Architecture for Online Prognostics for Pumps and Valves in Nuclear Power Plants

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ABSTRACT

The health of the safety-related equipment in a nuclear power plant is crucial to safe and reliable operation of the plant. To achieve this, a number of monitoring systems have been equipped and strict guidelines and procedures applied. Recently, several real-time diagnostics and predictive diagnostic concepts have been proposed. This paper presents an architecture for online prognostics to monitor, diagnose and prognose feed water pumps and pneumatic control valves in nuclear power plants. We describe the architecture from the following points: system design and process. Diagnostic method with positioner model for a double-acting pneumatic control valve is also presented. A pilot system, developed based on the proposed architecture and diagnostic method, is applied to the pneumatic control valve in a nuclear power plant. The result shows that the proposed architecture can be applied to online and real-time diagnostics and prognostics.

1. INTRODUCTION

Architectures that include online diagnostic and prognostic functions have been proposed in various fields such as e-maintenance (Muller, Marquez, and Iung, 2008), architectural framework (Kunche, Chen, and Pecht, 2012), integrated architecture (Chen, Brown, Sconyers, Zhang, Vachtsevanos, and Orchard, 2012), predictive maintenance platform (Efthymiou, Papakostas, Mourtzis, and Chryssolouris, 2012) or intelligent condition-based maintenance platform (Yang & Tran, 2012). Most of these works focus on the functional aspects of the architecture and the applications for verification are presented. However, there are fewer applications in the real world. In domestic nuclear power plants, large rotating machines such as main feed water pumps are equipped with a vibration monitoring system. For small and medium-sized rotary machines, the condition is monitored periodically by measuring vibration, oil temperature etc. Safety-related power-operated valves are also periodically checked their performances. In addition, various maintenance programs, such as preventive and predictive maintenance, are operated to ensure that the main equipment in the plant functions properly during its lifetime. Although diagnostics and predictive diagnostic functions are not yet implemented, a centralized real-time operating parameter monitoring and early warning system has also been established and operated. In this paper, we propose an architecture that implements the online predictive diagnostic function for the centrifugal feed water pumps and the pneumatic control valves. Diagnostic method for a pneumatic control valve is also presented and applied to the pilot system based on the proposed architecture.

2. SYSTEM DESIGN AND ARCHITECTURE

2.1. Three-tier System Design

The proposed predictive diagnostic system is designed with three tiers based on the client-server architecture as shown in Fig. 1.Tier 1 consists of Smart Data Analyzers (SDAs) and a data server installed in a power plant. SDA is developed to collect the sensor data from pumps and valves, extract features and transmit them to the data server. The network bandwidth can be expanded to connect multiple SDAs to a single data server. The main components of Tier 2 are diagnostic servers installed in the remote online monitoring (OLM) center. The servers manage data from multiple data servers, clients, and other diagnostic servers. Tier 3 consists of a number of clients in the OLM center and provides tools to diagnose and analyze the status of pumps and valves. Data and diagnostic servers are separately provided so that the load can be dispersed in the processing of data and diagnostic algorithm.

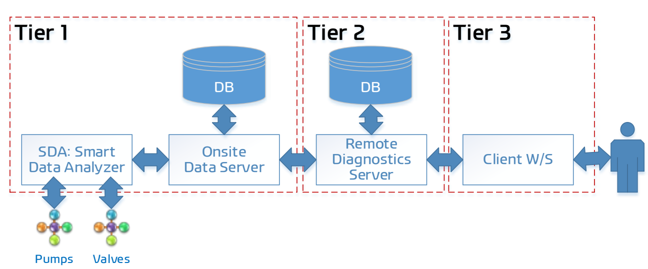


Figure 1. Overview of the proposed architecture

2.2. Process View of Architecture

The process view of the architecture is shown in Fig. 2 and the main processes that are handled by data server, diagnostic server, and client are summarized below. First, we describe similar processes that are common to each server and client, and then their independent processes.

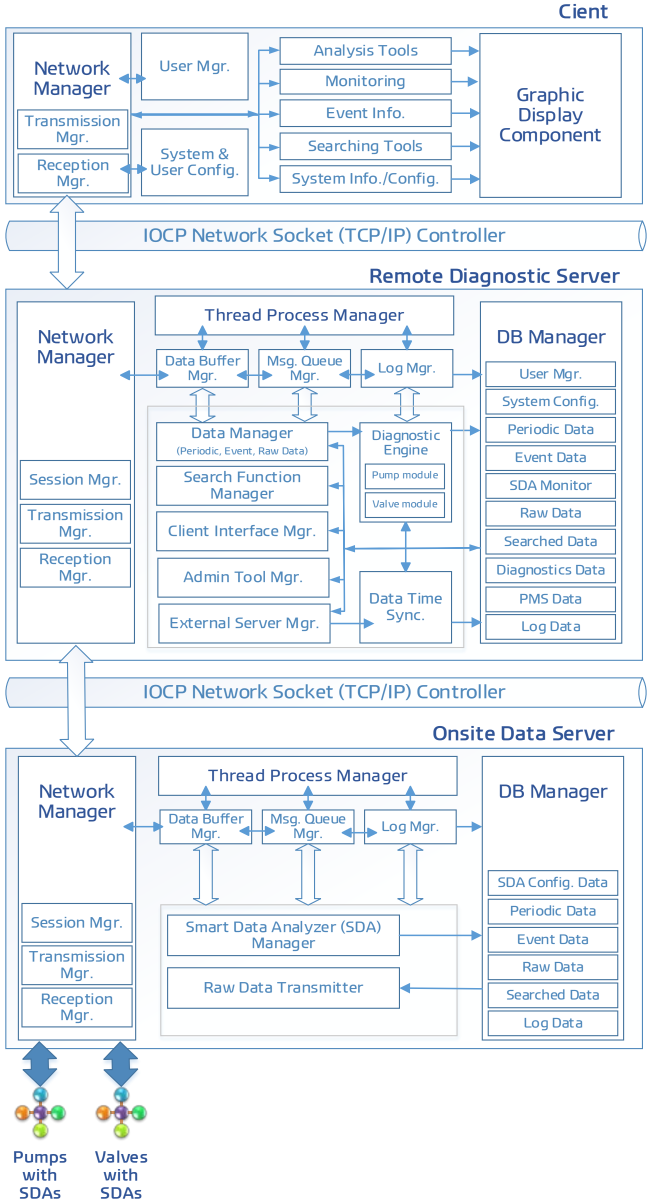


Figure **2**. Process view of the proposed architecture

2.2.1. Common processes

Network manager, database manager, and threaded process manager are similar processes that are common to each server. The network manager basically handles three functions such as session management, data transmission and reception. The database manager handles functions such as data addition, correction, deletion, and recovery that the database has to process. The threaded process manager handles data buffer and queues and synchronizes data processing of asynchronously executed processes in some cases.

2.2.2. Data Server

The SDA data manager of the data server processes the periodic state data and event data transmitted from the SDA and stores them in the database without loss. The raw data transmitter performs a function of dividing and transmitting a vast amount of raw data periodically so that the network bandwidth usage is minimized.

2.2.3. Diagnostic Server

The diagnostic server includes a model-based diagnostic engine for pump and valve predictive diagnostics. The diagnostic engine generates diagnostic results using the data transmitted from the data server and the operation data of the power plant. The server also synchronizes data from a number of data servers and plant operation data, groups them, and provides synchronized data to the diagnostic engine.

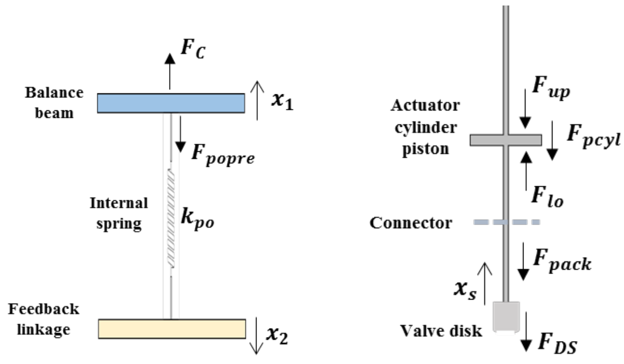
2.2.4. Client

The client collects the measured data and diagnostic results from the data server and the diagnostic server, respectively by user request. It also provides analysis tools and real-time comprehensive and status monitoring screens for analysis. In addition, it stores event information and displays all event history on the screen by request.

3. PNEUMATIC CONTROL VALVE DIAGNOSTIC MODEL

Diagnostic engine in diagnostic servers requires diagnostic models for pumps and control valves. The positioner, one of the main components of the pneumatic control valve, provides air from the air supply to the actuator according the output pressure from I/P converter. The displacement of the valve stem is fed back to the positioner for the stem to move to the desired position. In this study, a diagnostic model was developed for a pneumatic control valve with the double-acting cylinder.

The model mainly focuses on the positioner and includes main parts of the positioner such as diaphragm, balance beam, internal spring, pilot valve and feedback link. The feedback link is connected to the valve stem. The simplified model for positioner and control valve is shown in Fig. 3. In the figure, x_1 is the displacement of the balance beam or pilot valve stem, and x_2 is the displacement of the feedback linkage. It is assumed that the movement of the balance beam by the diaphragm force is the same as the movement of the pilot valve stem.



(a) Positioner (b) Control valve

Figure 3. Simplified model for positioner and control valve

From Fig. 3a, the force balance between the diaphragm and the internal spring of the positioner can be expressed as follows:

$$F_C - F_{popre} = k_{po}(x_1 - x_2) \quad (1)$$

where $F_C = P_C \cdot A_C$ is the force generated by the control pressure acting on the positioner diaphragm, P_C is the control pressure, and A_C is the cross-sectional area of the positioner diaphragm. F_{popre} and k_{po} are the preload and spring rate of the positioner spring, respectively.

As shown in Fig. 3b, the force balance between actuator and valve can be:

$$F_a \pm F_{pcyl} + F_{DS} \pm F_{pack} = F_{a\_act} \quad (2)$$

where, $F_a = F_{up} - F_{lo}$, the force difference by the pressure applied to the upper and lower sides of the actuator cylinder piston. F_{pcyl} is the friction of the cylinder piston, F_{DS} is the stem and plug weight, F_{pack} is the valve packing friction, and F_{a_act} is the force that drives the actuator and valve. Assuming that F_{a_act} and stem displacement are proportional, the following equation holds.

$$F_{a\_act} \div k_{air} = x_s \quad (3)$$

where k_{air} is a proportional constant, which can be regarded as the volume elastic modulus of the air inside the actuator cylinder, and x_s is the displacement of the valve stem.

From the force balance relationships described above, we define the model parameters to diagnose the control valve condition such as F_{popre}, G_{fb} and k_{air} which can vary depending on the state of the control valve system. Here, G_{fb} is the stem displacement feedback gain, which indicates the relationship between valve stem displacement and spring movement of the positioner. Its change means the state of the feedback linkage system connected to the valve stem is different from the previous one.

Figure 4 shows a flow diagram to monitor and diagnose the pneumatic control valve condition using the developed model. From the measurement of control pressure, stem thrust, and stem displacement, the model parameters can be estimated using MATLAB optimization toolbox. In normal condition, the estimated parameters can be regarded as reference values indicating the current state of the control valve. Then, the state of the control valve as it operates can be diagnosed in real-time by estimating the model parameters and comparing them with references. This process is shown in Fig. 4.

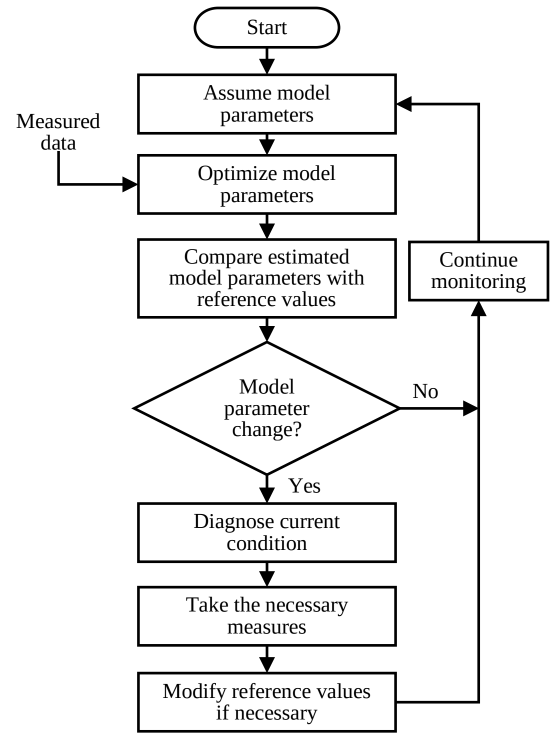


Figure 4. Flow diagram for the proposed monitoring and diagnostic method with positioner model

4. APPLICATION

A pilot system based on the proposed architecture was constructed for feed water pumps and control valves in a domestic plant, and online verification test was performed. The pneumatic control valve diagnostic model described above was implemented in the diagnostic engine and the online baseline test was performed to evaluate the reference values of the model parameters. Figure 5 shows monitoring screen of client on which the signal measured by the SDA is displayed and analyzed in real time. The right part of the screen shows the status of the feed water control valve. One can see that the measured signal is displayed on the graph in the real time measurement part in the lower right. The status indicator on the top center of the display shows the results of the diagnostic analysis. Figure 6 shows the valve diagnosis screen. When the control valve completes the ramp operation for diagnosis, the diagnostic server estimates the reference values using the signal measured by the SDA and stores the results in the database. These values are used to monitor the condition of the control valve during normal operation of the plant. At the bottom of the screen, the result of monitoring the positioner and valve packing conditions are displayed during operation. For the feed water pump, using the simulated vibration signal to the SDA installed in the power plant, we confirmed that the pilot system can transmit the vibration data to the remote diagnostic server via the onsite data server to monitor and analyze pump conditions.

Figure 5. Monitoring display of the pilot system

Figure 6. Diagnostic display for pneumatic control valve

5. CONCLUSIONS

In this paper, we propose an architecture for online predictive diagnostics for pumps and control valves. The major components of the architecture are smart data analyzers, onsite data server, remote diagnostic server, and a number of clients. The smart data analyzers collect and process various sensor signals installed on the target equipment. We also developed a positioner model for the control valve with double-acting pneumatic cylinder and constructed a pilot system using the developed model and the proposed architecture. Online verification test of the pilot system showed that using the proposed architecture, the real-time diagnostic and prognostic functions can be successfully performed.

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