CONDITION MONITORING USING EMPIRICAL MODELS: TECHNICAL REVIEW AND PROSPECTS FOR NUCLEAR APPLICATIONS

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The purpose of this paper is to extensively review the condition monitoring (CM) techniques using empirical models in an effort to reduce or eliminate unexpected downtimes in general industry, and to illustrate the feasibility of applying them to the nuclear industry. CM provides on-time warnings of system states to enable the optimal scheduling of maintenance and, ultimately, plant uptime is maximized. Currently, most maintenance processes tend to be either reactive, or part of scheduled, or preventive maintenance. Such maintenance is being increasingly reported as a poor practice for two reasons: first, the component does not necessarily require maintenance, thus the maintenance cost is wasted, and secondly, failure catalysts are introduced into properly working components, which is worse. This paper first summarizes the technical aspects of CM including state estimation and state monitoring. The mathematical background of CM is mature enough even for commercial use in the nuclear industry. Considering the current computational capabilities of CM, its application is not limited by technical difficulties, but by a lack of desire on the part of industry to implement it. For practical applications in the nuclear industry, it may be more important to clarify and quantify the negative impact of unexpected outcomes or failures in CM than it is to investigate its advantages. In other words, while issues regarding accuracy have been targeted to date, the concerns regarding robustness should now be concentrated on. Standardizing the anticipated failures and the possibly harsh operating conditions, and then evaluating the impact of the proposed CM under those conditions may be necessary. In order to make the CM techniques practical for the nuclear industry in the future, it is recommended that a prototype CM system be applied to a secondary system in which most of the components are non-safety grade. Recently, many activities to enhance the safety and efficiency of the secondary system have been encouraged. With the application of CM to nuclear power plants, it is expected to increase profit while addressing safety and economic issues.

KEYWORDS : Condition Monitoring, Nuclear Power Plant, State Estimation, State Monitoring

1. INTRODUCTION

Unplanned downtime is not a desirable occurrence in any industry because it requires expensive follow-ups to return the system to the normal state. The companies managing nuclear power plants (NPPs) know that downtime is not only costly, but it is also prohibitive. The causes of unexpected downtime can be found throughout the entire life cycle of NPPs, and the strategies to reduce or eliminate the downtimes may be different at different points in the life cycle. The purpose of this paper is to review condition monitoring (CM), which is an emerging technology in industry even though it is an old topic in academia, and to explore the feasibility of applying CM to the nuclear industry. CM alerts the user to the status of the system states so that maintenance can be scheduled optimally, thereby maximizing plant uptime. Currently, many systems do not have a process to identify the operational status of the system components. Most current maintenance processes are either reactive or preventive maintenance, but these maintenance strategies can be expensive or unnecessary. Such maintenance is increasingly regarded as poor practice because the component does not necessarily require maintenance, thus the cost and resources are wasted. Moreover, unnecessary maintenance can introduce failure catalysts into properly working components. [1]

One maintenance trend seen in leading companies is to integrate CM with predictive maintenance (PM). Integrating CM and PM allows companies to avoid time-

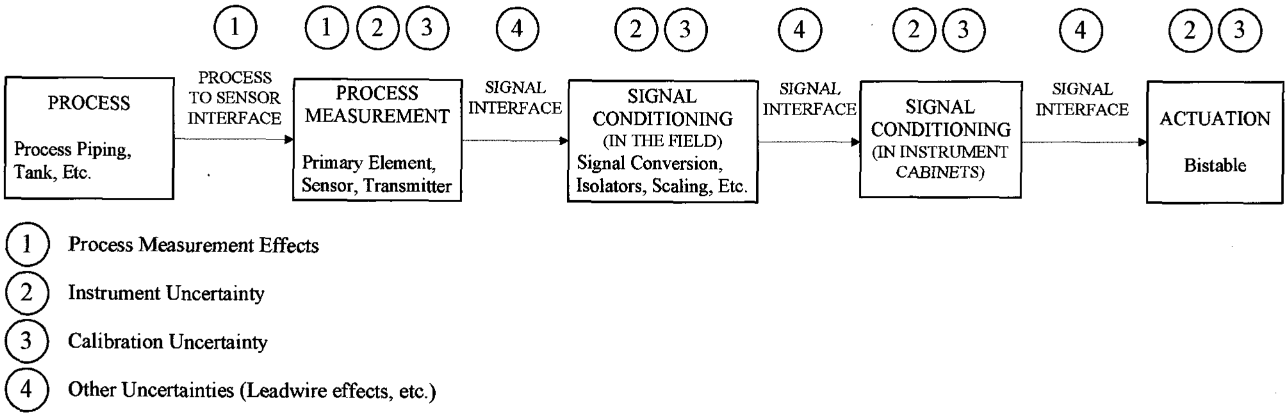

Fig. 1. Uncertainties in an Instrument Channel

consuming, expensive, and unnecessary maintenance. The historical data on failure rates, as well as the current status of the system, both determine the necessity of maintenance. Increased availability and efficiency resulting from decreased maintenance costs are the most obvious benefits which result in reduced maintenance requirements, longer periods between outages, fewer emergency shutdowns, more efficient use of labor resources, and better inventory control. Companies such as Toyota, GM, Samsung, ABB, IBM, and GE perceive investments in CM and PM to be the next step after lean manufacturing. [2-4] Since CM is based on computer systems, information technology, and instrumentation infrastructure, traditional industries may not be familiar with the uses of CM. However, considering current information technology, the application of CM, even in traditional industries, should not be limited by technical difficulties, but rather it should be recognized as a matter of importance. For instance, fossil fuel plants have only recently begun to increase profit through the use of CM. [1, 5] In NPPs which consider safety to be a top priority, scheduled and preventive maintenance continue to be the main maintenance activities. In order to compete with other sources of electricity and to survive under stricter safety standards, the introduction of CM into potentially applicable areas may become indispensable in the near future.

2. TECHNICAL REVIEW OF CONDITION MONITORING

Limiting the review to the nuclear field, there are two NUREG reports where the potentials of CM are outlined. NUREG/CR-6343 provides the technical aspects of CM as well as the results of research projects that the authors performed. [6] Even though it was published in 1995, it still provides the essential concepts and guidelines for engineers who are interested in CM. NUREG/CR-6895 was published in 2006. [7] This report provides many applications which have been developed recently. Particularly, the authors collectively organized their achievements, [8, 9] and this report is another essential reading to facilitate the understanding of CM. However, this paper is concerned with contents that are more technically-oriented than the above NUREG reports. By providing not only the details of the CM techniques but also an integration method for a CM system, it may be useful to those who wish to more fully catch the technical concept CM. Since a technical review facilitates the understanding of the essentials required to introduce CM into the nuclear field, it is thought that the next phase of CM will be to become a promising option to increase the competitiveness of NPPs. It is noted that the application of CM differs according to differing circumstances, but this section describes its common technical characteristics.

2.1 Capability of Condition Monitoring

In order to understand the purpose and capability of CM, it is necessary to recognize the sources of uncertainties in instrument channels. An instrument channel normally consists of a sensor, signal conversion, signal condition, and an actuator. In an NPP, the representative sensor types are thermocouples or resistance temperature detectors (RTDs) to measure temperature, pressure transmitters, flow-meters, neutron flux or radiation detectors, and vibration gauges that measure the integrity of the rotational equipment. The signal converter needs to transmit electrical signals through cables. Signal conditioning, sometimes called signal processing, includes amplification, logic calculation, isolation, or denoising. Actuators are used to control components such as reactor trips. All elements in an instrument channel, as well as their interfaces, have uncertainties as shown in Figure 1. [6] Sensor failure or sensor

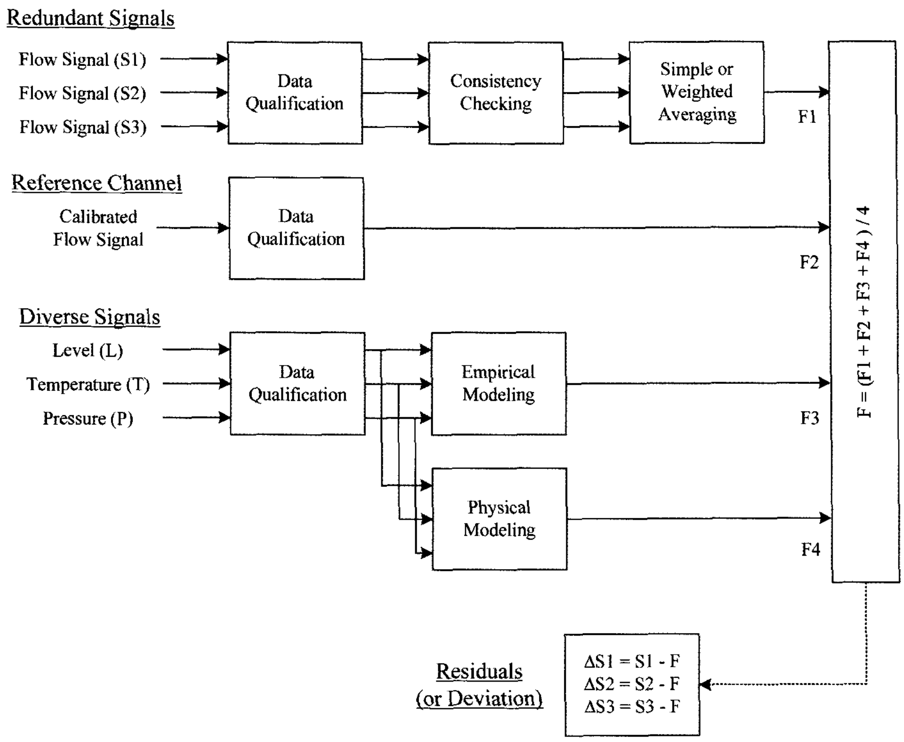

Fig. 2. Three Approaches for Condition Monitoring

drift indicates the mixed results of those uncertainties.

While monitoring a process, CM can confuse sensor failure with process variation. This variation results from operational changes, temporary transients, or process failures, and is an inherent characteristic of the system. The observations from failed sensors are an illusion of the intrinsic status. In particular, the confusion of process failures with sensor failures may result in performance degradation or, even worse, unexpected system shutdowns. The separation of these failure types is not easily achieved using the conventional technologies. The capabilities of CM suggest that this separation is the role that should be assigned to it. CM distinguishes process failures from sensor failures, and annunciates the severity of the process failure. CM also estimates the anticipated states of a system and detects the difference between the estimated state and the current measured state. In this study, 'state' refers to any one of the various conditions characterized by definite quantities in a process. [10] This paper outlines the technical features of two CM categories: state estimation and state monitoring.

2.2 State Estimation

State estimation is one of the two pillars supporting CM. The entire process of CM is described in Figure 2, which was taken from a NUREG report. [6]

Figure 2 shows that there are three state estimation techniques:

- State estimation using redundant signals
  If a large number of redundant signals are available, their simple or weighted average can provide a reasonable system state when a single reading cannot provide an appropriate estimation. This technique can be used with RTDs or thermocouples in a primary system. In addition, the redundant sensors have the advantage of being cross -calibrated, which means a single calibrated sensor can be a reference signal generator.
- State estimation using reference signals
  Usually a single sensor is installed at a single point so a single scan for a specific physical quantity can be read. In this case, the state estimation should be performed in a different manner. A calibrated reference instrument can enable the system to distinguish between process drift and instrument drift. For state estimation using redundant signals, one of the channels can be a reference channel that has been manually calibrated. In this approach, it is recommended that one of the redundant channels be calibrated periodically.
- State estimation using diverse signals
  This is another option when a large number of redundant sensors are not available. State estimation using diverse signals can be used in lieu of, or in addition to, a reference signal. While the detailed procedure of state estimations

using redundant or reference signals is simpler and more intuitive than that using diverse signals, most industries have difficulty in adopting the procedures based on redundant signals or reference channels unless they are safety-critical processes. It is also known that state estimation using diverse signals is more practical and advantageous. Both physical and empirical modeling techniques can be used, but the models must be carefully chosen since each one has its own advantages and disadvantages in specific circumstances.

As shown in Figure 2, state estimation using diverse signals can be divided into approaches based on (1) physical models and (2) empirical models. These two approaches have been complementarily developed over time. Figure 3 shows the overall scheme of state estimations using diverse signals. [11] The current trend in technology development appears more 'data oriented' over understanding systems' physics, which is strongly dependent upon the practicality of the methodology in use.

The following subsections delineate the conceptual description of the state estimation methodologies presented in Figure 3. In the literature, it is common for two or more methodologies to be combined to obtain better results, so occasional ambiguity occurs when distinguishing one technique from another. The following section will attempt to describe the unique features of each technique.

2.2.1 Physical Models

If we know the pressure at the outlet of a steam generator in a pressurized water reactor, we should be able to determine its temperature, since we know that the steam is saturated. This knowledge does not come from a measurement, but from a known physical fact and can be used as a representative physical model in predicting a system's state. The physical model based approach estimates a system's state using an analytical model that includes the mechanical, material, and operational characteristics of the system. The benefit of the physical model based approach is that it displays the behavior of a system before the system begins running. It also facilitates the diagnosis of a malfunction because physical models explicitly show the correlations between the system parameters. However, this methodology is only valid for specific problems, that is, physical models must be developed system-by-system. In addition, the feedback of the operational history is not easily input, which is disadvantageous.

- System modeling using first principles
  The system model using first principles is a method of state estimation which uses well-known physical or chemical principles such as mass and energy conservation, motion laws, thermo-dynamic principles, and hydraulic principles. This method is more commonly known as simulation. In areas requiring CM, this approach has

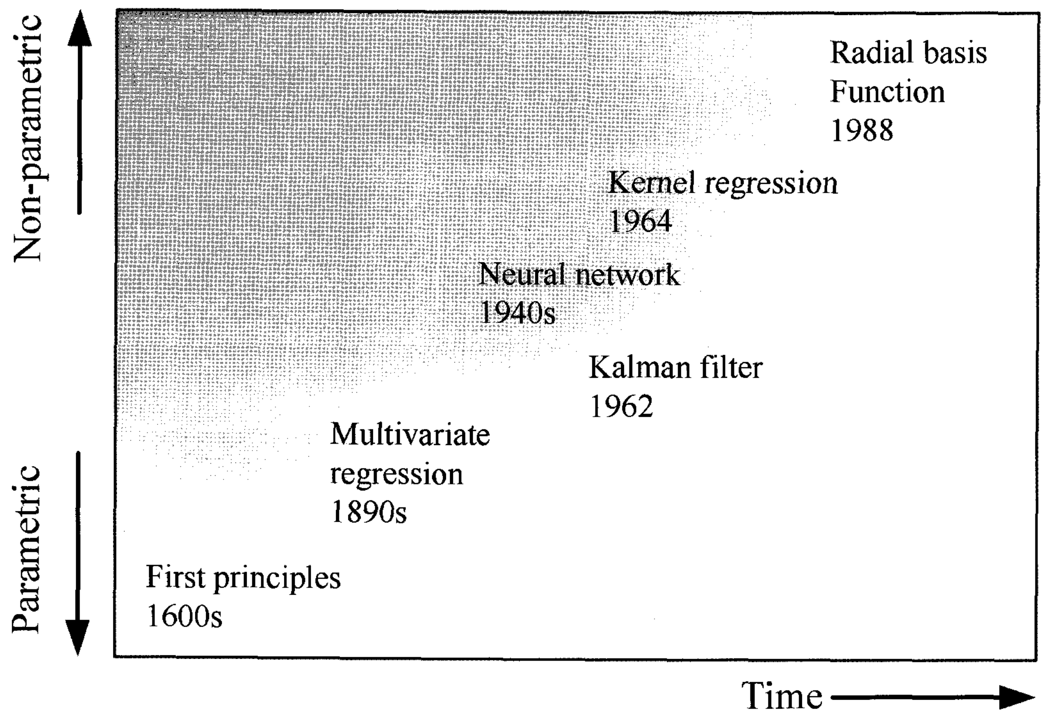

Fig. 3. Development of State Estimation Techniques

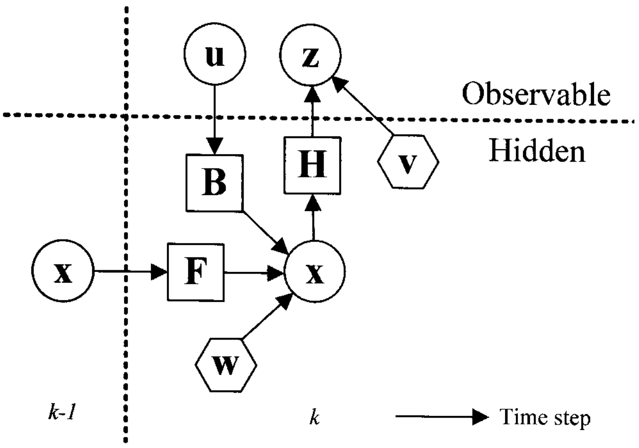

Fig. 4. Principles Used in the Kalman Filter

limited practicality, but system modeling using first principles should be a prerequisite because it aids the understanding of a system's mechanisms.

- Kalman filter

The Kalman filter was originally developed for use in spacecraft navigation. Later, it was discovered that the Kalman filter is very useful for estimating the system states that can only be observed indirectly. In mathematical terms, a Kalman filter estimates the states of a linear system at discrete points in time. The Kalman filter not only works well in practice, but it is theoretically appealing because it minimizes variances in the estimation error. Recently, an extended Kalman filter has been developed which has a robust noise distribution assumption and is available for nonlinear systems. [12, 13]

Figure 4 shows the principles used in the Kalman filter. It assumes that the state of the system is represented as a vector of real numbers such as the matrices $\mathbf{F}_k$, $\mathbf{H}_k$, $\mathbf{Q}_k$, $\mathbf{R}_k$, and, if necessary, $\mathbf{B}_k$ for each time-step, k, as in Equations (1) through (4). When these matrices are determined, the results of the system modeling using first principles may be required. The Kalman filter assumes the true state at a time, k, evolves from the state at (k - 1) according to:

$$\mathbf{x}_k = \mathbf{F}_k \mathbf{x}_{k-1} + \mathbf{B}_k \mathbf{u}_k + \mathbf{w}_k, \quad (1)$$

where $\mathbf{F}_k$ is the state transition model applied to the previous state ($\mathbf{x}_{k-1}$), $\mathbf{B}_k$ is the control-input model applied to the control vector ($\mathbf{u}_k$), and $\mathbf{w}_k$ is the process noise which is assumed to be drawn from a zero mean and multivariate normal distribution with a covariance $\mathbf{Q}_k$:

$$\mathbf{w}_k \sim N(0, \mathbf{Q}_k). \quad (2)$$

At time k, an observation, $\mathbf{z}_k$ in a visible or observable state and $\mathbf{x}_k$ in a hidden or true state, is made according to:

$$\mathbf{z}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{v}_k, \quad (3)$$

where $\mathbf{H}_k$ is the observational model that maps the true state space into the observed space, and $\mathbf{v}_k$ is the observational noise which is assumed to be a multivariate normal distribution with zero mean and covariance $\mathbf{R}_k$:

$$\mathbf{v}_k \sim N(0, \mathbf{R}_k). \quad (4)$$

The initial state and noise vectors at each step $\{\mathbf{x}_0, \mathbf{w}_1, ..., \mathbf{w}_k, \mathbf{v}_1 ... \mathbf{v}_k\}$ are assumed to be mutually independent. At each discrete time increment, a linear operator is applied to the current state to generate the new state. Then, another linear operator mixed with additional noise generates the visible outputs from the hidden state. This estimation is performed in a recursive manner, which means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. There are two more variables that complete the Kalman filter algorithm:

- $\hat{\mathbf{x}}_{i|j}$ which is the estimated state at time, i, using the state at time j, and
- $\mathbf{P}_{i|j}$ which is the error covariance or the estimated accuracy of the state estimate at time, i, using the error covariance at time j.

Figure 5 summarizes the mathematical algorithm of the Kalman filter using the above two variables. The prediction step uses the state estimate from a previous time step to produce an estimate of the state at the current time step. In the update step, observations from the current time step are used to refine the estimate to obtain a more accurate state estimate.

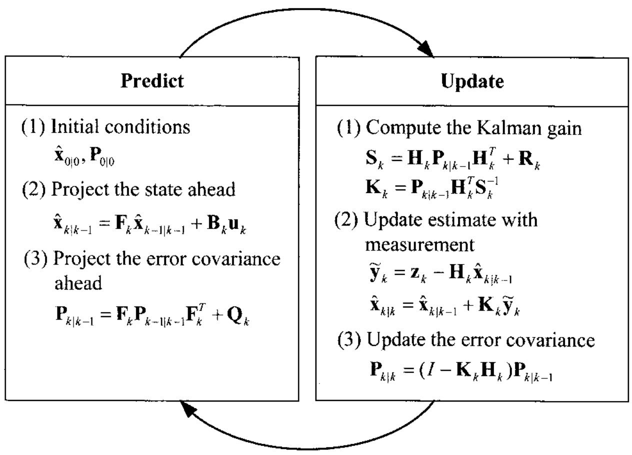

Fig. 5. Mathematical Algorithm of the Kalman Filter

The CM techniques using the Kalman filter have been used widely for nuclear applications as well. The detection of system or instrumentation failures based on system modeling is a primary application, [14-15] and the Kalman controller that regulates the level of steam generators has also been developed. [16]

2.2.2 Empirical Models

The empirical model based approach is opposite in nature to the physical model based approach. The empirical model can only be developed for systems that are in operation because it requires observational data that can only be obtained during operation. It does not provide any analytical correlations between the system's parameters, so it is sometimes called a 'black-box' model. One major advantage of this approach is that it is generic, which means that it can be applied to any type of problem. It is also easy to input a system's operational characteristics, such as ageing, which is typically difficult to characterize in a physical model. The most important technical concept used in developing empirical models is 'regression'. While a number of different regression models have been suggested in the literature, their theoretical background is identical in two aspects: 1) how to find a specific regression model to fit the operational observations and 2) how to predict a result when a new observation is scanned. In other words, all regression models address the prediction of dependent or response variables given known values of the independent or explanatory variables. Regression is a well-known topic in statistics, so this section will only describe two issues which are essential in developing empirical models: ill-conditioning caused by multicollinearity and overfitting caused by noise.

The first issue that needs to be understood is that the explanatory variables must be linearly independent. This means that it must be impossible to express any explanatory variable as a linear combination of other explanatory variables, a concept known as multicollinearity. If Equation (5) is satisfied, there is multicollinearity in the regression model:

$$\lambda_1 x_{1i} + \lambda_2 x_{2i} + \ldots + \lambda_p x_{pi} = 0, \qquad (5)$$

where the λ values are constants and the x values are explanatory variables.

The presence of multicollinearity simply indicates the redundancy of information in predicting a response variable. A principal danger of such information redundancy is the possibility of ill-conditioning when a regression model is developed. The ill-conditioning may cause not only high variances, but also inconsistent predictions. For example, the regression coefficients under ill-conditions will differ greatly with only very slight changes in the observational data, maybe due to only noise. Multicollinearity does not impact the reliability of the estimation as long as the explanatory variables follow the same multicollinearity pattern as the data in which the regression model is based, [17] but it is desirable to consider a regularized technique, such as a ridge regression, or a principal component analysis to effectively prevent the inconsistent predictions that result from noise instantiations in the explanatory variables, which will guarantee a robust model. There are three methods to reduce or eliminate multicollinearity: drop an explanatory variable to lessen multicollinearity, add a case to break multicollinearity, or estimate the regression coefficients from different observational sets. The principles of managing multicollinearity are valid in the development of all empirical models.

The other issue in empirical models is denoising or outlier reduction. An outlier is an observation that lies outside the pattern of a distribution. [18] This observation may not fit the model being studied or may be an error in measurement. While an empirical model attempts to fit itself to the given noisy observations, it is likely to be overfit. Model complexity in conjunction with noise causes overfitting, which occurs regardless of the existence of collinearity. In order to eliminate the outliers and to find the intrinsic signal, statistical tools such as scatter plotting or a low frequency pass filter using a Fourier analysis or wavelet analysis are available for the observations used during model development. This can be also achieved by optimizing the structure of the empirical models selected, for example, eliminating the free neurons, early training stop, or cross validation in neural networks. In a kernel regression, the model can be regularized by controlling the kernel bandwidth.

Among the regression based empirical models, three methodologies used in commercial applications will be described. The empirical models for industrial applications are limited to a few specific technologies because they require a high level of reliable, confidential, transparent, and proven technology.

- Linear Regression

The first model is based on a linear regression using multi-explanatory variables. Linear regression is one of the most well-known models in statistics. A linear regression with p parameters, called independent or explanatory variables, and n observations is represented by the following vectors and matrix with the associated errors:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} x_{11} & x_{21} & \cdots & x_{p1} \\ x_{12} & x_{22} & \cdots & x_{p2} \\ \vdots & \vdots & \ddots & \vdots \\ x_{1n} & x_{2n} & \cdots & x_{pn} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \qquad (6\text{-}1)$$

or

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \qquad (6\text{-}2)$$

The term $\boldsymbol{\varepsilon}$ represents the unexplained variation in the response variable and is assumed to be independent of the explanatory variables. A least-squares method is used to obtain the coefficient vector, β. The estimated values can be given as:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}. \tag{7}$$

The prediction of the multivariate regression model at $\mathbf{x}=\mathbf{x_0}$ is given by Equation (8):

$$\hat{\mathbf{y}} = \mathbf{x}_0(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}. \tag{8}$$

Some metrics may be required to evaluate the goodness of the fit for the model. The $100(1-\alpha)\%$ confidence interval for the parameter β_i is determined by Equation (9), and the $100(1-\alpha)\%$ mean response confidence interval at $\mathbf{x}=\mathbf{x_0}$ is given by Equation (10):

$$\hat{\boldsymbol{\beta}}_i \pm t_{\alpha/2,n-p}\hat{\boldsymbol{\sigma}}\sqrt{(\mathbf{X}^T\mathbf{X})_{ii}^{-1}}, \tag{9}$$

$$\mathbf{x}_0\hat{\boldsymbol{\beta}} \pm t_{\alpha/2,n-p}\hat{\boldsymbol{\sigma}}\sqrt{\mathbf{x}_0(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{x}_0^T}, \tag{10}$$

where t follows the Student's t-distribution with $n - p$ degrees of freedom, and $\hat{\boldsymbol{\sigma}} = \sqrt{\dfrac{\mathbf{y}^T\mathbf{y} - \hat{\boldsymbol{\beta}}^T\mathbf{X}^T\mathbf{y}}{n-p}}$, which is the estimated standard deviation.

Pearson's coefficient, R^2, which is a metric that measures the quality of the model's prediction of response variables, is given by Equation (11):

$$R^2 = \frac{SSR}{TSS} = 1 - \frac{ESS}{TSS}, \tag{11}$$

where the regression sum of squares is given by $SSR = \Sigma(\hat{y}_i - \bar{y})^2$, the error sum of squares is given by $ESS = \Sigma(y_i - \hat{y}_i)^2$, and the total sum of squares is given by $TSS = \Sigma(y_i - \bar{y})^2$.

The validity of the model can be checked using one of the following methods: 1) if the confidence interval in Equation (9) includes zero, the parameter can be removed from the model, 2) a smaller confidence interval in Equation (10) gives a better prediction, and 3) if the value of the Pearson's coefficient in Equation (11) is close to one, the regression is better. [17] There are also various ways to modify the least-squares analysis to obtain better results, including the weighted least-squares method, which is a generalization of the least-squares method, polynomial fitting, which involves fitting a polynomial to the given data, robust regression, and ridge regression.

· Kernel Regression

While a multivariate regression is based on an assumption regarding the distribution of explanatory variables (therefore called a parametric regression), kernel regression is one method of performing a non-parametric regression. A unique characteristic of non-parametric regressions is that the model does not have a predetermined form but is constructed according to the information derived from observations. To perform a state estimation, the system's state is determined by comparing the closest existing data with a new observation. A non-parametric regression, therefore, requires a larger sample size than parametric models because the data are used to determine the model's structure as well as the estimations it provides.

Kernel regression is a superset of local weighted regression methods such as K-nearest neighbor, radial basis function, neural networks, and support vector machines. [19] To perform a kernel regression, a set of weighted functions called 'kernels' are placed locally at each observational point. The kernel assigns a weight to each location based on its distance from the observational point. A multivariate kernel regression specifies how the response variable, $\mathbf{y}$, depends on a vector of explanatory variables, denoted by $\mathbf{X}$, as in Equations (12-1) and (12-2):

$$E(\mathbf{y} \mid \mathbf{X}) = m(\mathbf{X}) + \boldsymbol{\varepsilon}, \tag{12-1}$$

and

$$\mathbf{y} = m(\mathbf{X}) + \boldsymbol{\varepsilon}. \tag{12-2}$$

Based on these equations, the Nadaraya-Watson estimator in Equation (13) is derived, which is the average of y_is weighted heavier near x_0 using a kernel.

$$\hat{\mathbf{y}} = \hat{m}_h(\mathbf{x}) = \frac{\sum_{i=1}^{n} K_h(x - X_i)y_i}{\sum_{i=1}^{n} K_h(x - X_i)} = \frac{1}{n}\sum_{i=1}^{n} W_{hi}(x)y_i, \tag{13}$$

where K is a kernel with a bandwidth, h, and

$$W_{hi}(x) = \frac{nK_h(x - X_i)}{\sum_{j=1}^{n} K_h(x - X_j)}.$$

Even though any function that satisfies several mathematical requirements can be a kernel, [20] the Gaussian kernel in Equation (14) is usually used:

$$K_h(x - X_i) = e^{-\frac{(x-X)^2}{2\sigma^2}}. \tag{14}$$

In Equation (14), the kernel width is called the bandwidth, kernel radius, or metric window. Figure 6 shows how a kernel at a single observational point is

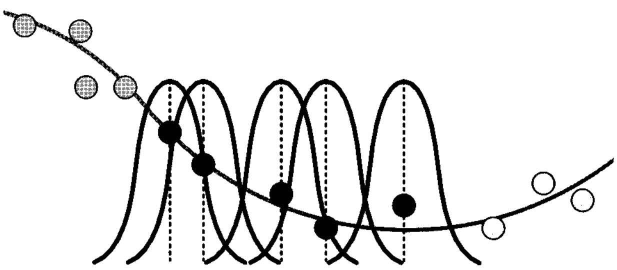

Fig. 6. Span of a Gaussian Kernel in a Kernel Regression

applied to weight the neighboring points inside the window. Data points outside the window are not affected by the kernel. [20, 21]

It is easy to expand a kernel regression into a multi-dimensional problem, and the least-square analysis remains effective in finding the solution of the following minimization problem:

$$\min_{\beta} \sum_{i=1}^{n} \{Y_i - \beta^T (x - X_i)\}^2 K_H (x - X_i), \quad (15)$$

where K_H is a multi-dimensional Gaussian kernel.

The solution to the problem can be found using Equation (16), and the estimated value at $\mathbf{x}=\mathbf{x_0}$ is given by Equation (17):

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{W}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}\mathbf{y}, \quad (16)$$

$$\hat{\mathbf{y}} = \mathbf{x_0}(\mathbf{X}^T\mathbf{W}\mathbf{X})^{-1}\mathbf{X}^T\mathbf{W}\mathbf{y}, \quad (17)$$

where

$$\mathbf{X} = \begin{Bmatrix} 1 & (x-X_1)^T \\ \vdots & \vdots \\ 1 & (x-X_n)^T \end{Bmatrix}, \ \mathbf{y} = \begin{Bmatrix} Y_1 \\ \vdots \\ Y_n \end{Bmatrix}, \text{ and } \mathbf{W} = \begin{Bmatrix} K_H(x-X_1) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & K_H(x-X_n) \end{Bmatrix}.$$

In practice, to use a kernel regression, the process of selecting the appropriate bandwidth and estimating the confidence intervals is tedious, even though it has a large impact on the state estimation. The detailed methods of determining these regression parameters can be found in the literature. [17, 22, 23]

The multivariate state estimation technique (MSET) developed by Argonne National Laboratory is a product which uses a kernel regression. The technical core of MSET consists of state estimation based on a kernel regression, state monitoring using the sequential probability ratio test (SPRT) which will be discussed later, and some proprietary components which make the method reliable and efficient. [24-27] The reliability, sensitivity, and efficiency of the MSET have been demonstrated in a wide variety of process monitoring, signal validation, and sensor operability surveillance applications in nuclear and non-nuclear areas. The MSET has already been commercialized and its technical achievements are accumulating. [25, 27]

· Artificial Neural Networks

The artificial neural network, or neural network, is a nonlinear regression technique that can be used to model complex relationships between inputs and outputs. Neural networks were originally mathematical models used to simulate biological neural networks, so they consist of interconnected groups of neurons, called nodes or perceptrons, and process information using a connectionist. Neural networks were first developed in the 1940s and were actively investigated as computing technology progressed in the 1980s. The most important characteristic of neural networks may be their parallel computing capability, which is particularly useful when dealing with problems such as pattern classification, pattern completion, or function approximation that a conventional sequential algorithm cannot solve. In its application to CM, it is notable that a neural network can be used as an arbitrary function approximation mechanism which learns from the observed data.

Figure 7 shows the general representation of a neural network. In Figure 7, a function, $f(x)$, is defined as a composition of other functions, $g_i(x)$, which can further be defined as the composition of other functions or input variables. [28] A widely used composition is the nonlinear weighted sum presented in Equations (18-1) and (18-2):

$$f(\mathbf{x}) = K'\left(\sum_j w'_j\, g_j(\mathbf{x})\right), \quad (18\text{-}1)$$

$$g_j(\mathbf{x}) = K\left(\sum_i w_{ij} x_i\right), \quad (18\text{-}2)$$

where K and K' are predefined functions such as a logistic function or a hyperbolic tangent function, and w_{ij} is the weight given to the arrow between two nodes.

While determining the coefficients vector, β, is the focus in regression analyses, the most important step of using neural networks is to determine the coefficients vector, $\boldsymbol{w}$, which is termed 'learning' or 'training'. Generally, updating the value of $\boldsymbol{w}$ is regarded as learning, but sometimes changing the structure of a network itself can be called learning in a specific neural network. There are numerous algorithms available for training a neural network. Most of these algorithms can be viewed as straightforward applications of optimization theories and statistical estimations, so a gradient descent method should be used to minimize the errors between the expected output sets and the calculated sets. [29, 30] If the learning algorithm and the scheme for minimizing errors are selected appropriately, the results of the neural network will be robust, in contrast with general regression models. This characteristic is of great use in CM applications. For nuclear applications, a variety of signal validation techniques that identify and/or classify transients or accidents have been steadily developed since the early 1990s. [30-36]

A candidate for CM application is the auto-associative neural network (AANN), which is a special feed-forward neural network. In feed-forward neural networks, the information only moves in the forward direction from an input layer, through hidden layers, and to an output layer. An AANN represents a combination of two feed-forward neural networks. Figure 8 shows a general feed-forward neural network and an AANN. An AANN has three hidden layers and the center hidden layer is termed the bottleneck layer. The number of nodes in the bottleneck layer is smaller than that in the other hidden or input/output layers. The structure of an AANN is symmetric around the axis of the

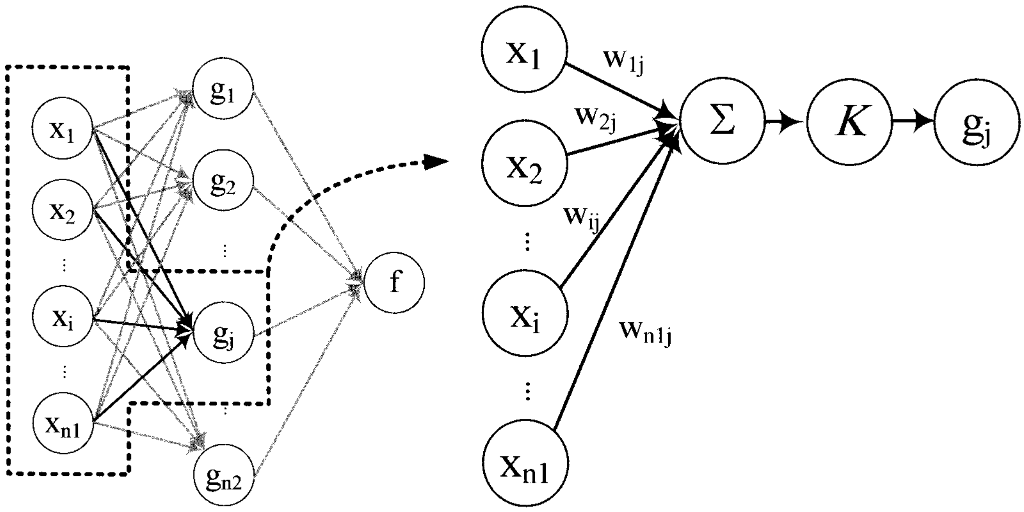

Fig. 7. Structure of a Neural Network

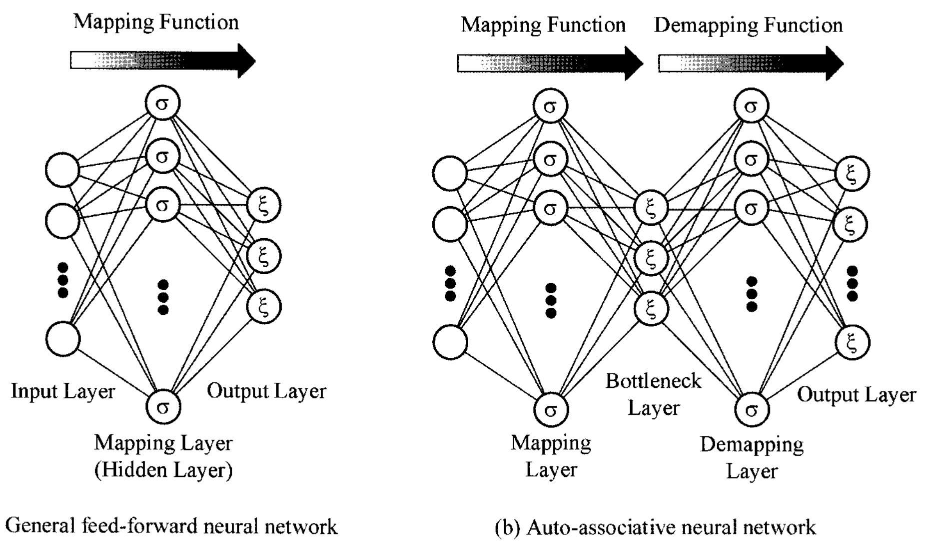

Fig. 8. Comparison of the (a) General Feed-Forward Neural Network and (b) Auto-Associative Neural Network Structures

bottleneck layer. This structure enables the synchronization of the set of input and output layers, which is termed 'auto-associate'. If a new observation is available, the trained network instantly improves its predictive ability and provides data approximations based on the previous training sets. The small number of nodes in the bottleneck layer plays a principal role in component analysis, so that a low frequency pass filtering is performed while the new observation passes through the bottleneck layer. [37-39]

It is standard to use the gradient descent method and back-propagation algorithm to train AANNs. Despite the many advantages of neural networks, the heuristic aspect in implementing neural networks is a shortcoming and limits their practical application. For example, when developing an AANN, the number of layers, the number of nodes, and the number and quality of training sets must be decided using engineering judgment or trial-and-error, but these decisions impact the network's fit to the observational data. However, it has been reported that analytically quantifying a neural network's confidence intervals is possible once the network model is established, which means a standardized performance metric is available. Rasmussen suggested a metric that provides the prediction interval of the neural networks by calculating the full Jacobian matrix based on the training data and the network's weight and bias. [7, 40] PEANO (process evaluation and analysis by neural operators), developed in the HAMMLAB of the OECD NEA Halden group, is distinguished as a promising product using neural network technologies. PEANO is a signal validation toolbox based on neuro-fuzzy techniques and is able to track the expected behavior of a complex process in both steady-state and transient conditions in real-time. It has been adopted to improve the accuracy of the feedwater flow measurement at the Halden HBWR reactor. The Halden group is currently developing advanced control concepts that focus on robustness, transparency, usability aspects, and the need for integration of operator supports. PEANO has an important role in achieving such advanced design of control rooms in NPPs. [41-43]

Neural networks can be implemented in a way that is equivalent to the use of kernel regressions. If, instead of the conventional transfer functions, the appropriate kernel functions, known as radial basis functions, are applied to a hidden layer in a three-layer feed-forward neural network, the interpretation of the output layer value is identical to that in a kernel regression model. In regression applications, neural networks using a radial basis function can be a good choice when the dimensionality of the input space is relatively small. [29]

2.3 State Monitoring

All of the state estimation techniques mentioned in Section 2.2 have uncertainties associated with their results. The sources of these uncertainties arise from the input signals, the integrity of the estimation model, and the process itself. However, informing users of the level of uncertainty may or may not be useful. A more efficient method is to provide detailed information to users only when requested, while the system provides the final results considering these uncertainties.

Therefore, state monitoring methods usually adopt statistical monitoring techniques which consider uncertainties such as the SPRT or control charts. The purpose of state monitoring methods is primarily to inform users if there is any potential problem in the processes or sensors. Therefore, the typical interest is in the residual, which is the difference between the system state predicted by the state estimation model and the current measurement. The decision is dependent on whether the residual exceeds a certain set point, which is principally determined by considering the importance of the response variables on the system's safety, performance, and/or maintenance characteristics. When deciding on the set point, the additional margins related to the control of the missed alarm rate, false alarm rate, and noise in the prediction should be considered. The major sources of uncertainty in calculating the residual are divided into two categories: 1) the uncertainty of the instrument channels and 2) the uncertainty of the state estimation model developed. The next subsection will first show how to determine uncertainty in the instrument channels and the estimation model, and then two kinds of state monitoring techniques, the SPRT and control charts, will be introduced.

2.3.1 Uncertainty Analysis

One of the origins of uncertainty is the instrument channels. The channel statistical allowance (CSA) is the term given to all types of quantifiable uncertainties which occur in an instrument channel, as shown in Equation (19).

$$CSA=\sqrt{PMA^2+PEA^2+(SCA+SD)^2+SPE^2+STE^2+(RCA+RD)^2+RTE^2}, \tag{19}$$

where PMS (process measurement accuracy) is the inherent noise in the process, PEA (primary element accuracy) represents the error due to the use of a metering device, SCA (sensor calibration accuracy) is the inherent accuracy of the sensor at the reference conditions, SD (sensor drift) is the observed change in sensor accuracy as a function of time, SPE (sensor pressure effects) and STE (sensor temperature effects) are sensors' denature under difference pressure or temperature, RCA (rack calibration accuracy), RD (rack drift), and RTE (rack temperature effects) are the uncertainties coming from the racks.

The CSA can usually be determined using data from the vendor or manufacturer of the sensors, or from previous operating experience. [6] However, the uncertainty in the state estimation model is not available from a vendor or manufacturer, and is sometimes difficult to quantify analytically. In particular, the uncertainty in empirical models is difficult to quantify since it is strongly dependant on the type, quantity, and reliability of the data used in the model's development. Therefore, a statistical method, such as the Monte Carlo method, may be a good way to determine the uncertainty in this type of model. [7, 40] Quantifying the uncertainty due to the instrument channels and state estimation model is necessary in the development of statistical state monitoring techniques because the uncertainty is needed to specify the standard deviation of the system.

2.3.2 Statistical State Monitoring

There are two key statistical process monitoring techniques: 1) the SPRT and 2) control charts, each with its own advantages and disadvantages.

- Sequential Probability Ratio Test (SPRT)

  The SPRT was developed by Wald [44] as a hypothesis test for sequential analysis. The SPRT can be used in a variety of different models which include either discrete or continuous variables. The advantage of the SPRT is that the number of samples to reach a conclusion can be saved, and the number of samples need not be fixed. The SPRT is, therefore, useful for process monitoring, product quality control, testing expensive or rare samples, and is particularly useful in the field of medicine. When performing conventional statistical tests, the sample size must be fixed before deciding to use either the null hypothesis or an alternative hypothesis. However, the SPRT does not require that the sample size be fixed. Instead, the SPRT has a stopping rule and a terminal decision rule to determine which hypothesis to use with the samples already collected or to continue collecting samples. This third option is not available in conventional statistical tests.

Consider two hypotheses: one is a null hypothesis characterized by a probability density function, p, and the other is an alternative hypothesis specified by a probability density function, q. At the n^{th} sample, their likelihood ratio is defined as in Equation (20):

$$R_n = p(X_n)/q(X_n). \tag{20}$$

The hypothesis testing follows, as given by Equation (21):

$$N = \inf\{n \geq 1 : R_n \leq B \quad or \quad R_n \geq A\}. \tag{21}$$

If R_n is less than B, the null hypothesis, H_0, is chosen. If R_n is greater than A, then the alternative hypothesis, H_1, is chosen. Otherwise, the sampling is continued until either hypothesis is chosen. The constants of the stopping rule in Equation (21) can be determined by the error probabilities:

$$\frac{1-\beta}{\alpha} \geq A, \frac{\beta}{1-\alpha} \leq B, \tag{22}$$

where $\alpha = p(H_0\ reject \mid H_0) = P(R_N \geq A)$ is the Type I error probability and $\beta = p(H_0\ accept \mid H_1) = P(R_N \geq B)$ is the Type II error probability.

The principles of the SPRT can be successfully applied to CM. In general, the average of the residual is monitored, which is the difference between the value predicted by a state estimation model and the value measured. Under normal operation, the residual mean should be zero within the statistical confidence level, which corresponds to the null hypothesis. If the residual mean exceeds a certain set point, then it is suspected that there is a failure in the process, which corresponds to the alternative hypothesis. It can be assumed that the probability distribution of the residual is, for example, a normal distribution. If the observed sample is in the exponential family of distributions, then the stopping rules and the likelihoods can be derived analytically. [44, 45] Even though the residual distribution is rarely normal in a strict sense, it is common to assume the residual is characterized by a normal distribution. Therefore, care must be taken in managing the spurious alarms resulting from the disturbed distribution. When the residual is assumed to have a normal distribution, a few useful equations can be derived for use in the SPRT. The standard deviation of the residual can be found from the results of quantifying the uncertainties of the instrument channels and the state estimation model. If the standard deviation of the residual remains unknown, it is possible to use the sample standard deviation instead of the population standard deviation. [46]

The null hypothesis is defined as H_0: $\theta = \theta_0 = 0$, and the alternative hypothesis is defined as H_1: $\theta = \theta_1 = set\ point$. The probability density function of the residual at the n^{th} sample is given by the normal distribution in Equation (23):

$$p = \frac{1}{(2\pi)^{n/2}\sigma^m} e^{-\frac{1}{2\sigma^2}\sum_{i=1}^{m}(x_i-\theta)^2}. \tag{23}$$

It is simple to take the logarithm to obtain the stopping rule, and finally the new constants, which characterize the hypothesis testing using Equations (24-1) and (24-2), and the corresponding metric are found as follows:

$$a_n = \frac{\sigma^2}{\theta_1 - \theta_0} \ln \frac{\beta}{1-\alpha} + n\frac{\theta_0 + \theta_1}{2}, \tag{24-1}$$

$$b_n = \frac{\sigma^2}{\theta_1 - \theta_0} \ln \frac{1-\beta}{\alpha} + n\frac{\theta_0 + \theta_1}{2}. \tag{24-2}$$

If $a_n < \Sigma x_i < b_n$, the samples are observed continually. If $\Sigma x_i \leq a_n$, the SPRT, which has resulted in the null hypothesis indicating that the process is normal, can be stopped. If $b_n \leq \Sigma x_i$, the alternative hypothesis is the result, and the system warns that the process is abnormal so that a maintenance plan can be begun. An important metric used to evaluate the performance of the SPRT is the average run length (ARL), which represents the average number of samples required to reach a conclusion. The ARL of the SPRT is given by Equation (25):

$$E_\theta(n) = \frac{h_1 + L(\theta)(h_0 - h_1)}{\theta - (\theta_0 + \theta_1)/2}, \tag{25}$$

where $L(\theta) \sim \dfrac{\left(\frac{1-\beta}{\alpha}\right)^h - 1}{\left(\frac{1-\beta}{\alpha}\right)^h - \left(\frac{\beta}{1-\alpha}\right)^h}$ and $h = \dfrac{\theta_1 + \theta_0 - 2\theta}{\theta_1 - \theta_0}$.

Equation (25) enables the recognition of the approximate number of observations required to reach a decision so that a proper sampling period can be determined. While fault classification is a role of the state estimation methods, fault detection should be the responsibility of the SPRT. Initial applications of the SPRT conventionally follow the stopping rule and terminal decision rule, [47-49] but recent achievements are evolving with the adaptive concept in determining such rules. [46, 50]

- Control Charts

  The control chart, also known as the 'Shewhart Chart', is a tool used to determine if an engineering process is statistically 'in control' or 'out of control'. In contrast to the SPRT, if a control chart indicates that the process is out of control, the variation pattern can help determine the source of the variation that must be eliminated to bring the process back into control. A control chart consists of the following three elements: 1) points representing the sampled values of a process characteristic, 2) a center line that usually represents a process mean, and 3) upper and lower control limits that indicate the threshold at which the process output is considered statistically out of control. These limits are usually set at $\pm 3\sigma$ (three standard deviations) from the center line. Upper and lower warning limits can also be added, and are typically 2σ above and below the center line. All control charts assume that the process observations are mutually independent. Figure 9 shows typical control charts with control limits and warning limits. There are three control charts can be recommended as candidates for CM.

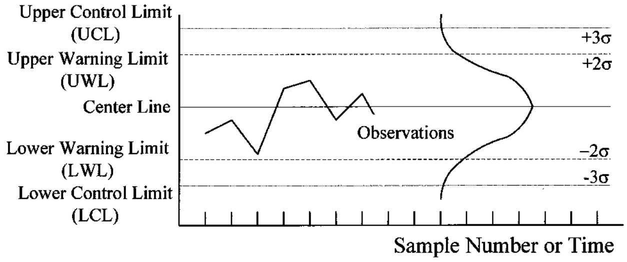

Fig. 9. Typical Control Chart

The $\overline{X}$-S control chart (a mean-standard deviation control chart) is used to analyze the mean or standard deviation when the distribution of the process characteristic is stable, allowing sample standard deviations to be obtained from a large number of

Table 1. Center Lines, UCLs, and LCLs of the Control Charts

	$\overline{X}$-S chart		$\overline{X}$-R chart	
	$\overline{X}$	S	$\overline{X}$	R
UCL	$\overline{\overline{x}} + 3\frac{\overline{s}}{c_4\sqrt{n}}$	$\overline{s} + 3\frac{\overline{s}}{c_4}\sqrt{1-c_4^2}$	$\overline{\overline{x}} + A_2\overline{R}$	$\overline{\overline{x}} + 3\frac{\overline{R}}{d_2\sqrt{n}}$
Center line	$\overline{\overline{x}}$	$\overline{s}$	$\overline{\overline{x}}$	$\overline{\overline{x}}$
LCL	$\overline{\overline{x}} - 3\frac{\overline{s}}{c_4\sqrt{n}}$	$\overline{s} - 3\frac{\overline{s}}{c_4}\sqrt{1-c_4^2}$	$\overline{\overline{x}} - A_2\overline{R}$	$\overline{\overline{x}} - 3\frac{\overline{R}}{d_2\sqrt{n}}$

wher $\overline{\overline{x}}$ is a grand mean averaging all observations, and c_4, d_2, A_2 are referred by a quality control handbook. [51]

samples. There are m preliminary samples, each of size n, and let s_i be the standard deviation of the ith sample. The average of the m standard deviations should be the center line as shown in Equation (26):

$$\bar{s} = \frac{1}{m}\sum_{i=1}^{m} s_i \,. \tag{26}$$

The upper control limit (UCL), lower control limit (LCL), and center line of the S chart are determined as shown in Table 1. [51] The parameters of the $\overline{\mathrm{X}}$ chart are also shown in Table 1: it is convenient to plot the $\overline{\mathrm{X}}$-S charts on a single page.

However, the $\overline{\mathrm{X}}$-R control chart (a mean-range control chart) is used when the sample size is relatively small. The range is an alternative to the standard deviation of the samples and is simply the difference between the largest and smallest observations. The UCL, LCL, and center line of the R chart are determined as shown in Table 1. If R_1, R_2, ..., R_k, is the range of k samples, the average range is $\bar{R} = \frac{1}{k}\sum_{i=1}^{k} R_i$. Similarly, the parameters of the $\overline{\mathrm{X}}$ chart are shown in Table 1.

It is necessary to know the ARL of the control charts to evaluate their performance. Since the $\overline{\mathrm{X}}$-S chart and $\overline{\mathrm{X}}$-R chart monitor levels which exceed $\pm 3\sigma$ from the normal value, the usual UCL or LCL Shewhart charts are good at detecting large changes in the process mean or variance, but they do not detect small changes well (such as a 1σ or 2σ change in the mean or variance). Other types of control charts, such as the CUSUM (CUmulative SUM) chart, can be good supplementary tools to detect smaller changes.

CUSUM charts make use of information gleaned from observations collected prior to the most recent data. While the principle of a CUSUM chart is not as intuitive as the Shewhart charts, CUSUM charts have been proven to be better at detecting small shifts in the process mean. Particularly, when a change in the process mean within 2σ or less needs to be detected, the ARL of the CUSUM charts is shorter than that of the Shewhart charts. In addition, the CUSUM chart is of great advantage in detecting a one-side increase or decrease. However, it should be noted that Shewhart charts are preferable to CUSUM charts for detecting large changes.

The CUSUM is determined by plotting Equation (27), which detects the variation from an in control mean, μ_0, to an out of control mean, μ_1:

$$S_m = \sum_{i=1}^{m} (x_i - k)\,, \tag{27}$$

where m is the sample number, k is a reference value, which is normally $k = \frac{\mu_0 + \mu_1}{2}$, and x_i is the i^{th} sample value.

The CUSUM chart is formed by plotting Equation (28-1) or (28-2):

$$S_i = \max(0, x_i - k + S_{i-1})\,, \tag{28-1}$$

$$S_i = \min(0, x_i - k + S_{i-1})\,, \tag{28-2}$$

where the common choice for S_0 is zero.

As long as the process remains in control with its center at μ_0, the CUSUM chart will show a random pattern around zero. If the process mean shifts upward, the points will drift upwards and vice versa if the process mean decreases. When the process mean drifts upward, Equation (28-1) is used, and for a downward drift, Equation (28-2) is applicable. Deciding upon a decision internal is not as straightforward as deciding upon a UCL or LCL for the Shewhart charts. Generally, k is equal to an acceptable change in mean divided by 2 S_m, as shown in Equation (27), so if the acceptable change in mean is identical to S_m, then $k = 0.5$. In this case, a recommended reference for a decision interval, h is 4.0 or 5.0. When S_i exceeds h, the process is regarded as being out of control. It is not easy to analytically derive the ARL of CUSUM, but a practical approximation can be recommended, as in Equation (29): [51]

$$ARL(\mu) \cong \frac{e^{-2b\Delta} + 2b\Delta - 1}{2\Delta^2}\,, \tag{29}$$

where $b = \frac{h}{\sigma} + 1.166$ and $\Delta = \frac{(\mu - \mu_0) - |k - \mu_0|}{\sigma}$.

The different control charts have different capabilities. Table 2 shows the relative merits of the different chart types when used to detect the changes listed in the first column.

The control chart is intended to be a heuristic, that is, it is not a hypothesis test. Investigating the patterns created with additional sampling, the source of variation that should be eliminated can be deducted. There are several rules depicting the patterns and their prescriptions. For example, there are Nelson rules to determine when a chart is out of control, as shown in Table 3. The rules are based around the mean value and standard deviation of the sample. However, it is difficult to apply these heuristic rules to the CUSUM charts to detect special causes.

In addition to the Nelson rules, the Western Electric rules or the Wheeler rules are useful. [51, 52] The heuristic aspect of the control charts can be a good compliment to the SPRT, and vice versa, when considering the data presented in the literatures. [53-55] When a point falls outside the control limits established for a given control

Table 2. Merits of the Different Control charts

Cause of Change	Chart Type			
	$\bar{X}$	R	S	CUSUM
Gross Error	Good	Fair		Poor
Shifts in Mean	Fair		Poor	Good
Shifts in Variability		Good		
Slow Fluctuation	Fair			Good
Rapid Fluctuation		Good	Fair	

Table 3. Nelson Rules for Detecting Out of Control Charts

Pattern	Source of variation or root cause
Rule 1: One point is more than 3 standard deviations from the mean.	Grossly out of control
Rule 2: Nine (or more) points in a row are on the same side of the mean.	Bias
Rule 3: Six (or more) points in a row are continually increasing (or decreasing).	Trend
Rule 4: Fourteen (or more) points in a row alternate in direction - increasing then decreasing.	Oscillation beyond noise
Rule 5: Two (or three) out of three points in a row are more than 2 standard deviations from the mean in the same direction.	Samples likely to be out of control
Rule 6: Four (or five) out of five points in a row are more than 1 standard deviation from the mean in the same direction.	Small likelihood for samples to be out of control
Rule 7: Fifteen points in a row are all within 1 standard deviation of the mean on either side of the mean.	Greater variation would be expected
Rule 8: Eight points in a row exist with none within 1 standard deviation of the mean and the points are in both directions from the mean.	Rarely random

chart, it must be determined if a problem has occurred in the process. If a problem is identified, then it should be eliminated, if possible. The rules depicting the characteristics of out of control charts may help to identify the problems.

3. APPLICATIONS

Several state estimation and state monitoring techniques have been reviewed. By combining these two techniques, various problems which occur in industrial settings, such as online sensor calibration which is the original object of CM using empirical models, monitoring performance degradation, implementing fault tolerant systems, or system simulation, can be managed. This section describes the implementation and application of condition monitoring systems.

3.1 Procedure for Developing Condition Monitoring Systems

As mentioned in Section 1, though CM can be used for generic purposes, the procedure of selecting and applying a specific CM is standardized. This section depicts the overall procedure for CM system implementation.

Figure 2 provides direction at the beginning of the system development process. By analyzing the relevant process or system, the appropriate approach or approaches can be chosen. In most cases, the empirical model is easily developed. However, this does not mean that the physical model based approach is ineffective. If the number of sensors in the boundary of a system is relatively small and their correlation is transparent, it is recommended that a physical model be developed. However, if there are too many sensors, and their physics is complex, the use of empirical models is appropriate. The following points must be considered when improving a condition monitoring system.

- Selection of an appropriate sampling period
  The period of data sampling affects the performance of state monitoring. To determine the appropriate sampling period, three areas should be considered: 1) the ARL of the state monitoring techniques, 2) the severity of the failures or the time to propagate a catastrophe, and 3) the preparatory period for maintenance, for example, the time needed to order inventories or secure manpower.
- Denoising
  All empirical models are sensitive to noise. Even though neural networks are known to be robust when outliers are present, denoising is a useful step in model development, as well as during model execution. Therefore, signal preprocessing for denoising is indispensable. When the sampling rate is much faster than the process dynamics, taking a periodic average, such as every 1 minute or every 10 minutes, is recommended as a simple denoising method. Averaging data usually creates time differences in the signals, but such time lag can be ignored when the process is in a steady state. More advanced methods, such as improved averaging (e.g. moving average), low pass frequency filtering (e.g. Fourier analysis or wavelet analysis), signal conditioning (e.g. principal component analysis), can be used. Most modern real-time databases include these types of signal processing functions by default.
- Linearity/Nonlinearity
  A CM myth is that nonlinear models are better at predicting a response variable than linear models. A linear model is simple and easy to develop, and it predicts system states sufficiently as long as the distribution of the system state guarantees linearity. The simplicity of linear models is an advantage to developers as well as users. Even though it may be less accurate, field engineers have more trust in a model that is easy to understand because they believe that they can manage it more effectively. Even if a system shows nonlinear behaviors, dividing the system's state into many short ranges can make the system behave linearly.
- Reasonable number of explanatory variables
  The multicollinearity of the explanatory variables was mentioned above. The number of explanatory variables is not only important in itself, but it is also related to the multicollinearity discussion. Another CM myth is that a large number of explanatory variables better predict a system state. However, a large number of variables is more vulnerable because it is more likely that some explanatory variables are corrupted, as well as having multicollinearity. As long as Pearson's coefficient is large enough to cover the variation of a response variable, it is better to select the minimum number of explanatory variables.
- Robustness
  While the limited number of relevant variables can enhance the accuracy of the models, the models become vulnerable easily when the explanatory variables are faulty. If only one or two relevant inputs are used to establish a model and one drifts or is faulty, it is natural to incorrectly think that the monitored variable is faulty. Robustness should be as important as accuracy in being applied. In order to enhance the robustness of the models, a strategy is needed when the explanatory variables are not perfect. The key notion of the strategy is to use the information redundancy well.

It is possible to backup several supplementary models which will secure the next level of accuracy in estimating a response variable. First, all candidates can be prioritized using Pearson's coefficient and the hardware reliability of the signal channels. The results of the prioritization are then rearranged by considering the integrity of the explanatory variables checked through signal conditioning or preprocessing. Finally, the top priority candidate is selected as the executable model.

Figure 10 shows the general strategy for developing empirical models for state estimation and monitoring. The development process is composed of two steps: model development and model execution. In the model development step, an empirical model using previously recorded observations is established. The development of an appropriate state estimation methodology is a major part of this step. In the model execution step, the current system's state is forecasted or estimated by inputting a new observation into the developed model. Any deviations between the estimated state and the measured state are detected and isolated using the state monitoring techniques. Usually, model development is an offline process, while model execution is online.

3.2 Development Experience

In this subsection, some products for which a CM method has been developed will be introduced to facilitate understanding the necessity of CM or developing customized

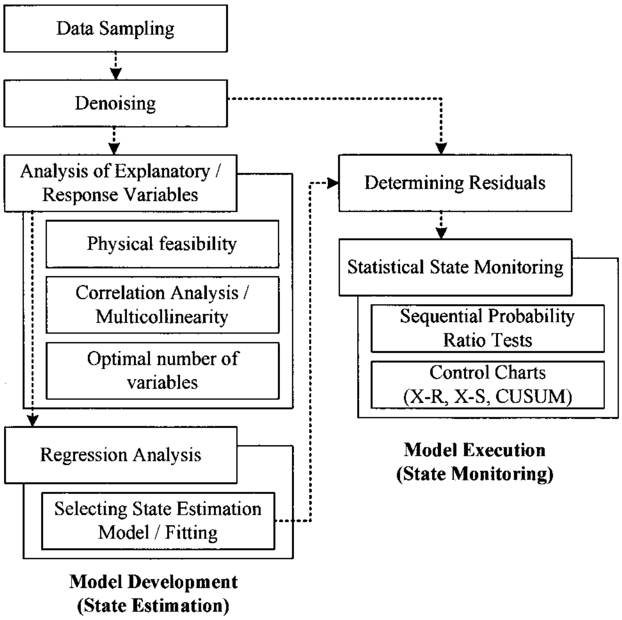

Fig. 10. Strategy for Developing Empirical Models

systems.

- Safety-related heat exchanger monitoring

  This is an example of using a physical model. Since the role of heat exchangers is important in a thermo-hydraulic system, monitoring the thermal performance of heat exchangers and their appropriate maintenance affect the efficiency and economical operation of power plants. However, excessive maintenance may result in performance degradation resulting from human errors or expensive inventory control. If the heat exchangers perform safety functions, monitoring them is even more important.

A method to detect thermal performance degradation of a letdown exchanger was developed as a demonstration of safety-related heat exchangers for Gori NPP Units 3 and 4. [46] The letdown heat exchanger is a shell and tube heat exchanger. The coolant leaving the reactor coolant system (RCS) flows through the tube. The component cooling water used to cool the letdown fluid flows through the shell side to maintain a temperature suitable for operation of the purification system. Fouling or scale deposited on the surface of the inside and outside tubes decreases the heat transfer capabilities of the letdown heat exchanger, thus it may threaten the integrity of the entire RCS.

For state estimation, a physical model derived from heat transfer correlations was used and it determined the fouling coefficients of the inside and outside tubes. [56, 57] The model predicts the anticipated fouling resistance of the inside and outside tubes under specific operating conditions, assuming that the heat exchanger is in a fresh state (a value known as the design fouling resistance). It also calculates the fouling resistance on the basis of the current operating conditions, known as the test fouling resistance. For state monitoring, the SPRT with an unknown process standard deviation was used. The SPRT detected the deviation of the residual between the design fouling resistance and the test fouling resistance. The set point, which warns of the necessity of maintenance, was determined to consider whether the letdown heat exchanger met its functional criteria under accident conditions or not. If the SPRT chose an alternative hypothesis, meaning that the heat transfer capability cannot meet the set point due to excessive fouling, the letdown heat exchanger needed to be fixed during the next outage. Since the SPRT accounts for the stochastic properties of the fouling phenomena, it did not raise a maintenance alert until it knew at a significant confidence level that the fouling resistance had increased. The advantages of the SPRT were found to be that it optimizes the timing of the heat exchanger's maintenance according to safety and economic considerations and reduces the number of tests that are required to determine the condition of the heat exchanger.

- Rector coolant pump seal monitoring

  The sealing package of the reactor coolant pumps (RCPs) belongs to the pressure boundary of nuclear safety, so that radioactive material can be released when a seal has failed. RCPs have three stages of sealing packages which operate under high pressures and temperatures, so their integrity must be monitored continuously. However, the only way to monitor the sealing packages is to analyze the signals from the RCPs, since operators do not have direct access to the sealing packages. Until now, the sealing packages of the RCPs have been replaced in a preventive manner, incurring the expenses of additional inventory and outages.

A US company, SmartSignal, has successfully installed an RCP seal monitoring system at Palo Verde NPP using their solution, Equipment Condition Monitoring™ (eCM). [58] SmartSignal's eCM detects statistically significant deviations in the seal stage pressure within 5 psia that indicate the onset of seal degradation, which is much smaller than the previous requirement of 10~15 psia deviations. It was reported that such a high sensitivity enabled the provision of as much as two months early warning compared with the traditional methods. Similarly, a RCP seal monitoring system was developed based on an empirical model using a multivariate linear regression.

To monitor the integrity of the RCP seal package in the Ulchin NPP Units 3 and 4, a linear regression model was developed. By using other readings, this model predicts the temperature and pressure signals that are essential to determine if there is a problem in the seal package. For state monitoring, an SPRT, an $\overline{X}$ chart, and a CUSUM chart were used to provide the redundant information on the residual mean. [59]

It was questionable whether or not a linear model would be sufficient. The validity of the linear model was reviewed using historical observations, and it was determined that a nonlinear model does not show significant advantages compared with the performance of a linear model.

- Virtual signal synthesis for thermal performance analysis
  This is another example of an empirical model based on a multivariate linear regression. Usually, the turbine cycle of an NPP has a small number of sensors for operation since it is not safety-grade. However, this number of sensors is insufficient to perform full-scope thermal performance tests corresponding to the ASME Performance Test Code 6. [60, 61] A few cases where the points necessary for performing these tests were unmeasured were investigated. A state estimation technique provided the information to replace the unmeasured points.

In Younggwang NPP Units 3 and 4, there were 9 points necessary for the full-scope thermal performance tests, a total of 21 variables, which were unmeasured. All of the points were flowrates at the drains of components such as reheaters and feedwater heaters. Since the behavior of turbine cycles is not easily determined with a simple analytical model, the state estimation technique was implemented using a multivariate linear regression. In order to prepare data representing the various conditions of the turbine cycle, PEPSE was used as a signal generator. [62] The empirical model installed in the real-time database was updated periodically using plant signals accumulated during a certain sampling time, and the result was regularly uploaded. When the full-scope thermal performance tests were performed, the results of the empirical model, which replaces the unmeasured signals, were logged. Since a full-scope thermal performance test is normally performed in a well-controlled condition minimizing the process fluctuation, the linearity of the behavior of the turbine cycle for which the state estimation model was developed could be guaranteed.

- Correction of feedwater flowmeter
  This is an example of an empirical model based on an AANN with signal preprocessing. Measurement errors due to fouling phenomena in the secondary feedwater flowmeters cause the reactor thermal power in the NPPs to be overestimated. [63] The secondary feedwater flowrate was a parameter used in the heat balance calculation to determine the reactor thermal power, and its overestimation results in the overestimation of the reactor thermal power. The result of this overestimation is the underutilization of the reactor fuel, or a failure to achieve the burn-up target. There has been good progress in the development of signal processing techniques to compensate for a degraded secondary feedwater flowmeter. [39, 64-66] One of the highlights of this research is a neural network based approach with good prediction capabilities.

In the state estimation, the feedwater flowrate was corrected using an AANN with denoising based on wavelet analysis. The object of the denoising was to eliminate outliers and any rapid fluctuations with frequencies significantly greater than that of the degradation caused by the fouling phenomena. In a demonstration using the simulator signals of Gori NPP Unit 2 and signal modeling, the performance of each method was validated.

4. CONCLUSIONS

This paper summarized the technical aspects of CM, as characterized by state estimation and state monitoring, to investigate the possibility of applying it in the nuclear industry. Many industries are adopting CM and PM in their process management plans to avoid time-consuming, expensive, and unnecessary maintenance. This practice is most common in manufacturing industries or industries looking for a critical lean process. The fundamental background of CM is already mature, even for use as a commercial product. Considering modern computational capabilities, the application of CM is not limited by technical difficulties, but by the company's desire to implement it. From this viewpoint, the attempts of fossil fuel plants to use CM are a predictable technical strategy. Furthermore, the systems that have a long operating history are proponing the necessity of CM, which is the case for nuclear applications.

For practical nuclear applications, it may be more important to clarify and quantify the negative impact of a CM failure than the advantages yielded when it is working. Most studies have concentrated on mathematical or theoretical development, and demonstrated benefits only when the monitoring is working correctly. It is necessary to standardize the anticipated failures and harsh operating conditions of CM and evaluate the capability of the proposed CM under such design basis malfunctions. In other words, while the issues regarding accuracy have been focused on so far, the concerns regarding robustness should now be concentrated on. The design basis malfunction should cover difficulties in the CM's entire phase from state estimation to state monitoring, even when missing, corrupted, and extremely high or low readings are input into the system. Another pending issue is to clarify the economic benefit when introducing CM. Normally, the direct benefit of adopting CM arising from the reduction of labor and plant downtime could be quantifiable, but this is not very attractive to stakeholders compared with the initial cost of installing a CM system. We may find a much larger benefit resulting from indirect aspects, such as improvement of plant safety and performance, workers' health, or public acceptance, which is not easy to analyze and very different according to the specific circumstances. Another chance can be found in conjunction with a prognosis which estimates the remaining life time of the equipment. Reliable prognoses enable optimized maintenance schedules, enable optimized stock control, and determine system lifetimes.

It is likely that a good opportunity exists to gather CM experience inside NPPs. Recently, there has been much interest in improving the levels of safety and efficiency of the secondary systems, such as the main steam or condensation systems in NPPs. Even though most components in a secondary system are non-safety grade, the accident that occurred in the turbine building of the Japanese Mihama NPP in 2004 was enough to stimulate the regulatory authorities to have serious concerns about the safety of the secondary systems. According to statistical analyses performed during the last six years in Korea, three fourths of unanticipated reactor shutdowns were caused by secondary systems. So while the regulatory authority is more frequently requesting tests or increasing the maintenance requirements for secondary systems, the utilities do not have the resources to accommodate them, particularly in Korean NPPs. A prototype CM system could be applied to such secondary systems, and the profit could be increased using the existing capacity while addressing the safety concerns, provided that the CM is working properly. It is a challenge to apply CM to the safety features considering the current technical level of CM. Nevertheless, CM is a promising option to increase the overall competitiveness of NPPs.

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