Health monitoring using statistical learning and digital twins

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I. Introduction

System monitoring aims at preventing failures. Potential failures induce financial risk (e.g. stopping a production line) or safety issues (e.g. malfunction of a nuclear plant component). Diagnosing the system consists in studying its health condition, in order to state or predict the failures and their cause. Performing regular diagnosis of the system enables to optimise the maintenance operations and forecast the remaining life expectancy of the system.

Data-driven monitoring for industrial processes has received large attention over the past years. Statistical learning methods such as clustering enable to use data from sensors to detect outliers and identify faults. However, data-driven monitoring requires lots of observations of the system to yield accurate results. There is also no possibility to include physical knowledge on the system under study in the diagnosis [1].

A digital twin is a numerical model representing the physics of an existing system. It uses real-time data of the system, collected by sensors, to reproduce at best its current state. We calibrate a digital twin via statistical learning method and monitor the system's health through its twin. Our purpose is to determine the optimal planning of the next maintenance operation.

For better understanding of the methods and the stakes, we focus on a case study. The observation data used here were fabricated for the purpose of illustration by adding random noise to numerical simulations. It is inspired from a real application [2].

We consider a cooling system relying on a centrifugal pump, activated by a motor (see Figure 1). A centrifugal pump converts rotational energy from a motor to energy in a moving fluid, which creates pressure. The motor-pump system is required to reach 90% of its nominal flow rate in less than 30 seconds. Otherwise it is considered unsafe.

In the following, we analyze observations of this system so as to infer maximal information from them. We create a physical model of the pump-motor system and calibrate it using the extracted information. The resulting digital twin enables to plan upcoming maintenance.

II. Extraction of information from observations

Three motor-pump system units are observed, called *Park*, *Colt* and *Monk*. These units have similar motors and pumps,

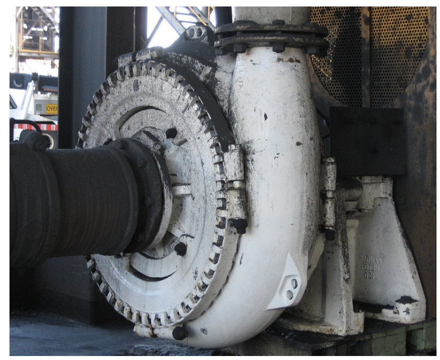

Fig. 1. Example of a centrifugal pump [3].

only they have been in service for different durations and have undergone different damage. When the motor starts, the fluid is pumped with increasing speed, and the nominal flow rate is reached after a few seconds. We have at our disposal one observation of the transient regime of each motor-pump unit per year, over the past 10 years. The last observed transient regime for each pump is represented on Figure 2.

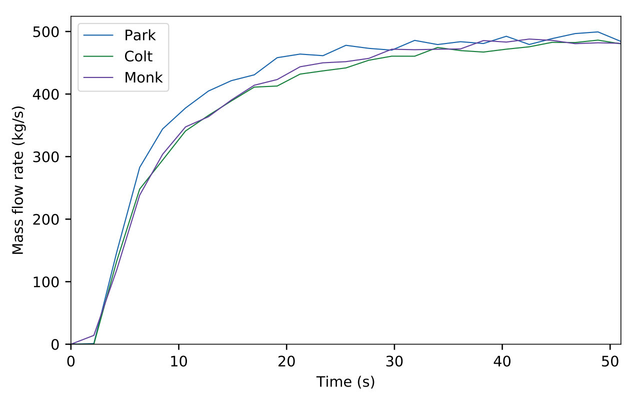

Fig. 2. A transient response for each unit.

For safety reasons, each pump is required to reach 90% of its nominal flow rate in less than 30 seconds. Figure 2 shows that the pump Park reaches its nominal flow rate faster than the two others. The time to 90% nominal has been observed for each pump during the past 10 years. These times are represented on Figure 3.

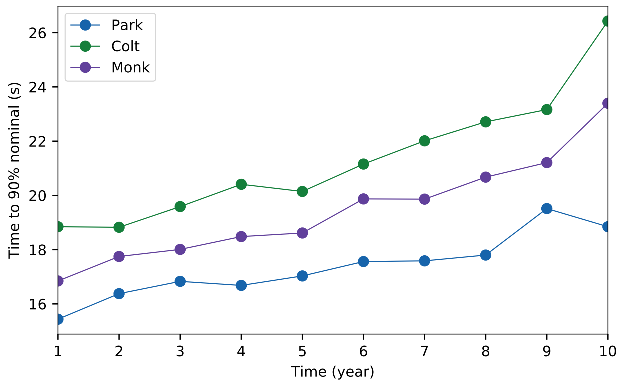

Fig. 3. The time to 90% nominal for each unit, over 10 years.

The time needed to reach the optimal mass flow rate increases over time. This increase get stiffer for the Colt and Monk pumps, which lets suspect a fault in the units. Without hints of the underlying physics, the fault origin can not be identified. The time of failure can be extrapolated from Figure 3 via non-linear regression, but with very poor reliability. Modeling the physics of the motor-pump system is necessary to identify the fault origin and its related time of failure.

III. Construction of Matching Physical Model

The pump-motor model is represented on Figure 4. It is designed with ThermoSysPro [4], a Modelica [5] library for modeling thermal-hydraulics systems. Statistical analysis is performed in Python, using the modules OpenTurns [6] and Otfmi [7].

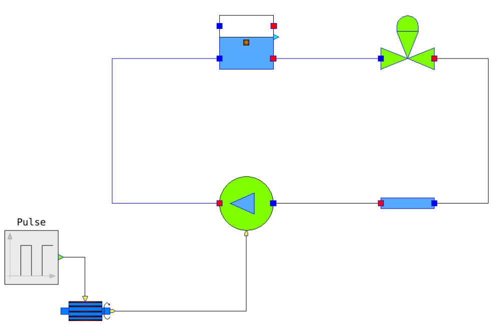

Fig. 4. The physical model using ThermoSysPro library.

The physical model represents the generic pump-motor system. The centrifugal pump, symbolized by a blue triangle within a green circle, is connected to the motor and to a circuit. This circuit is composed of a pipe resistance component, a valve and an open water tank. The model is simulated on a duration of 50 seconds. Its output is the mass flow rate during the transient regime of the system. As the discretization step is of one step every two seconds, the output of the model is composed of 25 scalar values.

The degradation mechanisms are modeled on 2 input parameters. The gradual degradation of each unit corresponds to an evolution of 2 input parameters. The first input parameter is the damping of the motor. The second is a characteristic parameter of the pump, linked to its efficiency. Hence the physical model used in the following has 2 (scalar-valued) input parameters and 25 (also scalar-valued) outputs.

The estimation of degradation parameters enable the calibration of the physical model, and thus its use as a digital twin for each pump. Bayesian inference is used in the following to estimate the parameter values (i.e. to inverse the model). However, Bayesian inference requires lots of model evaluations. Model reduction is first performed to circumvent heavy computations.

IV. Model Reduction via Statistical Learning

Model reduction consists in learning the behavior of a model via statistical methods [8]. Thereafter the statistical model can be run, instead of the physical one, at a lower computational cost.

A major obstacle in model reduction is the large dimension of the output of the model. Indeed, every single scalar output has to be learned. This is computationally expensive. Moreover, the information contained in the successive time steps is redundant. In our context, 25 scalar outputs is large.

To overcome this hurdle, principal component analysis is performed on the output of the model [9]. We choose to reduce the dimension of the output to 2 as the ratio of variance accounted for is 99.6%. Hence we have at our disposal the physical model which output has been compressed.

Gaussian process emulation [10] is used to learn the model with compressed output. Only 2 Gaussian processes have to be learned. The reduced model thus has 2 inputs, the motor damping and pump characteristic coefficient, and 2 outputs. To recover the original dimension of the output, inverse principal component analysis is applied.

The reduced model is learned on a set of 128 runs of the physical model, and tested on a set of size 64. The results of this model reduction are represented on Figure 5.

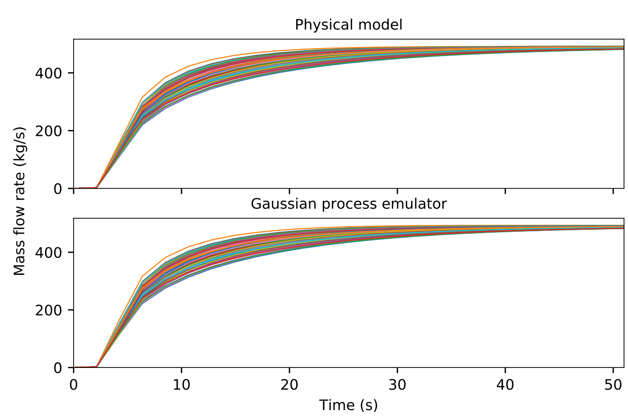

Fig. 5. Output of the physical and reduced models for the same inputs.

The relative error per time step on the prediction of the test sample is computed to assert the quality of the reduced model. The maximal relative error made on all time steps is 1.5%, the mean relative error is 0.2%: the reduced model reproduces well the behavior of the physical model. We estimate the degradation parameters on the reduced model, as its computational cost is much cheaper.

V. Digital twins calibration

To calibrate the digital twins and infer the time of failure of each system, we need to recover the input values from the observations of the transient responses. These values have to be computed for *each* pump-motor unit, at *each* observation year. The mathematical frameworks for this inference are model inversion and data assimilation.

Bayesian inference is a statistical inference method based on Bayes' formula. The probability distribution of the inputs of the model is assumed. The likelihood of the observations under this assumption is numerically estimated. Thanks to both, the probability distribution of the inputs *knowing the observations* can be computed. The bayesian estimate of the inputs is the mean or the median of the probability distribution, depending on the risk chosen.

We perform a Bayesian computation for each unit at each year, with the single corresponding observation. For the first year of each unit, the prior distribution on the input is chosen uniform. For the following years, the prior distribution is updated knowing the value of former years. The chosen probability distribution is Gaussian, centered of the most likely input value of the former year.

The results are represented on Figure 6. The computed pump characteristic coefficients are close to their true value for all units: the maximal relative error on all times and units is 7.1%, the mean relative error is 3.4%. The computed motor damping undergoes at worst 9.9% relative error, on the Monk unit. The mean relative error is 3.5%, similarly to the pump coefficient.

The digital twins representing the three units are calibrated using the Bayesian estimates from most recent observations. Before turning to failure prediction, we identify the origin of the suspected faults using the estimated degradation parameters.

Figure 6 shows that the pump coefficient degradation is slow for the Park and Monk units, faster for the Colt unit. We know that the pump coefficient is linked with the efficiency: high values correspond to a good functioning. For a system undergoing usual time degradation, the pump coefficient diminishes linearly with time. The rapid degradation of the coefficient of unit Colt is thus symptomatic of a problem in the pump.

Similarly, the motor damping values remain relatively steady over time for the units Park and Colt, whereas it increases linearly for the unit Monk. The motor damping represents mechanical losses in the motor. These losses are minimal in a motor working properly, and should not increase over time. The increase in motor damping of the Monk unit is thus characteristic of a motor problem.

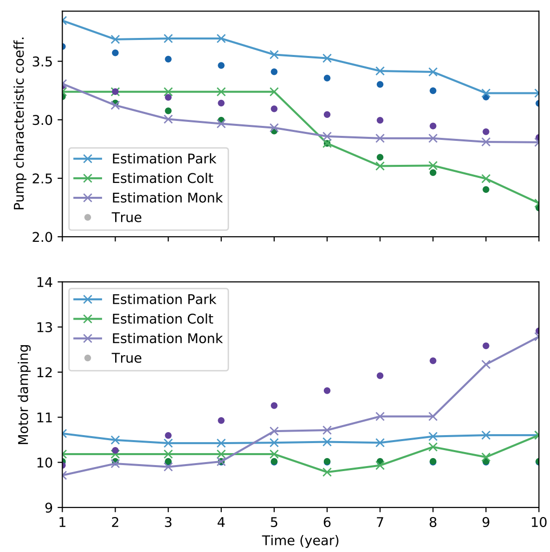

Fig. 6. Bayesian estimates of the model inputs for each unit. The estimates are represented by crosses, the real values by dots. Recall the experimental data were fabricated with addition of random noise.

In a nutshell: the Park unit is in good health, whereas the pump of the Colt unit and the motor of the Monk unit should be investigated.

VI. Prediction of the time to failure

We assume the evolution of the degradation parameters to be linear. We fit a linear regression on the estimated parameters of each unit. Figure 7 shows the regression straight lines, extended over 7 years. The 90% confidence interval for new observations is represented along the straight lines. The parameters true values lie in the confidence interval, which shows the quality of Bayesian estimates.

The failure of the pump occurs when its time to 90% nominal exceeds 30 seconds. We define the time to failure as number of years until the probability of failure exceeds 5%. We propagate the uncertainty on the forecast degradation parameters through the digital twins to estimate the time to failures. The probability distribution of each parameter at each year is normal (following the linear regression assumptions). The marginal probability distributions for Monk and Colt units are represented on Figure 8.

We propagate the uncertainty through the Colt digital twin. We observe that, when the pump coefficient is lower than 1.8, the digital twin enters a non-physical mode, corresponding to a breakdown in the unit. This nonphysical mode occurs with a probability exceeding 5% in year 12.

The Colt unit suffers of a motor damping increase, leading to an increase of its time to 90% nominal . Figure 9 shows the evolution of the time to 90% nominal probability distribution over the years. The Colt unit time to failure is estimated to 5 years, i.e. in year 15.

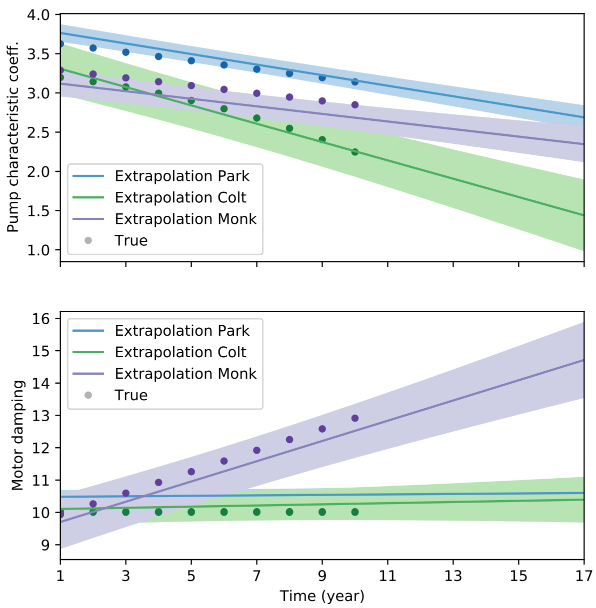

Fig. 7. Linear regression of the Bayesian estimates, represented with the parameters true value. The further we extrapolate, the larger the confidence interval for new observations gets.

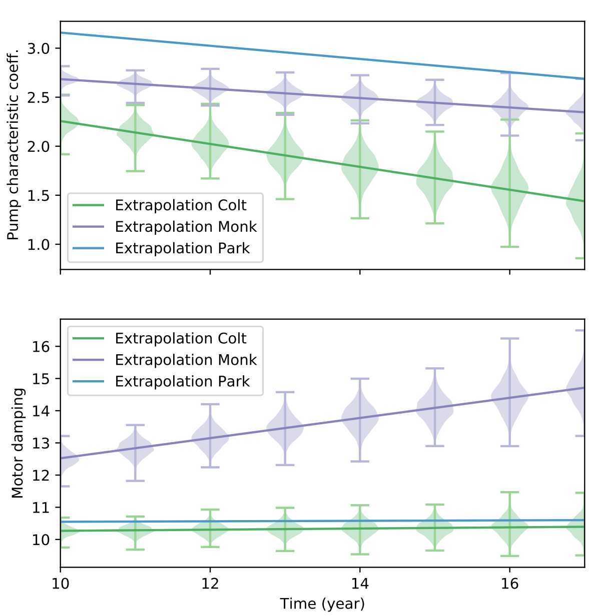

Fig. 8. Marginal probability distributions of degradation parameters for the units Colt and Monk.

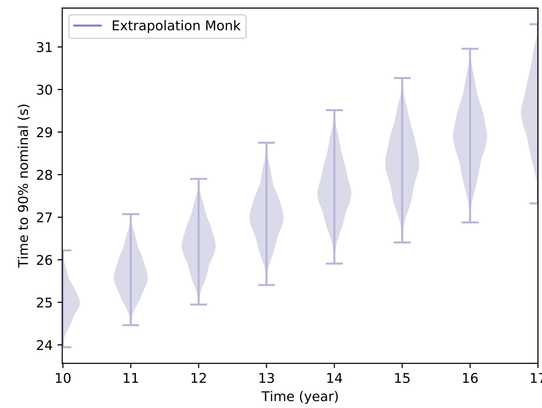

Fig. 9. Evolution of the time to 90% nominal probability distribution.

In a nutshell: the Monk pump should be fixed within 2 years, and the Colt motor replaced within 5 years.

VII. Conclusion

We combine statistical analysis of the observations with a physical modeling of the observed system. The analysis of the evolution trends of some system parameters, using the physical model and the observations, enables root-cause diagnosis and prognosis. This approach is illustrated on a fabricated example in Modelica, based on a real system. Main applications of this work are targeted and predictive maintenance.

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