



A Remaining Useful Life Prediction of a robot with 15 states

Jaouad BOUDNAYA¹

Marouan CHERRAT²

Ilham GHARIB³

Abdelhak MKHIDA⁴

^{1,2,3,4} Moulay Ismail University, ENSAM Meknes, Laboratory of Mechanics, Mechatronics and Control (L2MC), Marjane 2, PO Box 15290, Al-Mansour Road Agouray, 50500 Meknes, Morocco

Received: 07/05/2022,

Accepted: 19/10/2022,

Published: 31/10/2022

Abstract: Predictive maintenance is one of the methodologies to improve maintenance policies of industrial systems. It is based on a predictive model, which allows to determine the Remaining Useful Life (RUL) of critical components using the degradation phenomenon models. This approach is based on simulation results. The work presented in this paper consists of the identification of the degradation indicator and the prognosis of the Remaining Useful Life (RUL) of a robot system. This system is composed by a robot that can move within an area of 15 squares, it is made up of sensors, which detects obstacles in four directions: north, south, east and west. This system is modeled by Hidden Markov Model (HMM). This strategy is considered as a trigger of a maintenance operation.

Keywords: Remaining Useful Life (RUL), prediction, prognosis, robot, maintenance.

Résumé : La maintenance prédictive est l'une des méthodologies permettant d'améliorer les politiques de maintenance des systèmes industriels. Il est basé sur un modèle prédictif, qui permet de déterminer la durée de vie résiduelle des composants critiques à l'aide des modèles de phénomène de dégradation. Cette approche est basée sur des résultats de simulation. Le travail présenté dans cet article consiste en l'identification de l'indicateur de dégradation et du pronostic de la durée de vie résiduelle d'un système robotique. Ce système est composé d'un robot qui peut se déplacer dans une zone de 15 cases, il est composé de capteurs, qui détecte les obstacles dans quatre directions : nord, sud, est et ouest. Ce système est modélisé par un modèle de Markov caché. Cette stratégie est considérée comme un déclencheur d'une opération de maintenance.

Mots-clés : Durée de vie résiduelle, prédiction, prognostics, robot, maintenance.

¹ E-mail : j.boudnaya@gmail.com

² E-mail: marouancherrat@gmail.com

³ E-mail: ilhamgharib1997@gmail.com

⁴ E-mail: abdelhak.mkhida@gmail.com

Introduction :

Today, predictive maintenance is considered as one of the most relevant maintenance policies for improving maintenance management in systems where fault identification is more complex compared to systems has simple structures. It is conditional maintenance, which is based on crossing a critical degradation threshold to trigger a maintenance operation. It is based on the construction of a predictive model, which makes it possible to determine the Remaining Useful Life (RUL) of critical components using models of the degradation phenomenon. This model is based on simulation results.

It therefore requires on the one hand assessing the state of degradation of the system components, and on the other hand to predict the future occurrence of a failure. More precisely, it is about the RUL. Estimating a RUL is a real issue because the relevance and effectiveness of maintenance actions depend on the accuracy and precision of the results obtained.

In the literature, there are many works, which are interested in this topic using multiple methods. The authors of the paper (Yaguo L., et al., 2016), propose a model-based method for predicting RUL of machinery. The method is composed of two modules: indicator construction and RUL prediction. The paper (Okoh C., et al., 2014) reports the findings of a recent review of the literature relative to the use of prognostics. The techniques applied to determine the RUL of gas turbine components are also discussed. In the work (Yanting, Z., et al, 2020), an efficient and robust evaluation method has been established for remaining life predication of supercapacitors in the means of improving long short-term memory approach. The paper (Dragan B., 2009) proposes some aspects of Remaining Useful life in theory and in practice. The objective of our work is to determine the degradation indicator and to estimate the RUL of a robot system, which is composed by sensors, which detects obstacles in four directions: north, south, east and west. The proposed paper is structured as follows: section 2 presents the RUL Prediction, section 3 consists of the robot system description. In the section 4, we introduce the methodology of our study. Section 5 describe our case study when considering the hidden Markov Model of the robot and its environment as well as the results of the determination of the degradation indicator and the estimation of the RUL of a robot system. Then, we conclude the paper in the last section (section 6).

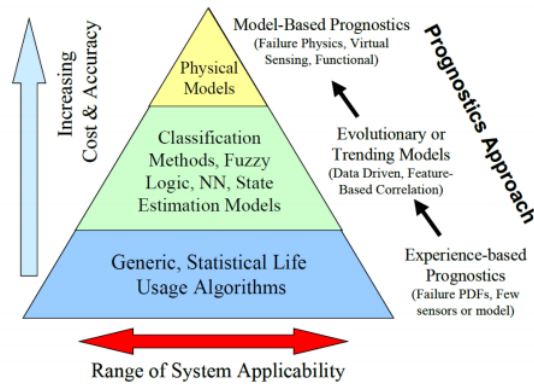
1. Remaining Useful Life Prediction

The prognosis is an essential step for the implementation of a predictive maintenance strategy. Its purpose is to estimate the Remaining Useful Life (RUL) of the selected components, that is to say the operating time remaining before these components fail or no longer function sufficiently. This makes it possible to adapt and optimize the maintenance schedule.

The prognosis has been the subject of increasing interest for several decades, and several methods have been developed, tested and improved as technology advances. There are three categories of prognosis:

- The prognosis based on physical models: it is based on mathematical and / or physical models of degradation phenomena.
- Data-driven prognosis: it consists of the analysis of datasets to find indicators of the component's health status.
- The experience-based prognosis: it is based on the exploitation of the knowledge acquired about the failure or the degradation of the component in the past.

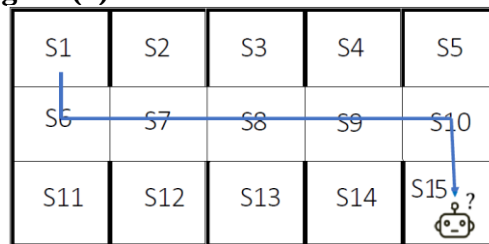
The figure (1) shows the range of prognostic approaches depending on their applicability to different systems, the cost of their implementation and their accuracy. Besides the classification of the different prognosis models:

Figure (1): Categories of prognosis

(Delmas, A., 2019)

2. Robot system description:

Our system to study is a robot, which can move within an area of 15 squares. In the mini-warehouse, there are eight shelves located between tiles S1S2, S2S3, S3S4, S4S5, S11S12, S12S13, S13S14 and S14S15. Therefore, the environment of the Robot consists of 15 discrete states (see figure 2).

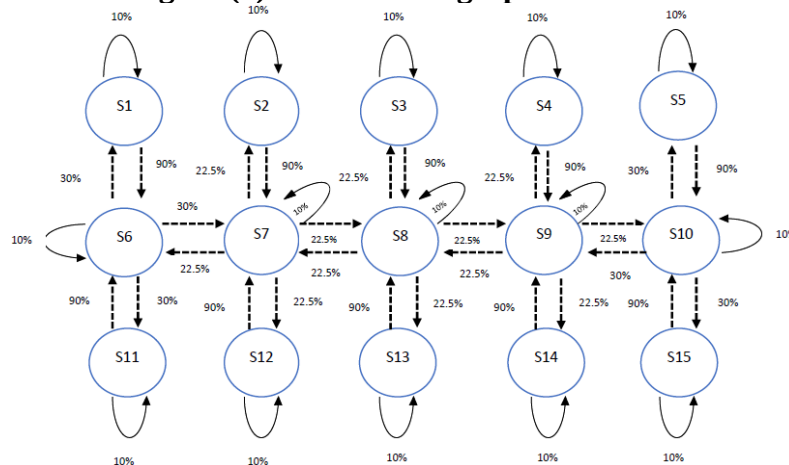
Figure (2): The Environment of the robot

(Boudnaya, J., et al., 2021)

The robot is programmed to change its position with a probability of 90% and moves randomly to a different neighbouring square.

Our system is made up of sensors, which detects obstacles in four directions: north, south, east and west. The sensor values are conditionally independent given the position of the robot when the robot makes a move; we receive four readings from the sensing system. Moreover, the sensors have an error rate of $e=25\%$ (Boudnaya, J., et al., 2020).

The probabilistic graphical model is represented in figure 3.

Figure (3) Probabilistic graphical model

(Boudnaya, J., et al., 2021)

3. Methodology of the study:

Our study consists of changing the error rate of the sensors fixed previously. This change can lead to a propagation error at the observation matrix and then at our peak of probability, which represents in our case the most favoured path when moving our robot.

The global RUL corresponds to a change in the prediction of the movement of our robot throughout the predetermine path, obviously the failure in our case is actually a failure of prediction of an error related to a sensor.

We vary the error rate of the sensors and we calculate the relative error according to the following formula: $e_r = |e_f - e_{ref}| / e_{ref}$

With e_r : Relative error, e_f : Failure error, e_{ref} : Failure of reference.

In our case, we want to make a prognosis of the RUL of components from the data collected (prognosis guided by the data) by monitoring means.

Our study is made on the components of the robot; we found that the component most likely to fail is the proximity sensors, the study made after focuses on a single sensor.

To estimate the RUL of a component, we have to build a model representing the evolution of the degradation of this component. It is therefore necessary to choose a type of model, then its topology, and finally it is necessary to calibrate this model by learning.

First, it is necessary to define the topology of the hidden Markov model (HMM) that we want to build (the number N of states that contains and the number M of observation symbols that may be emitted).

Indeed, a transition probability matrix A, an emission probability matrix B, and an initial distribution π define a hidden Markov model. The sizes of these matrices depend on the parameters N and M chosen.

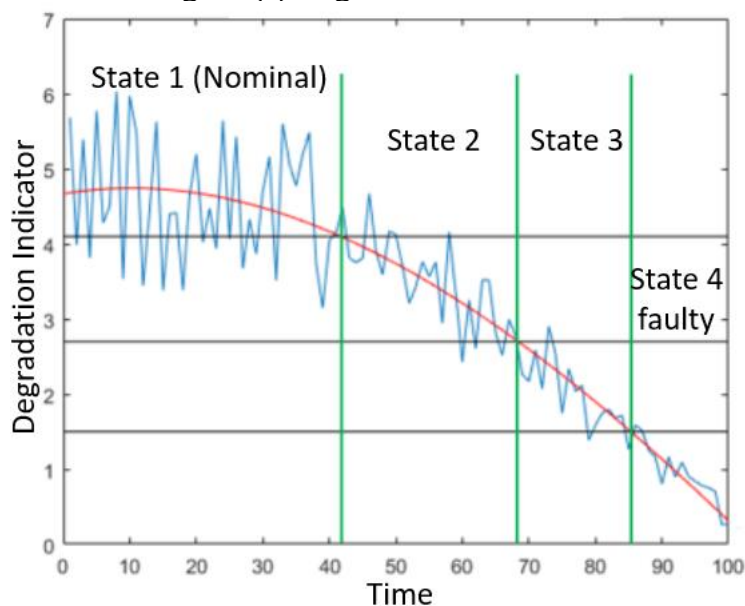
In our case, we are interested in an HMM with four states and five observation symbols modelling the simplified degradation of a component. We therefore consider that state 1 is "nominal", state 2 is "little degraded", state 3 is "degraded" and state 4 is "faulty".

4. Results and discussions:

Learning allows the model to be calibrated so that it matches the system being studied. In the case of a Markov model, we use the BaumWelch algorithm. The objective is to adjust the parameters (A, B, π) of the model to maximize the probability of obtaining the observation sequences that constitute the training data set (Delmas, A., 2019).

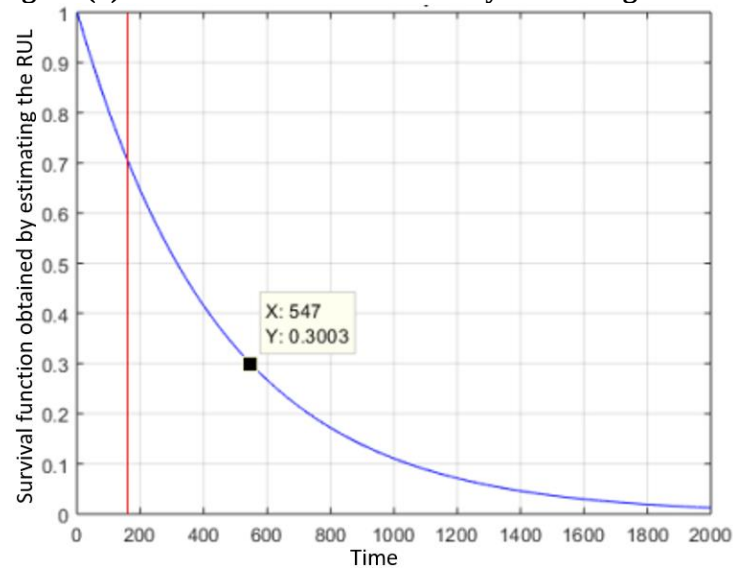
The figure 4 represents the discretization of the degradation indicator of our robot system:

Figure (4) Degradation Indicator



Then, we use the VITERBI algorithm to estimate the RUL of our System (**figure 5**).

Figure (5) Survival function obtained by estimating the RUL



This RUL is defined as the operating time remaining before the component fails. Let us denote by **Tcomp** the time that the component has already lived (from the initial moment until the moment of the last data collection). Then, we can consider that the half-life of this component is $T_{comp} + RUL$. Therefore, the survival function equation is $f(t) = e^{-\lambda t}$ with $\lambda = \ln(2)/(T_{comp} + RUL)$. By plotting this function as well as the line $x = T_{comp}$, we can easily see the date on which a maintenance action must be scheduled according to a previously chosen acceptability threshold.

For our case, the component has already lived 159 time steps. If we choose to take a maintenance action when it has a probability of 0.7 of failing (i.e. a probability of 0.3 of functioning correctly), it must be in $547 - 159 = 388$ steps of time.

Conclusion:

In this paper, we have presented the methodology of determination of degradation indicator and the prediction of the RUL of a robot system that can move within an area of 15 tiles. It is equipped with a sensing system, which can detect obstacles in four directions: north, south, east and west.

In our future works, we will try to develop this model by collecting more data or making more tests on the sensors of our system to have results that are more consistent.

Acknowledgments

In the term of this paper, we thank the Laboratory of Mechanic, Mechatronics and Control (L2MC) of the ENSAM MEKNES. We do not forget both our colleagues and experts for the information source. In addition, we thank the steering committee of the 1st International Symposium on Industrial Engineering Maintenance and Safety (IEMS'22) to allow us to communicate our works and results.

References:

Yaguo L., Naipeng L., Szymon G., Jing L., Stanislaw R., and Jacek D., (2016). A Model-Based Method for Remaining Useful Life Prediction of Machinery. IEEE TRANSACTIONS ON RELIABILITY, VOL. 65, NO. 3.

Okoh, C., Roy, R., Mehnen, J., and Redding L., (2014). Overview of Remaining Useful Life Prediction Techniques in Through-Life Engineering Services. Procedia CIRP 16 (2014) 158 – 163

Yanting, Z., Yanan W., Kai W., Le K., Fei P., Licheng W., Jinbo P., (2020). Hybrid genetic algorithm method for efficient and robust evaluation of remaining useful life of supercapacitors. Applied Energy 260-114169.

Dragan B., (2009). Remaining useful life in theory and practice. Metrika. 69:337–349 DOI 10.1007/s00184-008-0220-5.

DELMAS, A., (2019). Contribution à l'estimation de la durée de vie résiduelle des systèmes en présence d'incertitudes. Performance et fiabilité [cs.PF]. Université de Technologie de Compiègne, Français. ffNNT : 2019COMP2476ff. fftel-02178913f

Boudnaya, J., Charrat, M., Gharib, I., and Mkhida, A., (2021). Comparison between Filtering estimation with Evidence and Prediction Filtering without Evidence to predict a Robot localization states. The International Conference on Advanced Intelligent Systems and Informatics (AISII 2021), Cairo, Egypt.

Boudnaya, J., Haytoui, A., Eddayer, O., and Mkhida, A., (2020). Prediction of Robot localization states using Hidden Markov Models. The International Conference of Artificial Intelligence and Industrial Applications (A2IA'2020), Meknes, Morocco.