DEVELOPMENT OF A TRANSIENT SIGNAL VALIDATION TECHNIQUE VIA A MODIFIED KERNEL REGRESSION MODEL

Ibrahim Ahmed and Gyunyoung Heo*
Department of Nuclear Engineering
Kyung Hee University
1732 Deogyeong-daero, Giheung-gu, Yongin-si, Gyeonggi-do 17104, Korea
ibrahima@khu.ac.kr; gheo@khu.ac.kr

ABSTRACT

The demand for robust and resilient performance has led to the use of online-monitoring and signal validation techniques to monitor the process parameters and equipment conditions using several empirical models. One of these models is kernel regression (KR). Although KR is being used and performed excellently when applied to steady state, it has limitation in time-varying data that has several repetition of the same data point of the signals, especially if those signals are used to infer the other signals. In addition, many situations are related to variation and fluctuation during normal states, such as transient – start-up and shutdown mode. However, accurate estimation of the process signal can lead to the proper understanding of the equipment behaviours as well as enhance the online monitoring applications. In the sight of foregoing, this paper proposed a modified KR model, especially for transient signal validation to resolve the setback of conventional KR by improving the measure of similarities in the conventional KR. The performance of the proposed model is verified using both experimental data and the plant simulation data, and its results are compared with that of conventional KR. The results show that the proposed model has a greater robustness in particular situations compared to conventional KR, and it can be used to improve process and equipment monitoring applications.

Key Words: Kernel regression; On-line Signal validation; Time-varying signals

1 INTRODUCTION

On-line monitoring and signal validation techniques are the two important terminologies in the on-line process and equipment monitoring. The demand for robust and resilient performance has led to the use of online-monitoring and signal validation techniques to monitor the process and equipment parameters. These techniques are automated methods of monitoring instrument performance while the plant is operating [1,2]. To implement these techniques, several empirical models are used [1–4]. Developing an empirical model does not require in-depth understanding of the physics of the systems under consideration. One of these models is nonparametric regression model generally known as kernel regression (KR). Unlike parametric models, KR is an algorithmic estimation procedure which assumes no significant parameters. KR is the process of estimating a parameter's value in statistical modeling by calculating a weighted average of the historical observational values.

KR regression has been used for building several data-driven models, and demonstrated to be efficient in some situation and applications; in process anomaly detection [5], in nuclear forensic models [6], in general application of the steady-state process and equipment monitoring and prognostics [3,7,8], and in image processing and reconstruction [9]. Although KR performed excellently when applied to steady state or normal operating data, preliminary investigations showed that KR has limitation in time-varying data that has several repetitions of the same signals, especially if those signals are used to infer

* Corresponding Author

the other signals. In addition, many situations are related to variation and fluctuation in the normal operating state, such as transient – start-up and shutdown mode. The major shortcoming of KR (as discussed in section 1.2) in such a condition is that, the values of dependent variable in those points of the same value of the predictor variables assume value of the average of those dependent variable values.

Therefore, developing a model to functions in a wider range of application, especially, in time-varying signals or diverse signals will not only solving the problem associated with KR but also will lead to the provisions of early warning information about the transient condition of the system to the operator, and enhancement of operational performance of the plant. Thus, in this paper, we proposed a modified KR model for a more robust on-line signal validation to resolve this setback of conventional KR model taking the timing variation into consideration. The main objective of this research work is to develop a modified KR model through the improvement in the measure of similarity calculations in the conventional KR, in times of the time-series data or normal operation transient data for the possibility of generalizing the applicability of the KR model for a wider range of application in monitoring during operational period of the plant. This in fact, will improve the accuracy, the capability and applicability of the KR model for early warning alert and to be able to properly understand the process and equipment behaviors for efficient monitoring even in normal transient state.

1.1 Brief Overview of Kernel Regression Model

Kernel Regression is generally represented by the Nadaraya [10]-Watson [11] estimator, which is a weighted average of the historical observational values. Considering a multiple variables by given a matrix of memory data of predictor variables X and the response variable **y** as

$$X = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,p} \end{bmatrix}$$

$$\mathbf{y} = [y_1 \quad y_2 \quad \cdots \quad y_m]^T$$

where p is the number of predictor variables, n is the number of memory vectors, and $x_{i,j}$ is the ith observation of the jth predictor variable. For any observed query vector,

$$\mathrm{x}_q = \begin{bmatrix} x_{q,1} & x_{q,2} & \cdots & x_{q,p} \end{bmatrix}$$

the Euclidean distance d, which determined how far is the query vector from each vector of the memory data, the kernel weight (Gaussian kernel) k, which assigned a weight base on the calculated distance, and the estimated response variable, $\hat{y}$ are respectively calculated by eqns. (1), (2), and (3) as follows:

$$d_i(X_i,\, x_q) = \sqrt{\left(x_{i,1} - x_{q,1}\right)^2 + \left(x_{i,2} - x_{q,2}\right)^2 + \cdots + \left(x_{i,p} - x_{q,p}\right)^2} \tag{1}$$

$$K_i(X_i,\, x_q) = exp\left(\frac{-d_i^2}{2\sigma^2}\right) \tag{2}$$

$$\hat{y}_i(\, x_q) = \frac{\sum_{i=1}^{m} K(X_i,\, x_q).\, y_i}{\sum_{i=1}^{m} K(X_i,\, x_q)} \tag{3}$$

where σ is the kernel bandwidth.

Equation (3) is a weighted average of the response variable of the memory data y, which estimates the output. This equation can be used in inferential KR (IKR), auto-associative KR (AAKR) or hetero-associative form to estimate the variables as described in [3]. More details of KR and several other empirical models are well documented in [12].

1.2 Problem Definition

In order to channel the research work in a proper direction, it is important to effectively define the problem to be solved. Baraldi *et al* [13] proposed a modified AAKR through the similarity measure between the observational data and the historical data by applying a pre-processing step that project both the observed and historical data into a new space defined by a penalty vector, and then compute kernel weight with Euclidean distance of the data in the new space. The timing information and the impact of the previous data point on the evolution of the current data point are not considered. However in a time-varying data with several repetitions of the same signal value, it is necessary to incorporate the timing information of the location at which the data point occur into the conventional KR model for accurate signal prediction. Fig. 1 defined the problem associated with the conventional KR.

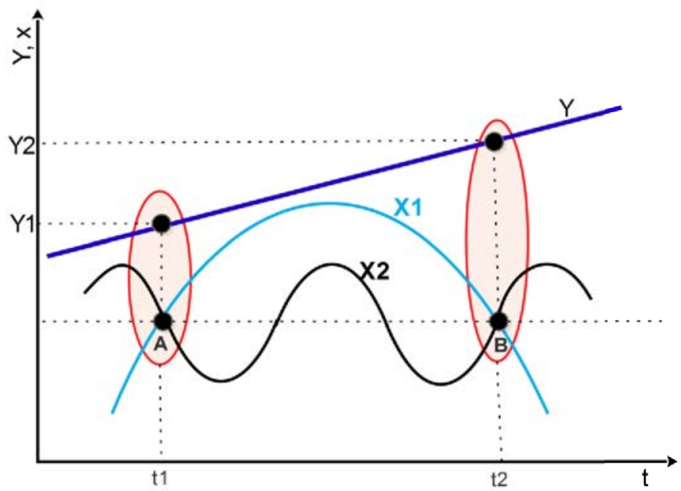


Figure 1. Problem definition (Estimation of Y given X1 and X2)

In Fig. 1, to estimate the variable Y given X_1 and X_2, the predictor vector at the point A which occurs at time t_1 is identical to the predictor vector at point B which occurred at t_2. In this case, the corresponding values of Y, y_1 and y_2 at the respective data points cannot be estimated correctly by conventional KR. This is because the traditional Euclidean distance used in KR will compute the same distance value to the two data vectors which in turn will result in KR inability to differentiate between the two data vectors. This leads to the wrong estimation of the corresponding Y values. The thorough investigation revealed that the estimates of the corresponding values of y_1 and y_2 assumed an identical value of the average of the expected values of the y_1 and y_2. Therefore, in order to resolve this drawback, it is necessary to incorporate into the conventional KR, a timing occurrence and information of the previous data points that leads to the evolution of the current data point, for proper implementation of the on-line validation of time-varying signals.

Therefore, in order to resolve this drawback, we developed a time-dependent KR model by considering the location where each data point occurs. The analysis of this timing/position application is discussed in section 2 of the methodology. The developed model is verified using experimental data and plant simulation data, and its applicability is evaluated and compared with the conventional KR.

2 METHODOLOGY

In this section, the approaches used in developing a modified kernel regression through the improvement in the similarity calculations are described. Section 2.1 discussed the developed transformation equation of the modified model. The gradient calculation methods in which the developed equation depends upon are described in section 2.2.

2.1 Development of Time-dependent Equation

To incorporate the aforementioned information discussed in section 1.2 into the conventional KR, a time-dependent transformation equation is derived using the Taylor series expansion of eqn. (4).

$$x(t+h) = x(t) + h\frac{dx(t)}{dt} + \frac{h^2}{2!}\frac{d^2x(t)}{dt^2} + \frac{h^3}{3!}\frac{d^3x(t)}{dt^3} + \cdots\cdots \tag{4}$$

From this Taylor series, the function at $x(t_2)$ can be approximated as

$$x(t_2) = x(t_1) + (t_2 - t_1)\frac{dx}{dt}, \tag{5}$$

with $\mathrm{h} = (t_2 - t_1)$, which is the time step interval. Equation (5) can then be rearranged as

$$x(t_2) = t_2\frac{dx}{dt} + x(t_1) - t_1\frac{dx}{dt}. \tag{6}$$

Thus, in a more general form, with reference to the eqn. (6), the time-dependent transformation equation for a multivariate function is given by eqn. (7) and eqn. (8),

$$\boldsymbol{\psi}_{i,j} = \boldsymbol{\psi}^{\mathbf{0}}_{i-1,j} + \boldsymbol{t}_i * \frac{\boldsymbol{dx}}{\boldsymbol{dt}_{i,j}} \tag{7}$$

$$\boldsymbol{\psi}^{\mathbf{0}}_{i,j} = \boldsymbol{x}_{i,j} - \boldsymbol{\psi}_{i,j} \tag{8}$$

where $\psi_{i,j}$ is the resulting transformed value of the current data point $x_{i,j}$, $\psi^0_{i-1,j}$ is the difference between $\psi_{i-1,j}$ and $x_{i-1,j}$, $dx/dt_{i,j}$ is the first derivative or gradient of the function at data point $x_{i,j}$, t_i is present time location of the data point $x_{i,j}$ of the *i*th predictor of the *j*th variable. Equation (7) represents the data point $x_{i,j}$ by incorporating the timing occurrence information and the information of the previous data points through gradient into Euclidean distance calculation. It can be observed that, the output of this equation has the same unit as that of the original value *x*. In this equation, the information from previous input vectors is incorporated into the KR through the gradient and the time of the current input vector. This in fact will gives a more details representation of the estimations compare to that of the conventional KR that ignored any information leading to the current data point.

Based on the eqn. (7) however, the memory/train data X and the query/test data can be transformed as follows:

$$\mathbf{X} = \begin{bmatrix} x_{1,1} & x_{1,2} & \cdots & x_{1,p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m,1} & x_{m,2} & \cdots & x_{m,p} \end{bmatrix} \Rightarrow \boldsymbol{\Psi} = \begin{bmatrix} \psi_{1,1} & \psi_{1,2} & \cdots & \psi_{1,p} \\ \vdots & \vdots & \ddots & \vdots \\ \psi_{m,1} & \psi_{m,2} & \cdots & \psi_{m,p} \end{bmatrix}$$

$$\mathbf{x}_{\boldsymbol{q}} = \begin{bmatrix} x_{q,1} & x_{q,2} & \cdots & x_{q,p} \end{bmatrix} \Rightarrow \boldsymbol{\psi}_{\mathbf{q}} = \begin{bmatrix} \psi_{q,1} & \psi_{q,2} & \cdots & \psi_{q,p} \end{bmatrix}$$

Thus, the corresponding Euclidean distance for any given query vector can be evaluated by eqn. (9).

$$d_i(\Psi_i, \psi_q) = \sqrt{(\psi_{i,1} - \psi_{q,1})^2 + (\psi_{i,2} - \psi_{q,2})^2 + \cdots + (\psi_{i,p} - \psi_{q,p})^2} \quad (9)$$

The computed distance by eqn. (9) is then used to calculate the kernel weight using Gaussian kernel function (eqn. (10)) and then estimate the dependent variables using eqn. (11). The model can also be used for AAKR. In that case, y_i and $\hat{y}_i(x_q)$ should be replaced with $x_{i,j}$, and $\hat{x}_i(x_{q,j})$ respectively.

$$K_i(d_i) = exp\left(\frac{-d_i^2}{2\sigma^2}\right) \quad (10)$$

$$\hat{y}_i(x_q) = \frac{\sum_{i=1}^m K_i(d_i).y_i}{\sum_{i=1}^m K_i(d_i)} \quad (11)$$

2.2 Derivative Approximation

The gradient/derivative at each data point indicated in eqn. (7) need to be calculated. The formula for numerically approximate the derivative can be derived from the polynomial equations.

Generally, the historical data use to build the empirical models are collected during plant operation. Let’s assume the data points are read at a particular time with a constant time interval of say h. That is, the data are evenly spaced with time interval of h sec. The derivative at a particular data point can be approximated using finite difference derivative approximation. For mxp matrix X of the given data, the first order backward difference derivative approximation based on three data points accuracy, at a data point $x_{i,j}$ can be calculated as

$$\frac{dx}{dt}_{i,j} = \frac{3x_{i,j} - 4x_{i-1,j} + x_{i-2,j}}{2h}. \quad (12)$$

The backward difference is chosen in this work in order to implement real-time monitoring. In the eqn. (12), it can be understood that the model needs initial three successive query vectors in order to evaluate the derivative of third vectors using backward finite difference derivative approximation that depends on three data points for evaluations. Therefore, for proper real-time monitoring, the modified model will start on-line monitoring from the third vector after initialization. Therefore, based on the backward difference formula of eqn. (12) that is selected for real-time monitoring, the model continues to stores the two immediate passed vectors and uses it to evaluate the derivatives of any subsequent available query vector. With this novel development, the information of the previous data point that led to the evolution of the current data point is incorporated into the KR, and the setback of the conventional KR due the traditional Euclidean distance that calculated identical distance for the data points that has the same values can be completely eliminated.

In order to increase the computational efficiency, a more general representation of eqn. (12) that simultaneously calculate the derivative for all the data points in the modified model is developed in matrix form. Hence, for mxp matrix X of the given data, the backward difference derivative approximations at all the data points are calculated as given in eqn. (13). The matrix, D is an mxm squared matrix, which can be represented as a sparse matrix with zeroes in most of the elements as shown below (for the case of two variables, i.e., m=9 and p=2). The matrix D can be formed with the leading diagonal that has all the elements as “3” except in the first two rows.

$$\frac{d}{dt}(X) = \frac{1}{2h} DX \tag{13}$$

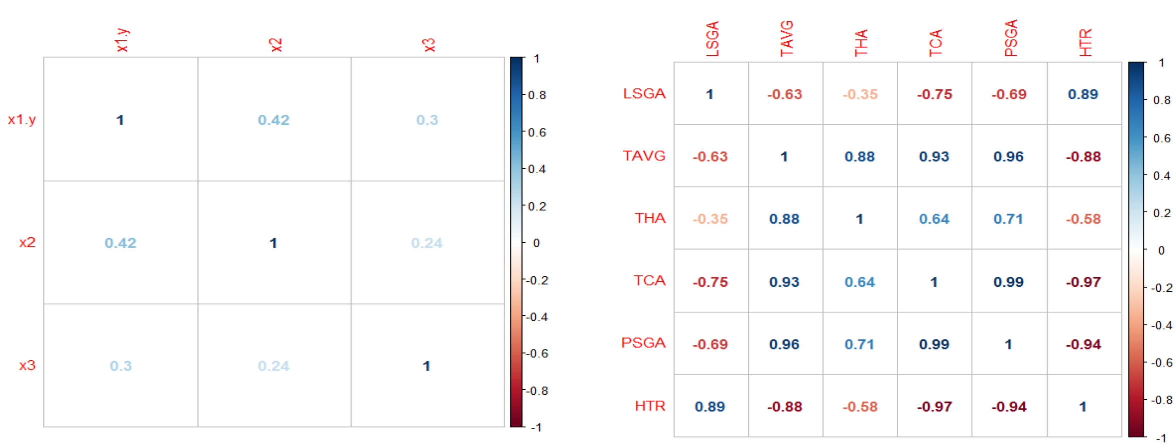
$$\frac{d}{dt}(X) = \frac{1}{2h} \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & -4 & 3 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & -4 & 3 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & -4 & 3 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & -4 & 3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & -4 & 3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & -4 & 3 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -4 & 3 \end{bmatrix} \begin{bmatrix} x11 & x12 \\ x21 & x22 \\ x31 & x32 \\ x41 & x42 \\ x51 & x52 \\ x61 & x62 \\ x71 & x72 \\ x81 & x82 \\ x91 & x92 \end{bmatrix}$$

3 VALIDATION WITH EXPERIMENTAL AND SIMULATION DATA

It is important to verify the validity and applicability of the proposed model for online monitoring and signal validations. To do this, two difference kinds of datasets are used in this work. Firstly, we used the lab experimental data generated from heat conduction experiment to evaluate the performance of the model and compared the results with the conventional KR. Lastly, we used the simulation data generated from the plant simulation model. This simulation data is collected during normal operating conditions as well as the LOCA accident induced condition. The data from normal operating condition are used to build the model while corrupted/faulted data are used to test the model. The degrees of correlation between the variables of the two datasets are shown in Fig. 2. Both inferential and auto-associative models are built and verified for both modified and conventional KR. For the first dataset, to verify the inferential model, y variable is chosen as dependent variable to be predicted from the other two signals, x1 and x2. In the second dataset, the LSGA (Level Steam Generator A) is chosen to be estimated using the other five (5) signals. For the case of auto-associative model, all the signals of the second dataset are used. The residual between the actual value and the estimated value are calculated by eqn. (14).

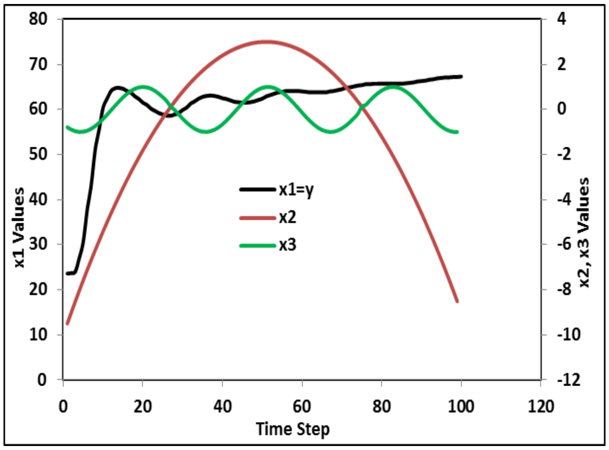
$$Residual_i = y_i - \hat{y}_i \tag{14}$$

The $\hat{y}_i$ is the estimated value and y_i is the actual value.

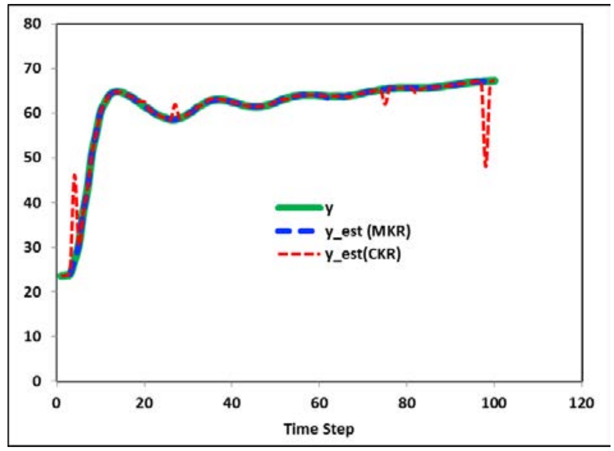


(a) **(b)**

Figure 2. Correlation plots: (a) Lab Experiment Data, (b) The selected signals to be monitored during normal operation from simulation data



(a)



(b)

Figure 3. Experimental Data (a) and the estimated results of y given x2 and x3(b)

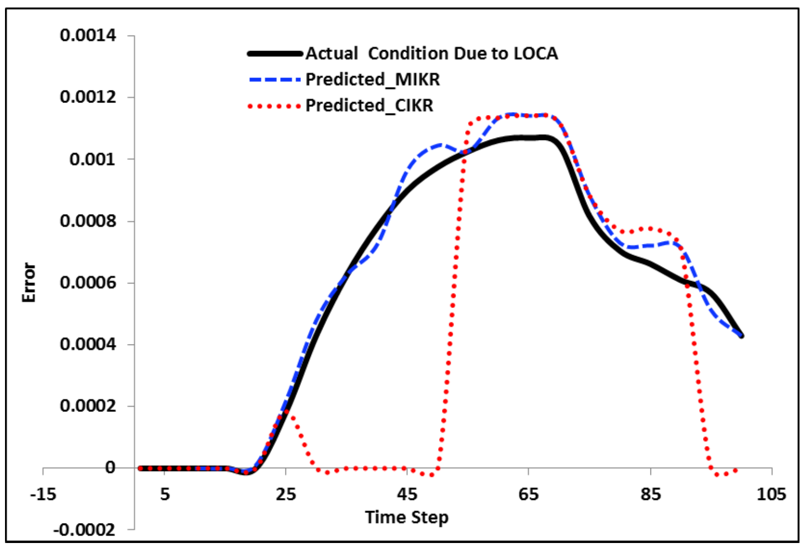


Figure 4. Residuals plot obtained from the test data that is corrupted as result of LOCA Accident (IKR)

Figure 3 (a) shows the results of the prediction of y from lab experimental data for both Conventional IKR (CIKR) and Modified IKR (MIKR). We discovered that the CIKR has several peaks due to the fact that, it does not take the previous information that leads to the evolution of the current data point into consideration. The MIKR has shown a greater robustness as shown in the figure. It was able to remove all the peaks shown in the conventional KR model and predicted the value of y correctly. Figure 4 shows the test results of the LSGA predictions. The MIKR was able to track the actual corrupted data compared to CIKR.

The residuals obtained from simulation data for both Modified AAKR (MAAKR) and Conventional AAKR (CAAKR) are presented in Fig. 5. The MAAKR provides the residuals that reflected the actual abnormal condition due to LOCA accident for all the signals, whereas the CAAKR provides the wrong indication of the actual situation.

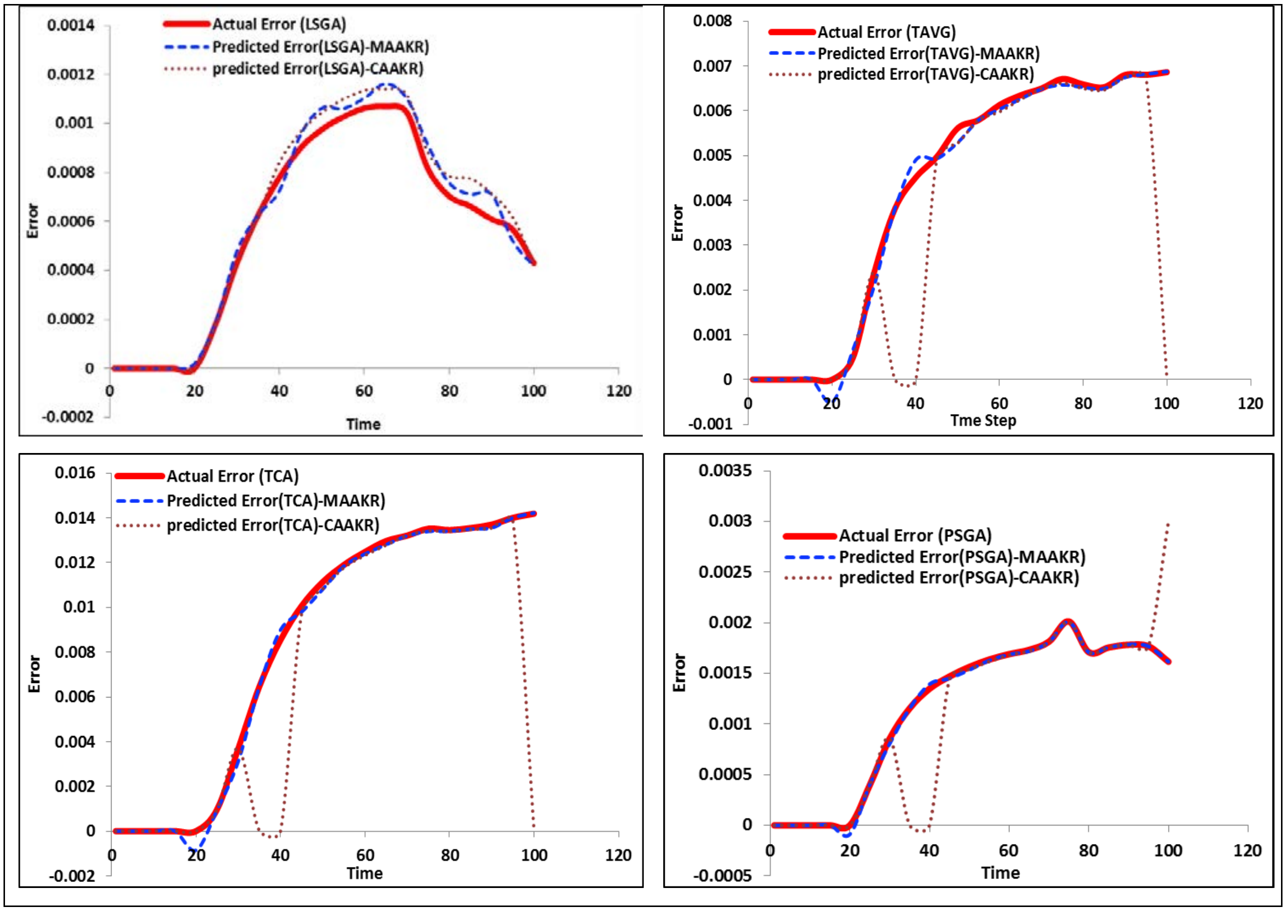


Figure 5. Residuals plot obtained from the test data that is corrupted as result of LOCA Accident (AAKR)

4 CONCLUSIONS

The conventional KR has limitation in correctly estimating the signals when time-varying data with repeated values are used to estimate the dependent variable especially in normal transient signal validation and monitoring, we proposed in this work a modified KR that can resolve this issue in time domain. A time-dependent equation is developed first to transform the data into another space prior to the Euclidean distance calculation considering their changes with respect to time. The derivative/gradient at each data point approximated using finite difference derivative approximations. The performance and robustness of the developed model is evaluated and compared with that of conventional KR using both lab experimental data and plant simulation data. The result shows that the proposed model, having demonstrated high robustness than that of conventional KR, is capable of resolving the identified limitation with conventional KR, and can improve the process signal validation and monitoring in steady-state and normal transient state.

5 ACKNOWLEDGMENTS

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