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A Study on System State Analyzer for Turbine Cycle Performance Tests

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Abstract

It is one of the oldest and the most important problems in signal processing to determine whether a system is abnormal or a sensor is failed through measured signals. The identification of sensor failure has been also focused for a long time in nuclear power plants(NPPs). Because only one sensor is installed at one point basically in turbine cycle in NPPs, it is not easy to detect system/sensor abnormality differently from the conventional diverse or redundant measurement systems. In this study, a novel system state analyzer(SSA) to discriminate system/sensor abnormality using measured signals in performance tests is proposed. Overall signal processing procedure and specific features of the SSA proposed were described respectively. Basically a statistical process control chart(SPC) is used for the identification of system/sensor abnormality, which is achieved by mean and variance change checking. To make a monitoring parameter of the SPC, signal innovation based on wavelet similarity check is proposed. For each methodology, simple demonstrations were shown.

I. Introduction

It is one of the oldest and important problems in signal processing to determine whether a system is abnormal or a sensor is failed through measured signals. The identification of sensor failure has been also focused for a long time in nuclear power plants(NPPs). Generally the discrimination between them makes plant operation and maintenance efficient. One of the most popular and the simplest technique may be voting technique in NPPs. Because sound sensors minimize the effect of failed sensors, the discrimination between system/sensor abnormality is accomplished. However voting technique is for only one-point multiple-sensors.

In turbine cycle in NPPs, the minimum number of sensors for operation is installed. That is one-point one-sensor on the whole. Because turbine cycle is less important for the safety viewpoint, one-point one-sensor system is not considered as severe problem. However economics of operating plants is getting focused, higher quality and more frequency of turbine cycle performance tests have been required than former days. Accordong to this trend, sensor accuracy in turbine cycle is getting more important. Although the requirements about sensor accuracy are well described in current performance test procedures, actual calibration work for each sensor is very troublesome especially in case of automatic data logging.

In this study, a system state analyzer(SSA) is proposed on the basis of wavelet similarity check and statistical process control chart(SPC) to improve sensor reliability under one-point one-sensor environment.

II. Development Strategy of a System State Analyzer

II.1. Concept of SSA

A SSA is a sort of annunciator to address system/sensor abnormality[1]. ‘State’ means the functional satisfaction of plant parameters at a specified time. Although the term ‘SSA’ is not used, a number of SSAs have been already studied. SSAs include fault detection and isolation, system monitoring, state estimation, and so on. Almost SSAs have architecture like Figure 1. At first, learned states taken from known normal states are prepared to use baseline states. After getting an observed state, it is compared the nearest learned state. If the deviation between the observed state and the learned state exceeds a criterion, the observed state is regarded as abnormal state. In this case, the justification for physical differences caused by plant operation conditions between observed states and learned states should be considered. If physical differences are not justified, learned states should be changed to another comparable states, called estimated states. As a result, observed states are compared with estimated states generally. In the state determination step in Figure 1, a SSA concludes observed state as a state among the following four states:

- Sensor and system normal
- Only sensor abnormal
- Only system abnormal
- Both sensor and system abnormal

We can conclude a good SSA has capability to clearly classify system state as four categories.

II.2. Implementation of a SSA

II.2.1. Generation of Estimated State

Learned states should be constructed using signals from sound sensors in sound systems. If learned states reflect all the operating conditions completely, we do not need to generate estimated state. However we may need a suitable method to generate estimated state in most cases.

In the previous studies, the generation of estimated states was the determination of normal operation boundary considering parameters' correlation. Because the purpose of SSAs is to monitor only whether a system is normal or abnormal, this approach is enough to identify system state. The concept of the determination of normal operation boundary is shown in Figure 2. For the correlation analysis among a number of parameters, multivariate statistics has been used widely. In multivariate statistics such as principal component analysis(PCA), partial least squares(PLS) method, or their modification, parameter dimension is compressed to easily identify parameters' correlation[2~7]. The compressed variables construct normal operation boundary in superficial space and they are advantageous in showing system abnormality graphically and determining system state.

However this approach is not suitable because each parameter's abnormality should be checked rather than overall system abnormality in performance tests. Therefore we need normal operation boundary for each parameter. This concept is shown in Figure 3.

II.2.2. Deviation Checking

Another important part in SSAs is to determine state, and it is related to deviation checking between estimated states and observed states. The basic idea is to check a specified deviation limit. For the most case, statistics-based techniques have been used considering parameters' random characteristic. Because observed states are continuously input, SSAs should have sequential deviation checking capability. A good representative of statistical techniques having this characteristic is sequential probability ratio test(SPRT)[7~10] and statistical process control chart(SPC)[2,6].

In typical SPRT, normal state is defined as a null hypothesis, and abnormal state is defined as an alternative hypothesis. Deviation measure is likelihood ratio, and likelihood ratio may be different according to monitoring parameters like mean deviation or variance deviation.

SPC has also similar concept with SPRT. However deviation measure is different according to a kind SPCs, for example, Schwart chart, cumulative-sum(CUSUM) control chart, or exponentially weighted moving average chart. SPCs have the wide spectrum of application due to flexible control limit and pattern analysis capability[11]. In this study a SPC is utilized for deviation checking between estimated states and observed states.

SPC in Turbine Cycle Performance Tests

Process control in a performance test may be defined by ‘conformation to design parameters according to operating condition’. Operating condition in turbine cycle performance tests is defined by a set of turbine cycle boundary parameters that is not easily controlled such as main steam conditions, condenser cooling water conditions, or component physical properties like heat exchanger tube number. Generally the vendor delivering turbines provides heat balance diagrams for design turbine cycle according to operating conditions. These are optimal parameter values to produce electricity as efficient as possible in given operating conditions. These sets can be considered as learned states. If there is system or sensor degradation, observed states become different comparing to the learned states.

In a SPC, learned states or estimated states become central line(CL), and upper/lower control limit(UCL, LCL) indicate abnormality criteria. Actually operating conditions in all performance tests cannot be always the same because of environment effect or core characteristics. This means that CL, UCL, and LCL can be changed according to performance tests. Therefore it is useful to regard the difference between observed states and learned states/estimated state as CL.

SPC Applicability

There is another implicit important principle in SPC approach. Originally SPC can be applied to random variable independently identically distributed. The observed state in which we are interested is correlated time-series. When correlated data is applied to SPC, its capability is decreased remarkably. Therefore signal de-correlation is important. Mainly there are two approaches for signal de-correlation. The one is to transform original space to orthogonal superficial space. PCA and PLS has this property. In case of monitoring of the estimated states generated by PCA or PLS, we can utilize this advantageous property at the same time. The other is to preserve original space. Instead of axes transformation, this approach is based on the property that the difference between well-estimated state and observed state becomes random variable has probability distribution such as normal distribution. The degree of ‘well’ estimating states is related to the level of de-correlation.

State estimation is classified into two categories, forward method and backward method. The forward method is that a system model based on physical characteristics already exists and this model generates estimate states. As representative examples, there are system simulation, system state model and Kalman filter model[8]. In the forward method, system model reflecting actual physical characteristics is difficult. In the backward method, after getting operating signals, they make estimated states. As representative examples of the backward method, there are Box-Jenkins time-series prediction model[7,9], neural network model, or probability density function prediction method. There is limitation to get a broad spectrum of learned states in the backward method.

<u>State Discrimination Using SPC</u>

The discrimination between system/sensor failures is not an inherent capability of SPCs. However this can do if deviation measure is the difference of mean or variance between observed states and estimated states. If we assume all operating conditions are included in estimated states, it is possible to analyze system and sensor state into the following four cases:

- No variance and mean change: This is clear normal state of both system and sensors.
- No variance change, but mean change: If there is any problem in a sensor, the responses of mean and variance of the sensor may be different. Therefore no variance change means that sensor is normally operating. However mean change shows some system problems.
- Variance change, but no mean change: In this case, we can doubt sensor integrity although mean value of the sensor is not changed. However we cannot identify exact sensor failure mode.
- Both change: This case is abnormal state of both system and sensor. However we cannot identify whether a system is abnormal or a sensor is failed.

In this strategy there are many shortcomings, but the identification about sensor failure will be helpful in performance tests. This strategy is shown in Figure 4 as a flowchart.

This strategy was validated by a simple example. In Figure 5, raw data of condenser tube-side outlet temperature in Wolsong NPP unit 1 is shown. To de-correlate data, a seasonal time-series model SARIMA$(0,1,1)\times(0,1,1)_{13}$ is applied[12]. We can assume that the difference of the estimated state from the proposed model and the observed states is normal distribution by appropriate probability distribution tests. In Figure 6, there are three CUSUM charts showing mean change and R charts showing variance change when noise is added to observed states. We can see severe deviation in CUSUM chart, but the effect in R chart seems to be negligible in Figure 6, (b). In the case (c), deviation in R chart is severe, but deviation in CUSUM chart is small.

II.3. State Estimation Using Wavelet Similarity Check

Basic of Wavelet Analysis

The basic concept of wavelet analysis is multi-resolution analysis(MRA) that decomposes signal into two parts, high frequency part and low frequency part. In wavelet decomposition, scaling function and wavelet function are used to make orthogonal axes for the location of approximations and details[13]. All the bases generated from scaling function and wavelet function are mutually orthogonal. Mathematically scaling function and wavelet function is corresponded to filter system. Scaling function corresponds to low frequency pass filter, and wavelet function corresponds to high frequency pass filter. That is, low frequency part is located on approximation axes, and high frequency part exists on detail axes. The results of the MRA for data of Figure 5 are shown in Figure 7.

Similarity Check in Turbine Cycle Performance Test

Each approximation and detail is calculated by convolution of original signal and scaling/wavelet function. Convolution may be one of similarity measures. At each translated position and scaled shape, a selected scaling and wavelet function is compared with original signal, and provides a degree of similarity, called approximation coefficients and detail coefficients by convolution. In other words, approximations and details mean a degree of similarity to the original signal. If approximations and details of two signals are similar, original ones are also similar. If the deviation between approximations or details is larger, they are different.

Similarity check using wavelet analysis can be used for the generation of estimated states. Basically, estimated states are made by the combination of learned states. As mentioned above, learned states are generated by plant simulation or actual plant signals. In this study, turbine cycle simulation model is used to simply demonstrate the concept of similarity check using wavelet analysis. Kori NPP unit 1 is modeled by PEPSE, which is a steam turbine cycle modeling tool[14].

The overall process of estimation state generation is shown in Figure 8. The upper left figure in Figure 8 shows the preparation of learned states. 19 learned states about temperature according to several main steam conditions and condenser vacuum are acquired at inlet/outlet of major turbine cycle components such as turbine, feedwater heater, or pump from PEPSE model.

Indexes from 1 to 19 are given respectively to each learned state to easily distinguish them. The next step is to prepare approximations and details of learned states using wavelet decomposition. This is the upper-right figure in Figure 8. As a wavelet function, Daubechies 1 function, called Haar, is used and its level is three. To demonstrate the course of estimated state generation, two case studies are accomplished. In Figure 9, there are an original signal and two modified signals, and their wavelet decomposition results. X-axis means sorted component identification number, and y-axis is temperature. The original signal is No. 1 learned state. Two modified signals are maded using the original signal and they can be considered as two observed states. Figure 9 (b) represents single sensor failure and (c) represents multiple sensor degradation with about 5% of original value. The next step is to calculate similarity measure to implement the lower-right of Figure 9. There may be a number of measures to check similarity. The representative measure is signal energy[15]. Energy of the signal decomposed by wavelet analysis is defined as follows:

$$\|A_0\|^2 = \|A_N\|^2 + \sum_{i=1}^{N} \|D_i\| \tag{1}$$

This equation implies that signal energy is invariant independently on wavelet decomposition. However its contrary is not always true. Therefore a little modified measure like a following equation is proposed. δ is a threshold value representing deviation criterion.

$$A^{estimated} = \min_{\substack{i \\ \left|A_i^{learned} - A^{observed}\right| < d}} \left(\left\| A_i^{learned} - A^{observed} \right\|^2 \right) \tag{2}$$

$$Dn^{estimated} = \min_{\substack{i \\ \left|Dn_i^{learned} - Dn^{observed}\right| < d}} \left(\left\| Dn_i^{learned} - Dn^{observed} \right\|^2 \right) \tag{3}$$

where n: wavelet decomposition level

i: learned state index

The comparison of approximation/detail vector sum is consistent with signal energy measure. The difference is that it is excluded from calculation if the difference exceeds a pre-defined threshold. This technique is introduced for the reliability improvement of similarity checking process. Table I shows the approximations and details of estimated states after similarity check. Intuitively we can expect the estimated state of Case1 and Case2 should be No. 1 learned state. In case of multiple sensor degradation, Case 2, the accuracy is somewhat lower. At last wavelet reconstruction based on the selected approximations and details is carried out to synthesize actual estimated states.

III. Implementation of Integral System State Analyzer

On the basis of SPC and wavelet similarity check, an integral SSA is proposed. In Figure 10, signal processing procedure in the integral SSA is shown. The summarization of each step is as follows:

- Data acquisition: This is data acquisition during a performance test. Data acquisition can be achieved by manual logging or automatic signal acquisition. A signal set at each sampling time construct one observed state.
- Basic check for single observed state: Basic check means fundamental signal processing methods such as sensor range check or fluid state check.
- De-noising: This is carried out for each parameter. Various techniques like wavelet analysis, Fourier analysis, or conventional digital/analog filters can be used for de-noising method. This is for the identification of main trend of each parameter.
- Similarity check: In this step, pre-defined learned states are required. Through similarity check using wavelet analysis, we can get estimated states reflecting operating conditions of the performance test. ‘Innovation’ means the difference between observed states and estimated states. Innovation for mean change and variance change is used as a monitoring variable in SPC.
- Mean and variance check: Generally CUSUM chart for mean change check and R-chart for variance change check is used. It is known that CUSUM chart is sensitive for mean change[11]. According to the results of this step, we can plan effective maintenance schedule or improve the accuracy of a performance test.

IV. Discussions and Conclusions

In this study, a novel SSA for turbine cycle performance tests in NPPs was proposed. Considering special characteristics of turbine cycles in NPPs, the methodology to discriminate system/sensor abnormality is developed.

Overall signal processing procedure and specific features of the SSA proposed were described respectively. Basically SPC is used for the identification of system/sensor abnormality, and signal innovation based on wavelet similarity check is implemented to support the capability of SPC.

However there are some shortcomings in the proposed SSA. These problems should be studied additionally:

- Background theory of the generation of estimated states: Although the method associated with the generation of estimated states was proposed and demonstrated using simple examples, its theoretical background is not established.

- Proposal of an improved similarity measure: The similarity measure used in this study uses a threshold value to exclude excess deviation in calculating similarity. However to determine a threshold value is heuristic and this may be troublesome.

V. References

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Table I. Results of similarity check for each case study

	A_3	D_3	D_2	D_1
Case 1	No. 1	No. 1	No. 1	No. 1
Case 2	No. 1	No. 8	No. 7	No. 1

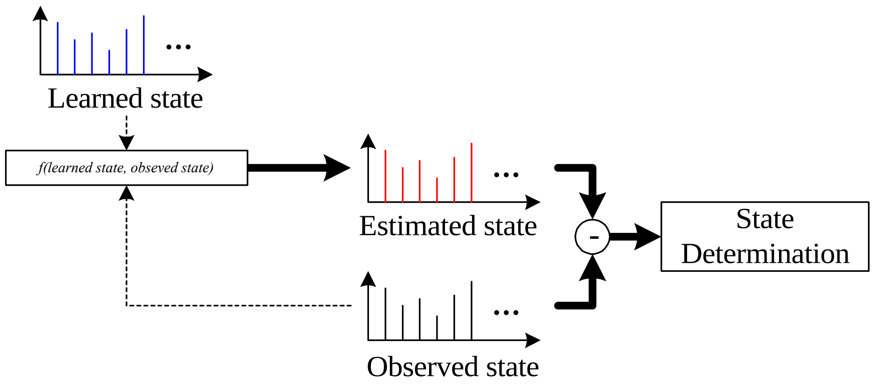


Figure 1. The concept of system state analyzer

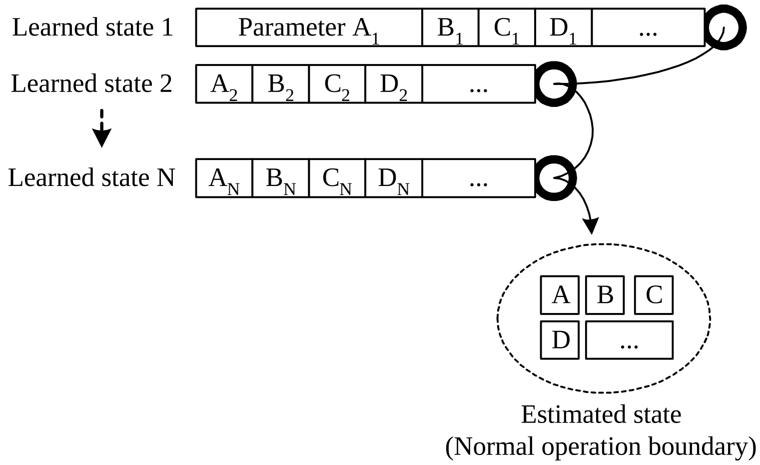


Figure 2. Generation of an estimated state(previous case)

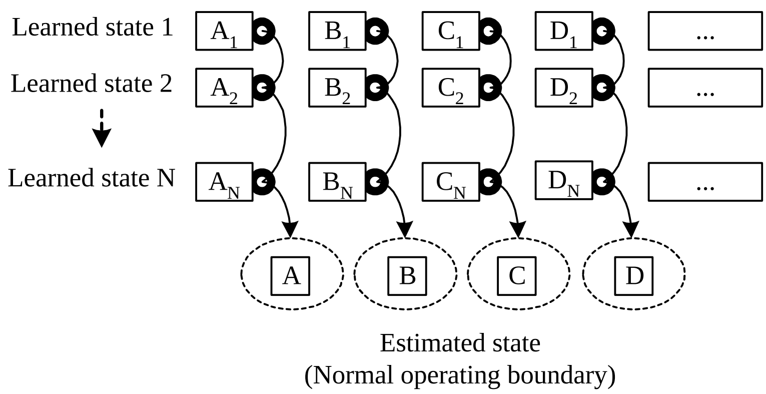


Figure 3. Generation of an estimated state(new case)

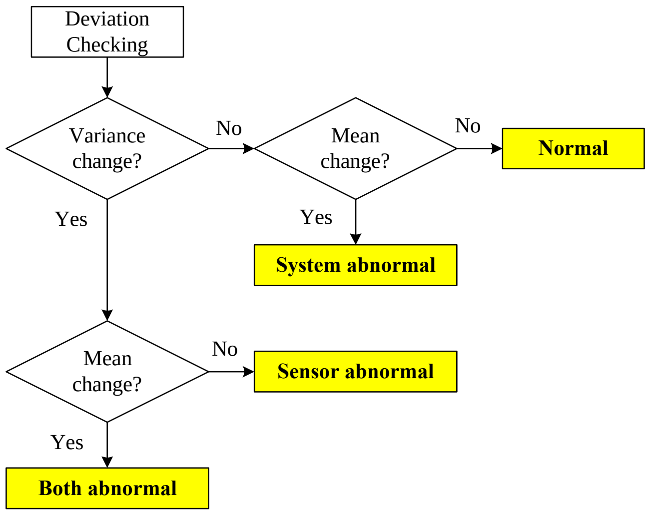


Figure 4. Overall deviation checking concept using SPC

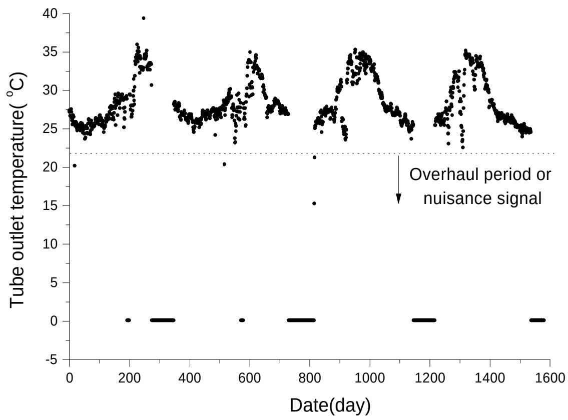
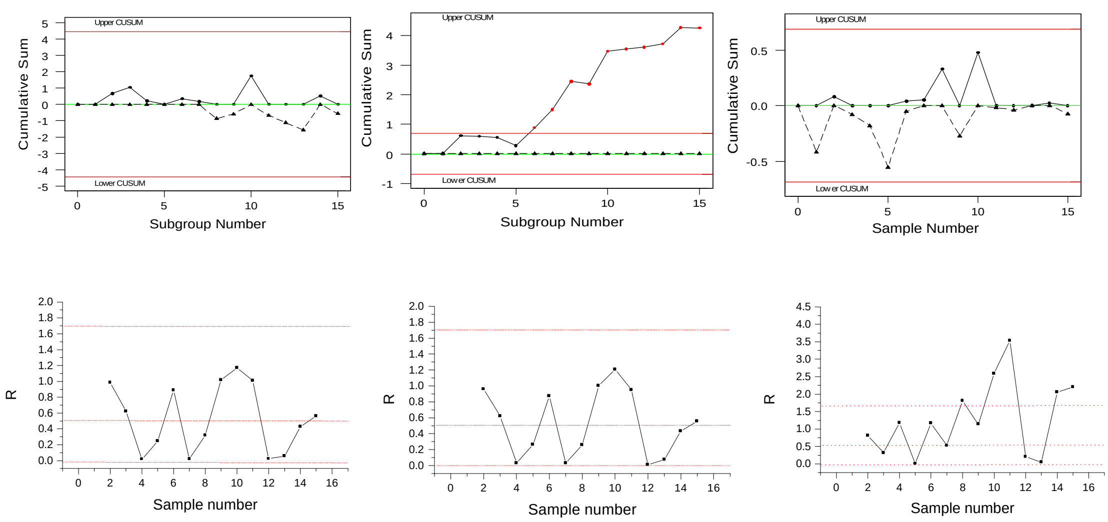


Figure 5. An example of time-series data for demonstration of SPC capability(Wolsong NPP unit 1, condenser tube-side outlet temperature)



(a) (b) (c)

Figure 6. Comparison of SPCs (a) original observed states, (b) mean change, adding N(2%, 0), (c) variance change, adding N(0, 1)

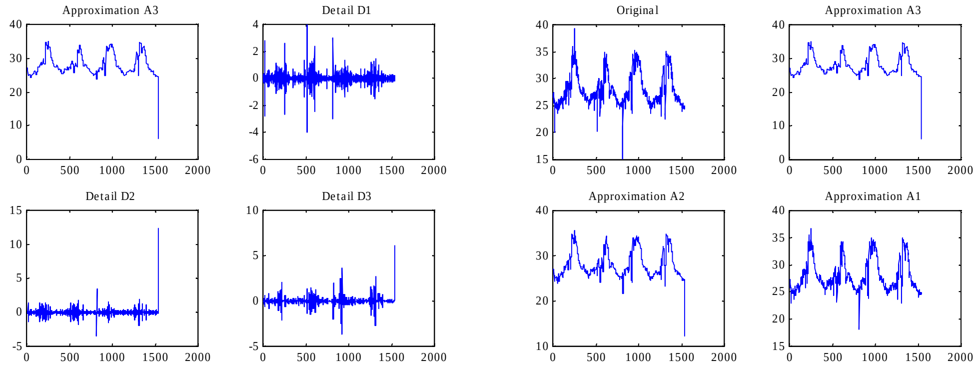


Figure 7. MRA results for Figure 5(wavelet: Daubechies 1, level 3)

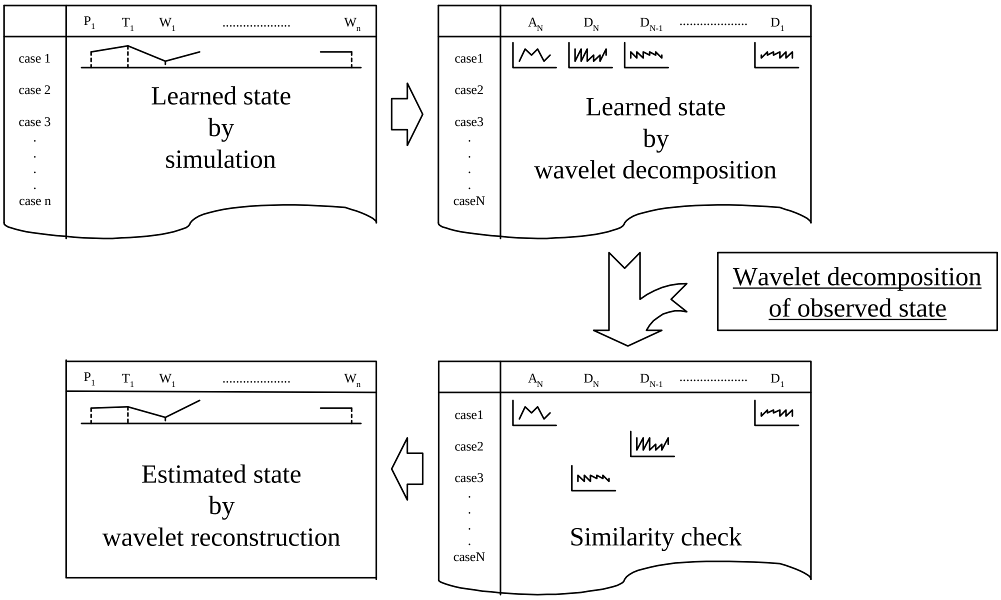


Figure 8. Estimated state generation using wavelet similarity check

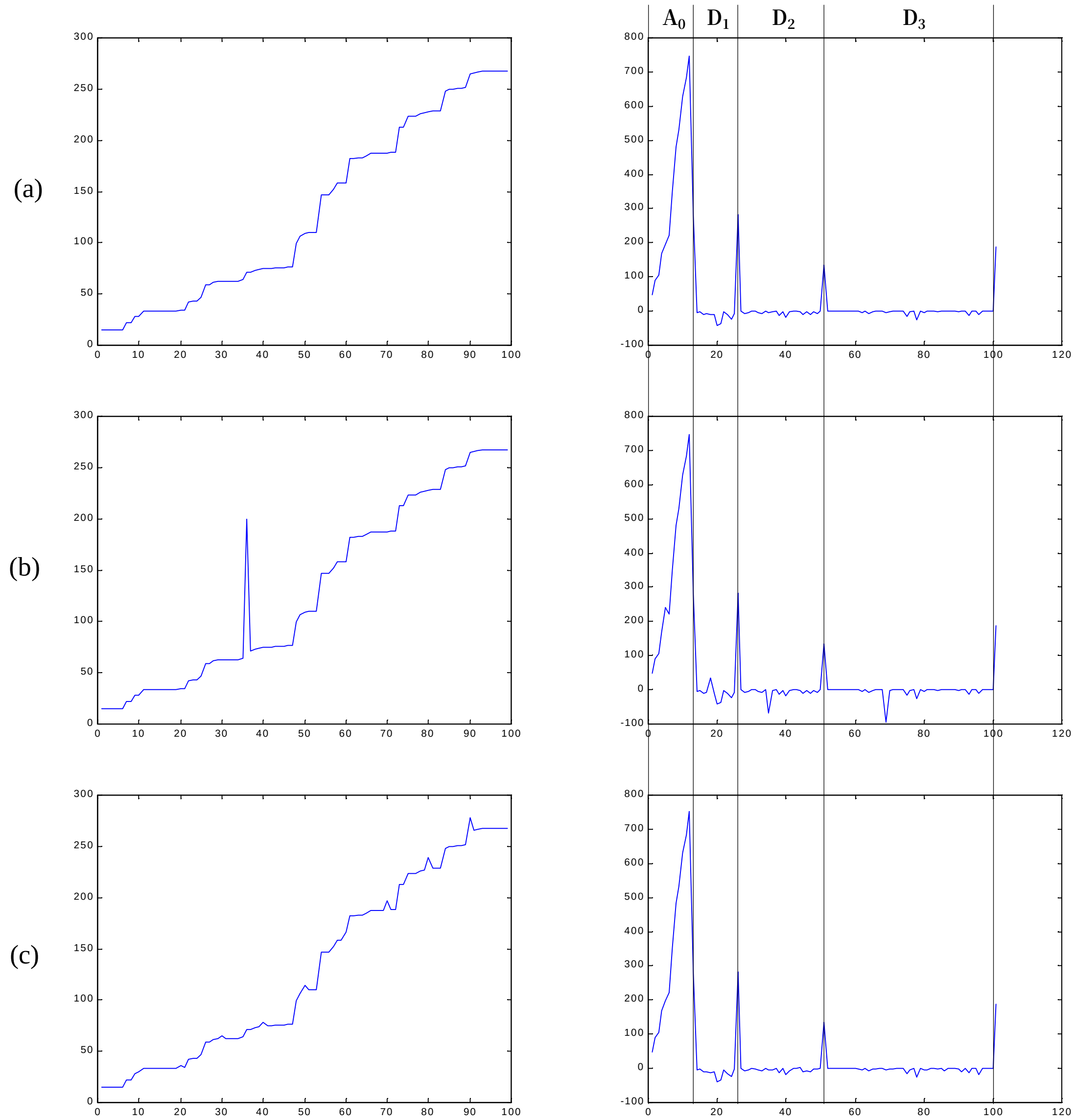


Figure 9. Case studies for the generation process of estimated states

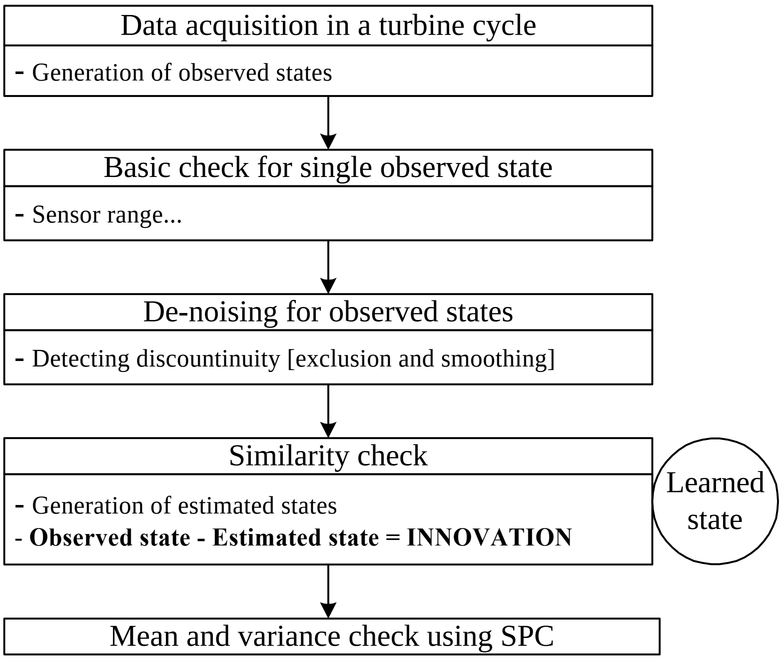


Figure 10. Flowchart for the implementation of integral system state analyzer