gaussian processes. In the Markov stochastic process, the present state of the process is independent of past and is dependent on the future. Markov chains and hidden Markov chains are used for RUL [48,49], degradation analyse [41], deterioration forecasting [50] and real-time failure prognosis [51].

Machine learning (ML) methods are use specialized learning algorithms to build models from data [52]. The main advantage of these methods is that they capture unseen relationships among data. In addition, dimension size is not crucially important in the use of these methods. As a important point, choosing ML method depends on the application and the available data [53]. The main disadvantage of ML methods is that the working principle of the model is hidden; therefore, human intervention cannot be applied.

In the area of PdM, there are five most commonly used ML configurations. First, multilayer perceptron neural networks are used for fault identification in wind turbine gearboxes [54], combustion engines [55], nuclear power plants [56] and rotary machines [57]. Second, recurrent neural networks have been applied to fault identification in industrial plants [58], gear boxes [59], and RUL estimation of jet engines [60], rolling bearings [61], and mill fans [62]. As a third configuration, convolutional neural networks are used for RUL estimation in turbofan engines [63], bearings [64] and in the fault diagnosis of bearings [65] and gearboxes [66]. Fourth, self-organizing maps have been applied to qua degradation modelling in railway point machines [67], cyber-physical systems [68], jet engines [69], and lithium-ion batteries [70]. In addition, there is a configuration for high-speed train bogits that aims at both fault detection and degradation modelling [71]. The final configuration is support vector machines, which are used for fault detection in electrical equipment [72], the chemical industry [73], management systems [74], and Tennessee Eastman process data [75]. Also, health estimation was predicted for battery cells with a support vector machine configuration [32].

2.4. Shortcomings of Single-Method Approaches

The advantages and disadvantages of single-method approaches are explained in the previous sections. Each method has different strengths. In general, single-models are mostly applied to simple specialized equipment. In predictive maintenance, combinations of these methods are preferred to increase the performance of more complex systems. Each combined method was analysed in [76].

However, there are a few papers that use all the methods together [77,78]. These multi-method approaches are extremely difficult to apply because of the complexity of the system.

3. MULTI-MODEL APPROACHES TO PREDICTIVE MAINTENANCE

There has been a growing adoption of multi-model predictive maintenance, a sophisticated approach that utilizes various data sources to predict equipment failures before they occur. Some examples of this approach as follows.

The initial example outlines a methodology that merges data-driven techniques with experience-based methods for Prognostics and Health Management (PHM) of roller bearings. The proposed methodology uses time-domain features as health indicators by extracting them from vibration signals. The degradation states in the bearings are detected by artificial ant clustering, which is an unsupervised classification technique. The approximation of the next degradation state is provided by the hidden Markov models. Furthermore, the remaining time before the next degradation state was predicted through multi-stage time-series prediction and an adaptive neuro-fuzzy inference system. The proposed methodology is validated by experimental results based on a set of bearing failure data, and shows that data-driven and experience-based approaches improve the PHM of roller bearings [79].

In the second example, a three-dimensional finite element analysis model of a solenoid valve was created using the ANSYS Workbench software, in which the temperature and mechanical stress fields were accurately calculated. The accuracy of the simulation results was verified through accelerated life tests. Furthermore, an accelerated life test for the solenoid valve was designed based on the finite element simulation results, and a comparison of the average temperature rise between the simulation and the test showed good agreement. In this paper, a prognostic method for the fault detection and diagnosis of solenoid valves based on the electrical resistance of coils and temperature change is proposed. Moreover, an optimizated design of the coils is proposed to improve the reliability of the health management of the solenoid valve. Finally, the study used a direct-acting solenoid valve as an example for modeling and analysis and presented information on the temperature and stress distribution of the valve [25].

The third example is that of a practical prognostic tool for effective condition-based maintenance. A proposed prediction model integrates fuzzy sets and Markov Chain to forecast equipment performance degradation. The exhaust gas temperature margin is considered as a performance indicator in a numerical example. The combination of Fuzzy-Markov chain streamlines computational processes, delivering precise prediction outcomes even with limited data samples and incomplete information. The prediction model outperforms linear regression, nonlinear regression, and Gray Model (1,1) in dealing with nonlinear and randomly fluctuating disturbance data. The implementation process involves partitioning the sample into fuzzy states and constructing a subdegree matrix. The model was validated using historical data and effective predictions were obtained [80].

The Fourth example proposes a knowledge-based prognostic framework for railroad track geometry degradation. The methodology was combined with a physics-based model for track degradation within a filtering-based prognostic algorithm for online data for track settlement. The suggested approach was illustrated and examined through a case study utilizing published data from a laboratory simulation of railway track settlement under cyclic loads. The findings indicate that the proposed methodology can offer precise forecasts of the system's RUL following a model training period of around 10% of the process lifetime [81].

As exemplified by these studies, the integration of multimodel predictive maintenance represents a paradigm shift in industrial maintenance practice. By harnessing the wealth of data available from diverse sources, organizations can unlock unprecedented insights into equipment health, enabling proactive interventions, and safeguarding operational continuity. As we venture further into the era of Industry 4.0, embracing such innovative approaches will be pivotal for sustaining competitiveness and driving transformative growth across industries.

4. MULTI-MODEL APPROACHES TO PREDICTIVE MAINTENANCE

4.1. Definition of the Problem

We assume that the equipment for predictive maintenance purposes has $D,\ D \geq 1$, sensor/s. $X = [x_1, x_2, \ldots, x_D] \in R^D$ where X denotes is readings from sensors. These sensors can measure the power, temperature, pressure, density, vibration, flow. For each physical value, more than one sensor was preferred for measurement. In practical predictive maintenance applications, $D \geq 10$ is common. Let us assume that estimation of error can be extracted from sensor readings, and the decent working range in D dimension measurement space is $R_{nom} \in R^D$. The boundaries of the area specified by physical limitations, experience from experts and previous warning/alarm/trip warning data from the past.

Let us consider $X_1, X_2, \ldots, X_t$, for periodic sensor readings as a time series. Under the instantaneous $X_t \in R_{nom}$ condition, the predictive maintenance problem is

$$\hat{T} = \underset{T}{\mathrm{ARGMIN}} X_{t+T} \notin R_{nom}. \tag{1}$$

where $\hat{T}$ denotes the remaining useful life in this estimation.

All different types of equipment failures are assumed in the measurement area $R^D \,/\, R_{nom}$. For this reason, breakdown types could not be identified in this setup. The predictive maintenance problem is addressed in this study. If the failure identification clear in the measure space, different failures, $K, K \geq 1$, can estimate the failures, $F_1, F_2, \ldots, F_K$. The failure regions can be found with the below formula,

$$R_{\{F1\}}, R_{\{F2\}}, \ldots, R_{\{FK\}}, i = 1,2, \ldots, K, \bigcup_{i=1}^{K} R_{Fi} = R^D - R_{nom'}. \tag{2}$$

In this regard, the smallest T_i value which provide the X_{t+T_i} equality presents the remaining useful life until F_i failure occurs.

4.2. Classification

In the described problem, linear classification methods are useful for the labelled data of the system. This is because the complexity of linear classification algorithms is lower than that of nonlinear algorithms. Therefore, linear classification algorithms are preferred for real-time systems. As an example of a classification algorithm, the support vector machine (SVM) determines the optimum boundary between classes. Given a set of failure samples from sensors $x_1, x_2, \dots, x_D$ and their class labels $y_1, y_2, \dots, y_K$.

In the support vector machine, we calculate the length of vector for D sensors,

$$\left||x|\right| = \sqrt{\{x_1^2 + x_2^2 +, \dots, x_D^2\}}. \tag{3}$$

and the direction of the vector is, X,

$$X = \left(\frac{x_1}{||x||}, \frac{x_2}{||x||}, \dots, \frac{x_D}{||x||}\right). \tag{4}$$

The hyperplane is described as,

$$\mathrm{a_1 x_1 + a_2 x_2, \dots, a_D x_D = b}, \tag{5}$$

where b is the bias parameter. And we define $w = (a_1, a_2, \dots, a_D)$, we get,

$$w^T X + b \ = \ 0. \tag{6}$$

After calculating the hyperplane, we can use it to make predictions for failure classes. And the hypothesis function h is,

$$h(x_i) = \begin{cases} +1 \ if \ wx + b \geq 0 \\ -1 \ if \ wx + b < 0 \end{cases}. \tag{7}$$

In the described problem, there are $K + 1$ classes owing to K failure areas and a nominal area. The measurement space was divided into $K + 1$ regions using the One-to-One SVM approach. The number of SVM classifiers is $(K + 1)(K + 2)/2$ in this approach. Each classifier separates only two classes, neglecting the third. After the optimization of the SVM classifiers, the measurement space was described for the nominal and failure areas.

As an alternative to SVM algorithms, multi-class linear discriminant analysis (MCDLA) is used to find differences between classes of data. Although it could be used for dimensionality reduction before classification, linear discriminant analysis was used to classify the failure regions in this study. MCLDA is a generalization of a two-class linear discriminant analysis. For each $K + 1$ region, MCLDA must be used separately to determine the weights, w_K.

MCLDA is based on the analysis of two scatter matrices, a within-class scatter matrix and a between-class scatter matrix. Given a set of failure samples from the sensors $X = [x_1, x_2, \dots, x_D]$ and their class labels $y_1, y_2, \dots, y_D$.

The within-class matrix is defined as:

$$S_w = \sum_{i=1}^{D} \left(X_i - \mu_{y_i}\right)\left(X_i - \mu_{y_i}\right)^T. \tag{8}$$

And the between-class scatter matrix is defined as:

$$S_b = \frac{1}{K+1} \ \sum_{i=1}^{K+1} n_k (\mu_k - \mu) \ (\mu_k - \mu)^T. \tag{9}$$

where, $K + 1$ is the number of failures and nominal areas, μ_k is the sample mean of the Kth failure, μ is the overall sample mean, and n_k is the number of samples in Kth class. Then, multi-class LDA can be formulated as an optimization problem to find a set of linear combinations (with coefficients w) that maximizes the ratio of the between-class scattering to the within-class scattering, as

$$\widehat{w_K} = \underset{w_K}{\text{ARGMAX}} \frac{w_K^T S_b w_K}{w_K^T S_w w_K}. \tag{10}$$

After finding $\widehat{w_K}$, decision criterion for ith and jth classes is,

$$\widehat{w_K}^T X > c \ \ where\ c = \frac{1}{2}\widehat{w}^T(\mu_i + \mu_j). \tag{11}$$

4.3. Remaining Useful Life Estimation

The remaining useful life of the physical parts in the system decreases with time. The decreasing trend of the performance of the physical parts over time is mostly known in datasheets. The sensor measurements easily check the failure area owing to these limitations. The least-squares lining method is useful for these types of failure.

As a classification problem, it could be solved by statistical and linear classification methods. The measuring space, $X = [x_1, x_2, \ldots, x_D] \in R_D$ is divided regions like,

$$a_1x_1 + a_2x_2 + \cdots + a_Dx_D \le b \ where\ a_i, b \in R, i = 1, \ldots, D, \tag{12}$$

These boundaries are equal to hyper-spaces in measurement space.

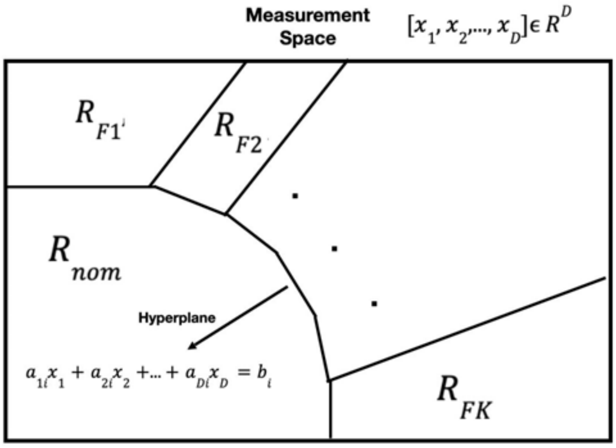

Figure 2. Failure area classification in measurement space

The working point of the system is moving from nominal area, R_{nom}, to failure areas, $R_{F1}, R_{F2}, \ldots, R_{FK}$ in the progress of time. The visualization of the failure areas in Figure 2. The boundary between R_{nom} and R_{Fi} regions is described as,

$$a_{1i}x_1 + a_{2i}x_2 + \cdots + a_{Di}x_D = b_i. \tag{13}$$

$$A_i^t X = b_i \ where$$

$$A_i = [a_{1i}x_1 + a_{2i}x_2 + \cdots + a_{Di}x_D]. \tag{14}$$

The distance between working point X_t and the edge of the boundary is calculated with

$$d_{i(t)} = \frac{\left|A_{i_t^t}X + b_i\right|}{||A_i||}. \tag{15}$$

In the align 15, $||.||$ denotes the l_2 norm distance.

Let's assume that failure region R_{FK} for $k, k \geq 1$ regions and $i, i \geq 1$ sensors. For simplifying and fasting the system, let's take start the sampling from $t - N$ through the time t for each sensor. So, our sampling space of observations becomes to N. The slope of the fitting line [82], $\widehat{d_\iota}(t) = c_1 t + c_2$, is

$$c_1 = \frac{N \sum_{j=t-N}^{t} j d_i(j) - \sum_{j=t-N}^{t} j \sum_{j=t-N}^{t} d_i(j)}{N \sum_{j=t-N}^{t} j^2 - (\sum_{j=t-N}^{t} j)^2}, \tag{16}$$

and bias parameter is

$$c_2 = \frac{\sum_{j=t-N}^{t} d_i(j) - c_1 \sum_{j=t-N}^{t} j}{N}. \tag{17}$$

R_{FK} boundaries can be estimated according to the parameters c_1 and c_2.

After the calculations of predicted fitting lines, $\widehat{d_\iota}(t)$, the align (15) allows us to estimate distances between failure regions R_{FK} and R_{nom}. And then, the estimation of the remaining times, T_i, can be calculated as $\widehat{d_\iota}(t) = 0$, if and only if $X_t \in R_{FK}$. The failing time estimations of each region, T_i, are predicted according to fitting lines of $\widehat{d_\iota}(t)$.

The proposed system and data processing pipeline is depicted in the Figure 3. In this paper, we have proposed a simple method for remaining useful life prediction based on Least Squares formulation. Alternatively, the evolution of $\widehat{d_\iota}(t)$, $i = 1, \ldots, K$, could be modeled as an ARMA series or one can obtain a linear regression for it from $\widehat{d_\iota}(t)$. Finally, the physical and process specifications of critical equipments could be modeled by Wiener or Kalman based approaches via the distances to hyper-planes, $\widehat{d_\iota}(t)$.

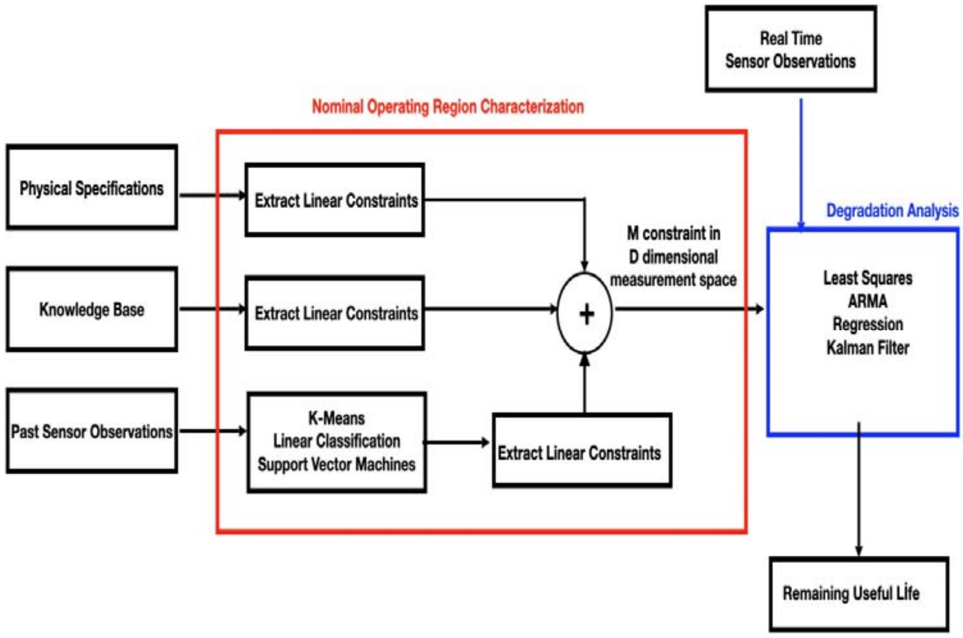

Figure 3. The proposed multi-model system and pipeline

5. SIMULATIONS

To simulate the problem defined in this article, a dataset was generated that is compatible with any device. The dataset simulates the Remaining Useful Life (RUL) value, which decreases over time from 100 to 0. For this simulation, the number of sensors (D = 10) used to observe the device was set at 10. The dataset was created by generating 100 different scenarios, resulting in a total of 100*100*10 data points. Each of these scenarios represents a unique situation or condition that the device might encounter. To introduce randomness into the dataset, normally distributed Gaussian random variables were used. These variables were characterized by a mean (μ) of 0 and a standard deviation (σ) of 1.

Moreover, since all 10 sensors were observing the same device, it was essential to account for the correlation between their readings. To achieve this, Spearman's rho, a measure of rank correlation, was set at 0.9. This high correlation coefficient ensures a significant degree of dependence among the sensors, reflecting realistic scenarios where sensors monitoring the same device often exhibit correlated behavior. This approach provides a robust dataset with realistic and correlated sensor readings, which can be used to simulate the defined problem effectively.

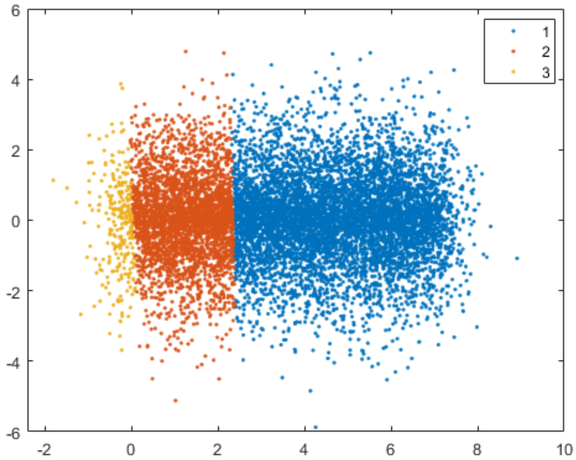

Figure 4. Distribution of generated datas and classes

For label classifications, the data was divided into three classes: nominal, warning, and failure. These classes were determined based on the RUL values as follows: 100-30 for nominal (group 1 in Fig. 4), 30-10 for warning (group 2), and 10-0 for failure (group 3). The distribution of these classes in the measurement space is illustrated in Figure 4.

The entire dataset was first subjected to dimension reduction using linear discriminant analysis and then trained with linear regression analysis. The model was tested in real-time using one of the randomly generated scenarios. The results are presented in Figure 5.

In Figure 5a, the measurement space is shown along with the data progression over time. It is evident that, over time, the data points move closer from the nominal region to the failure region. Figures 5b and 5c illustrate the distances between the working points and the two regions (warning and failure). Figures 5d and 5e display the true Remaining Useful Life (RUL) and the predicted RUL over time. These figures demonstrate the model's performance in predicting the RUL as the device transitions from nominal operation to failure.

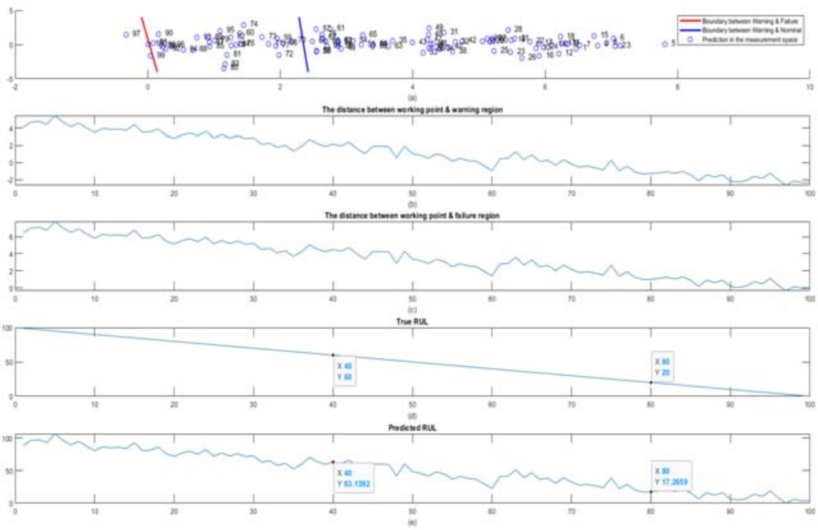

Figure 5. The simulation results for generated dataset

6. CONCLUSIONS

In this paper we have investigated the multi-model predictive maintenance problem. We have presented an overview for the single and multi model approaches and presented a problem formulation. Then, by utilising linear classification methods we have shown that the inputs from different models such as labeled/unlabeled sensor observation an expert rules can be easily incorporated into the proposed system. Finally, we have presented a simple remaining useful life calculation method by using simple least squares approach and simulated in MATLAB. We discussed the applicability of the proposed method and its generalizations.

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