Fault Diagnostic Method for Pump Running Conditions Based on Process Modeling and Neural Network

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This paper proposes a fault diagnostic method for pump running conditions. The method is a combination of a process modeling and a classification procedure. The pump head and hydraulic losses in the pipe system are modeled by two equations. The values of the coefficients in the equations are determined from measurable output variables of the pump. Since the pump running conditions affect the coefficient values, they are detected by classifying those values. A multi-layer neural network is employed for the classification. Three running conditions of a drainage pump are clearly detected by this method. The accuracy of detection is improved by increasing the hidden layers and their units in the neural network.

Keywords: Fault diagnosis, Process modeling, Neural network, Automatic operation, Drainage pump, Running condition

INTRODUCTION

Demands for the automatic operation of drainage pump stations have increased in recent years (Friedrichsen, 1993). In the drainage pump, the inlet is occasionally blocked due to the sedimentation of sludge, and the impeller is often impeded by litter suspended in the water. Since pump performance is generally diminished under such faulty running conditions, it is necessary to develop a fault diagnostic method if we are to realize the goal of automatic operations. Previous methods for

fault detection have been restricted to direct comparison of measurable output variables, such as the pump head and the flow rate, with fixed threshold values. The faults are, therefore, detected only after the variables have been considerably affected, and the faults are not clearly specified.

Process modeling is now attracting an interest for its possible role in the supervision and fault diagnosis of technical plants (Isermann, 1984; Isermann and Freyermuth, 1991a). Conditions inside the plant are modeled by equations composed of the plant's measurable output variables. The

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values of the coefficients in the equations are determined from the output variables. Since the coefficient values are affected by conditions inside the plant, the faults occurring in the plant are specified by classifying the coefficient values. Faults in centrifugal pumps, such as cavitation and abrasive wear, were detected by this method (Geiger, 1984; Nold and Isermann, 1988; Isermann and Freyermuth, 1991b). But the classification procedure depends on the supervisor, and the automatization of the diagnosis has not been accomplished.

In this paper, a fault diagnostic method for pump running conditions is proposed, which consists of a process modeling and a classification procedure. The pump head and the hydraulic losses are expressed by two equations. The faults are detected by classifying the values of the coefficients in the equations. For the classification, a multi-layer neural network (Rumelhart and David, 1989) is employed to diagnose automatically. This method is applied to a drainage pump station in order to specify the running conditions.

FIGURE 1 Experimental apparatus.

EXPERIMENTAL APPARATUS AND PROCEDURE

Experimental Apparatus

Figure 1 illustrates the general arrangement of the experimental apparatus at the Institute of Hydraulic Turbomachinery and Fluid Mechanics, Technical University of Berlin. A drainage pump having an axial-flow impeller driven by a submersible motor is used. Water from a tank is led to the pump and returned to the tank through a magnetic flow-meter and a regulating valve, successively. The diameter of the discharging pipe is 394 mm. One side of the tank is made of glass to allow observations. Static pressures at the pump inlet 1 and outlet 2 are measured by strain-gauge pressure sensors. The measuring instruments are connected to a personal computer through an A/D converter. The data sampling rate is 0.2 kHz.

The shape and dimensions of the pump inlet and impeller are shown in Fig. 2. The inlet diameter is 350 mm, the number of blades 3, the inlet blade angle 13.5° , the rotational speed 1470 rpm, the flow rate $22.8 \text{ m}^3/\text{min}$, the head 5.42 m and the specific speed 1975 [rpm, m^3/min , m]. The flow in the impeller is visible through the casing made of transparent acrylic glass. An entry cone with five radial guide vanes is mounted in front of the pump inlet, and five diffuser vanes are installed right behind the impeller. The clearance between the entry cone and the bottom of tank is maintained at 30 mm.

Experimental Procedure

A fault diagnostic method proposed in this study is applied to detect three running conditions listed in Table I; a normal condition (F0), a blocked condition in the pump inlet (F1), and a condition combined of inlet blockage and impeller impedance (F2). These running conditions are hypothesized to occur in drainage pumps (Friedrichsen, 1993).

For experiment F1, the entry cone is half covered by a thin plate as shown in Fig. 3(a). For experiment F2, an impeller with vinyl bands on the

TABLE I Pump running conditions

	F0	F1	F2
Running condition	Normal	Blocked	Blocked and impeded

pressure and suction sides of one of its blades, as illustrated in Fig. 3(b), is used together with the entry cone as seen in Fig. 3(a). The length of the band is 300 mm, the width 40 mm and the thickness 0.5 mm.

The experiments are carried out for flow rates ranging from 17.4 to $29.9 \text{ m}^3/\text{min}$ under the rated rotational speed.

FAULT DIAGNOSTIC METHOD

Process Modeling

On the basis of the process modeling (Geiger, 1984; Nold and Isermann, 1988), the pump head and the hydraulic losses in the pipe system are modeled so that they are expressed by equations composed of measurable output variables such as the pump head, the flow rate and the rotational speed.

It is postulated that the dimensionless head ψ is expressed by the following with use of the dimensionless flow rate ϕ

$$\psi = c_0 + c_1\phi + c_2\phi^2 + c_3\phi^3, \quad (1)$$

where $\psi = H/(u_2^2/2g)$, $\phi = Q/A_d u_2$ and c_0 – c_3 are constants.

The head H , the flow rate Q and the angular velocity of the impeller ω are represented by the sum of the time-averaged values ($\bar{H}$, $\bar{Q}$, $\bar{\omega}$) and the instantaneous deviations (ΔH , ΔQ , $\Delta \omega$) from the average:

$$H = \bar{H} + \Delta H, \quad Q = \bar{Q} + \Delta Q, \quad \omega = \bar{\omega} + \Delta \omega. \quad (2)$$

When Eq. (1) is linearized around the steady operating state of the pump by substituting Eq. (2), the dimensionless form of Eq. (1) including process

FIGURE 2 Shape and dimensions of drainage pump.

(a) Entry cone

(b) Impeller

FIGURE 3 Configuration for fault running conditions.

coefficients C_r and C_q is obtained:

$$\Delta\psi = C_r(\Delta\omega/\bar{\omega}) + C_q\Delta\phi, \quad (3)$$

where

$$\Delta\psi = \Delta H/(u_2^2/2g), \quad \Delta\phi = \Delta Q/A_d u_2, \quad (4)$$

$$C_r = 2c_0 + c_1\bar{\phi} - c_3\bar{\phi}^3, \quad C_q = c_1 + 2c_2\bar{\phi} + 3c_3\bar{\phi}^2. \quad (5)$$

Here $\bar{\phi}$ denotes the time-averaged value of ϕ .

Let us consider the losses in the pipe system. The following losses are assumed here; the loss due to the acceleration of fluid h_a , the losses caused by the friction on the pipe wall h_f and the mixing of the discharged water in the tank h_d , and the losses in the valve h_v , in the elbow h_e and at the entry cone h_i . They are expressed by the following:

$$h_a = \frac{l_d}{gA_d} \frac{dQ}{dt}, \quad h_f = \lambda \frac{l_d}{A_d^2 D} \frac{Q^2}{2g}, \quad h_v = \frac{\zeta_v}{A_d^2} \frac{Q^2}{2g}, \quad (6)$$

$$h_e = \frac{\zeta_e}{A_d^2} \frac{Q^2}{2g}, \quad h_d = \frac{1}{A_d^2} \frac{Q^2}{2g}, \quad h_i = \frac{\zeta_i}{A_s^2} \frac{Q^2}{2g},$$

where l_d and D denote the length and the diameter of the discharging pipe, respectively, and λ , ζ_v , ζ_e and ζ_i are the friction factors.

The relationship between the pump head H and the above mentioned hydraulic losses is written as

$$H = h_a + h_f + h_v + h_e + h_d + h_i. \quad (7)$$

When Eq. (7) is linearized by substituting the first and second equations of Eq. (2) and expressed in the dimensionless form using Eq. (4), an equation with process coefficients C_a and C_f is obtained:

$$\Delta\psi = C_a(d\phi/d\tau) + C_f\Delta\phi, \quad (8)$$

where

$$C_a = \frac{2l_d}{r_2}, \quad C_f = 2A_d^2 \left(\frac{\lambda l_d}{A_d^2 D} + \frac{\zeta_v + \zeta_e + 1}{A_d^2} + \frac{\zeta_i}{A_s^2} \right) \bar{\phi}. \quad (9)$$

The term τ in Eq. (8) denotes a dimensionless time defined as $\tau = \bar{\omega}t$.

Calculation of Process Coefficients

When the time-averaged values of the head $\bar{H}$, the flow rate $\bar{Q}$ and the angular velocity $\bar{\omega}$ are calculated from the variables measured over a duration of the sampling time, dimensionless deviations from the averages $\Delta\psi$, $\Delta\phi$ and $\Delta\omega/\bar{\omega}$ are obtained. The time derivative $d\phi/d\tau$ is estimated by numerical difference schemes. The values of process coefficients C_r , C_q , C_a and C_f are then calculated by substituting $\Delta\psi$, $\Delta\phi$, $\Delta\omega/\bar{\omega}$ and $d\phi/d\tau$ into Eqs. (3) and (8).

In this study, the sampling time is 5 s, and Eqs. (3) and (8) are solved by the least-squares method.

Classification of Process Coefficients by Neural Network

To detect running conditions F0–F2 (Table I), a procedure which classifies the values of C_r , C_q , C_a and C_f according to learning data sets (ϕ , C_r , C_q , C_a , C_f) is used. The learning data sets have been obtained before the detection. In this paper, a method employing a multi-layer neural network for the classification is proposed.

Figure 4 shows the architecture of a multi-layer neural network (Rumelhart and David, 1989) composed of L layers; an input layer, hidden layers and an output layer. The input and output layers consist of five and two units, respectively. In the hidden layers, the number of layers $L - 2$ and the number of units N are changeable. The outputs from the units in one layer are transmitted to the units in another layer through synapse.

The flow rate $\bar{\phi}$ and the process coefficients C_r , C_q , C_a and C_f are fed into the input layer. The unit in layer l receives inputs from the units in layer $l - 1$. The net input to the j th unit in layer l , $n_{l,j}$, is determined as (Rumelhart and David, 1989):

$$n_{l,j} = \sum_{i=1}^N w_{l,j,i} o_{l-1,i} \quad (2 \leq l \leq L), \quad (10)$$

FIGURE 4 Architecture of neural network.

where $w_{l,j,i}$ denotes the weight connecting the i th unit in layer $l-1$ to the j th unit in layer l , and $o_{l-1,i}$ is the output of the i th unit in layer $l-1$.

The output of the j th unit in layer l , $o_{l,j}$, is given by the following equations (Rumelhart and David, 1989):

$$o_{l,j} = \begin{cases} n_{l,j} & (l=1), \\ 1/[1 + \exp(-n_{l,j})] & (2 \leq l \leq L). \end{cases} \quad (11)$$

In the fault diagnostic method for the pump running conditions proposed in this paper, the running conditions are detected from the values of the outputs $o_{L,1}$ and $o_{L,2}$. It is given that $o_{L,1}$ and $o_{L,2}$ should take the target values f_1 and f_2 , respectively, for pump running conditions F0–F2 (as shown in Table II), when $\bar{\phi}$, C_r , C_q , C_a and C_f are fed into the neural network. This prescription is realized by a learning algorithm (Hush and Horne,

TABLE II Running conditions and outputs

	F0	F1	F2
f_1 (target of $o_{L,1}$)	0	0	1
f_2 (target of $o_{L,2}$)	0	1	1

1993), which specifies the values of weight $w_{l,j,i}$ in Eq. (10). When some learning data sets $\mathbf{x}_p = (\bar{\phi}, C_r, C_q, C_a, C_f)$ are known for every running condition listed in Table I, the values of the weight $w_{l,j,i}$ can be determined by minimizing the following error function E (Hush and Horne, 1993):

$$E = \frac{1}{2P} \sum_{p=1}^P \sum_{j=1}^2 [o_{L,j}(\mathbf{x}_p) - f_j(\mathbf{x}_p)]^2, \quad (12)$$

where $o_{L,j}(\mathbf{x}_p)$ and $f_j(\mathbf{x}_p)$ denote the values of $o_{L,j}$ and f_j for the learning data set $\mathbf{x}_p$, respectively, and P is the number of $\mathbf{x}_p$.

In this study, a common back-propagation algorithm (Hush and Horne, 1993) is employed for minimization of the error function E .

RESULTS AND DISCUSSION

Pump Performance and Process Coefficients

Figure 5 shows the pump performance, where the results for three running conditions (F0, F1, F2) are superimposed. The dimensionless head ψ , the dimensionless shaft power λ and the efficiency η are plotted against the dimensionless flow rate $\bar{\phi}$. The head ψ and the efficiency η for the blocked running condition (F1) are lower than for the normal condition (F0), though the shaft power λ for F1 is slightly higher than for F0. The difference in the head is larger at the higher flow rate.

Though the head ψ and the efficiency η for the combined condition of blockage and impedance (F2) are quite lower than for F0 and F1, the shaft power λ for F2 is almost the same as for F0 and F1. It is, therefore, difficult to detect the running conditions by comparing their shaft powers.

The process coefficients C_r , C_q , C_a and C_f are plotted against the flow rate $\bar{\phi}$ in Fig. 6. The coefficient C_r strongly depends on $\bar{\phi}$. No significant difference is found between C_q and C_f . This is because both coefficients have relation to the deviation of the flow rate. The coefficient C_a is independent of $\bar{\phi}$ as well as the running conditions. Because the value of C_a is determined only from the outer radius of the impeller r_2 and the length of the discharging pipe l_d as seen in Eq. (9).

Detection of Running Condition

When the coefficients C_r , C_q , C_a and C_f together with the flow rate $\bar{\phi}$ (Fig. 6) are used as the learning data sets x_p for Eq. (12), the neural network can be trained so that the outputs $o_{L,1}$ and $o_{L,2}$ take their target values in accordance with the pump running conditions (Table II).

Figure 7 plots the outputs $o_{L,1}$ and $o_{L,2}$ of a neural network against the flow rate $\bar{\phi}$. The

FIGURE 5 Pump performance.

numbers of the layers L and units in hidden layers N of the neural network are 3 and 5, respectively. The results for conditions which are normal (F0), blocked (F1), blocked and impeded (F2) are shown

FIGURE 6 Process coefficients.

in Figs. 7(a), (b) and (c), respectively. For the conditions F0 and F2, the outputs $o_{L,1}$ and $o_{L,2}$ are very close to their own targets, showing that the neural network clearly detects these running conditions. As the output $o_{L,1}$ for the condition F1

 FIGURE 7 Detection by neural network of $L=3$, $N=5$.

disperses in the wide range between 0 to 1, the condition is not completely detectable.

Figure 8 shows the results obtained by a neural network of $L=3$ and $N=10$. The outputs for the conditions F0 and F2 are almost the same as those

(a) Normal F0

(a) Normal F0

(b) Blocked F1

(b) Blocked F1

(c) Blocked and impeded F2

(c) Blocked and impeded F2

FIGURE 8 Detection by neural network of $L=3$, $N=10$.FIGURE 9 Detection by neural network of $L=4$, $N=5$.

in Fig. 7. The output $o_{L,1}$ for F1 approaches the target value (0) in the whole range of $\bar{\phi}$, indicating the increase in the accuracy of detection.

Figure 9 plots the results by ($L = 4$, $N = 5$). Since most of $o_{L,1}$ for the condition F1 are less than 0.44, the condition is detectable by the present neural network.

CONCLUSIONS

A fault diagnostic method for pump running conditions was proposed. In the method, the pump head and hydraulic losses in the pump stations are modeled by two equations, and the values of the coefficients in the equations are determined from measurable output variables, and then the running conditions are detected by classifying the coefficient values. A multi-layer neural network is employed in the classification.

The method was applied to a drainage pump station to specify the running conditions. The accuracy of detection is improved by increasing the numbers of the hidden layers and their units. It was confirmed that the running conditions are detectable by a neural network with $L = 4$ and $N = 3$.

NOMENCLATURE

A	: sectional area
C_a, C_f, C_q, C_r	: process coefficients
D	: diameter of discharging pipe
f_j	: target value of neural network
g	: acceleration of gravity
H	: pump head = $(p_d - p_s)/\rho g + (V_d^2 - V_s^2)/2g + z_d - z_s$
L	: shaft power or number of layers in neural network
$n_{l,i}$	: net input to i th unit in layer l
N	: number of units in a hidden layer
$o_{l,i}$	: output of i th unit in layer l
p	: absolute static pressure
Q	: volumetric flow rate
r_2	: outer radius of impeller
t	: time

u_2	: peripheral speed of impeller = $r_2\bar{\omega}$
V	: velocity of water
$w_{l,j,i}$	: weight connecting unit
$\mathbf{x}_p$	: learning data set = $(\bar{\phi}, C_r, C_q, C_a, C_f)$
z	: elevation from bottom of tank
η	: pump efficiency = $\rho g Q H / L$
λ	: dimensionless expression of shaft power = $L/(\rho A_d u_2^3/2)$
ρ	: density of water
τ	: dimensionless time = $\bar{\omega}t$
ϕ	: dimensionless expression of flow rate = $Q/A_d u_2$
ψ	: dimensionless expression of pump head = $H/(u_2^2/2g)$
ω	: angular velocity of impeller

Subscripts

d	: pump outlet
s	: pump inlet

Superscript

—	: time averaged
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