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Multi-criteria analysis of diagnostic and prognostic models for predictive maintenance

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Abstract. Predictive maintenance has made considerable progress within the framework of Industry 4.0, making this strategy an effective means of monitoring the proper functioning of industrial systems, which helps to make maintenance operations more environmentally friendly, for example reduction of any kind of failure that causes loss of production and energy. This strategy is implemented through a process of collecting data in online or offline mode of the industrial system whose purpose is to monitor and predict its future state. This article first presents the different single-model and multi-model approaches used for diagnostic and prognostic tasks. An analysis of these models is then carried out, based on a multi-criteria comparison, and highlights the performance of machine learning (ML) models in this context of current digitalization. These ML models can be more efficient by combining with the physics-based models in multi-model approaches. The relevance of the comparative study is argued by criteria impacting performance, effectiveness, efficiency, the possibility of processing heterogeneous data and mutual cooperation between models. Conclusions are then drawn, in order to give a clear vision for the choice of the diagnostic and prognosis approach of predictive maintenance adapted to the industrial system.

1 Introduction

Industry 4.0 covers a wide range of technologies, processes and systems mainly related to industrial digitization. Industry 4.0 use cases are categorized into three complementary areas: intelligent products, intelligent processes, and intelligent machines. These focus on the performance of industrial machines and on applications such as detecting any quality problem and predicting breakdowns. However, the most important use case of intelligent machines in terms of operations is predictive maintenance.

Predictive maintenance focuses on the organization of maintenance actions according to the actual state of health of the system, in order to provide indications whose objective is the planning of appropriate preventive interventions. It is carried out by specific techniques which allow a diagnosis and a prognosis on the state of health of the system.

It is implemented through a process that takes place in two basic steps, data collection, then data analysis and processing. The process of data analysis and processing is crucial in the decision support process. These are two main areas: diagnosis and prognosis. Two essential approaches can be deduced [1]:

- ***Single-model approaches****:* This approach exists in the form of three categories: models based on physics, on knowledge or on data;
- ***Multi-model approaches****:* This approach combines at least two models among those mentioned above.

1.1 Single model approaches

This subsection presents the unique approach methods used for diagnosis and prognosis. These models are classified into three categories:

- ***Knowledge-based models****:* This category is based on experiences that can be represented by rules, facts or cases collected during years of operation and maintenance of the industrial system. There are three types of models, those *based on rules* [2] or *cases* [3], or *fuzzy models based on knowledge* [4];
- ***Data-driven models****:* The data collected using the sensors is used to study component degradation, the health of the system in real time or its remaining useful life. These models are divided into three types:
    - ***Statistical models:*** They aim to analyse the evolution of the variables represented by data series. These models include *regression analysis*, *autoregressive* [5], and *Bayesian* [6];

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- ***Stochastic models**:* The three main stochastic processes identified are, the *Gaussian processes* [7], the *Markov chains* [4], and the *Levy model* [8];
- ***Machine Learning Models** (ML):* ML is an offshoot of artificial intelligence (AI), which relies on learning algorithms to create models using data. The analysis of the literature carried out by Thyago P & Co. [9], dealing with the themes of predictive maintenance, reveals a preference for certain machine learning methods: *Random Forest RF* [10], *Networks of Artificial Neurons* (*ANN*) [11, 12], *Support Vector Machines* (*SVM*) [13, 14], and *K-means* [2, 10].

— ***Physical models**:* They use physics equations to describe the evolution of component deterioration [15].

1.2 Multi-model approaches

The results of analysis and treatment of single models for complex systems are unsatisfactory, the research referred to have generally suggested complementary models to surmount their weaknesses.

The different varieties of multi-model approaches can be classified into seven groups [1]:

- *Multiple knowledge-based models:* This approach is rarely used in research work in the last decade;
- *Multiple Data-driven models:* If these models are associated, they offer for the same tasks, largely precise results as the single models;
- *Multiple physical models:* The equations of physical phenomena integrated in a mathematical context make it possible to improve the precision and the reliability of the diagnosis and the prognosis;
- *Data-driven models combined with knowledge-based models:* This architecture allows a predictive system to analyse heterogeneous data from sensors and information entered by operators or extracted from large databases using techniques exploration [16];
- *Knowledge-based models combined with physical models:* Studies based on this approach remain limited in research [17];
- *Physical models combined with data-driven models:* This approach is most prevalent in research studies of the last decade, by virtue of the reputation of data-driven models' processing capacity and their complementarity with the precision of modelling of physical models. Three main models were identified in combination with the *physical models* which are, the *statistical models* [18], the *stochastic models* [19], and the *neural network models* [20];
- *Three Single Model Approaches Combined:* This architecture is extremely delicate, due to its complexity and the difficulty of merging the results of each model.

2 Comparison of single model approaches

The following criteria are determined from the factors shown in the radar graphs in Figures 1, 2, 3. They are divided into those that affect the performance, reliability and efficiency of model:

— ***Performance:*** This is the set of actions that each model can perform as a diagnostic task; prognostic; diagnostic and prognostic combined with the same model; accuracy of results; possibility of implementation in multi-model approaches; reduced computing time and explanation of the results obtained.

— ***Reliability:*** this factor is based on the ability of the model to achieve diagnostic or prognostic results or both without the need for expert knowledge, sufficient previous data, and large volume of data and management theory of the uncertainty in the data.

— ***Efficiency***: this factor determines the capacity of the model to be more efficient with a minimum of resources relating to computing power, mathematical knowledge, and complementary model for prognostic or Data Mining.

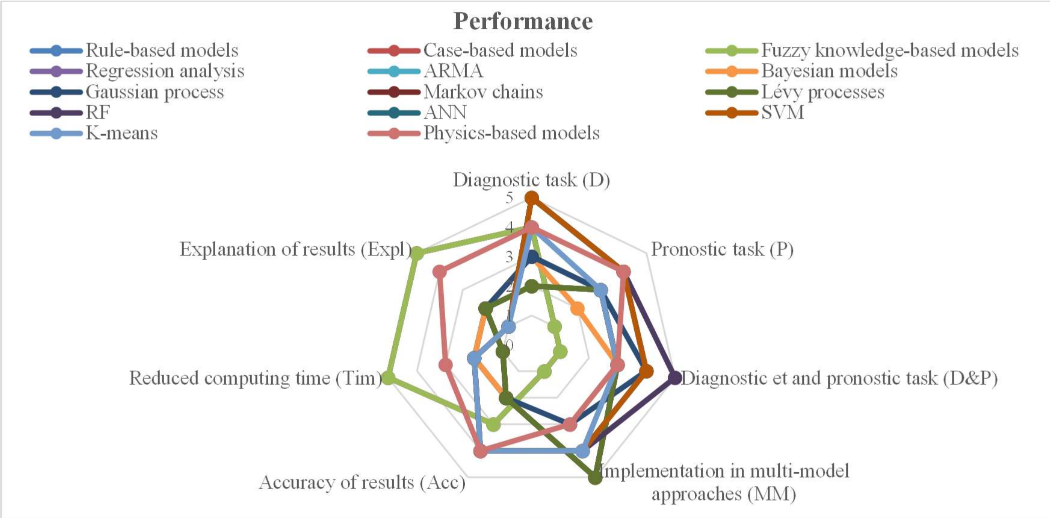

Fig. 1. Factors related to the performance of single-model approaches.

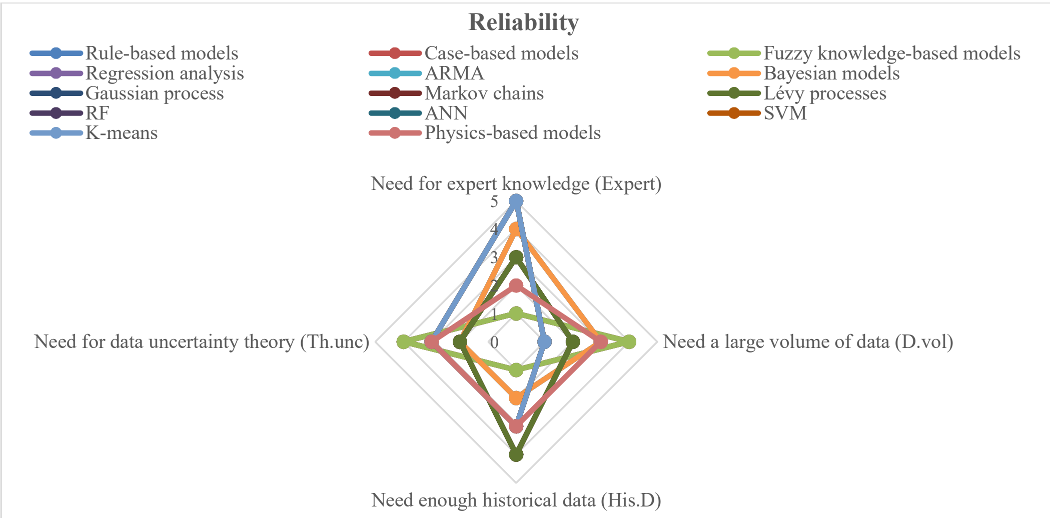

Fig. 2. Factors related to the reliability of single-model approaches.

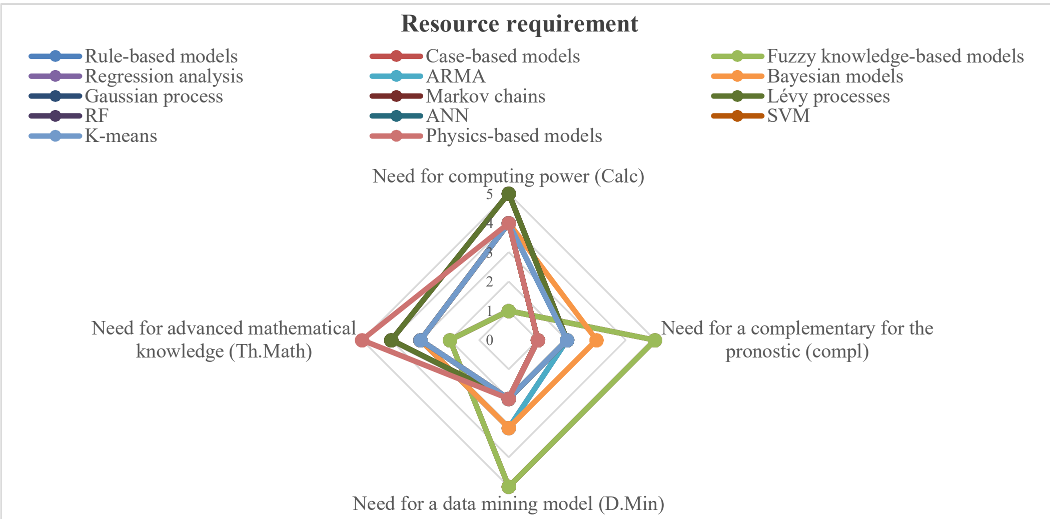

Fig. 3. Factors related to the resource requirements of single-model approaches.

While the comparative study of data analysis and processing approaches can be revealing for predictive maintenance, the ranking is less obvious if we consider the role of digital transformation in the improvement of services and maintenance activities, namely Big Data, Internet of Things and Artificial Intelligence. It is therefore difficult to compare these models in a meaningful way. Still, it is instructive to look at some trends, including the shift from knowledge-based models to data-driven machine learning models. Establishing a correlation between these different models and the factors considered is necessary in order to choose the appropriate model that is most suitable.

Among the multi-criteria decision support methods, we find the AHP (Analytic Hierarchy Process) method, where the criteria can be weighted by coefficients or weights, and arriving at a justified choice of comparison. Table 1 presents the weighting result of the comparison criteria (Performance, Reliability, and Efficiency), where the model evaluation equation (MEE) is as followed (1):

$$MEE = (0.54*Performance) + (0.3*Reliability) + (0.16*Efficiency) \quad (1)$$

Table 1. AHP Comparison Matrix.

1st Performance (Perfo) < 2nd Réliability (Reliab) < 3rd Efficiency (Effic)								
Criteria	Perfo	Reliab	Effic	Perfo	Reliab	Effic	Σ	Σ/3
Performance	1	2	3	0.55	0.57	0.50	1.62	0.54
Reliability	1/2	1	2	0.27	0.29	0.33	0.89	0.30
Efficiency	1/3	1/2	1	0.18	0.14	0.17	0.49	0.16
Σ	1.83	3.5	6	1	1	1		

In the same way, the weights of the factors of each criterion are calculated, whose equations (2), (3) and (4) are:

$$Performance = (0.35*D\&P) + (0.23*Acc) + (0.16*Tim) + (0.11*MM) + (0.07*D) + (0.05*P) + (0.03*Expl) \quad (2)$$

$$Reliability = (0.46*Expert) + (0.28*His.D) + (0.16*D.vol) + (0.1*Th.unc) \quad (3)$$

$$Efficiency = (0.46*Calc) + (0.28*D.Min) + (0.16*Compl) + (0.1*Th.Math) \quad (4)$$

All of the above-mentioned comparison results are shown in Figure 4.

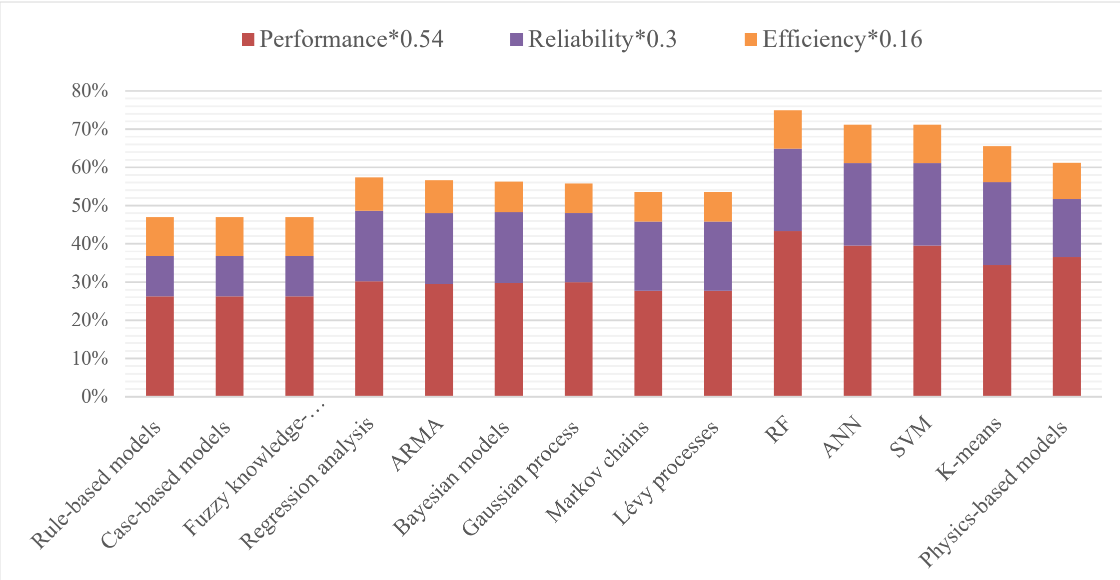

Fig. 4. Comparison results of single-model approaches.

The analysis carried out on this graph reveals the following strengths:

- Machine learning data-driven models "RF, ANN, SVM, and K-means" and specifically RF (Random Forest) are more efficient, and have extreme reliability and good efficiency. These models are able to process and capture complex relationships between data. Their main challenges are the management of the uncertainty related to the data, as well as the considerable time for the calculation;
- Physical models are more suitable for integration for diagnostic or prognostic tasks in multi-model approaches with statistical, stochastic or ANN neural networks models. In return, they require great skills in mathematics and physics for their application;
- Statistical models "Regression analysis, ARMA, and Bayesian models" are used to identify / assess the deterioration of equipment, and to calculate the residual life of the system. For predictive systems, statistical models are often implemented as part of multi-model approaches;
- Models based on knowledge "Rule-based models, Case-based models, and Fuzzy knowledge-based models" are the first models implemented in early 1990 as part of predictive maintenance to perform diagnostics. These models are based on the experiences accumulated over long periods of system operation and maintenance. These constraints limit their use for forecasting tasks. These models require the use of data mining techniques to extract knowledge;
- Stochastic models "Gaussian process data, Markov chains, and Levy processes", are probability models evaluating the evolution of parameters due to their regression capacities. However, they need high computing power and the integration of complementary techniques or models to manage uncertainties.

3 Comparison of multi-model approaches

The main criteria selected to compare the combinations of multi-model approaches are:

- ***Exploitation rate:*** this is the proportion of studies carried out using a multi-model approach compared to all the studies consulted.
- ***Possibility of processing heterogeneous data*** *from databases and sensors*.
- ***Efficiency of the approach:*** this factor determines the ability of the combination to be more effective in terms of improving the accuracy of the result obtained from the task (diagnosis, prognosis, management of uncertainties, data exploration);
- ***Cooperation*** *between models of the combination:* this criterion assesses the level of collaboration of the combined models to obtain results.

Figure 5 presents a comparison of multi-model approaches based on information collected from various sources and criteria weights, calculated using the AHP method, including the evaluation equation (MMEE):

$$MMEE = (0.46*Heter) + (0.28*M.coop) + (0.16*Effic) + (0.1*rate) \quad (5)$$

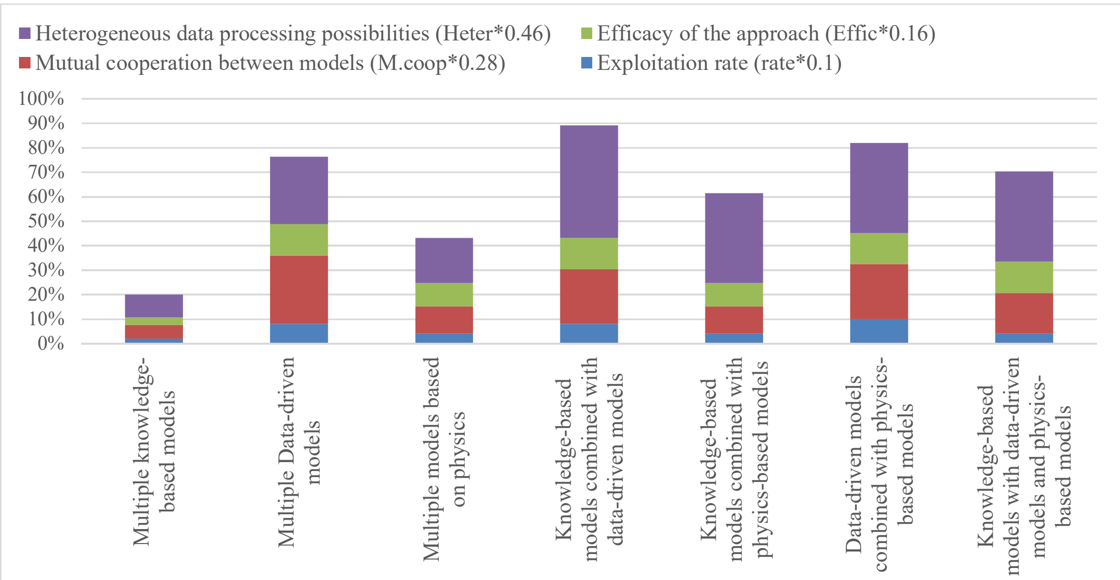

Fig. 5. Comparison results of multi-model approaches.

The first score goes to the approach combining data-driven models with knowledge-based models due to their ability to deal with more complex and heterogeneous data. Second is the approach of combining data-driven models with physical modelsdue to the complementarity and cooperation of data-driven models with the efficiency of physical models for the degradation modelling. In the last row, we find the knowledge-based multi-model approaches, due to their limitations for prognostics.

4 Conclusion

We have performed several comparative studies involving the characteristics required of diagnostic and prognostic approaches for predictive maintenance. The main conclusions are as follows:

- The most suitable models in the context of current industrial digitization are machine learning data-driven models "RF, ANN, SVM and k-means". The Random Forest algorithm (RF) is the most efficient of these.
- Models based on knowledge "Case-based models; Rule-based models; Models based on fuzzy knowledge" are based on experience and require the use of data mining techniques to extract knowledge, which limit it is for prognostic tasks.
- Physics-based models are among the most efficient in modelling degradation.
- Stochastic models based on "Gaussian process data; Markov chains; Levy processes" are relatively efficient. They are more suited to integration of diagnostic or prognostic tasks in multi-models approach to complex systems.
- The trends observed in research studies over the last decade lead to adopting multi-model approaches. The approach combining data-driven models with knowledge-based models or with physical models is the most common.

This work is a comparative study based on the syntheses of various researches in the field of predictive maintenance for the choice of a diagnostic and prognostic approach. To validate this work, a case study was initiated comparing two machine-learning models based on data from a rotor vibration recording. To extend this work, research can be conducted on the difficulty of merging types of data sources from complex systems.

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