

Data Driven Approach for Diagnostic and Prognostic of Vertical Motor-Driven Pump

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This paper will present on data architecture that is used to collect heterogeneous data from vertical motor-driven pumps and how the collected data is used by the feature engineering module to extract salient features associated with different faults. Once fault signatures are developed, diagnostics models like eXtreme Gradient Boosting are used for automating the fault classification process. Given the diagnostic outcome, a prognostic model like autoregression integrated moving average is used to forecast the health condition of the motor-driven pump. Along with prediction horizons for 12, 24, and 48 hours, uncertainty bounds are also computed. This allows nuclear power plants to achieve condition-based maintenance and reduce unnecessary downtime, achieving significant cost-savings.

Keywords: diagnosis, prognosis, autoregression integrated moving average, uncertainty bounds, classification, condition-based maintenance.

1. Introduction

Operations and maintenance (O&M) activities are key aspects of ensuring the availability and reliability of energy generated by nuclear power plants (NPPs) Ngarayana et al. (2019). O&M costs—including activities such as inspection, calibration, testing, and replacement—are some of the major non-capital costs contributing to the overall operation costs of these energy-generating sources. The energy industry employs three main maintenance strategies to ensure availability, reliability, and safety. These maintenance strategies are (1) time-based periodic maintenance, (2) failure-based maintenance, and (3) condition-based maintenance (CBM). Each energy plant, based on their regulatory and safety requirements, deploys these maintenance strategies at various levels across their structures, systems, and components.

This paper focuses on a CBM approach for a vertical motor-driven pump (MDP) which is part of a circulating water system (CWS) in an NPP. For details on CWS, refer to Agarwal et al. (2021). The rest of the paper is organized as follows. First, data-to-decision architecture is presented in Section 2. Diagnostic and prognostic model results for a diffuser fault mode observed in a vertical MDP are presented in Section 3. Finally, conclusions are presented in Section 4.

2. Data-to-Decision Architecture

The CBM approach in this paper (see Fig. 1) utilizes heterogeneous data from vertical MDPs and how the collected data is used by the feature engineering module to extract salient features associated with different faults. Once fault signatures are developed, diagnostics models are used to automate the fault classification process. Given the diagnostic outcome, a prognostic model is used to forecast the health condition of the MDP. In the architecture, prognostic outcomes are integrated with generation risk and economic models (which is outside the scope of this paper).

3. Diagnostic and Prognostic Models

The diagnostic model, using eXtreme Gradient Boosting (XGBoost), was developed to estimate the condition of the vertical MDP, based on the features extracted from the vibration and plant process data. In this case study, the diffuser fault in vertical MDP and associated measurements were the focus. A total of 502 input features extracted from vibration and process data were used for diagnosis of diffuser fault. The input feature space was split into 336, 108, and 46 for training, validation, and testing of XGBoost. The training, validation, and testing accuracy (i.e., correct diagnosis is presented in Table 1. Given the diagnostic outcome of the diffuser fault the

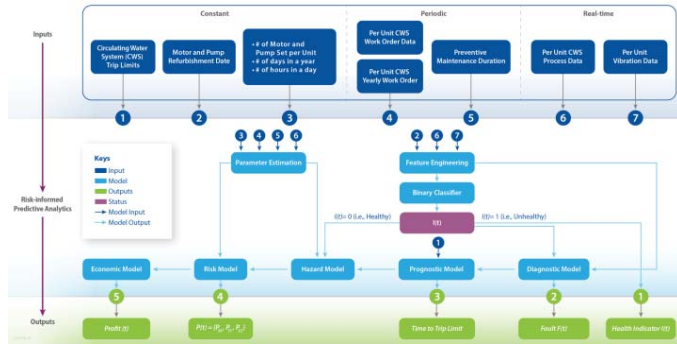


Fig. 1. Condition-based maintenance data architecture.

Table 1. Training, validation, and testing accuracy to diagnose diffuser fault.

Model	Training	Validation	Testing
Accuracy (%)	99.1	99	99.5

salient feature (which in this case was a vibration measurement) was forecasted using autoregressive integrated moving average (ARIMA) as a prognostic model. Forecasting was performed for 12-hour, 24-hour, and 48-hour prediction horizons, along with uncertainty bounds as shown in Fig. 2. In addition, the prognostic model performance was analyzed using residuals (defined as the difference between observations and corresponding fitted values). The residuals are useful for verifying whether the ARIMA model adequately captured the information within the data. The prognostic outcome was used to compute the degradation index for the generation risk assessment.

4. Conclusions and Path Forward

The paper summarizes the outcomes of a CBM approach on a vertical MDP. To achieve CBM, the approach used a modular data-to-decision architecture that combined heterogeneous data sources. The architecture leveraged XGBoost diagnostic model and ARIMA prognostic model with uncertainty bounds. As a path forward, the research is focusing on different fault modes.

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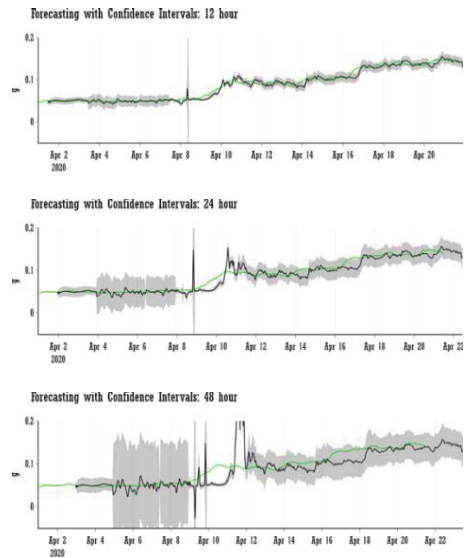


Fig. 2. ARIMA forecasting with a 95% confidence interval for 12 hours, 24 hours, and 48 hours.

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