Paper

Fault diagnosis system for hydraulic turbine generator

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A fault diagnosis system has been developed to prevent serious accidents in a hydraulic turbine generator by detecting anomalies in their early stages. The system predicts the bearing temperature change by using the physical dynamic model of the bearing related components, such as the bearing pad and lubricating oil cooler. The unmeasurable parameter values in the model, e.g. bearing gap width, are estimated on-line by minimizing the differences between the measured and calculated values of bearing and oil temperatures using a nonlinear optimization method. The system detects and diagnoses the anomalies based on the prediction results and estimated parameter values.

After evaluating the feasibility using a 1/3 scale test facility, the system was installed in the Okutataragi Pumped Storage Power Plant of the Kansai Electric Power Co., Inc. Accurate prediction performance was confirmed for the system which is now being used for commercial operation.

Keywords: *Pumped storage power generation, Hydraulic turbine generators, Bearings, Temperature, Fault diagnosis, Prediction methods*

1. Introduction

The head of hydraulic turbines and generating capacity of pumped storage power plants are increasing year-by-year. Therefore, if an accident occurs in a pumped storage power plant, its influence on the electric power system is large and a long term shutdown of the plant is required to diagnose the accident cause and repair the failed components. Therefore it is important to prevent major accidents by detecting anomalies in the hydraulic turbines and generators in their early stages. Additionally high-precision monitoring and anomaly detection are effective for decreasing maintenance cost, by realizing condition-based maintenance [(1)].

Many investigations have been devoted to improvement of monitoring and diagnosing in hydraulic power plants. A computerized on-line system for monitoring vibrations and temperatures in hydraulic turbine generators was developed [(2)], which monitors the vibrations to avoid serious outages. An advanced processing and diagnostic system was developed to monitor the vibration status of bearings in order to reduce maintenance and repair costs [(3, 4)]. Besides these, a new fault detection method using observers was applied to hydraulic turbine monitoring [(5)].

In hydraulic turbine generators, bearing temperature and shaft vibrations are important plant parameters. The bearing temperature and its time derivative value are monitored and anomalies are detected when the values exceed the threshold values in hydraulic power plants [(6)]. Since the anomaly is detected after the temperature has abnormally increased, early detection is impossible.

To detect an anomaly in bearing related components, a new fault diagnosis method based on temperature prediction is proposed. To detect and diagnose an anomaly sensitively, precise prediction is required; namely the model should simulate the bearing related components accurately. But plant characteristics generally change; e.g. in hydraulic power plants, cooling performance of the cooling pipe for the lubricating oil changes due to scale formation on the cooling pipe, and gap width between the shaft and bearing pad changes due to inclination of the shaft. Therefore in the proposed method, a physical dynamic model is adapted to reflect changing plant status. The unmeasurable model parameters are estimated by using measured data from a plant and the prediction is made after the model is fixed. In this model, accuracy is thus maintained and precise prediction is realized. After the method feasibility was evaluated in a 1/3 scale test facility, it was installed and evaluated in the Okutataragi Pumped Storage Power Plant of the Kansai Electric Power Co., Inc. This paper describes the proposed method and its evaluation results.

2. Method

2.1 System composition

A hydraulic turbine generator has guide and thrust bearings which have bearing pads, lubricating oil, cooling pipe, etc. The fault diagnosis system detects and diagnoses an anomaly in the bearing related components based on temperature prediction results. The system composition shown in Fig. 1 is used for prediction by a physical dynamic model of bearing related components. In the model, unmeasurable parameters, such as bearing gap width, are treated as unknown parameters. These parameter values are estimated by using plant data, such as bearing temperature and lubricating oil temperature. After the model parameter estimation, future changes are predicted. Anomaly detection and diagnosis are performed based on the prediction results and the estimated values of unknown parameters. The system shows the prediction results of temperatures, unknown parameter values, and fault detection and diagnosis results to plant operators.

2.2 Physical dynamic model

Modeled components and heat flow are shown in Fig. 2 for a guide bearing, such as the water turbine bearing. Heat is generated in the gap between the bearing pad and shaft. The generated heat is transferred to the shaft, bearing pad and lubricating oil. The pad and shaft are cooled by the surrounding oil. The heat in the oil is removed by coolant flowing in the cooling pipe. The shaft and oil are

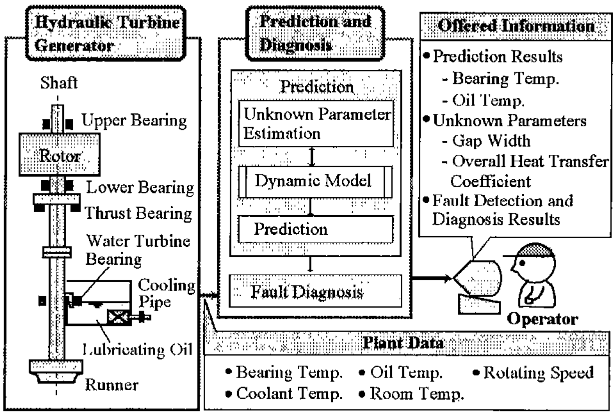


Fig. 1 System Composition

also cooled by surrounding air. To model these phenomena, the dynamic model is expressed by three time derivative equations for temperatures of oil T_o, pad T_p and shaft T_s:

$$\frac{dT_o}{dt} = \frac{1}{C_o}(Q \cdot D_o + U_{po}(T_p - T_o) + U_{so}(T_s - T_o) - U_{oc}(T_o - T_c) - U_{oe}(T_o - T_e)), \quad (1)$$

$$\frac{dT_p}{dt} = \frac{1}{C_p}(Q \cdot D_p - U_{po}(T_p - T_o)), \quad (2)$$

$$\frac{dT_s}{dt} = \frac{1}{C_s}(Q \cdot D_s - U_{so}(T_s - T_o) - U_{se}(T_s - T_e)), \quad (3)$$

$$\text{where} \quad Q = \frac{1}{G}\eta \cdot K \cdot v_s^2,$$

$$G = G_0 + (E_t(T_o - T_a) - E_p(T_p - T_a) - E_s(T_s - T_a)).$$

In the equations, C is heat capacity, D is heat distribution ratio, E is thermal expansion coefficient. Here the heat distribution ratio D is assumed to be constant regardless of temperatures of pad, oil and shaft. U is the overall heat transfer coefficient. Q is heat generation at the gap between the shaft and pad, which is calculated from the gap width G, viscosity of oil η, peripheral speed v_s, and constant K. The viscosity η is calculated by an empirical formula from pad and shaft dimensions, and oil temperature, etc. The suffixes c, e and t denote coolant, surrounding air and bearing pad support. T_a is the temperature at which the gap width is adjusted when the bearing is mounted. G_0 is the gap width at temperature T_a, which is called the adjusted gap width here.

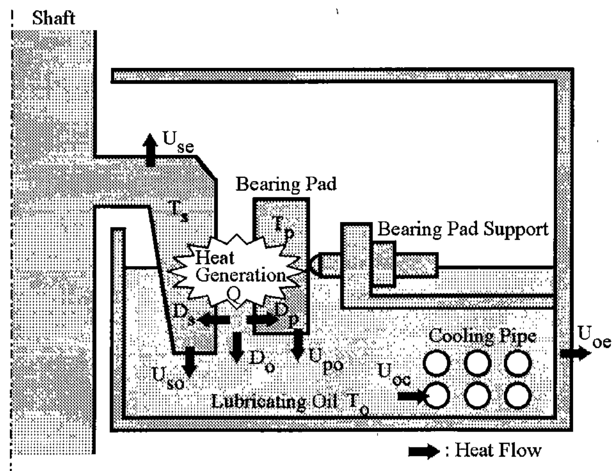


Fig. 2 Heat Flow Relating Bearing Considered in Dynamic Model

In determining the model coefficients, the heat capacity C and thermal expansion coefficient E are calculated from dimensions of components and physical properties of material. The heat distribution ratio D and the overall heat transfer coefficient U are determined to lessen the difference between measured and calculated temperatures using the measured values of temperatures. The values of coefficients are determined once before the model is installed in the fault diagnosis system.

As unknown parameters of the model, the adjusted gap width G_0, overall heat transfer coefficient from oil to coolant U_{oc}, and the shaft temperature T_s at the model initialization are selected. G_0 and U_{oc} are selected for three reasons: they have a large influence on the temperature changes; they change according to the anomaly occurrence; and they change according to aging effects, such as scale formation on the cooling pipe. These values cannot be determined directly from plant data.

2.3 Prediction of bearing temperature

Future changes of bearing temperature are predicted after the unknown parameter values are estimated and the model is fixed. Unknown parameters are model parameters which cannot be determined directly from plant data. The prediction is performed as follows (Fig. 3).

1) The values of unknown parameters are assumed.
2) The model is initialized at an arbitrary time using plant data and the assumed unknown parameter values. After the initialization, temperature change is calculated in a time interval.
3) The differences between the predicted and measured values are calculated for the bearing pad and oil temperatures.
4) If the differences are small, the iteration is stopped and the future changes are predicted. But, if the differences are large, the values of unknown parameters are modified to decrease the differences and the procedure returns to step 2.

In modifying each unknown parameter value, the squares of the differences between the measured and calculated values for the bearing pad and oil temperatures are set as the objective function J:

$$J = \int_{t_1}^{t_2} \left(\beta_P \left(T_p^m - T_p^c\right)^2 + \beta_o \left(T_o^m - T_o^c\right)^2 \right) dt. \quad (4)$$

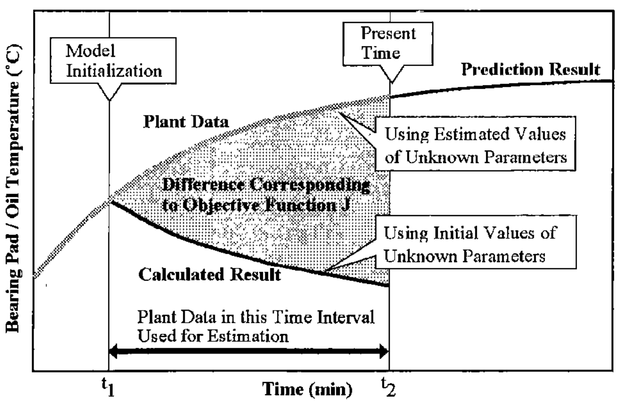


Fig. 3 Unknown Parameter Estimation Using Plant Data

In the equation, t_1 and t_2 are the model initialization time and the present time. The superscripts m and c denote measured and calculated values, and β is a weighting factor. The value of J is minimized by optimization and then the unknown parameter values are obtained as optimal values. In the optimization, the steepest descent method [7] is used which is a kind of nonlinear optimization method.

2.4 Anomaly detection and diagnosis

An anomaly is detected and diagnosed based on the temperature prediction results and estimated unknown parameter values. The following three methods are proposed.

1) Prediction at Plant Start-up: The unknown parameter values are estimated using the plant data of the last operation, namely the data from the last plant start-up to stop. The temperatures are predicted at plant start-up using the estimated unknown parameter values and plant conditions, such as bearing temperature, at the time. An anomaly is judged to occur when the differences between predicted and measured temperatures become large. The prediction assumes that the plant conditions during the last operation are normal.

2) Periodic Prediction: The unknown parameter values are estimated and the dynamic model is updated periodically based on the most recent plant data. The prediction is performed using the updated model periodically. An anomaly is judged to occur if the predicted temperature exceeds the alarm set point. From the prediction results, an operator knows the time margin to when the temperature will exceed the alarm set point if the anomaly condition continues. In the prediction, the model is updated periodically to reflect plant abnormal conditions so that the precise prediction is feasible even when the anomaly is advancing.

3) Estimated Parameter Values: From the estimated parameter values, the cause of an anomaly is identified. If an anomaly of heat generation at the gap occurs, the estimated value of the adjusted gap width G_0 will change. By contrast, if an anomaly occurs for heat removal in the cooling system, the overall heat transfer coefficient U_{oc} will change. Besides these, the long term change of the estimated gap width is also used to detect inclination of shaft caused by building deformation, etc.

3. Feasibility Evaluation by Test Facility

3.1 Test facility

Feasibility of the proposed method was confirmed using a 1/3 scale test facility (Fig.4) which simulates the water turbine bearing, and the bearing journal diameter is 500mm. There are 12 bearing pads, a part of each of them is soaked in the lubricating oil. The lubricating oil is cooled by the coolant flowing inside the cooling pipe in the oil tank. The shaft is rotated by an electric motor via a belt pulley and rated rotating speed of shaft is 500rpm. The rotating speed of the motor is controlled by an inverter and rotating speeds at start-up and shutdown are arbitrarily changed. In the facility, rotating speed of the shaft, and temperatures of bearing pad, oil, and inlet/outlet coolant are measured.

3.2 Evaluation result

Prediction accuracy and anomaly detection capability were evaluated off-line using data from the test facility.

1) Prediction Accuracy: The prediction accuracies were evaluated for prediction at start-up and periodic prediction.

a) Prediction at plant start-up: In an experiment, the test facility was started up and stopped and then it was restarted from the hot condition, namely the condition under which the pad and oil temperatures were still high. The unknown parameters were estimated using the data from 15-40 min during the first operation. Then, the prediction was performed at start-up of the second operation. In the prediction the estimated values of adjusted gap width and the overall heat transfer coefficient for the cooling pipe were used. For the initial shaft temperature, the measured pad temperature was used assuming that these temperatures were equal. Results are shown in Fig. 5. The prediction error is about 0.4 ℃ for pad temperature, and about 0.3 ℃ for oil temperature. Thus, accurate prediction is realized.

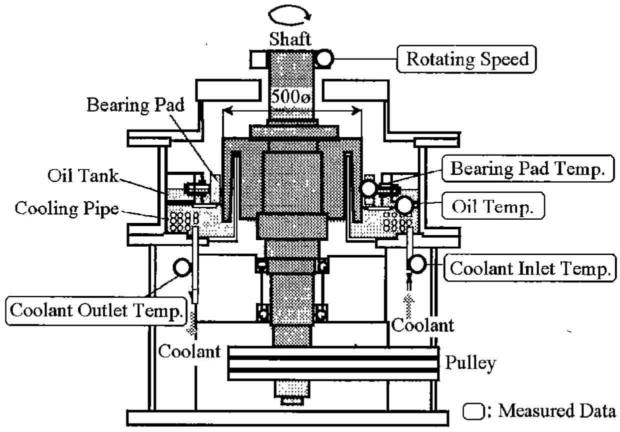


Fig. 4 Structure of 1/3 Scale Test Facility

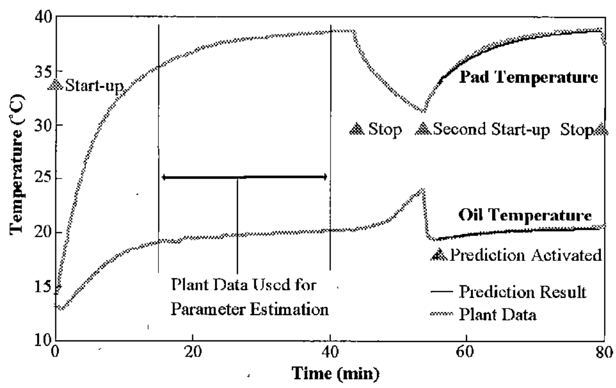


Fig. 5 Prediction at Start-up for Test Facility

b) Periodic prediction: The accuracy of periodic prediction was evaluated as follows. The prediction was activated twice, at 6 and 20 min after the facility start-up as shown in Fig. 6. The unknown parameters were estimated by using the data just before the prediction activation, namely the data during 4-6 min and 10-20 min respectively. The error in the next 20 min prediction is about 0.2 ℃ for pad and oil temperatures for the first prediction, and about 0.1 ℃ for the second prediction. Thus, accurate prediction, less than 1 degree error, is realized and anomaly detection, based on the prediction result, is judged feasible. For the periodic prediction, the prediction calculation is repeated periodically, so that the calculation time should be short. The cpu time for parameter estimation and prediction is only about 1-2 s in a workstation with 124 MIPS (million instructions per second), and on-line periodic prediction is confirmed to be feasible.

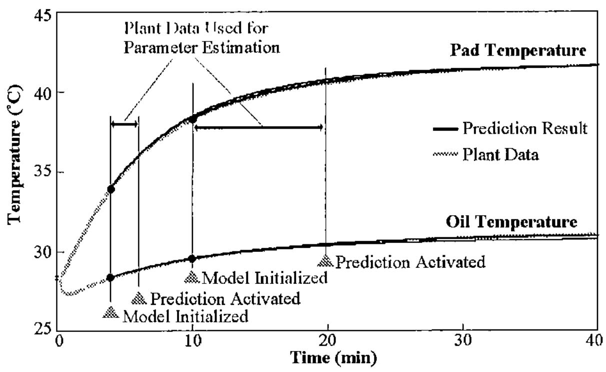


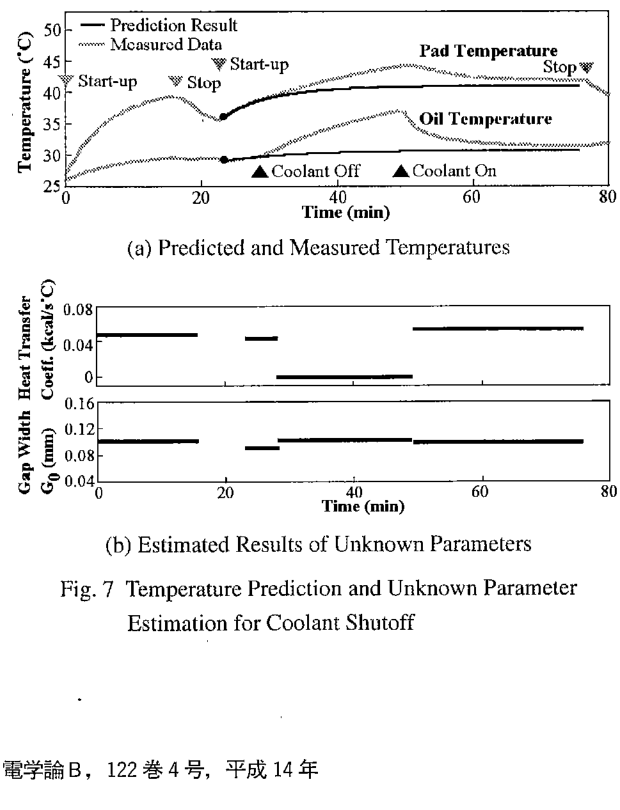
Fig. 6 Periodic Prediction for Test Facility

2) Anomaly Detection Capability: Two cases of the anomaly simulating experiment are described.

a) Coolant shutoff case: In this case, the facility was started up and stopped after a 16-minute operation. Then it was restarted from the hot condition. After re-start-up, coolant was shut off. After 20 minutes, coolant flow was turned on again, and then the facility was stopped.

At first the anomaly detection capability based on prediction was evaluated. The prediction was performed at the second start-up as shown in Fig. 7 (a). The difference between the measured and predicted temperatures began to increase after coolant was shut off. In particular, the difference for oil temperature rapidly increased and became more than 1 °C about 2.3 min after coolant shutoff. Thus the anomaly is detected by comparing the measured and predicted temperature values.

Next, the estimated values of unknown parameters were evaluated. The results are shown in Fig. 7 (b) for the overall heat transfer coefficient and adjusted gap width. The length of the graph bars shows the time interval during which the data were used for estimation. For example, the first bar shows that the values of heat transfer coefficient and gap width were estimated using 0-16 minutes' data.



(a) Predicted and Measured Temperatures

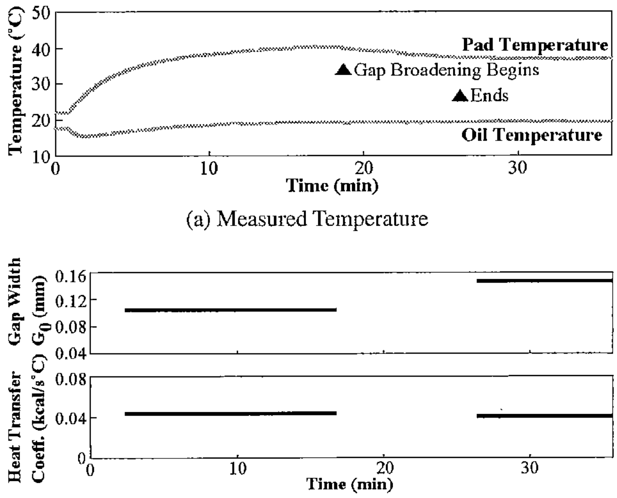
(b) Estimated Results of Unknown Parameters

Fig. 7 Temperature Prediction and Unknown Parameter Estimation for Coolant Shutoff

The overall heat transfer coefficient is nearly 0 during coolant shutoff, which is an adequate value. On the other hand the change of the estimated gap width is small. The anomaly detection is also feasible from the estimated parameter values and the anomaly cause can be identified as cooling system malfunction.

b) Gap width change case: In this case, the facility was started up and the gap width was changed during the operation by pushing the shaft in a horizontal direction.

Unknown parameters were estimated using experimental data. The results are shown in Fig. 8 for the overall heat transfer coefficient and adjusted gap width. The estimated value of gap width increases after the gap width was broadened. On the other hand, the change of the overall heat transfer coefficient according to the gap width change is small. The anomaly detection is feasible from the estimated parameter values and the anomaly cause can be identified as the gap width abnormal change.



(a) Measured Temperature

(b) Estimated Results of Unknown Parameters

Fig. 8 Unknown Parameter Estimation for Gap Width Change

4. Evaluation in Real Plant

4.1 Installation in plant system

After feasibility of the proposed method was confirmed by the test facility data, the system was installed in the supervisory control and data acquisition system of Okutataragi Pumped Storage Power Plant. It has six turbine generators, with a total generation power of 1,932 MW, and is the largest pumped storage power plant in Japan.

Each of its hydraulic turbine generators has four types of bearings: upper guide, lower guide and thrust bearings of the generator, and water turbine guide bearing. The dynamic model described in the section 2.2 is used for the generator upper bearing and water turbine bearing, which are guide bearings. On the other hand, the lower guide and thrust bearings of the generator have a common lubricating oil tank and the thrust bearing has a different type of structure. Therefore a different model is used for these bearings. The dynamic model is expressed by four time derivative equations for temperatures of the lower bearing pad, thrust bearing pad, oil, and shaft. In the model, unknown parameters are adjusted gap width of the lower bearing, initial value of shaft temperature, overall heat transfer coefficient of the cooling pipe, and load on the thrust bearing pad.

4.2 Evaluation of prediction accuracy

The prediction accuracy of the proposed method was evaluated in Okutataragi power plant. Some results are shown below.

The example prediction shown in Fig. 9 was performed at plant start-up using the parameter values estimated on the basis of plant data of the last operation, namely the data from the last plant start-up to stop. These are results for the water turbine bearing. In the figure errors during about an 80-min prediction are about 0.3 ˚C and 0.5 ˚C for bearing and oil temperatures, respectively. Thus, precise prediction within 1 ˚C is realized. This means that the anomaly detection is feasible using the difference between the predicted and measured temperatures in a real plant.

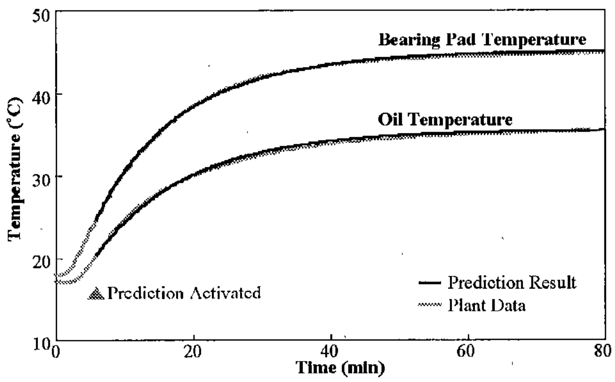


Fig. 9 Prediction at Plant Start-up for Water Turbine Bearing

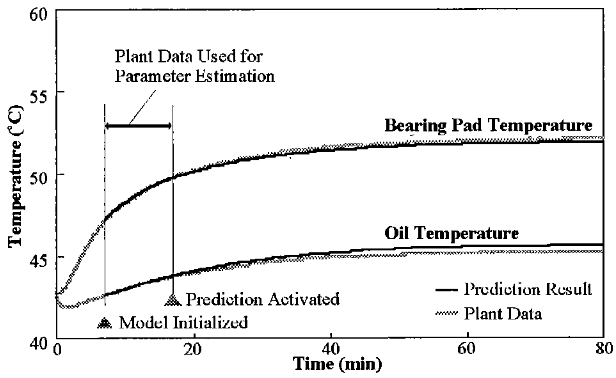


Fig. 10 Periodic Prediction for Generator Upper Bearing

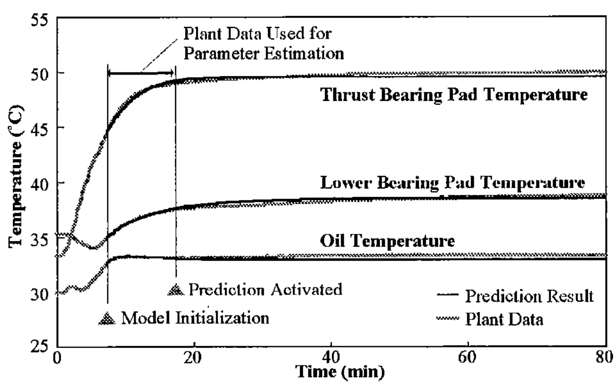


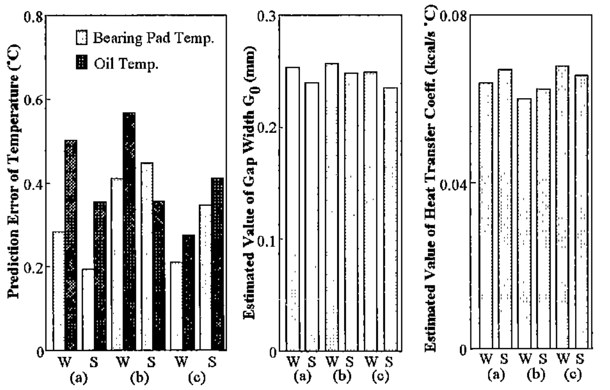
Fig. 11 Periodic Prediction for Generator Lower and Thrust Bearings

The example periodic prediction shown in Fig. 10 deals with the generator upper guide bearing. The periodic prediction was performed using the estimated parameter values based on the most recent plant data. The prediction was activated at 17.5 min after plant start-up based on the measured data during 10 min, namely from 7.5 to 17.5 min after start-up. The prediction errors are about 0.3 and 0.4 ˚C for the bearing and oil temperatures, respectively. Thus, accurate periodic prediction is feasible. Furthermore, the prediction offers information on the time when the temperature exceeds the alarm set point and on the time margin for coping with the anomaly. In the periodic prediction, the model is updated periodically, reflecting plant condition changes caused by the anomaly, so that an accurate prediction is feasible even under abnormal conditions.

Periodic prediction results for the generator lower and thrust bearings are shown in Fig. 11. As in Fig. 10, the prediction was activated at 17.5 min after plant start-up, based on the measured data from 7.5 to 17.5 min. The errors are about 0.4, 0.4 and 0.5 ˚C for thrust bearing, lower guide bearing, and lubricating oil temperatures, respectively. Thus the accurate prediction is also feasible on the generator lower and thrust bearings.

4.3 Evaluation of coolant temperature influence

In a plant, operating conditions, such as coolant temperature, change seasonally. To confirm the performance change of temperature prediction and unknown parameter estimation according to operating condition changes, prediction and estimation were done by using summer and winter plant data. In summer, coolant temperature was 25 ˚C and in winter, 12 ˚C. The start-up prediction, and periodic prediction for the next 20 min from 18 min and 26 min after plant start-up were performed. The prediction errors of temperature and estimated values of adjusted gap width and overall heat transfer coefficient for water turbine bearing are shown in Fig. 12. The prediction error is less than 0.5 and 0.6 ˚C for bearing pad and oil temperatures. Changes of estimated values of unknown parameters are small and less than 5% and 7% of the average values for gap width and overall heat transfer coefficient, respectively. Thus the influence of operation conditions on prediction and estimation is small. The results show that fault diagnosis using the predicted and estimated values is feasible all year round.



W: Winter (coolant temperature 12 ˚C), S: Summer (25˚C)
(a) Prediciton at Start-up, (b) Periodic Prediction from 18 min, (c) Periodic Prediction from 26min

Fig. 12 Prediction and Estimation Performance Change due to Coolant Temperature

4.4 Discussion

Feasibility of the proposed method was confirmed using the 1/3 scale test facility. Temperature prediction errors in the test facility are less than 1 ℃ and accurate prediction and anomaly detection using the result are feasible. The prediction performance was also evaluated using Okutataragi plant data. Again, accurate prediction is confirmed to be possible. The physical dynamic model assumes that the heat distribution ratios are constant regardless of temperatures of the pad, oil and shaft, and it neglects the temperature distribution in the lubricating oil and pad, etc. This simple model is sufficient to predict temperature changes.

Anomaly simulating experiments were performed in the test facility and estimation performance of unknown parameters was evaluated. Anomaly detection using the temperature prediction results and estimated parameter values is feasible. Additionally, it is confirmed that identification of the kind of anomaly is possible, namely the anomaly cause is identified as the abnormal gap width change or the cooling system malfunction from the estimated values of adjusted gap width and overall heat transfer coefficient at the cooling pipe.

The method is also proposed to detect inclination of the shaft from the long term change of estimated values of adjusted gap width, another anomaly type. Although feasibility of the method was not directly confirmed for this, the estimated value of gap width was confirmed to be changed when the gap width was broadened. Additionally the estimated values of adjusted gap width and overall heat transfer coefficient do not fluctuate significantly for plant operating conditions, such as coolant temperature in the real plant. From these results, the inclination of shaft should be detected from the long term change of estimated gap width.

The fault diagnosis system is now being used in a commercial operation as one function of the supervisory control and data acquisition system in Okutataragi power plant.

5. Conclusion

The fault diagnosis method was proposed which predicts bearing and lubricating oil temperature changes by using the physical dynamic model and detects an anomaly in the bearing related components from the prediction results. The unmeasurable parameters in the model are treated as unknown parameters and are estimated in the model initialization phase. The estimated parameter values are also used to detect and diagnose an anomaly.

The feasibility of the method was confirmed using a 1/3 scale test facility. Then the method was installed as a fault diagnosis system for the supervisory control and data acquisition system of the Okutataragi Pumped Storage Power Plant. Accurate temperature prediction was confirmed for the plant, regardless of seasonal environment changes. Commercial operation of the installed fault diagnosis system is continuing.

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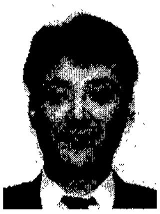

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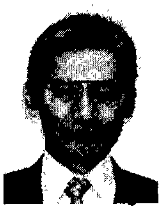

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