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Condition monitoring of power plants using extended Kalman filtering

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Extended Kalman Filtering (EKF) is applied to the condition monitoring of hydro-power production plants. This method is well suited to real-time failure detection and identification. This paper presents one important application: monitoring of hydraulic performance of hydro-power plants.

The method uses a number of parallel Kalman filters based on plant models to describe the normal operational condition and a selection of the most frequent and critical failures that may occur. These include sensor failure.

Hypothesis testing is carried out based on the innovation sequence resulting from each of the filters. The probability density function for each set of observations is calculated from these sequences, and the model with the highest likelihood of being observed is taken to represent the plant.

Simulations show that this approach provides both unbiased estimates of nonmeasurable states and fairly good estimates of the process parameters. The two main fields of application are optimum individual setpoint control in large power stations and better maintenance planning. The method will be tested in a Norwegian hydro-power plant in 1988. This field test has been supported by the Norwegian State Power Board (Statkraft).

1. Introduction

The problem of supervising power plants with respect to production efficiency and potential failure often implies a complicated measurement system with high redundancy to avoid shutdown caused by sensor failure. Many of the interesting quantities are often difficult to observe by direct measurements, a good example being the volume flow through a hydro turbine.

In such high-cost plants it is vital to have an adequate way of discriminating between serious changes in the process that may lead to shutdowns which in cases will mean periods with high loss-of-production costs, and in other cases less critical process changes and sensor faults.

We have found that the combination of good measurements, satisfactory process model, state estimation of unmeasured, interesting quantities, and parameter estimation of process parameters and sensor bias, constitutes a promising method for the condition monitoring of power plants.

Such a model reference approach has many advantages over direct measurement methods using high/low alarm limits in the observed values, since the latter have the tendency to give false alarms during normal start/stop transients and normal dynamic responses to various switching operations in the connected power grid.

The availability of industrial equipment has become important as a result of increased operational costs. Redundancy is an expensive solution, and is no longer common. Instead, advanced systems for monitoring and control are installed. However, in addition to collecting data, it is necessary to have such data analyzed by an expert. Since the number of experts is limited and they are often far away

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from the plant where they are needed, there should be a means of automating the evaluation of collected measurements.

It was decided to examine the possibilities offered by knowledge-based systems in order to make the process of analysis more independent of human experts. The main task of knowledge-based systems is to incorporate a restricted amount of the expert's knowledge in computer systems and let the systems automatically evaluate the data.

A computer system which is capable of diagnosing the state of the machinery would be cheap to use and would provide continuous surveillance of the machinery. The operator could use the information to improve maintenance planning. Today, machinery maintenance is usually performed at fixed time intervals.

Norwegian hydro-power plants are not usually equipped with reliable monitoring systems that are able to detect efficiency losses in the region of 1–2 per cent of the total energy produced.

The main reason for this is that volume discharge sensors, i.e. ultrasound doppler types with a measurement accuracy better than 5 per cent, are considered to be unreliable, costly and complicated to operate and maintain. Pressure sensors, however, are much easier to operate, they have better performance both in terms of accuracy and long-term stability and are cheaper and more robust. If they are combined with a good mathematical model of the plant, they can provide satisfactory flow estimates.

Many authors have discussed the use of Kalman filtering applied to failure detection, for example Mehra and Peschon (1971), a survey of design methods for failure detection, Willsky (1976), Isermann (1982). The most promising results for power plant condition monitoring were found in the multiple model hypothesis probability test method (MMHPT) first published by Digernes (1980).

2. Plant model

In general terms, a continuous-time plant model which includes normal operation, process failure, and observation failure may be defined as:

(*a*) Process model

$$dx/dt = \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{\Theta}(t), \boldsymbol{u}(t)) + \boldsymbol{v}(\boldsymbol{\Theta}(t), t) \tag{1}$$

(*b*) Observation model

$$\boldsymbol{y}(t) = \boldsymbol{g}(\boldsymbol{x}(t), \boldsymbol{\mu}(t)) + \boldsymbol{w}(\boldsymbol{\mu}(t), t) \tag{2}$$

where t = time variable
$\boldsymbol{x}$ = state space vector
$\boldsymbol{u}$ = control vector
$\boldsymbol{\Theta}$ = parameter vector defining the process failures
$\boldsymbol{v}$ = process noise vector
$\boldsymbol{f}$ = nonlinear vector function describing the deterministic process behaviour
$\boldsymbol{y}$ = measurement vector
$\boldsymbol{\mu}$ = parameter vector defining the sensor failures (biased sensors)
$\boldsymbol{w}$ = measurement noise vector
$\boldsymbol{g}$ = nonlinear vector function defining sensor behaviour

With a simple Euler discretization $\boldsymbol{x}(k+1) = \boldsymbol{x}(k) + \tau \boldsymbol{f}(\cdot \cdot k \cdot \cdot)$ where $\tau = t(k+1) - t(k)$ is the discrete time interval, eqns. (1) and (2) can be rewritten in discrete form.

The noise vectors $\boldsymbol{v}$ and $\boldsymbol{w}$ are assumed to be approximately Gaussian white noise $\boldsymbol{v} \sim N(0, V)$ and $\boldsymbol{w} \sim N(0, W)$ and statistically independent.

The discrete-time prediction of error covariance is

$$X(k+1) = \Phi(k+1, k)\, X(k)\Phi(k+1, k)^{\mathrm{T}} + V(\Theta(k), k) \tag{3}$$

where Φ is the transition matrix.

3. Estimator

A failure identification system has an estimator as its basic component. In this case we have used standard filtering and prediction equations from the Extended Kalman Filter (EKF). Prediction is simplified as we only consider steady state operation, the only dynamics being the result of the noise processes, updating states and parameters.

Mathematically, however, there is no difference between state variables and estimated process parameters in the stationary case.

Linearization of the measurement function $\boldsymbol{g}$ is done for each time step and the discrete measurement matrix H is:

$$H(k+1) = \partial \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{\mu}(k+1))/\partial \boldsymbol{x}^{\mathrm{T}} \mid \boldsymbol{x} = \bar{\boldsymbol{x}}(k+1 \mid k) \tag{4}$$

where $\bar{\boldsymbol{x}}(k+1 \mid k) =$ *a priori* estimate of state vector at time $k+1$.

4. Hydraulic performance in a hydro-power plant

There is increasing interest in developing and improving methods for volume flow measurements in hydro-power stations. Reliable flow measurements are needed to determine the efficiency of the hydro-power units and the head loss coefficients of the waterway. These parameters should be known in order to calculate optimal operation of hydro-power stations. The changes that take place over a period of time, such as packing of trashracks, sliding in tunnels, wear and leakage in turbines etc., are also very important when determining the best and most economic maintenance plan. A preliminary calculation of the expected benefit from introducing loss monitoring equipment has been made by Skarstein *et al.* (1984). This calculation shows that in Norway it is possible to save more than NOK 30 million per year by having such equipment permanently installed. The purpose of the 'Efficiency monitoring in power plants' project is to develop the methods and instrumentation required for the surveillance of the hydraulic losses in power plants.

Total efficiency η_{tot} including the generator is the ratio between produced active electrical power P_{e} and natural available power, P_{N}, i.e.:

$$P_{\mathrm{e}} = \eta_{\mathrm{tot}} \cdot P_{\mathrm{N}} \tag{5}$$

$$P_{\mathrm{N}} = \rho g Q H \tag{6}$$

where ρ = density of water,

g = acceleration due to gravity,

Q = discharge,

H = gross head of water.

The total efficiency is the product of the efficiencies of the tunnel, trashrack, pressure shaft, tailrace, turbine and generator.

An adequate monitoring method for hydraulic performance should meet the following requirements:

provide a reliable means of estimating the discharge,

give information about changes in the head loss coefficients and turbine and generator efficiencies,

take into consideration that some of the sensors might be erroneous and thus lead to bias in the above estimates.

Such a method has been developed and is about to be implemented in a simple power plant as shown in Fig. 1.

Using state estimation we are able to exploit the fact that the pressure differences along the tunnel, the pressure shaft and the trashrack are dependent on the flow. Consequently, these pressure differences are an independent set of measurements for flow monitoring. The guide vane positions and the turbine output can also be used in the same way. By comparing the calculated discharge based on all these 'sensors', it should be possible to improve the accuracy of the discharge calculation and point out within certain limits, the most probable faults in some of the sensors, if any.

5. Measurement scheme

When monitoring a plant, like that in Fig. 1, we use the following measurements:

H_{oy} = upper reservoir level (m)

H_{g1} = pressure head upstream of the trashrack (m)

H_{g2} = pressure head downstream of the trashrack (m)

H_{t1} = pressure head upstream of the turbine (m)

H_w = pressure head difference within the spiral casing (Winther–Kennedy measurement) (m)

H_{uy} = tail water level (m)

P_e = power output of the generator (MW)

α = guide vane angle (°)

It is possible to measure these units very accurately. The best pressure transducer has a tolerance of approximately 0·01%. Angle transducers with a tolerance of 0·7° are available. The measurement of the output power is dependent on the accuracy of the MWh-meter in the power station. Precision meters of classification 0·2 (the tolerance is 0·2% of full scale) are available. This is comparable to the accuracy of the measurement transformers.

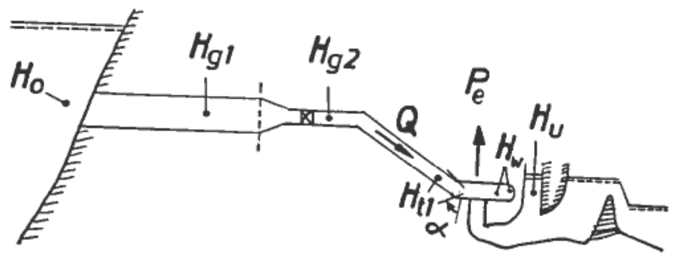

Figure 1. The pilot plant with a gross head ranging from 20 m to 60 m, one turbine unit with 15 MW rated power and nominal discharge 20 m^3/s.

6. Mathematical model

For the simple power station in this study, the interesting quantities are the discharge and the gross head. Given these, and with all the parameters known, such as the turbine characteristics and all the loss coefficients, the intention is the prediction of the measurements listed in the previous section. In addition, we need to know the absolute level of either the upper reservoir or the tail water. The mathematical relationship between the hydraulic losses and the measurements are nonlinear, but rather simple.

The following equation describes the hydraulic head losses in stationary flow

$$\Delta H = k \, . \, Q^2 \tag{7}$$

where k is a head loss coefficient. The losses in the tunnel, trashrack, pressure shaft and the tailrace can be described by means of this type of relationhip. The same equation also applies to Winther–Kennedy measurements.

The electrical power output is

$$P_e = \eta_e \, . \, \eta_t \, . \, \rho g H_e \, . \, Q, \tag{8}$$

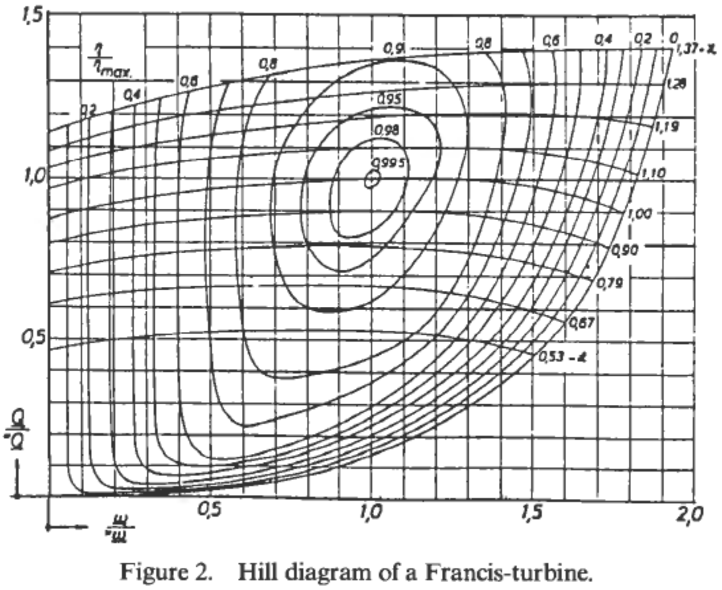

Figure 2. Hill diagram of a Francis-turbine.

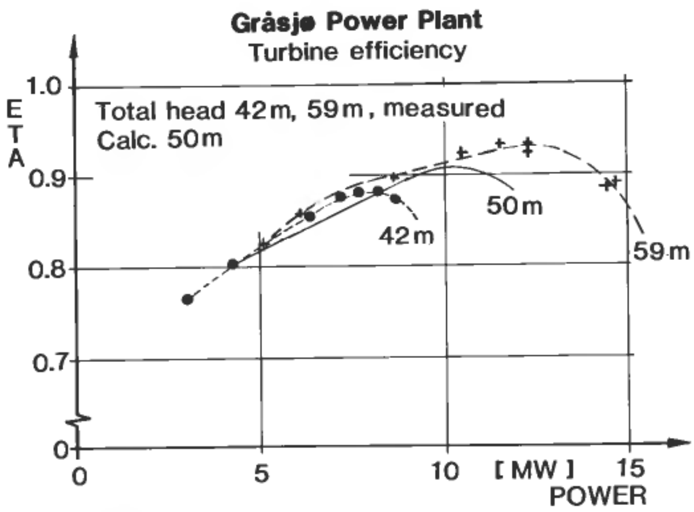

Figure 3. Turbine efficiency as a function of electrical output power, for three different gross head values.

where H_e is effective head of the turbine. From the definition of the relative guide vane opening κ

$$\kappa = \frac{Q}{{}^*Q} \tag{9}$$

where Q is the reduced discharge, $Q = Q/\sqrt{2gH_e}$ (the asterisk indicating the design point of the turbine), it follows that the effective head is

$$H_e = \frac{\text{const}}{\kappa^2}\, Q^2. \tag{10}$$

The actual measurement, the guide vane angle α, is an almost linear function of κ. The deviations from linearity must be determined for each individual power plant.

The turbine characteristics can be represented by a Hill diagram determined by measurements on a scaled model turbine as shown in Fig. 2. This diagram can be verified by efficiency measurements on a full-scale turbine. Interpolation between the measured values is done by use of the affinity equations. The result is shown in Fig. 3 for three different values of head. Full-scale measurements have been made for two values of gross head, 42 m and 59 m.

These two data sets are the basis of the interpolation. This method for efficiency representation gives a tolerance better than 1%.

As we can see from Eqns (7)–(10), discharge Q can be calculated in different ways. Consequently, we have more measurements than strictly needed to determine the discharge Q. However, since all measurements have noise, the measurement redundancy can be used to improve the accuracy of the calculation of Q.

7. State space model

As we have only taken into account stationary conditions, the state model of Eq. (1) reduces to

$$\boldsymbol{x}(k+1) = \boldsymbol{x}(k) + \boldsymbol{v}. \tag{11}$$

The elements of the state vector must be chosen in such a way that all the measurements can be uniquely expressed in terms of the vector function $\boldsymbol{g}$ of Eqn. (2). This is done by choosing the following three quantities as the elements of the state vector $\boldsymbol{x}$:

H_{ox} = estimated level of upper reservoir,

H_{ux} = estimated tail water level,

Q = discharge.

Discharge Q is essential and is found in almost all of the measurement equations. In the case of several parallel turbine units, the state vector should contain one element for each individual Q for the turbine units. The upper and lower water levels are independent of the number of units. For example, a plant with four parallel turbines will be described by a state vector of six elements, the two water levels and four discharges.

The 8 elements of the measurement vector as given above are connected to the state variables by the following measurement model for the system:

$$H_o = H_{ox} \tag{12}$$

$$H_{g1} = H_{ox} - (k_t) \cdot Q^2 \tag{13}$$

$$H_{g2} = H_{ox} - (k_t + k_g) \cdot Q^2 \tag{14}$$

$$H_{t1} = H_{ox} - (k_t + k_g + k_s) \cdot Q^2 \tag{15}$$

$$H_w = k_w \cdot Q^2 \tag{16}$$

$$H_u = H_{ux} \tag{17}$$

$$P_e = k_e \cdot \eta(H_e, Q) \cdot H_e \cdot Q \tag{18}$$

$$\alpha = g_\alpha(k_\kappa \cdot Q/\sqrt{H_e}) \tag{19}$$

where

$$H_e = H_{ox} - H_{ux} - (k_t + k_g + k_s) \cdot Q^2 \,. \tag{20}$$

Quantity H_e is the effective head of the turbine and is used as shorthand notation in the equations. Factors k_t, k_g and k_s include both the loss of pressure and changes in the velocity head. Function g_α in Eqn. (9) is assumed to be linear in the simulations. Corrections must be added after having gained some experience with the model applied to the pilot plant.

8. Method of identification of hydraulic condition

The purpose of condition monitoring is to identify possible changes in the hydraulic losses throughout the whole waterway. The method is based on estimation using the Extended Kalman Filter (EKF). Because the discharge is defined as a state variable in this filter, this method gives a direct estimate of the discharge in which the information from all the measurements is taken into account depending on their individual relative accuracy.

The ability to estimate the discharge is however only one out of three requirements that the identification method must meet. Changes in the loss conditions in the waterway and sensor faults must also be taken care of. The Extended Kalman

Filter provides an effective means of estimating parameters of a state space model. This is done by extending the state vector with as many of the system parameters that we want to estimate. Though this has to be paid for in terms of reduced observability, with the high measurement redundancy it is still possible to estimate parameters. The higher the redundancy, the greater the number of parameters that can be estimated. Sensor faults can be treated in exactly the same manner. A bias in a sensor can be added to the state vector as an ordinary system parameter. By doing this we refuse to 'trust' the particular sensor, and we 'ask' the other sensors in the system what measurement value this 'bad' sensor should show. This obviously leads to reduced observability for states and parameters, but is an efficient way of identifying single sensor faults.

The slow variation of the parameters and sensor bias with time can be identified by making a model of each of the most common changes in the losses in a power plant, combined with the optional assumption that one of the sensors has failed. This situation is modelled as a number of distinct hypotheses. The hypotheses are based on the estimation of parameters in the expanded state vector, as explained. In this study we have used hypotheses for 6 parameter changes and 5 sensor faults. Only single faults are considered in the simulations. In principle, the number of hypotheses is only limited by computer time and reduced observability. These single faults give a total of 12 hypotheses (one hypothesis is to account for the normal condition).

Having different hypotheses, and corresponding models, the task is to find which model fits the data from the current (unknown) situation best. This hypothesis will also give the best estimate of the discharge. To find the best hypothesis, we have used a method called the Multiple Model Hypothesis Probability Test (MMHPT). This method iteratively finds the relative probability of each hypothesis. The method is based on the estimation error of each hypothesis and the distribution of this error. It uses Bayes' formula in the iteration process.

Assume that we wish to test a specific number (NH) of hypotheses:

$H_i(k+1)$: process model P_i and measurement model M_i are true at time $k+1$, $i = \{1, 2, \ldots, \mathrm{NH}\}$

Estimated probabilities for each hypothesis are denoted:

$\bar{q}_i(k+1)$: $\Pr\{H_i(k+1) \mid Y(k)\}$ = *a priori* probability for hypothesis $H_i(k+1)$ being true given all measured data up to and including time k.

$$Y(k) = \{y(1), y(2), \ldots, y(k)\},\ i = \{1, 2, \ldots, \mathrm{NH}\}$$

$\hat{q}_i(k+1)$: $\Pr\{H_i(k+1) \mid Y(k+1)\}$ = *a posteriori* probability for hypothesis $H_i(k+1)$ being true at time $k+1$ given all measured data up to and including time $k+1$, $i = \{1, 2, \ldots, \mathrm{NH}\}$

The relation between these two probabilities is given by Bayes' rule

$$\hat{q}_i(k+1) = \frac{\Psi_i(k+1 \mid k)\bar{q}_i(k+1)}{\sum_{j=1}^{\mathrm{NH}} \Psi_j(k+1 \mid k)\bar{q}_i(k+1)},\ i = \{1, 2, \ldots, \mathrm{NH}\} \tag{21}$$

in which $\Psi_i(k+1 \mid k) = \Pr\{y(k+1) \mid H_i(k+1), Y(k)\}$ is the conditional probability density of the innovation $\varepsilon_i(k+1 \mid k) = y(k+1) - y(k+1 \mid k)$ based on hypothesis

$H_i(k+1)$. If $Y(k+1)$ is Gaussian we have

$$\Psi(k+1\,|\,k) = c \exp\left(-\tfrac{1}{2}\varepsilon^T(k+1\,|\,k)R^{-1}(k+1\,|\,k)\varepsilon(k+1\,|\,k)\right) \qquad (22)$$

where $c = (2\pi)^{-m/2}\,(\mathrm{Det}\,R(k+1\,|\,k))^{-1/2}$.
m is the dimension of the y-vector. $R(k+1\,|\,k)$ and Det $R(k+1\,|\,k)$ is the *a priori* innovation covariance at time $k+1$ and its determinant respectively. These variables are available from the estimator:

$$R(k) = D(k)\bar{X}(k)D^T(k) + W(k) \qquad (23)$$

If we assume that we have considered all the possible hypotheses likely to represent the plant, we have approximately

$$\sum_{i=1}^{NH} \hat{q}_{i(k)} = \sum_{i=1}^{NH} \bar{q}_i(k) = 1 \qquad (24)$$

The prediction of these probabilities are static with a lower bound

$$\begin{aligned} \bar{q}_i(k+1) &= \hat{q}(k) \qquad \text{if} \quad \hat{q}_i(k) \geqslant q_{1\mathrm{im}}(k) \\ &= q_{1\mathrm{im}}(k) \quad \text{if} \quad \hat{q}_i(k) < q_{1\mathrm{im}}(k) \end{aligned}$$

The choice of the lower limit is a matter of experience. A typical value is 10^{-4}.

Figure 4 schematically shows how the calculations in the diagnostic system are done.

If we cannot find an obvious winning hypothesis, it is still possible to find an estimate of the discharge and loss parameters. In this case, we have to calculate the weighted means of estimated parameters, the weighting factors being the probabilities of each hypothesis. This is not included in the present state of the model, but can easily be added if necessary.

The method can consequently find the most probable change in the loss conditions, estimate the amount of change and, at the same time, give an estimate of the discharge.

The condition monitoring program system is made so that it can estimate several parameters. The system is thereby able to consider a combination of faults, but this means that the number of hypotheses necessary to cover all possible combinations increases rapidly. As the system is designed to monitor the loss conditions at different times (for example once a month), it does not run in real time. In principle, this will be possible, but having many hypotheses, the estimation task can easily become too time-consuming. With the present implementation on an IBM/AT personal computer, it takes about 30 minutes to run through the 12 single fault hypotheses after the raw data have been stored on file. One complete set of measurements consists of 400 samples from each of the 8 sensors. The sampling interval can be chosen between approximately 1 second and up to several minutes. The software for the Kalman Filter is based on a general program package EXKALM, from CAMO (1985), which interfaces with the special application subroutines developed and coded in standard FORTRAN 77. EXKALM has proved to be well-suited for this kind of offline estimation applied to condition monitoring.

9. Simulation of changes in hydraulic loss conditions

In order to test the capabilities of the estimation method, we have simulated changes in the hydraulic loss coefficients, the turbine efficiency, as well as single

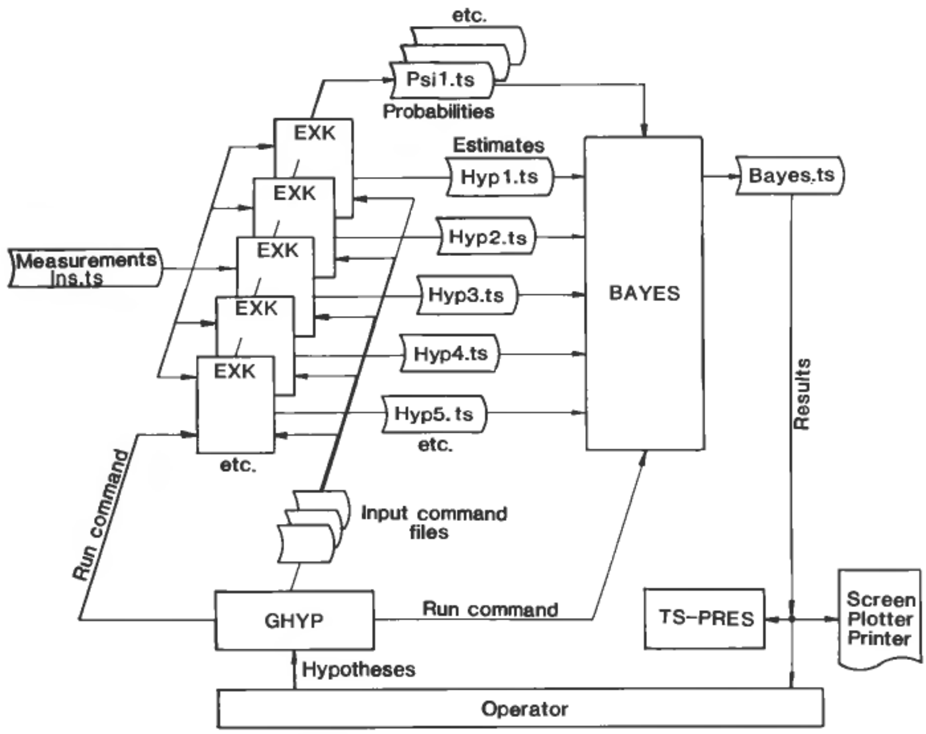

Figure 4. Schematic diagram of the calculation sequence in the diagnostic system. The parallel hypothesis models EXK produce state and parameter estimates, innovations and their probability densities. These probabilities are converted into normalized hypothesis probabilities by BAYES formula, parallel time series are output. The operator runs the system by defining hypotheses (GHYP) and interpreting the probability time series and their corresponding parameter estimates, thereby determining the condition of the plant.

faults in the sensors. These simulations are also done using the EXKALM program. With this simulator it is possible to develop a quite detailed model of the hydraulic behaviour of the power plant. Before the data are transferred to the estimator, mea-

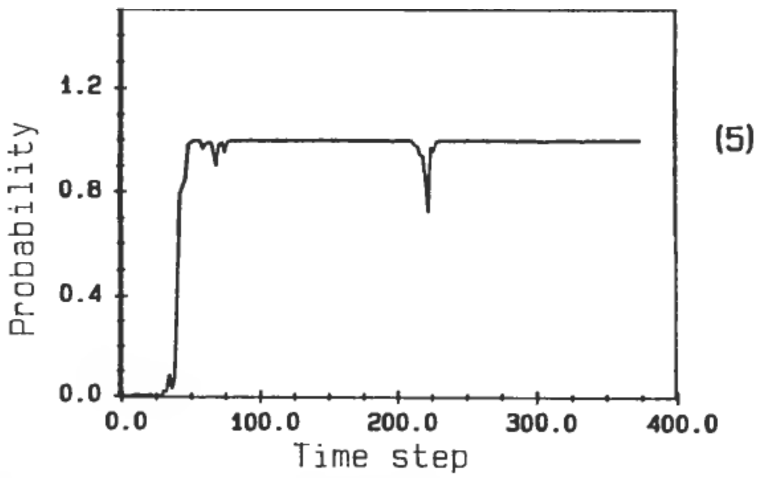

Figure 5. Calculated probability for Hypothesis no. 5, which assumes that the efficiency of the turbine is changed, (*Case a*).

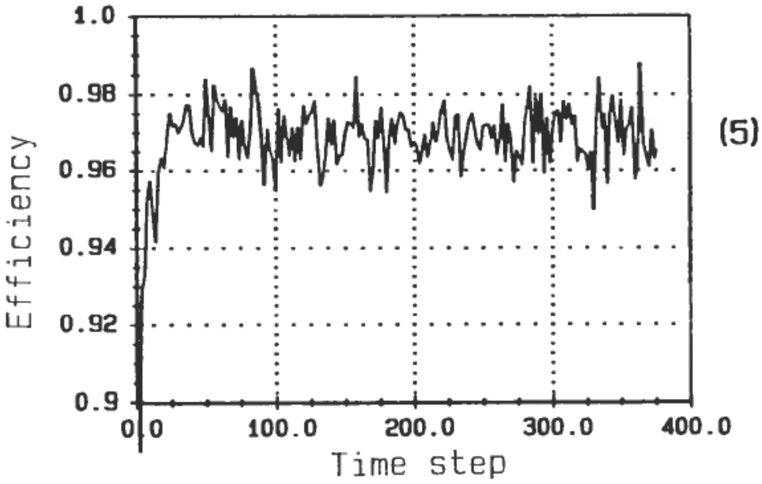

Figure 6. Estimated efficiency (0·97 of original value) for this case (*Case a*).

surement noise is added to the stationary values. In this way, quite realistic measurements can be simulated.

To illustrate the properties of the state and parameter estimation method as well as the mthod of hypothesis tests, we have simulated three faulty events:

Case a The efficiency of the turbine is reduced by 3% from its normal value. This is done for all points on the turbine efficiency curve. All other parameters are kept unchanged.

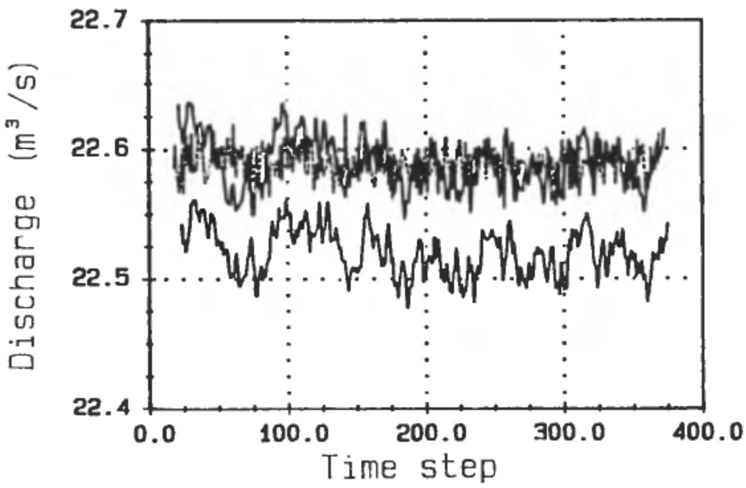

Figure 7. Upper curve: Estimated discharge using the correct hypothesis (solid curve), correct discharge as calculated by the simulator (dotted curve). These two curves have the same mean values and are difficult to distinguish from each other, (*Case a*). Lower curve: Estimated discharge assuming that the state is normal. This is not the currect hypothesis in *Case a*, and the estimate is seen to be biased by some $-0{\cdot}25\%$, which is 10 times the standard deviation of the estimate itself.

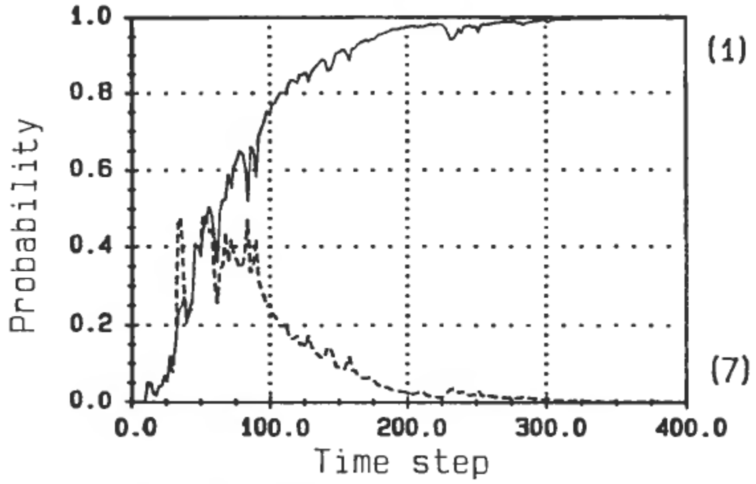

Figure 8. *Case b.* A simulated increase in the head loss coefficient of the headrace tunnel by 25%. Hypothesis no. 1, which is the correct one, initially competes with Hypothesis no. 7, which assumes that there is a bias in the upper reservoir level sensor.

Case b The head loss coefficient in the headrace tunnel is increased by 25% from its normal value, a case that has a negligible effect on the discharge. All the other parameters in the system are kept constant at their normal values.

Case c A bias in the measurement of the pressure head upstream of the trash-rack of −5 cm is simulated. All the parameters and other measurements are as normal.

The results are shown in the Figs 5–11.

By visually inspecting the raw measurements themselves it can be very difficult to distinguish between a pure measurement error and measurements indicating an increase in head loss parameters. In our simulations we have used quite large stan-

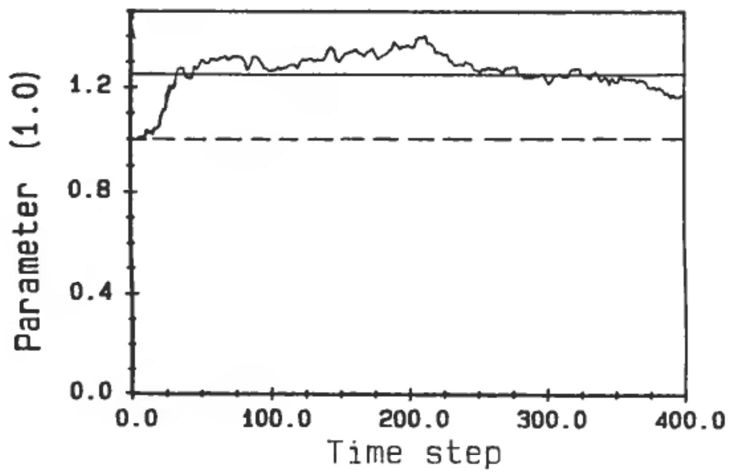

Figure 9. *Case b.* The head loss coefficient (per unit). Broken line is the normal value. Solid line is the simulated value and the solid curve is the estimated value.

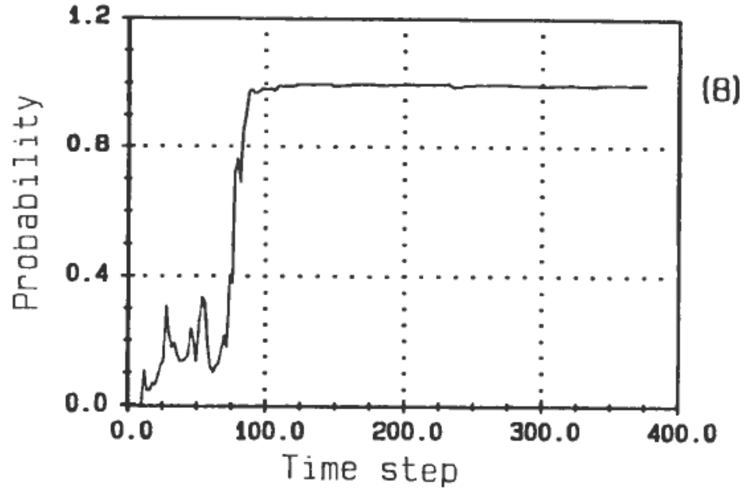

Figure 10. *Case c*. Simulated sensor bias. Probability of Hypothesis no. 8, bias in sensor 2, pressure upstream of the trashrack.

dard deviations in the measurement noise. For example, the pressure head upstream of the trashrack has a standard deviation which is 50% of the total head loss in the tunnel. The advantage of the MMHPT method is that the measurements are combined in a complete model of the hydraulic behaviour of the power plant, and the hypothesis of having the model that best corresponds to the measurements is taken to represent the condition of the power plant. This also shows that it is important to be aware of the fact that all hypotheses, with their corresponding models, give an estimate of both the states and parameters which will converge even if the hypothesis is wrong. Estimating parameters and discharge in this way means that we must be critical about which hypotheses we use. We should not rely on the state estimates without making sure that the corresponding hypothesis has a reasonably high probability of representing the plant.

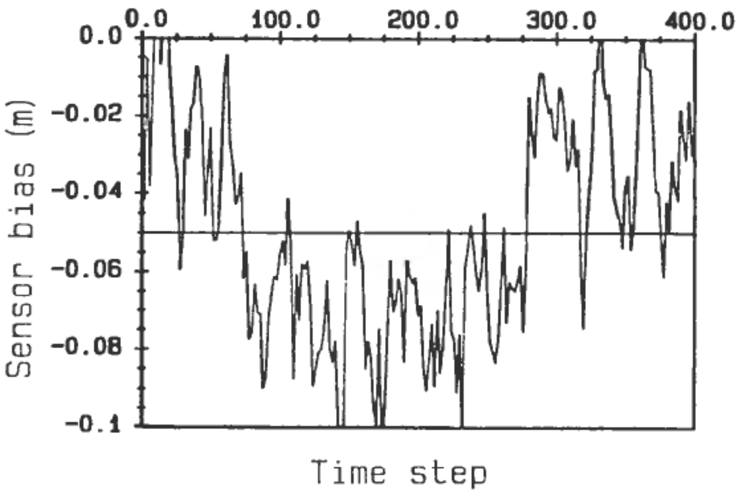

Figure 11. *Case c*. Solid line is the simulated bias (−5 cm), and solid curve is the estimated bias.

When two hypotheses compete as shown in Fig. 8, it is because of bad observability. The only thing that is different between measurement errors in the upper reservoir level sensor, and a change of head loss in the headrace tunnel is that a bias in the reservoir level measurement is obviously independent of the discharge, while the head loss in the headrace tunnel is proportional to the square of the discharge. This is the reason why the estimation method still reaches the right conclusion in this particular case, even for steady state flow conditions.

We have assumed random noise in all measurements. The variance of this noise is probably realistic in our simulations, but in practice, the noise will be oscillatory with only a few separate frequency components. These can be elastic pressure oscillations in the headrace system having a period of just seconds, or slow level hunting if there is a balancing reservoir or an airfilled pressure cavity on top of the pressure shaft. Furthermore, the controller equipment will impose hydraulic pressure oscillations as a result of variations in the frequency of the electric grid.

Once the installed measurement equipment becomes operative, hopefully during the summer 1988, we should be able to gain experience with respect to equipment reliability and calibration, the quality of our hydraulic model, and the ease with which the monitoring system can be operated by power plant maintenance staff.

The method described above has also been successfully introduced on the monitoring of gas turbines. DIAMOND (Diagnose and Monitoring Device) is a knowledge-based prototype system developed by Kongsberg KVATRO. The main task of the system is to diagnose a gas turbine driven generator set in steady state situations. This research has been reported by Skatteboe (1985, 1986) and Skatteboe, Tangen and Berge (1987).

10. Conclusions

A separate sensor for measuring the discharge with the same accuracy as the other measurements would of course make the loss monitoring more reliable, accurate and simpler, but the development of such sensors is expensive. Today's discharge meters have tolerances of the order of a few percent, typically 5%. Therefore, state estimation techniques might be worthwhile investigating more carefully, if accuracy of the order of 1% or less is required.

With permanently installed sensors it is possible to carry out condition monitoring of the hydraulic system during operation. The remote data acquisition system which can be added at a relatively low cost makes this monitoring system well suited for installation in the process computer or background computer in the control centre, as a tool for maintenance planning.

For larger power plants with several parallel hydraulic turbines, this monitoring system can also be used as a tool for adjusting the power output setpoints in order to make optimal use of the water during normal operation.

The estimation of conditions and parameters indicates the cause of many problems more directly. The result is improved direct diagnosis and a decreased need for the diagnostic system to know many alternative sources of faults in each case.

It is easier to construct and modify the diagnostic system if the measurement model of the process is known. It is for instance possible to add to the complexity of the functional description without having to change the monitoring hardware which has been installed.

The integration of this monitoring method into a knowledge-based system (expert system) is possible in two ways. First, the expert system might act as a front end between the operator and the simulation and estimation routines. Second, it might work as an inference machine acting upon a number of estimated parameters and states.

Mathematical models and modern recursive estimation techniques might well be part of the knowledge base of expert systems applied to condition monitoring and fault identification.

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