Review Article

Noise Reduction in a High Temperature Chaotic Dynamical System to Improve Process Control

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Abstract

Noise reduction in time series of multidimensional non-stationary chaotic systems is done in several steps. This is followed by determination of time delay and embedding dimension and then Lyapunov exponent. Correlation dimension is determined from embedding dimension and time delay. After knowing correlation dimension and Lyapunov exponent the underlying process dynamics can be better understood. A non-stationary time series of a chaotic system of a high temperature thermal and chemical reaction system pertaining to rotary sponge iron kiln operating between 800-1250 °C is considered in the present work. Effect of using moving average, moving median, Kalman Filter, and nonlinear polynomial filters are demonstrated. Efficacy of different methods of noise reduction is compared. The impact of noise reduction on process improvement is demonstrated.

Keywords: Noise reduction; Time series; Chaos; Filter; Sponge iron

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Introduction

The presence of noise in the time series usually misleads the control model because the noise increases unwanted chaos in data [1-4] and also increases embedding dimension (discussed in section 1.6). The pre-processing of the data for noise reduction is, therefore, the first step [5-8]. In this paper, an analysis has been done of a chaotic system that contains noise and belongs to a high temperature thermal (800-1250 °C) and chemical reaction system (reduction of iron oxide in a sponge iron rotary kiln).The time series selected in this work are non- stationary [9,10] in nature because the mean and standard deviation are found to change with time. An example is shown in Figure 1 for the case of Multi Louver Damper (MLD) which is used in the process for pressure and flow control in the rotary kiln. The pressure and gas flow control, as discussed later, directly affect the quality of product made (measured as %Fe in sponge iron). The combination of methods selected for noise reduction and evaluation in the present work include, as shown in Figure 2, moving average, moving median, Kalman filter [11-17] and non-linear polynomial filter (or nonlinear adaptive filter) [18]. Following this, in order to determine data similarity and noise type in the time series, the techniques of Horizontal Visibility Graph (HVG) and Detrended Fluctuation Analysis (DFA) are applied.
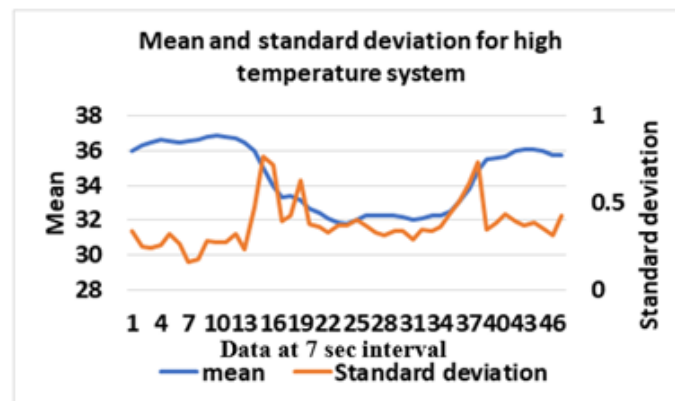
Figure 1: Mean and standard deviation of MLD used in a high temperature thermal and chemical reaction system; at a time 500 data sets are considered with an overlap of 250 data on either side and the set of 500 moves forward based on" last in first out strategy".
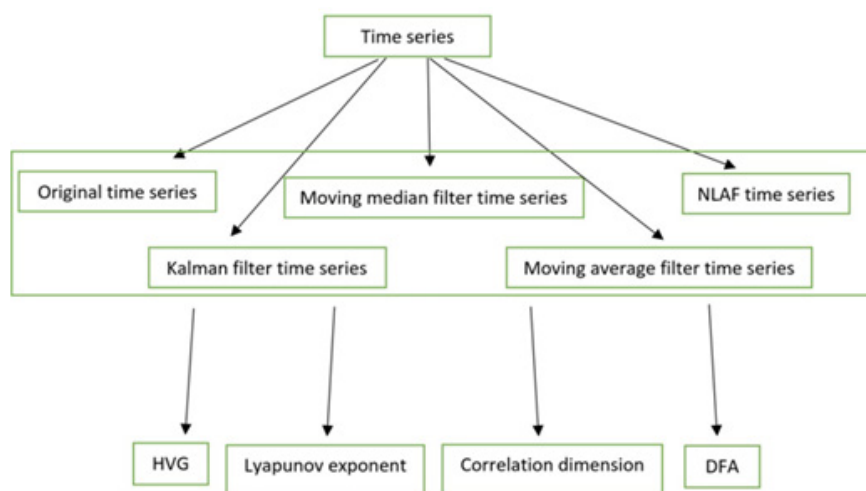

Figure 2: Steps adopted for analysis of chaotic time series.

The usefulness of present work is that it demonstrates the sequence of steps which should be followed, as also outlined in Figure 2. The effect of noise reduction on process control is discussed in section 3. The practical importance of noise reduction, especially for a chaotic system, is that it warns of a transition from a chaotic to non-chaotic regions, and vice versa, at different times. The process control strategy has to be changed accordingly, as discussed at the end (section 3).

Application of Kalman noise filter and nonlinear polynomial filter

Kalman filter is a well-known statistical noise reducer. It can be used for noise reduction in both stationary and non-stationary systems and details are provided in [19]. The nonlinear adaptive de-noising algorithm, as explained the detail in [18], fits a smooth polynomial in the whole noisy time series. First, it takes the time series and divides it into the pre decided number of segments of length w=2n+1, such that each consecutive segment has an overlapping of n+1 points. In the second step, a polynomial of degree K is fitted to each of the segments. In the overlap regions, there will be two different polynomials. So, the values of the consecutive polynomials are taken with proper weights to fit a smooth curve through the entire dataset. In the present work,

the approach is slightly improved and a weighted value of the consecutive polynomials is used to generate new time series. In the first and last segments, 'n' data points are not overlapped. To get the final fitted time series, the polynomial value (K) of non-overlapped region and the weighted polynomial value of overlapped region is combined. This step yields a smooth curve. In the present work, the values of polynomial fit of order K and n are respectively, 2 and 50.

After noise filtration by Kalman or NLAF filters, there is a change in fluctuation pattern in the actual data as shown in Figure 3 for the different parameters of rotary kiln. The parameters are pressure, MLD (Multi Louver Damper), Relative Humidity (RH), Inlet Temperature (KIT), Relative Ambient Temperature (RT) and Gas Volume (GV). Pressure variation is controlled by MLD. It can be seen that without noise removal, there is a sudden surge in MLD because it acts on noisy pressure data (due to noise in the pressure data). This disturbs the reduction atmosphere in the furnace (rotary kiln) and creates an unexpected drop in quality of sponge iron, as shown in Figure 4. The other parameters (RH, KIT, RT, GV, RH) are also known to affect the system performance. For good process control noise reduction is necessary so that control action is taken on right magnitude of a control parameter. Trend of noise reduction in pressure variation (mm of water column) is shown in

Figure 3(a); on MLD in Figure 3(b); on relative humidity in Figure 3(c); on kiln inlet temperature (°C) in Figure 3(d); on gas volume (Nm³/hr) in Figure 3(e) and on relative ambient temperature

(°C) in Figure 3(f). It can be seen that noise reduction by NLAF is superior to Kalman filter; the noise is considerably reduced in all the cases in Figure 3(a) to 3(f).
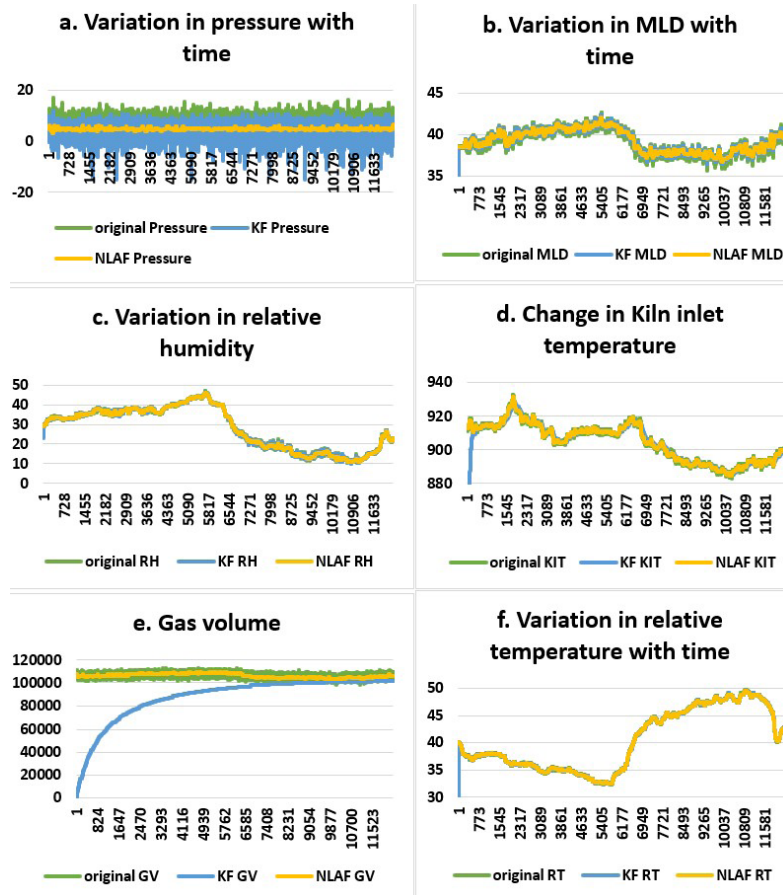

Figure 3: Effect of noise reduction by Kalman Filter (KF) and Nonlinear Adaptive Filter (NLAF); (a) pressure variation (mmwc); (b) MLD variation (percent opening); (c) Variation in relative humidity; (d) variation in kiln inlet temperature (°C); (e) gas volume variation (Nm³/hr) and (f) variation in relative ambient temperature (°C).

Figure 4: Change in quality of sponge iron product as a function of time (time step is one hour).

The impact of using noisy data (without noise removal) on product quality is evident from Figure 4. It can be seen that there is a sudden fall in quality of sponge iron from 82.3 to 75. Caused by an abnormal change in MLD. Due to the presence of noise in data, the MLD got wrongly activated to change the pressure resulting in quality drop at around 15:00 hours.

Application of moving average filter

Moving average filter is a linear filter. Average of a subset of 500 data points are selected at a time with forward shifting. The size of subset can be changed. The moving average reduces both the peak amplitude and the frequency of fluctuation in data. It acts like a low pass filter [19,20]. This filtration technique, however, modifies

amplitude of actual data and in most cases, it was not acceptable for a dynamical system. A comparison of moving average filter (moving batch size of 500) and the original signal is shown in Figure 5.
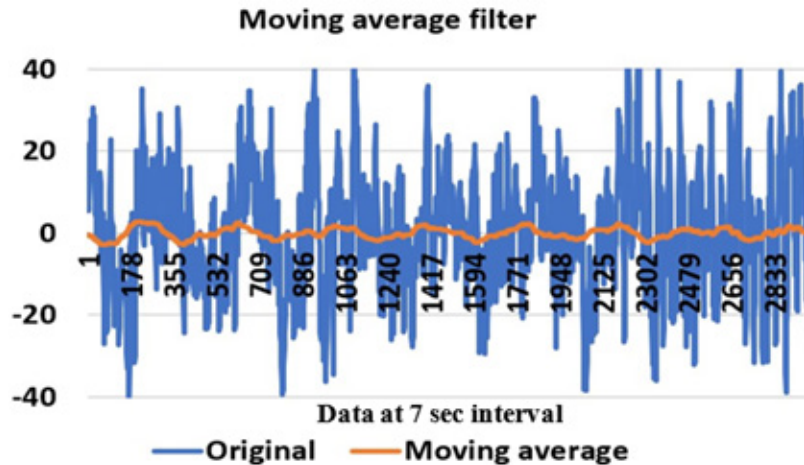

Figure 5: Situation after application of moving average filter and original data.

Application moving median filter

Moving median filter is similar to a nonlinear noise reduction technique [21]. This method eliminates the unwanted peaks. But as in the case of moving average filter, it also modifies the actual data.

Moving median for a sample signal is shown in Figure 6. Similar to moving average filter, moving median filter also kills (see Figure 6) large data information. Due to loss of information, the obtained time series is not useful for efficient process control in a chaotic dynamical system.
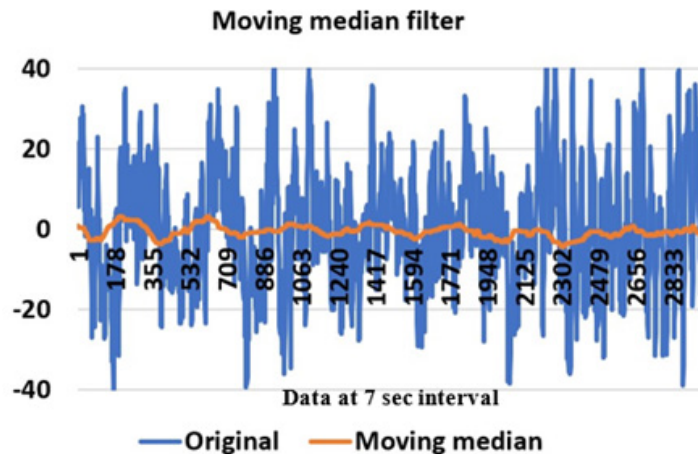

Figure 6: Situation after application of moving median filter and original data.

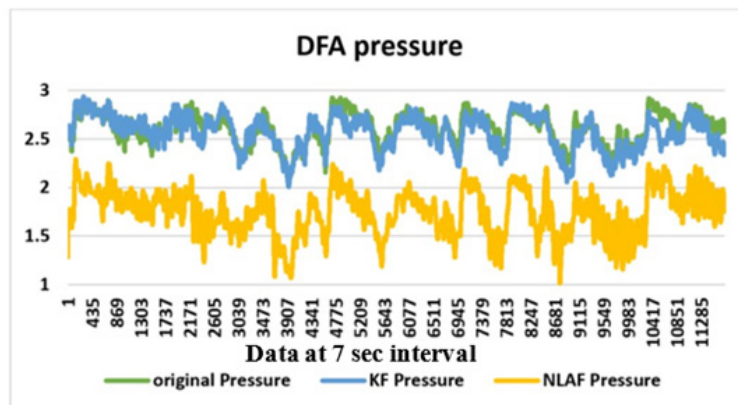### Application of detrended fluctuation analysis (DFA)

Figure 7: DFA analysis of pressure changes inside the vessel.

DFA is used to determine the self-similarity of the time series [22,23]. The major advantage of DFA is that it can be applied to a non-stationary system as well it is also easy to link DFA to decide the type of noise present in the time series. Which is the purpose in the present work. If value of DFA is equal to or greater than unity then it indicates that the system is non-stationary and unbounded, and if it is higher than 1.5 then it shows corruption with brown noise. After application of filter, there is a reduction in value of DFA of pressure but still (Figure 7), it is higher than 1.5. In Figure 7, in some regions of NLAF the DFA values are less than 1.5 (close to 1) which is perhaps a conversion of brown noise (known as a random walk) into pink noise [24].

Determination of time delay

The time series follows a particular pattern of time delay with respect to all affecting parameters and knowledge of time delay is required in finding embedding dimensions (discussed in section 1.6). There are two popular methods for estimation of time delay. The first method computes time delay by using autocorrelation [25-27] and the second method is based on Average Mutual Information (AMI). The time delay by auto correlation gives linear lag whereas time delay by AMI gives nonlinear lag. The preferred method adopted in this paper for time delay calculation in chaotic time series, as suggested in the literature [28], is AMI. The position of first minimum value is considered as the point for determining time delay for the chaotic time series. The time delay by autocorrelation is shown in Figure 8 and by AMI in Figure 9. The time delay by autocorrelation is 21 units whereas time delay by AMI is, as shown in Figure 9, 17 units. It is our experience that for a chaotic system AMI gives more reliable time delay values. Units are related to the frequency of measurement.

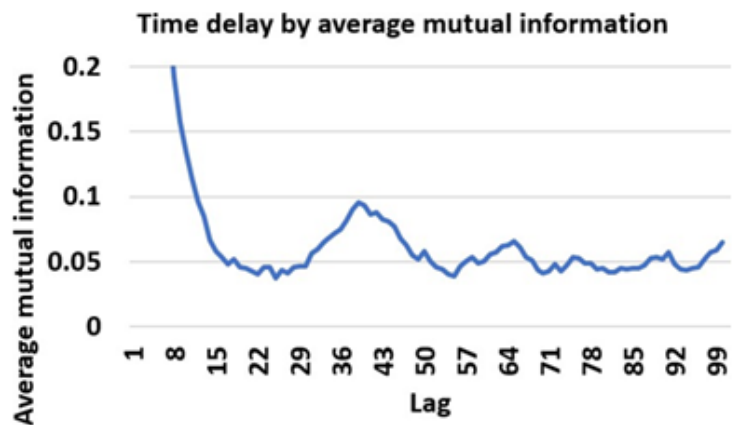**Figure 8:** Calculation of time delay by autocorrelation.

Figure 9: Time delay calculation by AMI.

A high level of noise in the system results in a lower time delay due to introduction of additional chaos (in the form of additional embedding dimension). In Figure 10 a comparison of time delay has been done. It is clear that there is a significant increase in value of time delay after noise reduction; a process with large time delay can be controlled more easily. In case of pressure in the rotary kiln the value of time delay increases from 2 units to 16 units when the time delay is computed after noise reduction by NLAF.
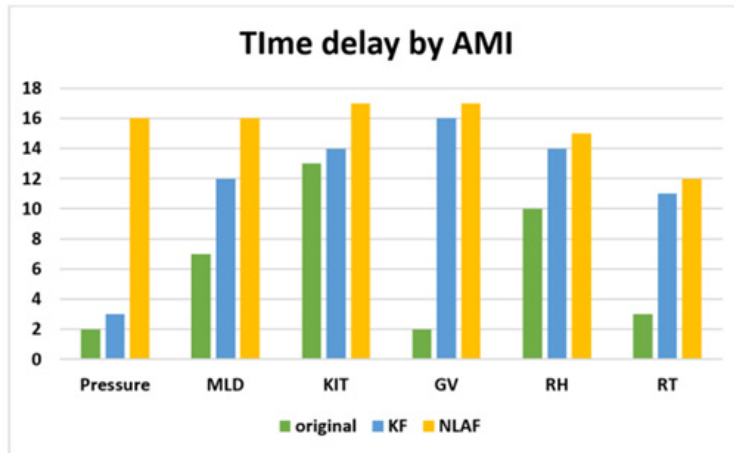
Figure 10: Variation in time delay before and after noise filtration.

Determination of embedding dimension

The embedding dimension gives information about the number of parameters that are affecting the time series. The method used for the calculation of embedding dimension in the present work is the False Nearest Neighbor (FNN) method [29,30].The minimum embedding dimension obtained by FNN is shown in Figure 11. If the difference in the percentage of FNN is less than 10 percent (than the previous point) or there is a sudden change in steepness of curve then that point is considered as a minimum embedding dimension in the present work. The embedding dimension for pressure signal in rotary kiln is 4, as pointed by the arrow in Figure 11. After noise reduction by NLAF there is an obvious decrease in embedding dimensions. The effect of noise reduction on value of embedding dimension is compared for Kalman filtered series and original time series in Figure 12 for several parameters of rotary kiln.
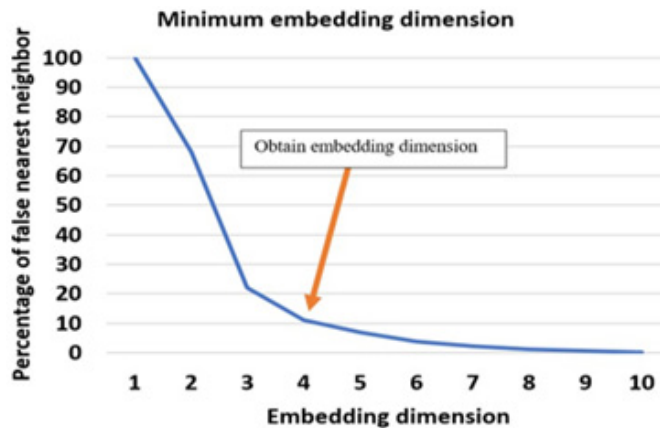

Figure 11: Calculation of embedding dimension by the false neighbor method.
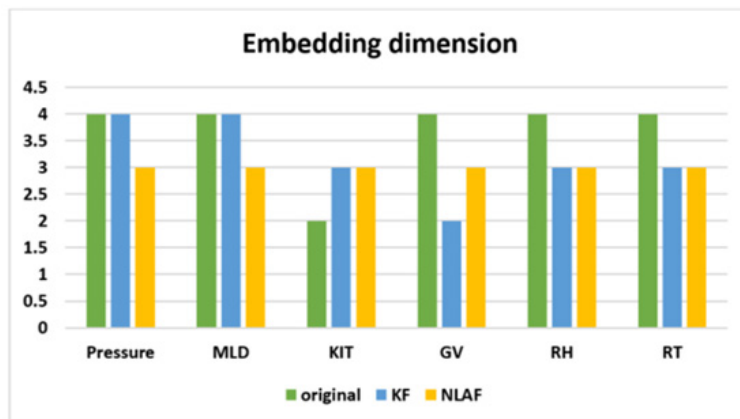

Figure 12: Comparison of change in embedding dimension for pressure, Multi Louver Damper (MLD), Kiln Inlet Temperature (KIT), Gas Volume (GV), Relative Humidity (RH) and Relative Ambient Temperature (RT).

Determination of correlation dimension

The correlation dimension [31] gives the most effective dimension for a 'm' dimensional space (where m is embedding dimension).The correlation dimension for the original pressure series is shown in Figure 13. The obtained correlation dimension is 3.77 which is close to embedding dimension of 4 as determined earlier in section 1.6. But in some cases, the correlation dimension can become much less than embedding dimension (see Figure 14) and then it is more convenient to construct phase space with reduced dimensions. In fact, after noise reduction by NLAF, there is a decrease in correlation dimension (compared to embedding dimension in Figure 13). In this respect, our experience is that noise reduction by NLAF is better than Kalman filter. For process control purpose phase space is to the reconstructed later from correlation dimension.
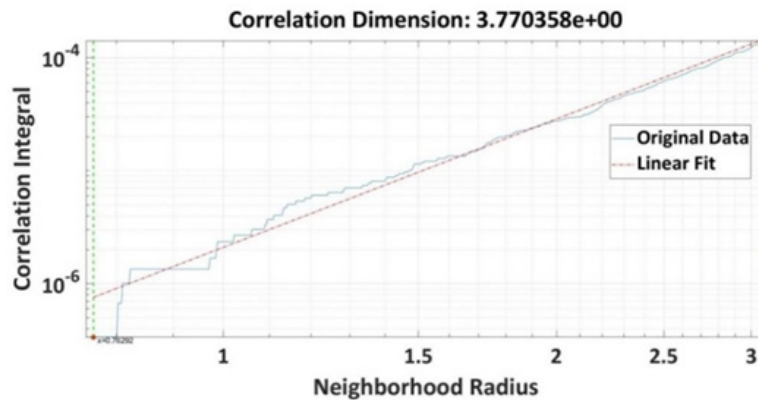

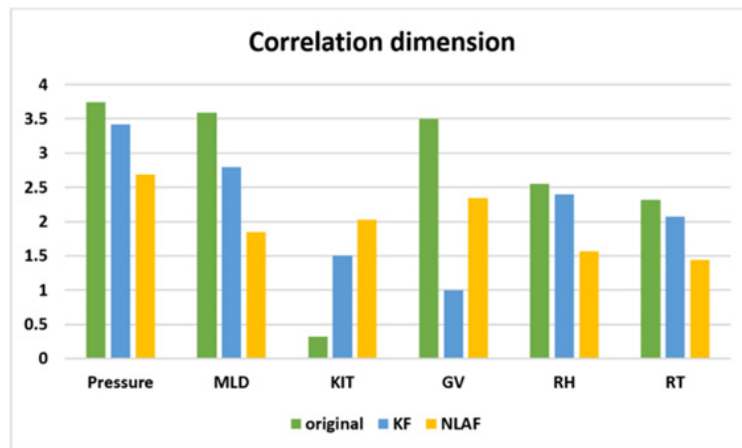**Figure 13:** Correlation dimension for raw pressure series.

Figure 14: Comparison of change in correlation dimension of original, KF and NLAF time series.

Determination of maximal Lyapunov exponent

After determining time delay and embedding dimension, we can determine Lyapunov exponent of time series. If the Lyapunov exponent is positive then the system may be chaotic. Chaotic systems show dependence upon the initial conditions. If two initial conditions have a small difference 'δx' [32], then their difference after time 't' will be $\delta xe^{\lambda t}$, where λ will be the exponential separation. Thus, a little difference in an initial condition can significantly alter future values. The value of λ is called the Lyapunov exponent. A unidimensional system is characterized by a single Lyapunov exponent. Maximal Lyapunov exponent means the maximum Lyapunov value out of all dimensions in a multidimensional system.

The sign of Lyapunov exponents itself gives only a qualitative information about the dynamics of the system. But in some cases, Lyapunov exponent can used to reconstruct the phase space of the system from time series. When noise reduction is done by NLAF the Lyapunov exponent is considerably reduced and becomes less than zero at certain times, as shown in Figure 15. It shows the importance of removal of noise in process control. The trend of Lyapunov exponent is directly used in process control algorithm. It is also used for event detection, for example when an accretion breaks inside the kiln then fluctuation pattern of Lyapunov exponent changes abruptly. Thus, from online data, a process change is identified and accordingly control actions are initiated by the expert system [33-37].
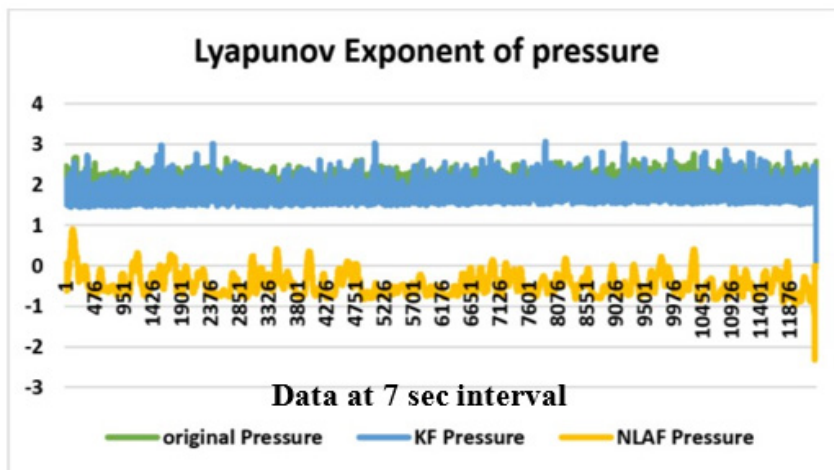
Figure 15: Maximal Lyapunov exponent for original, KF and NLAF pressure series.

Horizontal visibility graph

Horizontal visibility algorithm draws a horizontal line between the nearest neighbor points [38]. If one of the horizontal lines connects to a nearby neighbor without intersecting other than these two points are known as connecting nodes as explained in [39-42].

However, the presence of noise in data converts the maps into a complex network. A higher value of HVG indicates data similarity. In Figure 16 there is an increase in the value of HVG after removal of noise by NLAF, as compared to KF and original series. In the overall scheme of process control at the plant HVG is used as an additional confirmation or checking measure in control of rotary kiln.
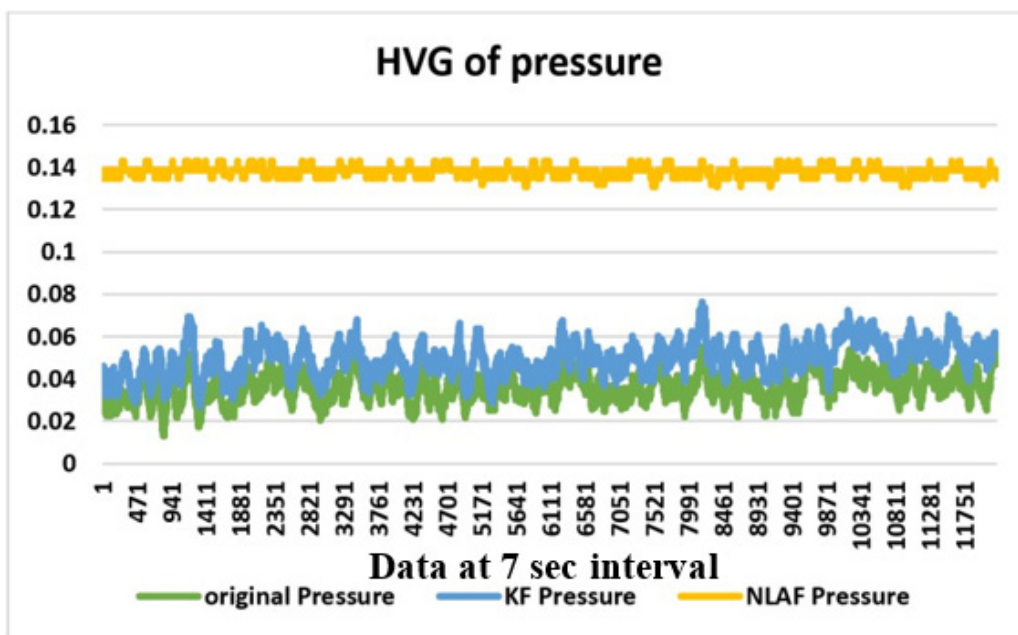

Figure 16: Variation in HVG for pressure.

Discussion

After implementation of NLAF, the quality variations are significantly reduced and its average value has increased. The average and standard deviation for quality before and after improvement are shown in Figure 17, are 78.6±2.05 and 82.5±1.32 respectively. From the results of analysis discussed earlier, it is also clear that in the case of noisy chaotic time series the moving average and moving median kill valuable information in data as compared to Kalman and NLAF filters. Hence they are not recommended for process control. Before application of Kalman filter it is essential to know about the type of noise present in time series. In our case, we find that it is brown noise since the value of DFA is higher than 1.5. An additional point to be considered is that the observation error for Kalman filter is assumed as 1% of the measured value. This assumption is not needed in non-linear adaptive filter. We find that noise removed by nonlinear adaptive filter is generally more efficient for the case of high temperature reaction system of present work than Kalman filter. In the present work, this is also shown by a lower value of Lyapunov exponent of the time series pre-treated with nonlinear adaptive filter (compared to that with Kalman filter).

Figure 17: Improvement in quality after noise removal.

Conclusion: Significance of Noise Reduction for Dynamic Process Control

The control strategy for a nonlinear chaotic system is significantly different from nonlinear nonchaotic systems. In order to distinguish between the chaotic and nonchaotic conditions of process it is essential to reduce noise from data because the noise generates additional chaos in the data and thereby confuses the online control system. In the particular high temperature industrial system of sponge iron rotary kiln chosen in the present work the pressure is directly controlled by Multi Louver Damper (MLD). The MLD has to control pressure in a specific range but due to noise in data, it created a condition where it made MLD function accordingly. It caused a sudden drop in quality of sponge iron due to an abrupt change in MLD. Also, the noise makes MLD fluctuate more rapidly creating a risk of mechanical failure of MLD. To handle such a system, various methods of removal of noise have been tried in this work in order to find out the best method of noise reduction as well as to evaluate their effect on features after noise reduction. Noise reduction by NLAF has shown a significant decrease in DFA, embedding dimension and correlation dimension values, as well as an increase in time delay and HVG. Noise also affects Lyapunov exponent values. After using NLAF filter there is a significant reduction in value of Lyapunov exponent; in most regions, after noise removal the negative values of Lyapunov exponent are obtained, which indicates that system may not be chaotic in those regions of operation. This is the true advantage of doing noise reduction from the dynamic control strategy point of view. Besides, there is an increment in HVG values after noise removal by NLAF which indicates an improvement in data similarity. As a result, due to the implementation of noise removal system, the variation in quality which was previously 78.6±2.05 improved to 82.5±1.32 without affecting input cost. This has contributed significantly to improvement in plant efficiency, productivity and resource utilization [33-37].

The system is now observed (event detection and warning) online and generates control strategy and signals as per situation depending upon whether it is in chaotic or nonchaotic regions. For example, when accretions inside the kiln are dislodged then chaos increases, as also shown by increase in Lyapunov exponent. The associated temperature and pressure profiles, in particular, become more chaotic and noise content is also seen to increase. In order to take care of transition from chaotic to non-chaotic regions and vice versa, an expert control system has been developed based on change in measured parameter ranges.

The results of this work clearly show that it is essential to pre-treat chaotic time series for noise reduction so as to improve online dynamic control system. In fact, as a consequence of improved control the accretions have been reduced and quality has improved considerably at Tata Steel Long Products limited by following this approach. For the chaotic time series used in present work the Nonlinear Adaptive Filter (NLAF) is found to be more effective. Surprisingly, the same advantage has been found for the case of analysis of epilepsy data obtained from EEG (to be discussed in another work). As for other systems, the present work demonstrates the importance of noise reduction for chaotic processes for better control. All such efforts are an important step towards Industry 4.0 and the plant was recognized for the same with an industry 4.0 award.

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