USING SUPPORT VECTOR MACHINE FOR MONITORING NUCLEAR POWER PLANT COMPONENTS CONDITION

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ABSTRACT

In this paper, approach for the prediction of the condition of Nuclear Power Plant (NPP) components is proposed, for the purposes of condition monitoring. It builds on a modified version of the Probabilistic Support Vector Regression (PSVR) method, which is based on the Bayesian probabilistic paradigm with a Gaussian prior. Specific techniques are introduced for the tuning of the PSVR parameters, the model identification and the uncertainty analysis. A real case study is considered, regarding the prediction of a drifting process parameter of a NPP component.

KEYWORDS: Support vector machine, nuclear power plant, prediction, condition monitoring

INTRODUCTION

Energy generation systems are becoming increasingly complex and demand sophisticated methods to anticipate, diagnose and control abnormal events in a timely manner, as the consequences of unexpected faults can bring high economic losses[1].

For the optimized operation, conditions of nuclear power plant or NPP components and systems are usually monitored at regular intervals (Condition Monitoring), and a warning is triggered when the monitored signals exceed predefined thresholds (Fault Detection)[2].The plant operators must identify the plant state and the components out of control (Diagnostics), and predict the future development of the scenarios (Prognostics) to decide the actions to take to regain safe control of the plant. Then, while diagnostics aims at identifying the cause of the deviation from normal behavior and at determining the state of the parameters critical for the plant operation and safety, prognostics aims at the prediction of the Residual Useful Life (RUL) of the components[3].

In general, there are two strategies for the condition monitoring, detection, and diagnostics are possible: either based on physical models, or based on data-driven approaches. In the case of complex systems, physical models can be built only after simplification of the physical relations. Then, in most cases, they cannot timely provide the plant operators with a sufficiently precise diagnostics of the plant situation. On the contrary, data-driven approaches are attractive for NPPs, also considering that most components are monitored since the commissioning of plants, and, hence, a large amount of measured data is available to drive the tuning of the models.

There exists no prognostic process that is ideal for every situation. There are variety of methods have been developed for specific situations or specific classes of systems. In this paper, we propose a method for prediction with uncertainty quantification, in the context of NPP components condition monitoring and prognostics. We address the problem of predicting process variables under conditions of fault of a NPP component. A modified Probabilistic Support Vector Regression (PSVR) is developed and used to provide in output the PIs of a process variable[4].

DATA PRE-PROCESSING

Since the dataset we are going to analyze contains both missing data and outliers, we have to deal with both these issues. First of all, we will remove anomalous data, since their extreme values would affect the results of the analysis. Outliers can be easily detected by deciding some constraints, e.g. the limits $\bar{x} \pm 3 * \sigma x$ where $\bar{x}$ is the mean of all the data points and σx is their standard deviation. These limits are needed to detect the outliers, selected as those data points bigger than $\bar{x} + 3 * \sigma x$ or smaller than $\bar{x} - 3 * \sigma x$, and subsequently removed[5].

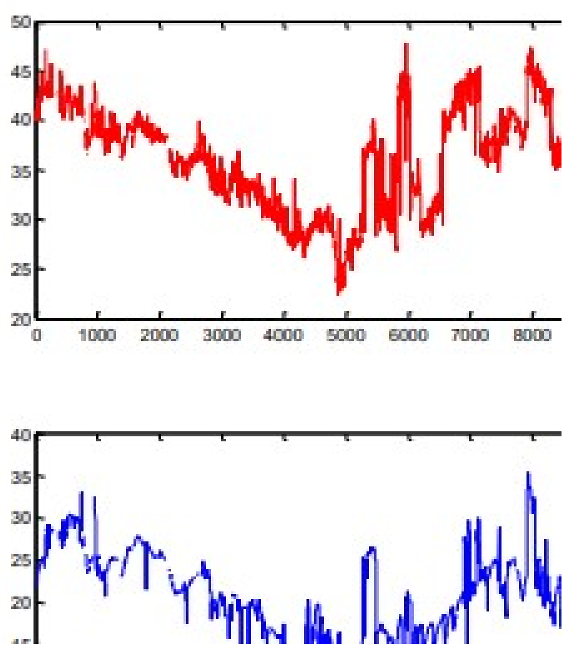

Figure 1: Evolution of the datasets

MODEL IDENTIFICATION

In order to select the most proper variables to be included as inputs in the PSVR model for improved prediction accuracy and reduction of the computational burden, a correlation analysis is carried out between the target variable and the other internal and external variables. The inputs are chosen to be the variables maximizing their correlations with the target. Correlations are measured by the classical Pearson correlation coefficient. Table 1 shows the results of the analysis[6].

Correlations	Internal variables					
	IntVar 1	IntVar 2	IntVar 3	IntVar 4	IntVar 5	IntVar 6
IntVar 9	0.03128	0.48797	0.55268	0.50926	0.50701	0.58884
Correlations	**External variables**					
	ExtVar 1	ExtVar 2	ExtVar 3	ExtVar 4	ExtVar 5	ExtVar 6

Table 1: Correlations of the target variable with other internal and external variables.

TUNING OF THE PARAMETERS

In order to achieve good prediction performance, we need to select the values of the parameters C, ε and γ. The values of the parameters influence the results of PSVR but a unifying method to determine their values has not yet been established. We propose a novel method which gives promising results. A comparison with two alternative methods is also conducted[7].

CONCLUSION

In this paper, an approach is proposed for prediction of parameters of NPP components under fault conditions. It includes pre-processing for data reconstruction and model selection, and PSVR for estimation of the prediction interval and conditional predictive distribution of the target of interest. The results of the application to a real case study of leak flow in the first seal of a RCP are satisfactory. The coverage of the prediction interval is 91.50% with a confidence level of 95%. The conditional predictive distribution provides the probability distribution of the values of the target. These two indicators, the PI and the predictive distribution, are very informative for the NPP operators in case of accident.

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