Sensor Fault Detection in Nuclear Power Plants Using Multivariate State Estimation Technique and Support Vector Machines

by

Nela Zavaljevski and Kenny C. Gross

Reactor Analysis Division
Argonne National Laboratory
9700 S. Cass Avenue
Argonne, IL 60439

*Work supported by the U. S. Department of Energy, Nuclear Energy Programs under Contract W-31-109-Eng-38
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SENSOR FAULT DETECTION IN NUCLEAR POWER PLANTS USING MULTIVARIATE STATE ESTIMATION TECHNIQUE AND SUPPORT VECTOR MACHINES

N. ZAVALJEVSKI AND K. C. GROSS*

Reactor Analysis Division, Argonne National Laboratory
9700 South Cass Avenue, Argonne, Illinois 60439, USA

ABSTRACT

Recent developments in artificial intelligence at Argonne National Laboratory (ANL) have culminated in the capability to perform nuclear power plant sensor validation and early fault detection in an integrated package called the Multivariate State Estimation Technique (MSET). Nuclear reactor signals are validated by comparing signal prototypes with the actual reactor signals. Residuals from these comparisons are used in a sensitive hypothesis testing method, the Sequential Probability Ratio Test (SPRT). The SPRT examines the stochastic components of the residuals and can detect if the statistical characteristics begin to change. The signal prototypes are estimated based on empirical data. The property of an estimation algorithm to make predictions on limited amount of data is designated as generalization ability. It is a very important issue in algorithm selection. Recently, we included a new machine learning algorithm called the Support Vector Machines (SVM) in the estimation module of MSET. In the SVM algorithm, the input data space (set of reactor signals) is transformed into a high-dimensional nonlinear space using a kernel function, and the learning problem is formulated as a convex quadratic programming problem with a unique solution. In particular, we implemented and tested several kernels developed at Argonne National Laboratory. Our recent results indicated that the combination of MSET kernels with the SVM method has better noise reduction and generalization properties than the standard MSET algorithm. In this paper we compare fault detection properties of these algorithms.

*Present address: Sun Microsystems, 901 San Antonio Road, Palo Alto, CA 94303, USA
1. INTRODUCTION

The accurate adaptive modeling and prediction of nuclear power plant systems coupled with analysis of process information is crucial for validation of plant signals and for early annunciation of incipient anomalies. One current approach makes use of artificial intelligence (AI) techniques. This approach assumes that there is a set of signal prototypes, often computed using empirical models. An integrated AI algorithm, consisting of estimation and fault detection modules, has been developed recently at Argonne National Laboratory and applied successfully to nuclear power reactor signals [1]. However, the ability of MSET to make predictions on the basis of available finite training data is not well understood. Another problem is related to sub-optimal training algorithms. A new learning paradigm called the Support Vector Machines (SVM) [2] has recently been implemented in the estimation module of the MSET algorithm. This modification ameliorated both of the aforementioned potential shortcomings [3].

In SVM, the input data space (set of reactor signals) is transformed into a high-dimensional feature space using a kernel function, and the learning problem is formulated as a convex quadratic programming problem with a unique solution. In particular, we implemented and tested several kernels developed at Argonne National Laboratory. Our recent results indicated that the combination of MSET kernels with the SVM method has better noise reduction and generalization properties than the standard MSET algorithm. However, one of the most important MSET applications is to detect subtle sensor degradations. This task is performed in the fault detection module of MSET. Residuals between the estimated and measured signals are used in a sensitive hypothesis testing method, the Sequential Probability Ratio Test (SPRT). The SPRT examines the stochastic components of the residuals from any type of physical sensors and can detect if the statistical characteristics begin to change. The fault detection based on residuals generated in standard MSET and SVM-improved MSET estimation modules is presented in this paper.

2. METHODS

2.1. Multivariate State Estimation Technique (MSET)

The system modeling in MSET uses data representative of the normal operating states of a system to learn the interrelationships that exist among the variables used to define the state. The collected data can be arranged in matrix form, where each column vector (a total of m) in the matrix represents the measurements made at a particular state. The number of columns of this matrix is equal to the number of observations, and number of rows is equal to the number of sensors. If we define the set of measurements taken at a given time \( t_j \) as an observation vector \( \tilde{X}(t_j) \)

\[
\tilde{X}(t_j) = [x_1(t_j), x_2(t_j), ..., x_n(t_j)]^T
\]

(1)

where \( x_i(t_j) \) is the measurement from sensor i at time \( t_j \), then the data collection matrix is defined as the process “memory” \( D \). The number of columns of this matrix is equal to the number of observations, and number of rows is equal to the number of sensors.
If a new observation is made and the sensor measurements from this matrix represent correlated phenomena, then it can be assumed that the estimate of the new state is related to the data matrix in the following way:

\[ \tilde{x}_{est} = \tilde{D} \cdot \tilde{W} \]  

(2)

The weight vector \( \tilde{W} \) is computed in MSET using a proprietary set of nonlinear operators. In a general operator form, the solution for the weight matrix in MSET is given by the following expression:

\[ \tilde{W} = (\tilde{D}^T \otimes \tilde{D})^{-1} (\tilde{D}^T \otimes \tilde{X}_{obs}) = \tilde{K}^{-1} \tilde{A} \]  

(3)

where symbol \( \otimes \) represents a nonlinear operator applied to the input data. The goal of this operation is to transform the input data space into another space, called the feature space, which reveals the similarity between new states and previous states that are stored in the process memory matrix. The matrix \( \tilde{K} = \tilde{D}^T \otimes \tilde{D} \) has components \( K_{ij} = \tilde{X}_i^T \otimes \tilde{X}_j \) and is designated as the similarity matrix. Several nonlinear operators have been invented and implemented in the MSET algorithm for a variety of applications in the areas of nuclear power plant signal validation and fault identification.

To improve numerical accuracy and stability, Tikhonov regularization has been implemented in MSET [4]. The Tikhonov regularized solution \( \tilde{W}_\lambda \) is obtained as the solution to the following minimization problem:

\[ \min_w \{ \| \tilde{K}\tilde{W}_\lambda - \tilde{A} \|^2 + \lambda \| \tilde{L}\tilde{W}_\lambda \|^2 \} \]  

(4)

where \( \lambda \) is the regularization parameter and \( \tilde{L} \) is a convenient regularization matrix that controls the smoothness of the solution.

The solution of the regularized problem is

\[ \tilde{x}_{est} = \tilde{D}\tilde{W}_\lambda = \tilde{D} (\tilde{K} + \lambda I)^{-1} \tilde{K}(\tilde{X}_{obs}) \equiv \tilde{Y} \tilde{K}(\tilde{X}_{obs}) \]  

(5)

Here \( \tilde{K}(\tilde{X}_{obs}) \) is a column vector. Each component \( (\tilde{K}(\tilde{X}_{obs}))_i = K(\tilde{X}_{obs}, \tilde{X}_i) = \tilde{X}_{obs}^T \otimes \tilde{X}_i \) can be regarded as a kernel evaluated at the points \( \tilde{X}_{obs} \) and \( \tilde{X} \) in the input space.

The estimation problem in the input space (first equality in equation (4)) has been transformed into an estimation problem in the feature space (last equality). Nonlinear features are defined using kernel \( K \).

2.2. Support Vector Machines (SVM)

To exploit an SVM approach, the first quadratic error term in (3) should be replaced with Vapnik’s \( \varepsilon \)-insensitive error function [2] of the form
The optimization problem for new regularized functional is more difficult than the problem for the quadratic functional (3). Using the technique of Lagrange multipliers it can be proved that the solution is equivalent to the solution obtained using SVM.

The SVM-based approximation scheme for any new variable $y$ takes on a form similar to the last equality in equation (4), except that a constant term $b$ is added for numerical stability

$$y = \sum_{i=1}^{m} \gamma_i K(\tilde{x}_i, \tilde{x}_1) + b = \sum_{i=1}^{m} (\alpha^*_i - \alpha_i) K(\tilde{x}_i, \tilde{x}_1) + b$$

(7)

The expansion coefficients $\alpha_i$ and $\alpha^*_i$ are the solutions of the following quadratic programming (QP) problem

$$\min R(\alpha^*, \alpha) = \varepsilon \sum_{i=1}^{m} (\alpha^*_i + \alpha_i) - \sum_{i=1}^{m} y_i (\alpha^*_i - \alpha_i) + \frac{1}{2} \sum_{i,j=1}^{m} (\alpha^*_i - \alpha_i)(\alpha^*_j - \alpha_j) K(\tilde{x}_i, \tilde{x}_j)$$

subject to the constraints:

$$0 \leq \alpha^*_i, \alpha_i \leq C = 1/\lambda$$

$$\sum_{i=1}^{m} (\alpha^*_i - \alpha_i) = 0$$

$$\alpha_i \alpha^*_i = 0$$

(9)

The order of the QP problem is $2m$, where $m$ is the number of observations. Due to the nature of this problem, only a number of the coefficients $\alpha^*_i - \alpha_i$ will be different from zero, and the input data points associated with those that are nonzero are called support vectors. The number of support vectors depends on $C$ and $\varepsilon$. The parameter $C$ weighs the data term with respect to the smoothness term, and is related to the amount of noise in the input reactor signals. The parameter $\varepsilon$ controls the tolerance level in the objective function error. A larger tolerance improves the generalization ability, but values that are too large can lead to unacceptable bias. The constant term $b$ is obtained from the necessary and sufficient conditions for the global minimum of the regularized functional [2].

The selection of an appropriate QP algorithm is important since the number of variables can be enormous, and standard algorithms are not appropriate. Since the number of variables is equal to the number of data points, and the quadratic form is completely dense, memory requirements grow with the square of the number of data points. Therefore, decomposition
and scalability become important issues. In the present version we implemented a modification of Sequential Minimal Optimization [5], a convenient decomposition algorithm that does not require storage of the complete quadratic form.

2.2. Fault Detection

During monitoring, the MSET modeling technique is used to estimate the state of the system. This estimated state is then compared to the current measured state. The difference between the estimated and measured state is analyzed using an extended version of the Sequential Probability Ratio Test (SPRT) [6].

Normal signal behavior in a SPRT is defined to be that for which the signal data adheres to a Gaussian probability density function (pdf) with mean 0 and variance $\sigma^2$. Normal signal behavior is referred to as the null hypothesis, $H_0$. MSET utilizes three specific SPRT hypothesis tests. Each test determines whether current signal behavior is consistent with the null hypothesis or one of three alternative hypotheses. The tests are known as the positive mean test, the negative mean test, and the variance test. For the positive mean test, the corresponding alternative hypothesis, $H_1$, is that the signal data adhere to a Gaussian pdf with mean $+M$ and variance $\sigma^2$. For the negative mean test, the corresponding alternative hypothesis, $H_2$, is that the signal data adhere to a Gaussian pdf with mean $-M$ and variance $\sigma^2$. For the variance test, the corresponding alternative hypothesis, $H_3$, is that the signal data adhere to a Gaussian pdf with mean 0 and variance $V\sigma^2$. The SPRT technique provides a quantitative framework that permits a decision to be made between the null hypothesis and an alternative hypothesis with specified misidentification probabilities. If the SPRT accepts one of the alternative hypotheses, then the measured signal from which the residual signal is formed in MSET is declared to be degraded. It has been proved that the SPRT provides the earliest possible annunciation of the onset of a subtle disturbance in a noisy process variable.

3. RESULTS

We will present modeling results for a standard data from Argonne's archive, a set of 10 signals from Experimental Breeder Reactor (EBR-II). The first half of 1000 data is used for training and the second part for testing.

In a previous paper [3] we studied generalization performance of several kernels. For this data set, the best generalization performance has been achieved for the Hermitian kernel

$$K(x, y) = \exp(\alpha (x \cdot y)) \exp(-\alpha \|x - y\|^2 / 2 \cdot \beta^2)$$

(10)

with a data-dependent normalization factor $\alpha$ and a free parameter $\beta$ that controls the width of the Gaussian. This parameter has effect on smoothing properties, as in standard kernel regression. Better adaptation to data could be obtained using a properly selected parameter $\sigma$. This parameter should follow the input data variability, but in practice it is not easy to find the proper value. The selection is normally based on the minimum of the generalization error. Since in this application we are more interested in correct fault detection, we selected parameter $\beta$ in such a way to optimize that performance. After some experimenting we found out that the optimal parameter is 0.3. Comparison of the training and testing errors for the standard MSET and the SVM estimation using the Hermitian kernel is given in Table I.
Table I. Training and Testing Errors for EBR II data

<table>
<thead>
<tr>
<th>Standard MSET with the Hermitian kernel</th>
<th>SVM with the Hermitian kernel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of vectors</td>
<td>Training Error</td>
</tr>
<tr>
<td>65</td>
<td>0.1868</td>
</tr>
<tr>
<td>15*</td>
<td>0.3324</td>
</tr>
</tbody>
</table>

* minimum number of training vectors permitted in MSET for this data set

The superior performance of SVM is obvious from the table. The optimal subset of training vectors is very small, enabling fast on-line estimation. We compared the performance of MSET and SVM using the same number of support vectors. These vectors are selected automatically in SVM, while the number of training vectors in MSET should be given a priori and selection is a norm-based sub-optimal procedure. As a result, both testing and training errors in SVM are much smaller. Measured and estimated values for one of the selected signals are presented in Figure 1.

To study fault detection, slow linear ramp degradation has been introduced in the testing data, with the maximum amplitude equal to 3 standard deviations ($\sigma_{in}$) of the input data. Fault detection results for a standard positive mean SPRT setup (pre-specified false alarm probability = pre-specified missed alarm probability = 0.001; signal disturbance magnitude = 3 $\sigma_{in}$) are given in Figure 2.

This example shows that properly tuned SVM algorithm can also improve fault detection. A very subtle disturbance has been announced earlier when estimation is performed with the SVM estimation module than when the standard MSET is used for estimation.
Figure 1. Unperturbed signal from EBR II estimated using SVM with the Hermitian kernel ($\varepsilon = 0.25$)

Figure 2. Slow degradation detection using the Hermitian kernel
3. CONCLUSIONS

A recently proposed learning paradigm called the Support Vector Machine (SVM) has been applied to nuclear reactor state estimation. The generalization error of this methodology is improved by transformation of the input data into another space, called feature space, using an appropriately defined kernel function. In addition, optimal training is achieved using a convex quadratic programming approach that results in a unique solution. The selection of proper kernels is an open research problem. As an illustration of the method, we used in this paper a kernel based on the Hermite polynomials. Preliminary results on the presented data set from the Experimental Breeder Reactor II show that the SVM learning algorithm improves sparsity of data representation, generalization error, and fault detection.

REFERENCES


