

A Study on Health Diagnosis and Prognosis of an Industrial Diesel Motor: Hidden Markov Models and Particle Filter Approach

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Abstract. The paper presents a study on health diagnosis and prognosis of an industrial diesel motor. Two well-known approaches, Hidden Markov Model (HMM) and particle filter (PF), are applied from real recorded data with different measurements. The recorded data is firstly pre-processed and health indicator is then chosen before implementing each used approach. The obtained results are analyzed and discussed. The use and advantages of each approach are finally highlighted.

Keywords: Faults diagnosis · Prognosis · Hidden Markov Models · Particle filter · Diesel motor

1 Introduction

Health diagnosis and prognosis plays an important role to avoid catastrophic failures, reduce downtime, and eventually minimize operation and maintenance costs. In the sense, various works on health diagnosis and prognosis have been developed and successfully applied in industrial engineering. An excellent review can be found in [6]. In various industrial applications such as transport, automotive, marine, diesel motors are widely used. However diagnosing faults and/or predicting its future health condition of a such motor still remains widely open due to its complexity from both structural and functional point of view [2].

The diagnosis and prognosis approaches can broadly be classified into three main classes: experiences-based methods, models-based methods and data-driven ones. The first kind of methods based on the exploitation of knowledge on the failure or degradation of the system is quite simple and less expensive to implement see [6]. However, these approaches are hardly applicable in a dynamic environment. Model-based methods are mainly based on analytical/mathematical models to describe the behavior of the system and mechanisms of the degradation phenomenon [4]. The main advantages of model-based approaches are its high accuracy and flexible in configuring input data. However, nonlinear and stochastic characteristics of industrial system may increase the difficulty to build the

analytical model. Real-time modification of model parameters is limited according to the flexible configuration of the system. Data-driven methods allows to identify the trend/patent of developing fault and predicting the remaining useful life (RUL) [7] using information from historical treated data (trained data). These approaches can identify the real-time health condition of system. Moreover, this kind of approaches is more precise than the first type of approaches, their ability to link with recognized system behavior by experience methods. Despite no specific physical model is needed, the data-driven approaches require a monitoring system, learning time [2,6].

It is shown that particle filter (PF) [5] (a model-based approach) and hidden Markov model (HMM) [1] (a data-driven method) are two interesting approaches for fault diagnosis of a gear box [3]. In this paper, these approaches are applied for health diagnosis and prognosis of an industrial diesel motor (IDM). Recorded data is used to fit both HMM and PF models. A discussion is then conducted in order to analyze the results of diagnosis and prognosis given by the HMM and PF methods.

The rest of the paper is organized as follows: Sect. 2 is interested to problem statement on the application case, and the description of used approaches in the health diagnosis and prognosis. In Sect. 3, is devoted to present the application results of the methods and assess and analyze the performance of the two methods. Section 4 concludes the paper work and draws some future works.

2 Descriptions of the Case Study and Applied Methods

2.1 The Case Study

In the case study, an industrial diesel motor (IDM) used as an alternator to supply electricity in a ship is considered. The IDM is monitored by a number of sensors which allow to measure the temperature of the compressor output, the engine torque and the fuel consumption every minutes. These data are collected and pre-processed by PREDICT company¹.

To reduce the data processing time and improve the performance in diagnosis and prognosis, the main feature allowing to represent the best the IDM's health condition among all collected data has to be identified. To this end, an analysis based on expert system and principle component analysis are realized. As result, the temperature of the compressor output ($T3p$) is chosen for this study. The choice of the temperature as the main indicator can be justified since the temperature evolution plotted in Fig. 1 is directly related to the failures of IDM within the considered period.

Once the main indicator temperature is identified, the diagnosis and prognosis processes can be applied to extract the health condition of the IDM. In this study, Hidden Markov Models and Practical Filter methods, two well-known diagnosis and prognosis methods, are chosen and implemented. The general principle of the two methods will be described in the next section.

¹ Industrial enterprise specialized in the development of solutions monitoring, diagnosis and prediction of failure for industrial facilities. Website: www.predict.fr/.

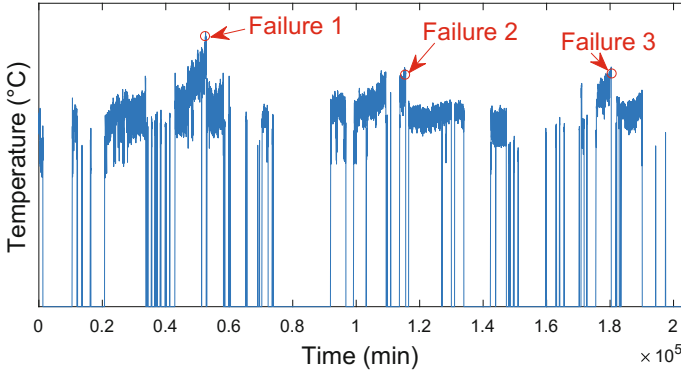


Fig. 1. Temperature of the compressor output overtime

2.2 Hidden Markov Models (HMM)

The HMM is a statistical method for modelling systems that evolve through a finite number of states. The states of the considered system are hidden. HMM allows to get knowledge about these hidden states based on the observed states. A typical HMM is defined by the model λ given by the following equation:

$$\lambda = (A, B, \pi), \tag{1}$$

where,

- A is transition matrix representing the transition probability among hidden states,

$$A = \{a_{ij}\} = Pr[s_{t+1} = j | s_t = i], \quad 1 \leq i, j \leq N, \tag{2}$$

where N is the number of hidden states, s_t is the system state at time t .

- B is the emission matrix representing the probability that the observation v_k is emitted from the hidden state j .

$$B = \{b_j(k)\} = Pr[o_t = v_k | s_t = j], \quad 1 \leq j \leq N, \quad 1 \leq k \leq M, \tag{3}$$

where M is the number of observed states.

- π the initial state distribution, $\pi = \{\pi_i\}$.

2.3 Particle Filter Method (PF)

The particle filter (PF) method is a technique developed based on the Sequential Monte Carlo and the Bayes theorem. The main idea is to approximately represent the posterior density function by a set of random samples (particles) with associated weights (w_k).

Generally the process of PF is based on the state function f and the measurement function h . Let x_k denote the system state at k^{th} iteration, it can be calculated as follows

$$x_k = f(x_{k-1}, u_k) \longleftrightarrow p(x_k | x_{k-1}) \tag{4}$$

$$z_k = h(x_k, v_k) \longleftrightarrow p(z_k|x_k) \tag{5}$$

where, u_k is noise process, z_k is the measurement data and v_k is measurement noise at iteration k .

The prior probability distribution of the system state x_k at time k , is determined starting from the probability distribution $p(x_{k-1}|z_0 : k-1)$ at time $k-1$ via the Chapman Kolmogorov equation.

$$p(x_k|z_{0:k-1}) = \int p(x_k|x_{k-1})p(x_{k-1}|z_{0:k-1})dx_{k-1} \tag{6}$$

At time k , new measurement z_k is collected and used to update the prior distribution via Bayes rule. The posterior distribution can be determined as

$$p(x_k|z_{0:k}) = \frac{p(z_k|x_k)p(x_k|z_{0:k-1})}{p(z_k|z_{0:k-1})} \tag{7}$$

The behaviour of the considered system is learned, and the unknown parameters of the models are adjusted by the filter consequently.

3 Implementation and Result Discussions

To reduce the time and improve the performance in diagnosis and prognosis, the collected data of the temperature of the compressor output ($T3p$) is selected and pre-processed. The proceeded data set containing 46300 samples of $T3p$ is plotted in the Fig. 2. The figure indicates that there was a failure of IDM at instant $t = 27200$. The maintenance was immediately carried out to restore the IDM to the operational state. The given data is then divided into two parts. The first part, containing the first 27200 measures from 1 to 27200, is used to train the HMM and PF. The second part, containing the last 19101 measures from 27201 to 46302, is used to test and verify the performance of HMM and PF. The learning and testing process of the two methods will be described in more detail in the next sections.

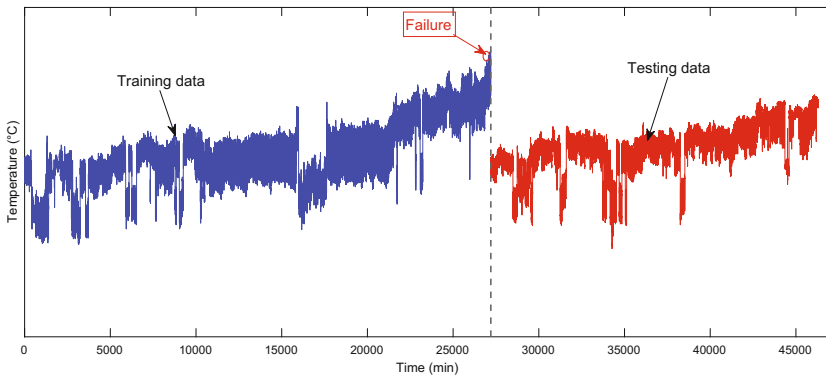


Fig. 2. Temperature of the compressor output overtime

3.1 Implementation of HMM Method

In this section, the implementation of a hidden Markov model applied to our case study is explained step by step as following.

Step 1: State Definition and Discretization.

As mentioned above in the theoretical parties, the HMM works with discrete hidden and observed states. Therefore, in this step, these discrete states are firstly defined, and then the given data are discretized into their corresponding discrete states.

Thanks to the knowledge about the IDM and discussions with experts (operation engineer, reliability engineer, maintenance engineer), we decided here to consider three hidden states $S_1, S_2,$ and S_3 permitting to represent the different health conditions of the IDM. In addition, four observed states are distinguished as: $O_1, O_2, O_3,$ and O_4 .

Given that the temperature data are continuous, these data need to be discretized before it can be used to train or to test the HMM. The discretization is then done for both training and testing sets. Figure 3 shows the discretization for the training data set.

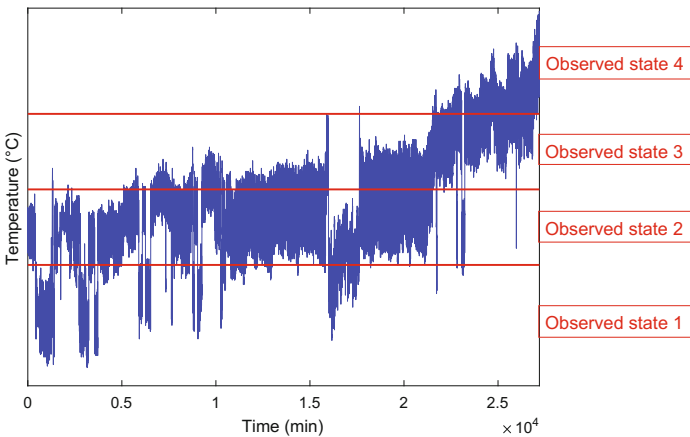


Fig. 3. Discretization of Temperature data in the training data set

Step 2: Health Condition Diagnosis by Using HMM.

In this step, the discrete training data obtained from the previous step is used to train the HMM (estimate transition and emission matrix).

In more detail, the Baum-Welch algorithm was used to train the HMM. The estimated transition and emission matrix are given below.

$$\hat{A} = \begin{bmatrix} 0.8258 & 0.1329 & 0.0413 \\ 0.0573 & 0.9427 & 0 \\ 0.1032 & 0 & 0.8968 \end{bmatrix} ; \quad \hat{B} = \begin{bmatrix} 0 & 0.0023 & 0.9977 & 0 \\ 0.2123 & 0.7877 & 0 & 0 \\ 0 & 0 & 0.0041 & 0.9959 \end{bmatrix}$$

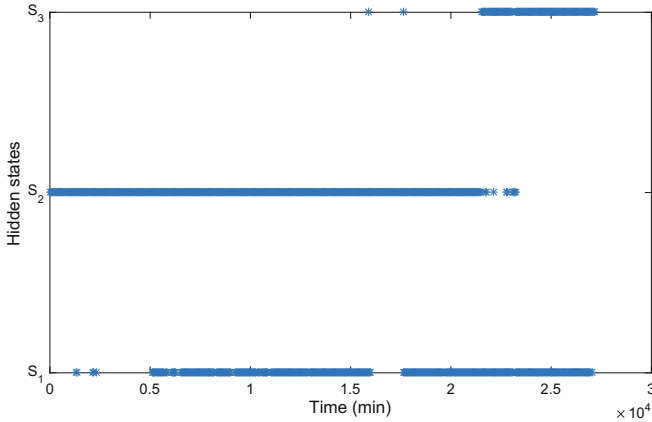


Fig. 4. Diagnosed hidden state sequence

From the two above estimated matrix, each time when the observed measure is available, the HMM allows to diagnose the corresponding hidden state. By using the Viterbi algorithm, the most likely sequence of the hidden state, which is matched with the observed states in the training set, can be determined and plotted in Fig. 4. From the Figure above, we can diagnose that, for example, the system is almost in the health condition 2 (hidden state S_2) in interval from 0 to 5000.

Step 3: Health Condition Prognosis by Using HMM.

In this step, thanks to the estimated transition and emissions matrix, the probability that the system will be in state S_i at time t in the future can be predicted. Figure 5 shows the results for 50 steps ahead prediction beginning from

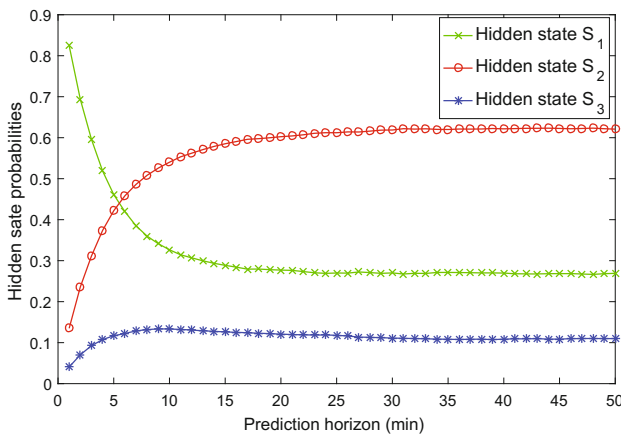


Fig. 5. Predicted hidden state probabilities

instant $t = 27200$. From the Figure, we can conclude that there is a high probability that the system will be in condition state 2 within interval $[27200, 27250]$.

3.2 Implementation of PF

Different from the case of HMM, the implementation of PF does not need to discretize the data because it works directly with continuous variables. However, with PF, it is important that appropriate models of state and observation functions must be firstly defined for specific applications.

Step 1: Model Definition.

Thanks to the dependency analysis among the data provided by the different sensors, the following state model of the diesel motor is designed.

$$x_k = x_{k-1} + a \cdot C_{k-1} \quad (8)$$

where C represents the torque of IDM, which also has an important impact on the evolution of the IDM's health condition.

In addition, the observation function is defined as follow

$$z_k = x_k + v_k = x_k + N(0, b) \quad (9)$$

where $N(0, b)$ is a white Gaussian noise with mean value equals zeros, and variance equals b .

a and b are unknown parameters, and will be estimated in the next step.

Step 2: Health Condition Diagnosis by Using PF.

In this step, the training data is used to estimate the unknown parameters of PF. Firstly, 5000 samples (particles) of x_0 , a_0 , and b_0 are randomly generated by using uniform distribution within intervals $(200, 300)$, $(0, 2.5)$, and $(3.0, 5.0)$ respectively. These particles and their weights are then updated step by step by using the training data and the designed models. Finally, we found the best particle with $\hat{a} = 1.8325$ and $\hat{b} = 3.4631$. During the training step, the evolution of the IDM's health condition x_k is also diagnosed. Figure 6 shows the evolution of the best particle. Diagnosis using PF allows us concluding that, for example, the IDM's health condition is equal to 370.7334, at instant $t = 5000$ with probability $w_{50000} = 0.89$.

Step 3: Health Condition Prognosis by Using PF.

Once the behavior of the IDM's health condition is learned, the state model can be used to predict the future condition of the IDM. Note that, different to the case of the diagnosis above, in the prediction, the torque values are unknown. Therefore, the torque is assumed to be followed a specific mission profile within the predicted horizon. The obtained results of 50 steps ahead prediction are plotted in Fig. 7.

From Fig. 7, we can predict that, for example, the system is at condition $x_{30} = 264.6376$ at time $t = 30$.

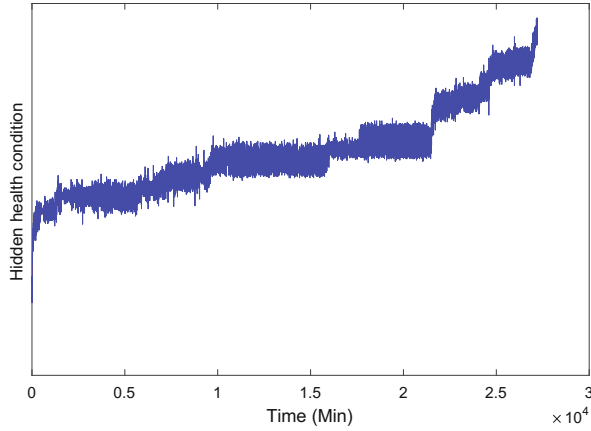


Fig. 6. Evolution of the IDM’s health condition over the training period

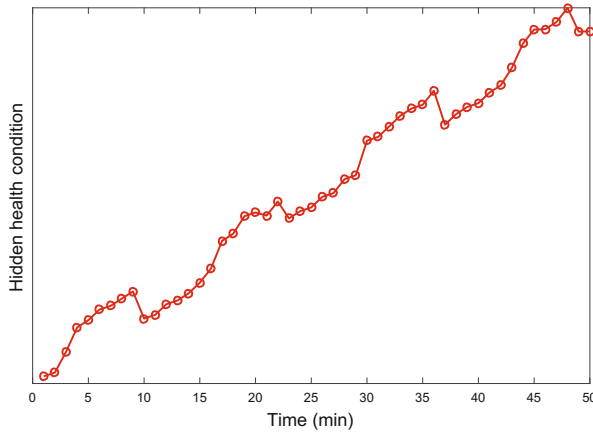


Fig. 7. Evolution of the IDM’s health condition over the predicted horizon

3.3 Discussions on HMM and PF Methods

In the above sections, we explained how to use the training data to teach our HMM and PF, and how to use the two methods to diagnose and predict the IDM’s health condition. However, we do not know if our diagnosed and predicted results are far from the real conditions or not, because actually the real conditions of the system are hidden and unknown.

Given that the hidden states are unknown, we will never be able to evaluate the performance of the two methods in diagnosis. Otherwise, we can at least assess their performance in prediction indirectly through their ability in simulating the observed temperature. To do this, the two trained models of HMM and PF are firstly applied to predict the observed state (the temperature of the

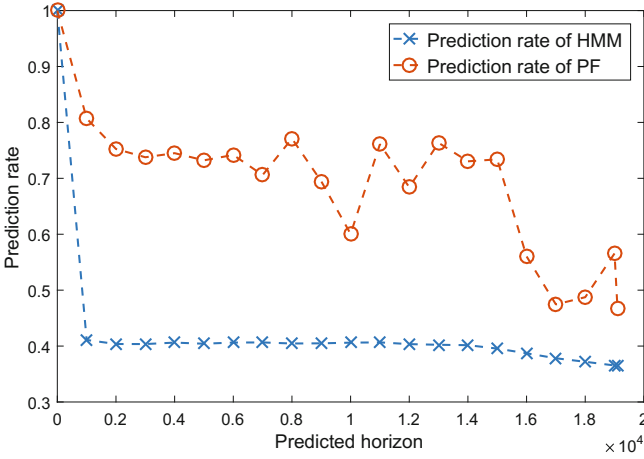


Fig. 8. Prediction performance of HMM and that of PF vs length of predicted horizon

compressor output) along the test set. Note that in order to compare to the HMM, the predicted temperature provided by PF has to be discretized. The prediction rate is then calculated by comparing the predicted temperature to the real one in the test set. The predictions were done for the different length of predicted horizon from 0 to 19101. The obtained results are shown in Fig. 8.

In the figure above, the prediction rate of PF decreases from 81 % to 47 % when the length of predicted horizon increases from 1000 to 19101 min. For HMM, the prediction rate decreases from 42 % to 36 %. It is clear that, when the length of the predicted horizon increases, the uncertainties rise, and as a consequence, the prediction performance of the two methods decreases. Therefore, in real applications, it is recommended that the long predicted horizon is divided into small ones, and the prediction is then done repeatedly for each sub-horizon.

Figure 8 also shows that the prediction performance of PF is always better than that of HMM thanks to its ability to deal with noises of data, with continuous values of condition state, and to take into account the impacts of relevant indicators such as torque of the IDM. The low performance of HMM can be understandable since its performance strongly depends on the quantity and quality of the collected data.

Given the low performance in prediction, HMM is still used in a number of applications. Indeed, from the practical point of view, the implementation of HMM is more simple than that of PF since it does not require the knowledge about the considered system.

4 Conclusions

In this paper, a study on the application of HMM and PF methods in health condition diagnosis and prognosis of an industrial diesel motor is presented.

To implement the HMM, the hidden and observed states are firstly defined. The temperature data must be discretized before it can be used to estimate the transition and emission matrix of the HMM, and test its performance in prediction. Otherwise, the implementation of PF does not need to discretize the temperature data. The data can be used directly to estimate the unknown parameters in the state and observed functions. A sensitivity analysis of the prediction performance of the two methods are also realized. The analysis shows that the PF provides the better results than those provided by HMM. However, the implementation of PF is more complicated than that of HMM since it requires the knowledge about the considered system to design its models. In addition, through the study, some related issues are identified and needed to be addressed in future researches such as difficulties in introducing the torque in HMM, in designing the state and observed functions to improve the performance of PF, and also in assessing the diagnosis and prognosis performances of the two methods.

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