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A new methodology for estimation of dynamic Remaining Useful Life: A case study of conveyor chains in the automotive industry

Behnam Einabadi^{a,b}, Armand Baboli^{a,*}, Eva Rother^b,

^a*LIRIS Laboratory- INSA-Lyon-20 Avenue Albert Einstein, 69621 Villeurbanne, France*

^b*FPT Industrial, Avenue Emile et Claude Puzenat, 71140 Bourbon-Lancy, France*

Abstract

In the context of industry 4.0 and digital transformation, the predictive maintenance (PdM) approach plays an important role in the efficiency of maintenance, as breakdowns and over-maintenance. Remaining Useful Life (RUL) is the main part of the prognostic aspect of maintenance. RUL is also one key piece of information that feeds the PdM and needs to be dynamically readjusted in a global approach and procedure. In this paper, a new methodology for the prognostic aspect of PdM, and a dynamic RUL estimation method have been proposed. In this way, general methodologies and processes of prognostics have been presented that outline a more coherent vision toward RUL estimation. Within the dynamic RUL method, it is proposed to use from Prophet prediction model in a dynamic algorithm to better estimation of RUL based on the Health Indicator (HI) trends updates. The applicability and efficiency of the proposed procedure and method have been applied and validated in the conveyor chains of an automotive company which their failure results in production stoppages and significant damages. The performance of the prediction method has been presented with a comparison to deep learning and statistical prediction methods. Following the dynamic RUL estimation, a maintenance strategy has been proposed for the studied case to improve maintenance planning.

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Keywords: Dynamic Predictive Maintenance; Remaining Useful Life (RUL); Dynamic RUL; Health Monitoring; Industry 4.0

* Corresponding author. Tel.: +33 472 43 62 01; fax: +33 472 43 62 01.

E-mail address: armand.baboli@insa-lyon.fr

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1. Introduction

One of the essential aspects of Industry 4.0 deals with the availability and usage of real-time data. Prescriptive decision-making and predictive Maintenance are some of the applications of Industry 4.0. The general idea of PdM is to increase the efficiency and productivity of the production system. This is typically followed in the objectives of increasing the availability of production machines by minimizing the production machine failures and reducing the excessive corrective and preventive maintenance activities. Sensor data through Industrial Internet-of-Things (IIoT) or condition monitoring through embedded systems serve as the basis toward achieving the new system of maintenance management. The application of PdM is being largely used in various types of industries, and researchers are trying to find the solutions for the PdM projects. However, there is still a long way to go ahead, and we are merely at the beginning of the fourth industrial revolution.

One key point of PdM concerns the initial step as it is not cost-efficient to employ the PdM approach for the whole production machines, as the criticality levels of the machines are different, and resources are limited. Moreover, the PdM approach could be primarily implemented in the most critical equipment or machines when real-time data is present. However, in a critical machine, sometimes, it is unfeasible to install the sensors and monitor all the components of the machine with real-time data. Once the critical equipment and components are identified and connected to the IIoT platform, a general process should be followed to propose a dynamic maintenance planning system. In this paper, a new realistic approach of dynamic prognostic is proposed and presented. Dynamic prognostic represents a subset of decision support systems that helps in prescriptions for the decision-makers.

In this approach, which will be detailed further, we can find the methods to employ real-time data and identify HI and then RUL. In the literature, Statistical and Deep Learning (DL) methods are developed for RUL estimation mostly in a static manner. However, in the industrial condition, calculating the static RUL can not be helpful because of the dependency of RUL to the operational condition. Furthermore, the model design, tuning, precision, and interpretability of the RUL estimation models should be taken into account. In this paper, we propose a new dynamic RUL estimation method by considering the mentioned elements and industrial exigencies and limitations, which have been less considered in the literature. This is one of the important contributions of this paper, followed by presenting and applying this method in an industrial case. It has been used from sensor data for maintenance of conveyor chains equipment in FPT Industrial Company, These sensor data is used in the experimentation phase of our dynamic RUL method. In continue, through the benchmark study of prediction methods, the more appropriate methods for industrial cases are selected and used in the validation phase of our proposition.

The rest of this paper is organized as follows: Section 2 describes the last research works and our contribution; Section 3 the dynamic prognostic approach and RUL methodology; section 4 presents the case study and results; Section 5 presents conclusions and perspectives of future works.

2. Literature Review

Some international standards and references have been developed relating to predictive maintenance. These norms are well categorized by [1] [2]. The International Standard Organization (ISO), the Institute of Electrical and Electronics Engineers (IEEE), the Machinery Information Management Open Standards Alliance (MIMOSA), and some other organizations have presented the standards in the field of Condition-based Maintenance (CBM) and Prognostic and Health Monitoring (PHM) [1]. Regarding the data processing, diagnostic and prognostic it can be referred to as ISO 13374 [3], ISO 13379, ISO 13381, and OSA-CBM [4].

Data processing steps as defined in the standards begin with data acquisition, and then data manipulation, state detection, health assessment, prognostic assessment, and advisory generation or decision support [3] [4].

Fig. 1 depicts the prognostic approach that is mainly referred to in the literature. Although this is quite a general overview, it is perceived that there is a lack of concise procedures and methods for the prognostic (prediction) and maintenance management system [2] which are the most important element in PdM.

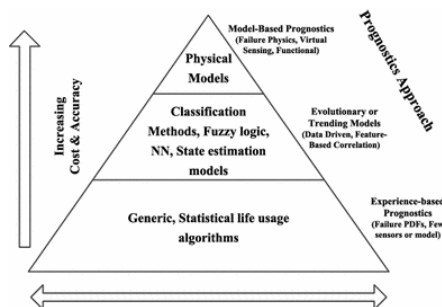


Fig. 1. The main prognostic approaches in the state of art [5]

2.1. RUL estimation methods

In general, RUL methods in the literature are based on physical model-based, data-driven, or a combination of both (Hybrid models) [6]. Finding the failure function is usually followed in physical model-based approaches by studying physical failure mechanisms. This is highly differentiated case by case and depends on a variety of parameters [7]. However, in data-driven methods, pre-targeted time series data and signals are collected and processed that could represent the degradation or healthy state of the equipment or component. In this way, time-series data processing should result in Health Indicators (HI) construction [8] as HI is an essential and key element for RUL estimation [9]. This is the main applicable approach to most of the cases that initially identify the health state (whether categorical classes or continuous trend-based) and then predict the future trend until the failure or near to failure state. However, there is another approach that is called pattern matching or similarity-based approach [10] [11] when there are already available run-to-failure data sets. The degradation is checked and classified to the closest degradation profile and found the RUL based on the identified pattern [12].

As it will be explained in the presented prognostic procedure of this paper, RUL methods in the majority of cases in state-of-art are obtained using statistical prediction models [13], DL [14], and a mix of them [7] [15].

Several types of regression methods have been used for the RUL estimation such as Support Vector Regression on the Turbofan (C-MAPSS) dataset that is largely used in the literature [16]. Gaussian Process Regression was applied on the lubrication oil remaining useful life [17]. [18] have used an exponential degradation model based on the random coefficient statistical method for health state prediction. The triple exponential smoothing method has been used for RUL estimation of the cyclic process by [19]. The Autoregressive Integrated Moving average (ARIMA) method has been adopted by [20] on the rotor test rig for the state prediction purpose.

Deep learning methods are widely used in image processing and voice recognition applications and less in the RUL estimation domain [14]. However, researchers are attempting to find solutions for RUL estimation by configuring input, hidden and output layers in different formats to provide a NN that adapts to each kind of problem.

Artificial Neural Network (ANN) as a feed-forward NN [21] has been deployed on the historical and vibration data of a rotatory pump. Vibration data is also used in a Multilayer Perceptron (MLP) Neural Network for the RUL estimation of rolling-element bearing [22]. Convolution Neural Network (CNN) is been applied in the famous turbofan data set [23]. These methods utilize forward direction which means the process is started from input layers, then hidden, and finally output layer. Moreover, the seasonality changes are not captured in these methods. While, Recurrent Neural Network (RNN) is another DL method that has feedback connections between hidden and output layers, and it is said to be more pertinent for the prediction of sequential data as time series data. Long Short-term Memory (LSTM) is a type of RNN that has been proposed by [24] to expose the hidden pattern of sequential data. LSTM was used by [22] to predict the failure time and consequently the RUL of rolling bearing with vibration data.

Although deep learning methods are developed and applied in time series data, other aspects of interpretability and complexities should be considered. The black-box nature of deep learning methods may be complex for parameter indications and interpretation [15]. On the other side, statistical methods such as ARIMA may not capture the seasonality patterns (long fitting time or hard tuning of autoregressive parameters) and imply large trend errors. However, the Prophet prediction method has shown the capability of self-adjusting and tracing long trends and seasonality patterns for large data sets [25].

Concerning the contribution of this paper, a new dynamic prognostic procedure is proposed to estimate the RUL in dynamic mode as the new real-time data are acquired. Then, for the dynamic RUL estimation, it is proposed to use the open-source prophet prediction package. A dynamic method based on the prophet algorithm has been presented that can self-tune and predict continuously. The presented method can be regarded as a new approach for dynamic RUL estimation when there is a reliable Health Indicator.

3. Methodology

3.1. Dynamic Prognostic Procedure

For the RUL estimation, the target must be identified priorly. This target could be the remaining life before arriving the failure for a component, equipment, or a specific failure mode in whole equipment [26]. Based on this target, condition monitoring data are identified and achieved through IIoT platforms. These real-time data are normally stored dynamically in data lakes or databases. Based on the presented approach in Fig. 2 health state indicators are defined at the current time of data acquisition. They could be presented in the form of categorical classes or continuous values such as a percentage. Here, specific knowledge of the equipment, and the targeted failure mode plays an important role in finding the right health indicators, as there are highly case-dependent parameters.

In terms of methodology, HIs are determined with the help of Feature Extraction, Clustering, Classification, or Reinforcement Learning methods. There are three main approaches in feature extraction as 1- Time domain, 2- Frequency domain, and 3- Time-Frequency domain approaches [27]. In the case of high-volume data, fusing methods such as Principal Component Analysis (PCA) could be implemented using multiple real-time data [28]. In this way, the interdependency between the data and the aggregated indicator could be found. Clustering methods are used when there is a lack of knowledge in the correlation of real-time data and failure. Hence, the clusters (which corresponds to the real conditions of targeted failure mode or equipment) can be obtained and regarded as the featured data containing sensible information. Once the features are set, machine learning algorithms such as K-Nearest Neighborhood (KNN) [29], or reinforcement learning should be used to classify or identify the current health state right as the new data are received. The obtained health indicator model is a basis for the health assessment and monitoring of the machine, or equipment. This is illustrated in Fig. 2 at the left bottom of the figure.

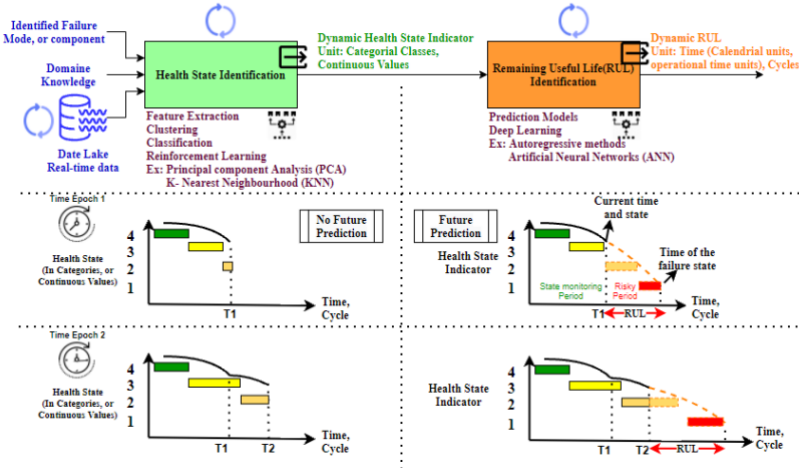


Fig. 2. Dynamic Prognostic Procedure

In the HI determination phase, we are in the actual instant without any prediction for the upcoming events during the next hours, days, etc. We can simply maintain health monitoring when we are at the normal state, while at the risky state the RUL estimation becomes more important. As it is seen on the right side of the figure, this risky period depends also on the risky threshold of spare part replenishment lead time and the needed time for the intervention of the maintenance team.

For the prognostic aspect, the RUL estimation model should take the HI trend to find the failure time and calculate the RUL. The RUL unit can be the calendar units as days or production cycles as the number of produced parts. As explained in the literature section, the most pertinent methods are statistical, deep learning, or a combination of both that could find the learning function of the HI trend. As seen on the right side of Fig. 2, this is not the same approach that is presented in [5], as the classification methods could help in identifying the current state and not the future state. While prediction and statistical methods widely help in trend prediction which is suitable for the predictions and RUL estimations.

For the dynamic aspect of the prognostic, an interval of readjustment should be identified depending on the criticality of the case and its parameters. In each of these intervals, new real-time data are achieved and processed to update the RUL value. This is because the RUL value is highly dependent on the operational usage of components or equipment. It could be extended or decreased as it is depicted in the schematic example at the bottom of the figure in the time epochs.

3.2. Dynamic RUL method

Regarding the literature analysis of the pros and cons of different prediction methods, the applicability of the methods, and the ease of use in real cases, the Prophet method [25] has been chosen for RUL estimation. Prophet uses a decomposable time series model that is seen in (1). This model aside from trend prediction function $g(t)$ considers the periodic $s(t)$ variations (as daily and weekly changes) and irregular events effects $h(t)$ as holidays. These last two features are less considered in the other prediction models. The ε_t represent the peculiar changes supposed to be normally distributed.

$$Y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (1)$$

Regarding the trend function, Prophet mainly uses linear piece-wise growth functions (2).

$$g(t) = (k + a(t)^\top \delta_t)t + (m + a(t)^\top \gamma) \quad (2)$$

Trend changes are incorporated in the growth function by defining changepoints S_j $j = 1, \dots, S$ and δ_j responds to the change rate happened in changepoint j . Where k is the basic growth rate, $a(t)^\top \delta_t$ is the change rate at time t . m is the offset parameter, $a(t)^\top \gamma$ is the offset adjustment at time t . Automatic changepoint detection is based on (2) with a sparse prior on $\delta_j \sim \text{Laplace}(0, \tau)$ that impacts the growth rate model.

Seasonality and periodic change effects are obtained based on (3) by inspiring from Fourier series:

$$s(t) = \sum_{l=1}^N \left(a_l \cos\left(\frac{2\pi lt}{P}\right) + b_l \sin\left(\frac{2\pi lt}{P}\right) \right) \quad (3)$$

Where P is the regular period value based on days, $2N$ is the number of parameters to be estimated that best fits the prediction problem. Equation (3) can be written in the form of $s(t) = X(t) * \beta$ as $\beta = [a_1, b_1, \dots, a_N, b_N]$. To impose a smooth prior β is considered as $\text{Normal}(0, \sigma^2)$.

Effect of the event in the daytime as D_i on the past and future days are considered by an indication function to check if date t is in the events or not, and a seasonality prior scale of $k \sim \text{Normal}(0, v^2)$.

Three main components are most important to avoid overfitting and underfitting as 1- Changepoint scale (τ), 2- Seasonality scale (σ) and 3- Predictable events (like holiday) scale (v).

The best Prophet prediction parameters can be identified using a cross-iterated table of changepoint, and seasonality prior scale values. The performance metrics as Root Means Square Error (RMSE) Mean Absolute Percentage Error (MAPE) or Tracking signal can be obtained to identify the best prediction parameters where y_i is the actual value, and \hat{y}_i is the predicted value. In this problem, we have used RMSE as it punishes the large errors, and it has the y units. MAPE is an appropriate metric when we have datasets at different scales. The tracking signal is the managerial metric that presents the error volume and if RUL is estimated sooner or later than its actual failure.

As in PdM, we are dealing with real-time data, dynamic models must provide the last updated prediction based on the evolution of health indicator's trend. As it is depicted in Fig. 3, in the first step of the proposed dynamic RUL method, a set of historical real-time data are obtained. Then, health indication values would be identified based on the HI method pertinent to each case. Next, the best-tuned prediction parameters are achieved with the cross-validation

function that has the minimum performance error. RUL of the case is obtained and will be sent to the decision-maker or maintenance planning system.

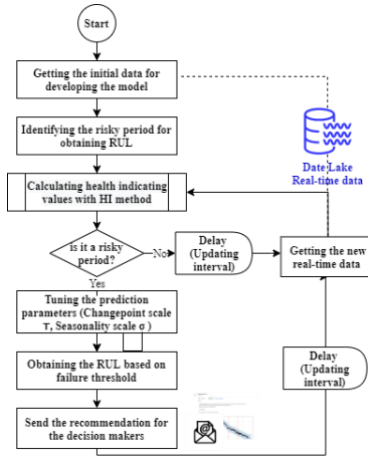


Fig. 3. Dynamic RUL methodology

This algorithm works continuously to self-adapt based on the last obtained real-time data in a predefined updating interval.

4. Case Study and Results

FPT Industrial Company is a brand of CNH industrial and one of the leading world players in the development, and production of on-road, off-road, marine, and power generation engines. In their assembly line, 5 conveyor chains are leading the engines produced in several assembly lines into the painting station. In this study, one of the critical conveyor chains (see Fig. 4 left) is considered for the prognostic and RUL study.

These conveyor chains are driven by a motor and two gears. There is also a tensioner system with the help of 6 bar jack that keeps the tension of the chain and maintains the equilibration. These chains are degraded until they are broken or stretched enough to cause production stoppages. There are male and female I-Beam chain links that are connected in series. The principal causes of degradation are due to the weight of lifted engines as well as the ups and downs of the conveyor chain path (causes the elongation of the chain). The whole chain behavior is monitored based on the position of the tensioner system. Concerning the experimentation of the proposed prognostic approach and dynamic RUL, it is targeted to estimate the dynamic RUL of the whole chain. This has been put into action using an ultrasonic sensor that measures the position of the tensioner system in real-time per second and is registered in the cloud Data Lake. The information of failure threshold is available in this case.

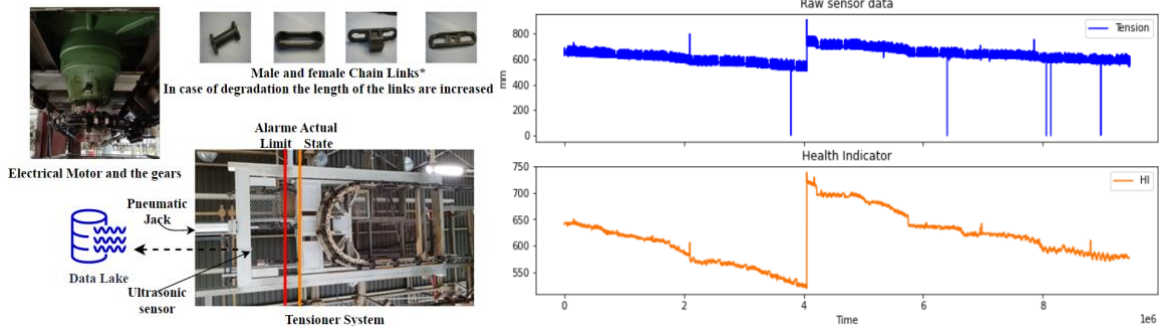


Fig. 4. Left: Conveyor chain system and its elements, Right: Raw sensor data and Health Indication data

To find the RUL of the whole conveyor chain, as described in the dynamic prognostic procedure, a HI is obtained based on a statistical approach for this case. As Root-Mean Square (RMS) [18] has been selected for identifying the

health state. RMS is calculated in a regular period (P) that can keep the degradation characteristics. therefore, RMS of period j is obtained by (4) which p_j is the starting time of period j and N is the total number of periods in the dataset.

$$RMS_j = \sqrt{\frac{1}{P} \sum_{i=p_j}^{P+p_j} x_i^2}, \quad j = \{1, \dots, N\} \quad (4)$$

Fig. 4 (right) illustrates raw data without health indicator (the top chart) and the data after HI transformation (the bottom chart). Based on the replenishment, time to intervention, and criticality of the case, the risky period is identified as 14 days. If the model at the running time is in a risky period, then the prediction parameters are tuned, and RUL is obtained. This will continue in every updating interval as the new data are achieved. The result of the prediction model and RUL estimation is illustrated in the following Fig. 5:

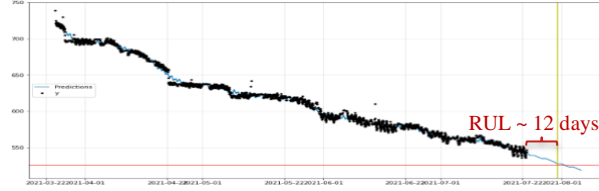


Fig. 5. HI, Prediction, and estimated RUL

It is clearly seen that the periodic changes are well captured in and based on the failure threshold the obtained RUL is well achieved from the health indicator data points. The performance of the Prophet method has been compared with ARIMA [20], Holt-winter (Triple exponential smoothing) [19], and LSTM method Fig. 6. The idea is to compare the results with statistical, exponential, and deep learning methods. For the comparison, 80% of the dataset has been considered as a train set (in blue) and 20% for the test (the orange part) of the prediction model. The green points are the prediction values of each method.

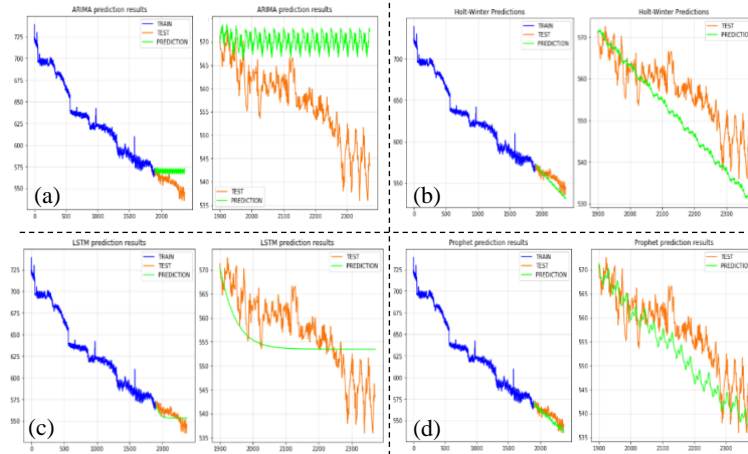


Fig. 6. ARIMA (a), Triple Exponential Smoothing (Holt-Winter) (b), LSTM (c), and Prophet (d) prediction results

It is observed that the prophet and Holt-Winter's model can provide mid-term prediction, however, the ARIMA and LSTM methods give better predictions for small horizons rather than long horizons. In fact, despite their right training, for instance, LSTM worked well in less than 10 periods, but the number of periods increased, it worked with less accuracy. This is probably due to the sequential nature of LSTM that gives predictions in different iterations based on the trained model. On the contrary, we observe that Holt-Winter can trace the seasonality, but not as good as the Prophet model. Concerning performance metrics, RMSE and Tracking signal of the four models are obtained in Table I, which Prophet method works better among them. Although Prophet is created for business time series, we observed that it can also work well for the RUL estimation. It can provide a prediction for the data with a non-fixed interval of periods, while other mentioned methods need a fixed interval between the periods.

Table I. Performance metrics of prediction methods

	Prophet	ARIMA	Holt-Winter	LSTM
RMSE	5.5101	15.4380	8.4070	6.5881
Tracking signal	368.179	-473.690	384.265	369.341

With the help of the presented method, the RUL of the whole chain is obtained continuously that runs in a local Edge system. The next step of this study is adopting an applied maintenance strategy based on RUL information. When the RUL is identified in the risky period, the maintenance team controls the length of 10 chain links randomly. If the lengths of the chains are quite equal (homogenous degradation), two chain links should be removed to keep the equilibration of the whole chain. If not, the degradation is not homogenous and fault localization of most degraded chain links should be identified and changed.

5. Conclusion

RUL estimation is one of the key elements in Predictive Maintenance strategy, as it helps to better planning of maintenance activities and reduce breakdowns and over maintenance at the same time. Yet, a prognostic approach and procedure are required to determine RUL. In this paper, a comprehensive procedure is presented to conceptualize the path of estimating RUL from the raw inputs, and the general methodologies of calculating Health Indicator and RUL of the targeted failure type, component, or machine. Following this procedure, a dynamic RUL estimation method has been proposed to obtain RUL dynamically based on continuous real-time data.

The proposed approach and dynamic RUL are implemented and proved in conveyor chains of FPT Industrial Company. The health indicator of the whole chain degradation is obtained based on RMS calculation. The Prophet prediction method has been found interesting for the RUL estimation, based on the study of prediction methods in state-of-art, which is rarely considered for RUL estimation to the best of our knowledge. In this problem, deep learning methods, like LSTM, may increase the complexity in parameter tuning that results in a long training time. LSTM and ARIMA models do not perform well in mid/long-term predictions. On the other hand, the triple exponential smoothing model can provide better predictions, but still, it requires the identification of the seasonality period. While, Prophet model self-detects the changepoints and seasonality periods, and it captures the seasonality and irregular events better than the triple exponential smoothing method. Its performance is proved by comparing with ARIMA, triple exponential smoothing, and LSTM methods that can provide more reliable predictions and hence RUL estimation. Regarding industrial problems, triple exponential smoothing, or the Prophet method may be sufficient for RUL estimation that depends on the desired level of prediction exactitude.

The proposed dynamic RUL method self-tunes the model parameters and re-estimates the RUL following the new real-time data in the time epochs. The efficiency of computational time and needed resources for applying in an industrial environment (as in, Edge, Fog, or Cloud) can be studied in future research.

RUL determination remains a part of the information that must be served for maintenance strategy identification and maintenance planning. Future research could be the development of mathematical maintenance planning methods based on an optimization approach that considers the RUL information and the other maintenance-related parameters, to identify the best intervention schedule. The optimization approach can be mainly cost-based that can consider maintenance dependencies between multi-component equipment, or machines.

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References

- [1] G. W. Vogl, B. A. Weiss, and M. A. Donmez, "Standards for prognostics and health management (PHM) techniques within manufacturing operations," in *PHM 2014 - Proceedings of the Annual Conference of the Prognostics and Health Management Society 2014*, 2014, vol. 2013,

- pp. 576–588.
- [2] “The Standardisation Roadmap of Predictive Maintenance for Sino-German Industrie 4.0/ Intelligent Manufacturing,” p. 27, 2018, [Online]. Available: <https://www.dke.de/resource/blob/1711308/ad04db2c91a6749c86e7311c1a294644/the-standardisation-roadmap-of-predictive-maintenance-for-sino-german-industrie-4-0-data.pdf>.
 - [3] “International Organization for Standardization. ISO 13374-2:2007 Condition monitoring and diagnostics of machines — Data processing, communication and presentation — Part 2: Data processing,” 2007.
 - [4] K. Swearingen, W. Majkowski, B. Bruggeman, D. Gilbertson, and J. Dunsdon, “An Open System Architecture for Condition Based Maintenance Overview,” *IEEE Aerosp. Conf.*, pp. 1–8, 2007.
 - [5] A. M. R. Hatem M. Elattar, Hamdy K. Elminir, “Prognostics : a literature review,” *Complex Intell. Syst.*, vol. 2, no. 2, pp. 125–154, 2016, doi: 10.1007/s40747-016-0019-3.
 - [6] B. Einabadi, A. Baboli, and M. Ebrahimi, “Dynamic Predictive Maintenance in industry 4.0 based on real time information: Case study in automotive industries,” in *IFAC-PapersOnLine*, 2019, vol. 52, no. 13, pp. 1069–1074, doi: 10.1016/j.ifacol.2019.11.337.
 - [7] J. Wu, K. Hu, Y. Cheng, H. Zhu, X. Shao, and Y. Wang, “Data-driven remaining useful life prediction via multiple sensor signals and deep long short-term memory neural network,” *ISA Trans.*, no. July, 2019, doi: 10.1016/j.isatra.2019.07.004.
 - [8] E. T. Bekar, P. Nyqvist, and A. Skoogh, “An intelligent approach for data pre-processing and analysis in predictive maintenance with an industrial case study,” *Adv. Mech. Eng.*, vol. 12, no. 5, pp. 1–14, 2020, doi: 10.1177/1687814020919207.
 - [9] D. Wang, K.-L. Tsui, and A. Q. Miao, “Prognostics and Health Management: A Review of Vibration Based Bearing and Gear Health Indicators,” *Ieee Access*, vol. 6, pp. 665–676, 2018.
 - [10] T. Wang, J. Yu, D. Siegel, and J. Lee, “A Similarity-Based Prognostics Approach for Remaining Useful Life Estimation of Engineered Systems,” *Int. Conf. Progn. Heal. Manag.*, pp. 0–5, 2008.
 - [11] W. Yu, I. I. Yong, and C. Mechefske, “An improved similarity-based prognostic algorithm for RUL estimation using an RNN autoencoder scheme,” *Reliab. Eng. Syst. Saf.*, vol. 199, no. March, 2020.
 - [12] *Predictive Maintenance with MATLAB*. MathWorks, 2020.
 - [13] X. S. Si, W. Wang, C. H. Hu, and D. H. Zhou, “Remaining useful life estimation - A review on the statistical data driven approaches,” *Eur. J. Oper. Res.*, vol. 213, no. 1, pp. 1–14, 2011, doi: 10.1016/j.ejor.2010.11.018.
 - [14] Y. Wang, Y. Zhao, and S. Addepalli, “Remaining useful life prediction using deep learning approaches: A review,” in *Procedia Manufacturing*, 2020, vol. 49, no. 2019, pp. 81–88, doi: 10.1016/j.promfg.2020.06.015.
 - [15] O. Triebe, N. Laptev, and R. Rajagopal, “AR-Net: A simple Auto-Regressive Neural Network for time-series,” vol. d, pp. 1–12, 2019, [Online]. Available: <http://arxiv.org/abs/1911.12436>.
 - [16] R. Khelif, B. Chebel-morello, S. Malinowski, and E. Laajili, “Direct Remaining Useful Life Estimation Based on Support Vector Regression,” *IEEE Trans. Ind. Electron.*, vol. 0046, no. c, 2016, doi: 10.1109/TIE.2016.2623260.
 - [17] M. Tanwar and N. Raghavan, “Lubricating Oil Remaining Useful Life Prediction Using Multi-Output Gaussian Process Regression,” *IEEE Access*, vol. 8, no. 1, pp. 128897–128907, 2020, doi: 10.1109/ACCESS.2020.3008328.
 - [18] M. Macchi, L. Cattaneo, M. Macchi, P. Leonardo, and P. Leonardo, “A digital twin proof of concept to support machine prognostics with low availability of run-to-failure data,” *IFAC-PapersOnLine*, vol. 52, no. 10, pp. 37–42, 2019.
 - [19] L. M. De Marco, J. O. Trierweiler, and M. Farenzena, “Determination of Remaining Useful Life in Cyclic Processes,” 2019, doi: 10.1021/acs.iecr.9b03182.
 - [20] W. Wu, J. Hu, and J. Zhang, “Prognostics of machine health condition using an improved ARIMA-based prediction method,” *ICIEA 2007 2007 Second IEEE Conf. Ind. Electron. Appl.*, pp. 1062–1067, 2007, doi: 10.1109/ICIEA.2007.4318571.
 - [21] Z. Tian, L. Wong, and N. Safaei, “A neural network approach for remaining useful life prediction utilizing both failure and suspension histories,” *Mech. Syst. Signal Process.*, vol. 24, no. 5, pp. 1542–1555, 2010, doi: 10.1016/j.ymssp.2009.11.005.
 - [22] A. Rohani Bastami, A. Aasi, and H. A. Arghand, “Estimation of Remaining Useful Life of Rolling Element Bearings Using Wavelet Packet Decomposition and Artificial Neural Network,” *Iran. J. Sci. Technol. - Trans. Electr. Eng.*, vol. 43, no. July, pp. 233–245, 2019, doi: 10.1007/s40998-018-0108-y.
 - [23] X. Li, Q. Ding, and J. Q. Sun, “Remaining useful life estimation in prognostics using deep convolution neural networks,” *Reliab. Eng. Syst. Saf.*, vol. 172, no. November 2017, pp. 1–11, 2018, doi: 10.1016/j.res.2017.11.021.
 - [24] S. Zheng, K. Ristovski, A. Farahat, and C. Gupta, “Long Short-Term Memory Network for Remaining Useful Life estimation,” *2017 IEEE Int. Conf. Progn. Heal. Manag. ICPHM 2017*, pp. 88–95, 2017, doi: 10.1109/ICPHM.2017.7998311.
 - [25] S. J. Taylor and B. Letham, “Forecasting at Scale,” *Am. Stat.*, vol. 72, no. 1, pp. 37–45, 2018, doi: 10.1080/00031305.2017.1380080.
 - [26] A. Angelopoulos, E. T. Michailidis, N. Nomikos, P. Trakadas, A. Hatziefremidis, and S. Voliotis, “Tackling Faults in the Industry 4.0 Era—A Survey of Machine-Learning Solutions and Key Aspects,” vol. 20, no. 1, 2020, doi: 10.3390/s20010109.
 - [27] Y. Lei, N. Li, L. Guo, N. Li, T. Yan, and J. Lin, “Machinery health prognostics : A systematic review from data acquisition to RUL prediction,” vol. 104, pp. 799–834, 2018.
 - [28] B. Einabadi, M. Mohammad Amini, A. Baboli, and E. Rother, “Dashboard proposition for health monitoring of production system in the automotive industry,” *IFAC-PapersOnLine*, 2021.
 - [29] R. Liu, B. Yang, E. Zio, and X. Chen, “Artificial intelligence for fault diagnosis of rotating machinery : A review,” vol. 108, pp. 33–47, 2018.