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Thème visé : « Jumeaux numérique et calibration de modèle »

Jumeau numérique d'une boucle hydraulique : application à la détection de défauts et estimation de paramètres

Or

Digital twin of a hydraulic loop: application to fault detection and parameter estimation

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1. Introduction

Hydraulic systems are used in several industrial applications, including manufacturing, automobiles and energy for example. Monitoring the condition of hydraulic equipment is essential to maintain high productivity and reduce the costs of system process. Best practices have been evolving from reactive maintenance to predictive maintenance, with intelligent fault diagnosis, using recent advances in industrial Internet of Things, artificial intelligence, edge computing, etc. Beyond design, the digital twins offer advantages in predictive maintenance and provides a new paradigm for fault diagnosis. The CETIM's "Fluid & Sealing Technologies" department proposes to present its R&D work to illustrate the concept of a digital twin of a fluidic loop. Digital twin includes the virtual space, physical space and the interaction between the two. The virtual model mimics its physical entity in terms of geometry, behaviors, and rules, it can reflect, predict, and verify the performance of physical entity.

2. Our physical and simulated hydraulic system

For this purpose, a closed hydraulic loop has been instrumented. It is equipped with a pump, a heat exchanger, a tank, a regulation valve and three piping sections. The hydraulic loop diagram is shown in Figure 1. Its function is simply to provide the flow, pressure and/or temperature requested by the operator. Several control devices have been added to generate some defects artificially in the future.

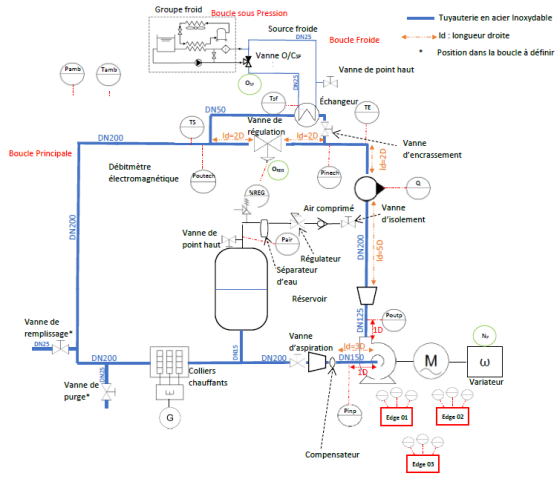


Figure 1: Hydraulic loop diagram (left) and physical bench (right)

Our hydraulic system operates as follows. The pump, driven by the variable speed electric motor, controls the working fluid through the circuit. A control valve is used to regulate the fluid flow. A heat exchanger, cooled by a cooling unit, is placed in parallel to the control valve to regulate the temperature. The loop is pressurized by a tank connected to the site's compressed air circuit. Some components have been designed to generate malfunctions: heating collars, one manual valve placed at pump suction (to generate cavitation) and one placed upstream of the exchanger (to degrade its performance). Finally, an air pressure regulator allows to disturb the pressure level of the whole loop.

3. Methodology

The objective of the study is to identify process faults (pipe clogging, exchanger performance degradation, etc.). These defects are manifested by a difference between the process variables (pressure, flow, and temperature) evaluated by the model and measured on the physical loop. If the deviation exceeds a certain threshold, an alarm is activated (see Figure 2).

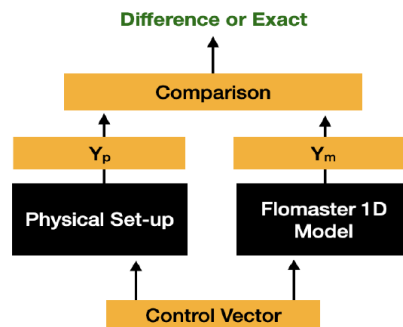


Figure 2: Architecture of the proposed fault diagnosis system

To estimate a state change, a methodology based on Machine Learning models has been developed. A large set of data for each default is typically required, which is hard to obtain from any physical hydraulic system for an exhaustive combination of faults and control actions. Instead, a simulation model of the system was used with Simcenter Flomaster software. In a first approach, transient phenomena have not been considered. The 1D model of the hydraulic loop is shown in Figure 3.

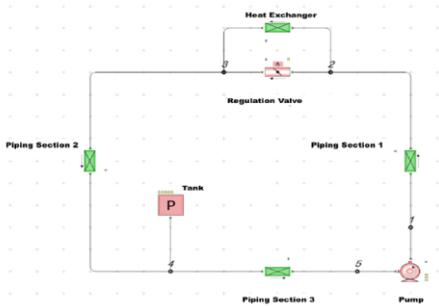


Figure 3 : Case study 1D Flomaster model

The fault location strategy is based on two decision trees. Indeed, some parameters are strongly correlated (pump rated flow and pump rated head). After investigating this coupling, we find out that there some operating points where this coupling is weak, which allows the second decision tree algorithm to distinguish between them easily.

Once the defect is located, a Support Vector Machine model is used to estimate the new characteristic of the component. An estimation model exists for each of the 6 components of the loop. Figure 4 illustrates the complete structure of the proposed machine learning algorithm.

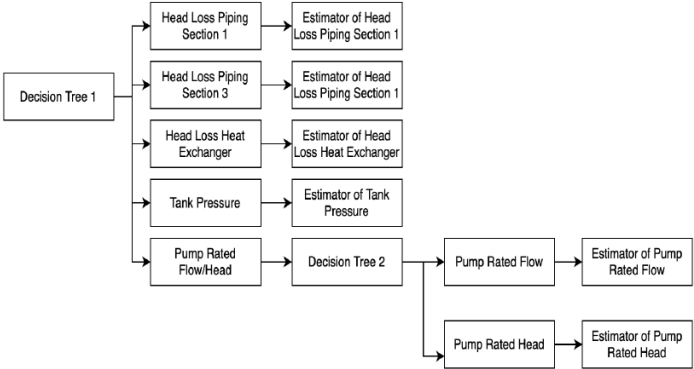


Figure 4 : Full structure of the proposed solution

4. Results and discussion

The database contains 6 930 samples: 77 operating point (control point) x 6 hydraulic loop parameters (component vector) x 15 different values for each. We used 80% of the database to train the model and 20% to test the model.

Model	Accuracy
Decision Tree 1	91.5%
Decision Tree 2	92.5%
Head Loss Piping Section 1 Estimator	95%
Head loss Piping Section 3 Estimator	97.8%
Head loss Heat Exchanger Estimator	93.6%
Tank Pressure Estimator	98.6%
Pump Rated Flow Estimator	98%
Pump Rated Head Estimator)	95.8%

Figure 5 : Detection and Estimation Result of proposed algorithm

Figure 5 shows the results when the proposed algorithm was tested against the operating points with which it was trained. Another database was created with 300 new different operating points to verify the relevance of our approach. Two options were available to run the test: use the nearest operating point's database or use the four surrounding operating points. For example, Figure 6 shows a situation when the test sample is at the operating point (star) of pump speed=80% (800 rpm) and the valve opening is equal to 33%. The selected operating point (black circle) in the database corresponds to pump speed = 80 % and valve opening =30%. The four surrounding points are included in the red box.

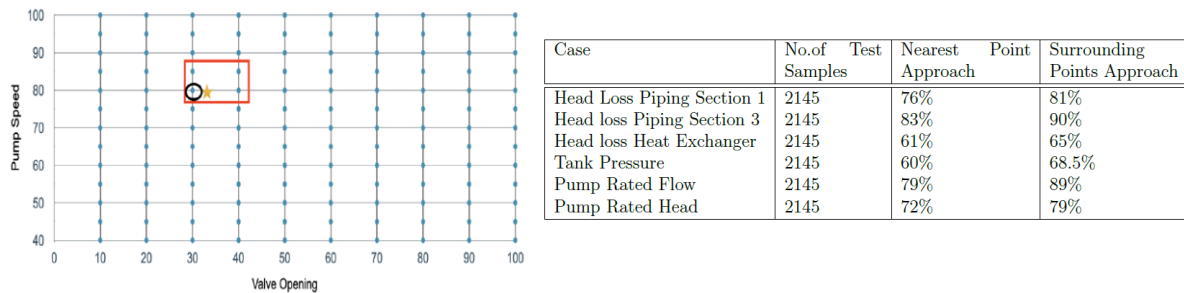


Figure 6 : Operating points map and results at different operating point than trained ones

The table above shows the first decision tree's result using the two approaches.

5. Conclusion and future work

This first exploratory work should be continued because the proposed algorithm can estimate only a single change (and not a succession of state of the system). Indeed, one parameter changes have been considered while all the other parameters remain the same as their nominal (known) values in the Machine Learning model construction. Once the model will be reliable, it can be tested with experimental data from the loop. Another idea is to mix the simulated data with a small amount of the experimental data (hybrid approach) to study whether the performance of the model is improved or not.

Thanks to its ability to estimate the system state changes, the proposed algorithm is the first step to have a live digital replica of the hydraulic loop.