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Development of temporal model for analysis of heat transfer equipment subjected to fouling

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Abstract. Soot blowers are employed in a predefined sequence and schedule to clean the ash particles on heat exchanger surface. However, considering the detrimental effects of frequent soot blow operation a criteria based system has to be adopted that involves soot blow activation based on a predefined cleanliness level. This insists the need for an online monitoring model to predict the Cleanliness Factor (CF). This paper analyzes the deposition of ash in power plant reheater with the objective of developing accurate prediction model for CF using Autoregressive Integrated Moving Average with eXplanatory variables (ARIMAX) model. In practice the covariates that should be included in the model is not known a priori and often with more number of candidate variables. The findings in this work reveal that the ARIMAX model including flue gas input temperature, 1 lag value of flue gas output temperatures, air flow rate, coal flow rate and attemperator flow rate in time series analysis of CF dataset produces a more robust predictive model. The model performance is quantified by two indicators namely and Root Mean Square Error (RMSE) and Akakie Information Criteria (AIC). To ensure the adequacy of the model residual diagnostics was performed which revealed that the Auto Correlation Function (ACF) plot of the residuals are uncorrelated and there is no considerable departure from white noise as the test statistic clearly shows that the p-values exceeds the 5% significance level for all lag orders. The recommendation suggested in this study can be applied to criteria based soot-blow operation where the soot blowers are operated when a predefined CF is reached.

Keywords. Ash fouling; heat transfer coefficient; cleanliness factor; dynamic regression; ARIMA.

1. Introduction

Energy conservation is an equal partner with efforts to increase energy supplies and to achieve global goals in reducing emission of greenhouse gas, fossil fuel (coal, hydrocarbons or natural gas) usage and a wide range of other benefit. In Asia-Pacific region, coal is the dominant source of fuel in primary energy consumption and pollutant emissions. Hence many approaches to control and optimize thermal power plant boilers have become extremely significant aiming at reducing pollutant emissions and increasing energy efficiency [1–4].

Coal combustion in thermal power plants produce two types of residues namely fly ash and bottom ash. Fly ash gets entrained in flue gas and gets deposited on the boiler heat exchanger surfaces. It leads to loss of thermal efficiency which may add up to 1% under typical operating conditions. Therefore, it is important to minimize effect of ash deposition from both economic and environmental point of view [5, 6]. Ash deposition in coal-fired power plants is of two forms mainly slagging and fouling. Slagging occurs in radiative heat transfer surfaces such as boiler water wall tubes and fouling occurs in connective heat transfer surfaces like superheater, reheater and economiser. The conventional method adopted to minimize ash deposition is soot blowing [7, 8]. Soot blowers are activated periodically at predefined sequence and in many cases this may lead to over-blowing. Hence few coal fired plants have replaced such time scheduled soot blowing with criteria based soot blowing which includes initiation of soot blowers on a predetermined cleanliness level. Cleanliness Factor (CF) is used as an indicator to predict ash fouling level and is greatly inclined towards change in input-output relation of the operational parameters [9]. There is no instrumentation to measure cleanliness of heat exchanger directly.

Existing research works on fouling detection are either instrument based (i.e. direct measurement using heat flux sensors) or model based. Considering practical installation or usage of sensors in harsh environments, very limited

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works have been proposed in instrument based detection. In model based detection two important aims including prediction and explanation should be distinguished. There are plenty of modelling studies focusing on prediction [10–15]. In prediction, irrespective of the model structure (neural network, support vector regression), accuracy of the model and mean square error in N-step ahead prediction are considered as important criteria for model adequacy. Though the model obtained shows a good fit and low prediction error, it may not include significant variables while including in-significant variables, which involves coefficients that are systematically biased. Such a model does not satisfy the explanatory aim. This could be the reason for unsatisfactory results of the models.

In explanatory modeling, the influential predictors are identified to gain more knowledge into the relationship between variables and the output. In reality, though many variables are considered to be significant predictors, only a few are influential. In general, for a case analysis with many significant variables and an explanatory aim a reliable regression model that fits the data reasonably and simple enough to be analyzed has to be built. Regression time-series related methods and advanced Machine Learning (ML) methods use computational methods to understand the information directly from relating data without relying on a predetermined model equations. Hence such methods are considered to be more promising for the complicated problem such as fouling. In the related literature, researchers proposed new machine learning algorithms that suggest methodological advances and improvement in accuracy. However, limited objective evidence exists for relative performance as standard prediction tool [16]. Neural-network based machine learning models have been applied more frequently for fouling detection by many researchers. The experimental operating conditions can be simulated more comfortably if neural network models are used for fouling estimation [17]. Neural network model has been developed to predict efficiency and outlet temperature of shell and tube heat exchanger [18, 19]. The efficiency is defined in terms of CF using wavelet neural network [20]. Artificial neural network based probabilistic model has been presented [21] and the soot-blow effectiveness on each unit load has been predicted by using adaptive neuro-fuzzy inferencing system with degree of cleanliness after soot-blow, current relative cleanliness and unit load as inputs. Slag deposits have been predicted using a deposition model which relates static contact angle, viscosity and surface energy [22]. Recent study evaluated that the machine learning methods could not outperform classical regression modelling [23].

In view of the above, classical methods such as ETS (Error Trend and Seasonality), ARIMA and others are usually encouraged to be used as an initial step before exploring more complicated methods and the inference from those simple methods can be used as a baseline performance to complicated methods so as to justify their practice. Considering this and the fact that fouling is a complex phenomena, a dynamic model based on Auto Regressive Integrated Moving Average with eXogenous inputs (ARIMAX) is proposed in this paper for CF monitoring in reheater. ARIMAX model is developed to estimate cleanliness factor using the empirical data from power plant, understanding the effects of predictors and identification of important predictors using variable selection algorithms ('explanatory' aim) and the model with good prediction criteria ('prediction' aim).

2. Materials and methods

2.1 *Case study*

A case study on fouling of Reheater (RH) tubes in Neyveli Lignite Corporation (NLC) in Tamil Nadu, India is considered. The net heating value of lignite varies between 2200 and 2350 kcal/kg. In order to run the thermal unit at full load (210 MW), 190-215 tonnes of lignite is burnt for 1 hour.

The reheater available at NLC is a single unit with two stages of reheater, RH1 and RH2. RH1 is located between second stage of superheater and economizer. It has 115 coils of 7 tubes each in 2 loops with a total heat transfer area of 8392 m^2. RH2 is located between second and third stage of superheater. It has 58 coils of 6 tubes each in 2 loops with a total heating surface of 3447 m^2. The detailed scheme of RH is shown in figure 1.

The superheated steam temperature from the outlet header of RH1 is at 417°C. This is brought down to 409°C with the help of attemperator located on both sides of the RH1 outlet headers. In order to maintain an even temperature at the two individual inlet headers of RH2, the piping arrangement has been designed in such a way that the right side outlet header of RH1 is connected to the left side inlet header of RH2 and vice versa for other inlet header of RH2. The temperature of the reheated steam entering the IP turbine is an average of left and right outlet of RH2. The imbalance in the reheater outlet temperature is predominant in tangentially fired boilers. This is influenced by various gas and steam side factors including the fly ash deposition. It is further observed that in the existing RH2 set-up the effect of soot blow results in a change in steam output temperature and this is quite predominant in the right side of RH2 than its left side. Hence, right side tubes of RH2 alone are considered for the analysis.

Soot-blowers are employed to clean the fire side of heat transfer surfaces permitting the boiler to operate at peak efficiency. Three pairs of IK-4M type soot-blowers are arranged in each tier with three blowers each positioned at the right side and left side of the boiler. The soot blow steam is taken from the second stage of superheater and it is conveyed to blowers after pressure reduction. The total time taken for one complete soot-blow cycle is 120 minutes

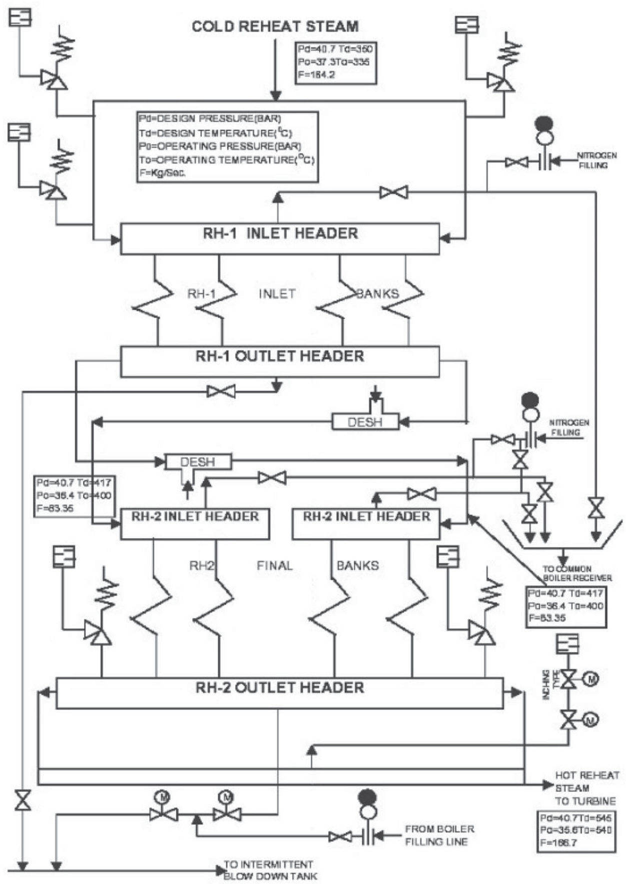

Figure 1. Schematic of Reheater. Source: NLC boiler manual.

with each soot-blower activated for 5 minutes. This consumes 750 kg of steam per operation.

2.2 *Real-time data*

The real time data from NLC related to RH2 was obtained for 3 months duration with a sampling period of 1 hour resulting in 2142 samples. The data collected contains 30 predictors including input and output temperatures of flue gas and steam, mass flow rates of combustion air, coal and RH attemperator, load, metal tube temperatures from 22 sensors.

CF is the ratio of average heat transfer coefficient of the fouled RH tubes to that of cleaned tubes. It ranges between 0 and 1, with 1 as indicative of clean reheater. The evolution of CF in the previously defined intervals is obtained by using the lumped parameter model of heat exchanger [24].

The model expressed by Eq. (1)-(2) is applied to determine the fouled heat transfer coefficient. The average heat transfer coefficient of the reheater during fouled conditions is indirectly obtained through parameter (α, β) estimation. In order to obtain stable parameter estimate Dual Extended Kalman Filter is used [25].

$$\frac{d\,T_{h,ij}(t)}{d\,t} = \left(1-\frac{\alpha_{ij}}{2}\right)\tau_h^{-1}\,T_{h,ij-1}(t) - \left(1+\frac{\alpha_{ij}}{2}\right)\tau_h^{-1}\,T_{h,ij}(t) + \frac{\alpha_{ij}}{2\tau_h}\,T_{c,i-1j}(t) + \frac{\alpha_{ij}}{2\tau_h}\,T_{c,ij}(t) \tag{1}$$

$$\frac{d\,T_{c,ij}(t)}{d\,t} = \left(1-\frac{\beta_{ij}}{2}\right)\tau_c^{-1}\,T_{c,i-1j}(t) - \left(1+\frac{\beta_{ij}}{2}\right)\tau_c^{-1}\,T_{c,ij}(t) + \frac{\beta_{ij}}{2\tau_c}\,T_{h,ij-1}(t) + \frac{\beta_{ij}}{2\tau_c}\,T_{h,ij}(t) \tag{2}$$

α, β, τ_h, τ_c are the model parameters and it is denoted by

$$\alpha_{ij}(t) = \frac{\alpha^* \dot{m}_h^* U_{ij}(t)}{\dot{m}_h(t) U^*}; \quad \tau_h(t) = \frac{\tau_h^* \dot{m}_h^*}{\dot{m}_h(t)}; \quad \beta_{ij}(t) = \frac{\beta^* \dot{m}_c^* U_{ij}(t)}{\dot{m}_c(t) U^*}; \quad \tau_c(t) = \frac{\tau_c^* \dot{m}_c^*}{\dot{m}_c(t)} \tag{3}$$

Where the heating surface area is represented by A (m^2), U refers to the coefficient of heat transfer (W/m^2K), M – the mass of the fluid, $\dot{m}$ is the mass flow rate (kg/s) and the symbol for specific heat is c (J/kg/K). The h and c subscripts refer to hot fluid (flue gas) and cold fluid (steam), respectively. The position of the flue gas and steam section are denoted by i and j of which i = 1, n and j = 1,…, s.

In general, the convective heat transfer coefficients of heat exchanger are function of many variables including pipe geometry and fluid properties such as thermal conductivity and specific heat. In order to calculate the heat transfer coefficient, the correlation among the variables should be reduced by empirical correlation using independent dimensionless parameters. There are various dimensionless numbers used for free convective heat transfer namely Nusselt number, Grashof number, Prandtl number, etc. In this work, Nusselt number is used for both hot and cold sides. It represents the dimensionless temperature gradient and it is a measure of convective heat transfer, given by Eq. (4).

$$Nu = \frac{hd}{\kappa} = 0.023(Pr)^{4/5}(Re)^{y} = 0.023\left(\frac{c\mu}{\kappa}\right)^{4/5}\left(\frac{\dot{m}d\rho}{\rho A\mu}\right)^{y} \tag{4}$$

With d representing tube diameter, κ-thermal conductivity of fluid, h-convective heat transfer coefficient, Pr-Prandtl number, Re-Reynolds number, μ-dynamic viscosity, ρ- density of fluid. Rearranging the terms in Eq. (4) gives Eq. (5)

$$h = \leftrightarrow \underbrace{0.023\frac{c^{4/5} d^{(y-1)}}{A^{y}}}_{i} \leftrightarrow \underbrace{\mu^{(4/5-y)}\,\kappa^{(1/5)}}_{ii} \leftrightarrow \underbrace{\dot{m}^{y}}_{iii} = K\left[\mu^{(4/5-y)}\,\kappa^{(1/5)}\right]\dot{m}^{y} \tag{5}$$

The terms i, ii, and iii represent constant, temperature dependent variables and mass flow dependent variables, respectively. Neglecting the temperature dependence variables Equation (5) simplifies to

$$h = C'\dot{m}^{y} \tag{6}$$

Hence the overall heat transfer coefficient of the cleaned RH tubes is obtained by theoretically using Eq. (7).

$$\frac{1}{UA} = \frac{1}{U_h A_h} = \frac{1}{U_c A_c} = \frac{1}{h_h A_h} + \frac{1}{h_c A_c} + \frac{R_f}{A_h} \tag{7}$$

The flue gas convective heat transfer is represented by h_h (W/m^2K) and the steam convective heat transfer is represented as h_c (W/m^2K). The fouling factor, R_f (W/m^2K) of a clean RH tube is equal to zero. The CF hence obtained is shown in figure 2a, which shows that the cleanliness factor of the RH has a decreasing trend between successive soot blow cycles. However, it is also observed that though the duration of soot-blow is constant the degree to which the RH tubes are clean varies towards the end of each cycle. This shows that the fly ash deposition rate is uneven which is substantiated from figure 2b as the mean values between successive soot-blow cycles are different.

2.3 *ARIMAX model*

In the present study, an attempt is made to create a dynamic regression model using ARIMAX to predict CF of reheater. The variation of CF with respect to time is very slow and hence ARIMA is chosen as it can well illustrate a slow drifting time series and hence applicable to slow changing inputs [26]. ARIMA model which is represented by ARIMA (p, d, q) is a combination of Auto-Regressive (AR) and Moving Average (MA) parts with differencing, d to make the model stationary. p and q denote the maximum time lag related to dependent variable and residual, respectively. Exogenous variables X(k) added to ARIMA model result in ARIMAX model represented by ARIMAX(p,d,q). If the dependent variable is denoted by $\{Y_t\}$ and the exogenous variable set represented as $\{X_{1t}\},\{X_{2t}\},\ldots,\{X_{kt}\}$,The linear expression to define ARIMAX model is

$$\Delta^d Y_t = \delta + \sum_{i=1}^{k} \varphi_i X_{t-i} + \sum_{i=1}^{p} \xi_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{8}$$

Where φ_i, ξ_i and θ_i denote the estimated coefficients, k represents the maximum time lag related to the input sequences and δ is a constant.

The steps involved in developing an ARIMAX model are as follows [27].

(1) The assumption made while developing ARIMAX model structure is that the mean and covariance of considered time series is stationary and their autocovariance depend only on the respective time lags. So it is essential to examine the time series of $\{X_t\}$ and $\{Y_t\}$ for integrating type non-stationarity using the ACF plot and the unit-root tests based on null hypothesis test.
(2) A non-stationary time series can be made stationary by differencing two successive observations. Determine the degree of differencing, d required to stationarize the time series by applying KPSS test, a statistical hypothesis test of stationarity. The null hypothesis is that the data is stationary and this test looks for the evidence to reject the null hypothesis.
(3) Determine the order of p and q in ARIMAX model by examining the sample Auto-Correlation Function (ACF) and Partial Autocorrelation Function (PACF) of the differenced series. Alternatively, p, q may be selected via an information criteria like AIC. The model with least value of the AIC is chosen to be the best model for forecasting.
(4) After identifying a best fit ARIMAX model, the model residual (difference between predicted and observed data) must be analyzed to check if the model assumption is satisfied. The model residual should be Gaussian white noise in order to ensure that there is no useful information left over after fitting the model.

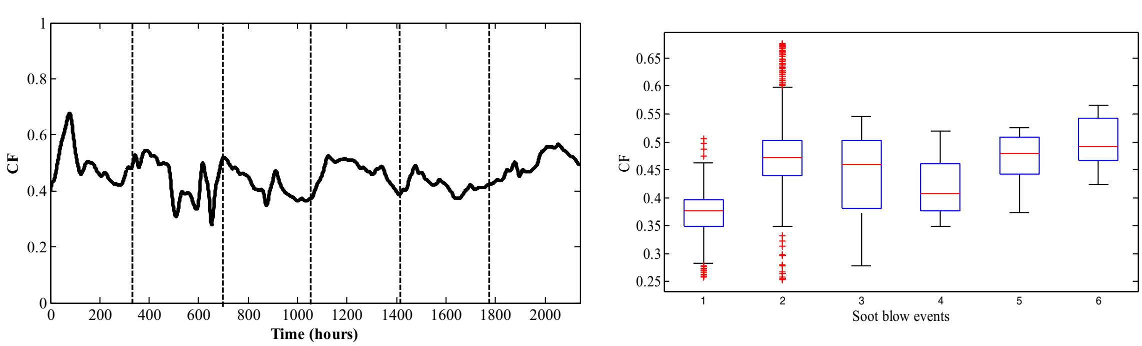

Figure 2. a) CF and b) Box plot of CF.

3. Results and discussion

3.1 *Variable selection*

The intensity of correlation between predictor variable and dependent variable is quite complex and hence it is complicated to determine quantitatively. The predictors identified through preliminary analysis of the available information contain redundant variables with weak correlations. Hence in order to develop simplified and accurate model, it is essential to select the important variables. There are different methods for variable selection and each method provides different variable ranking list. In order to address this, rank aggregation method has been proposed to combine the ranking results of different methods [28]. In this work, six variable importance analysis methods including Sub-window Permutation Analysis (SPA), Random Frog (RFG), Partial Least Square-Variable Importance in Projection (PLS-VIP), Uninformative Variable Elimination (UVE), Random Forest (RF), and Relief (RLF) have been employed to generate the rankings of variable importance. The optimal subset of predictor variables which gives high accurate prediction is selected by applying rank aggregation. Rank aggregation integrates the individual ordered rank list. It is performed using Monte Carlo Cross Entropy (CE) algorithm with the Spearman footrule distance. Spearman footrule distance is the sum of absolute value of difference between rank of unique variable in the ordered list. The rate of convergence of CE algorithm is shown in the first plot of figure 3 with the path of objective function scores at each iteration. The algorithm stops when smallest value of the objective function does not change at successive iterations. The smallest value or the global minimum of objective function is 13 which is reached at 11th iteration. The second plot of figure 3 shows that the probability distribution of final Monte Carlo sample is less heterogenous and hence less variability in the outcome. The rank list of rank aggregation plot shows the optimal predictor variables as Fluein, Flueout, Steamin, Airflow, attempflow, coalflow and the obtained solutions along with the average ranking. Figure 4 shows the real time data of the influential predictor variables.

3.2 *ARIMAX model selection*

In order to check if the gaussianity assumption in linear time series model holds, the histogram of CF series is examined which is shown in figure 5a. It shows that gaussianity holds mildly with positive skewness of 0.3. This small deviation from ideality is ignored. The non-stationarity of the CF time series is analysed using the correlation plot shown in figure 5b which shows a slow decay, suggesting the possibility of integrating effects coupled with stationary behaviour. This feature results in variation of mean and variance to change with time and hence the efficacy of the model is highly influenced. Differencing the time series i.e. determining the difference between successive observations will stabilize the mean value of the time series by reducing trend or seasonality patterns. In order to determine the number of differences required for eliminating the integrating effect, a unit root test is conducted which suggests the order of differencing to be 1. The differenced series and the corresponding

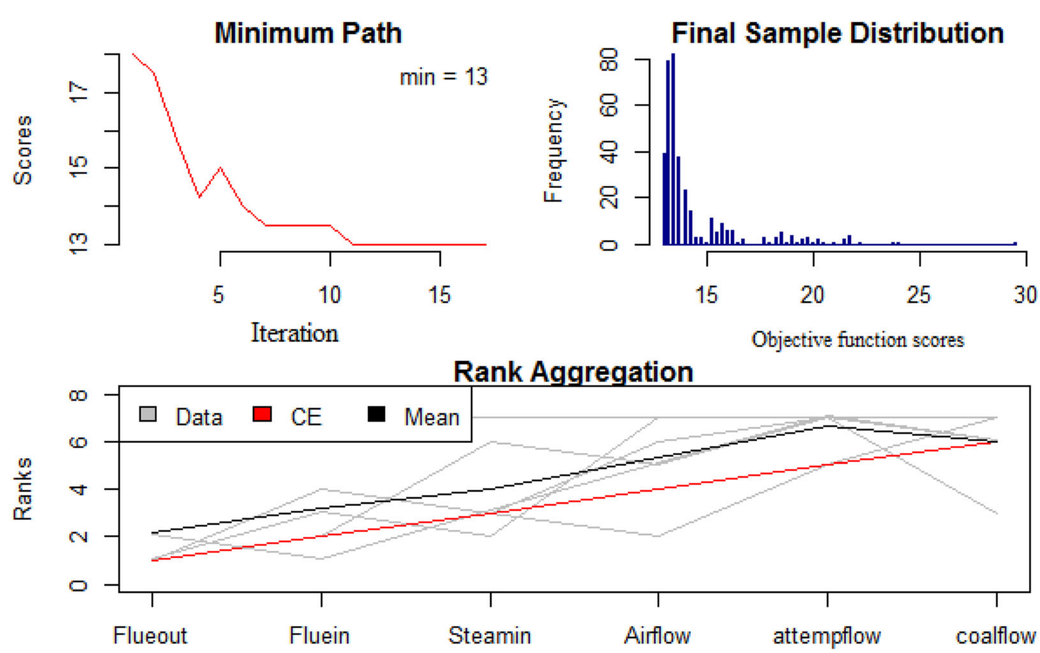

Figure 3. Selection of optimal predictors using rank aggregation.

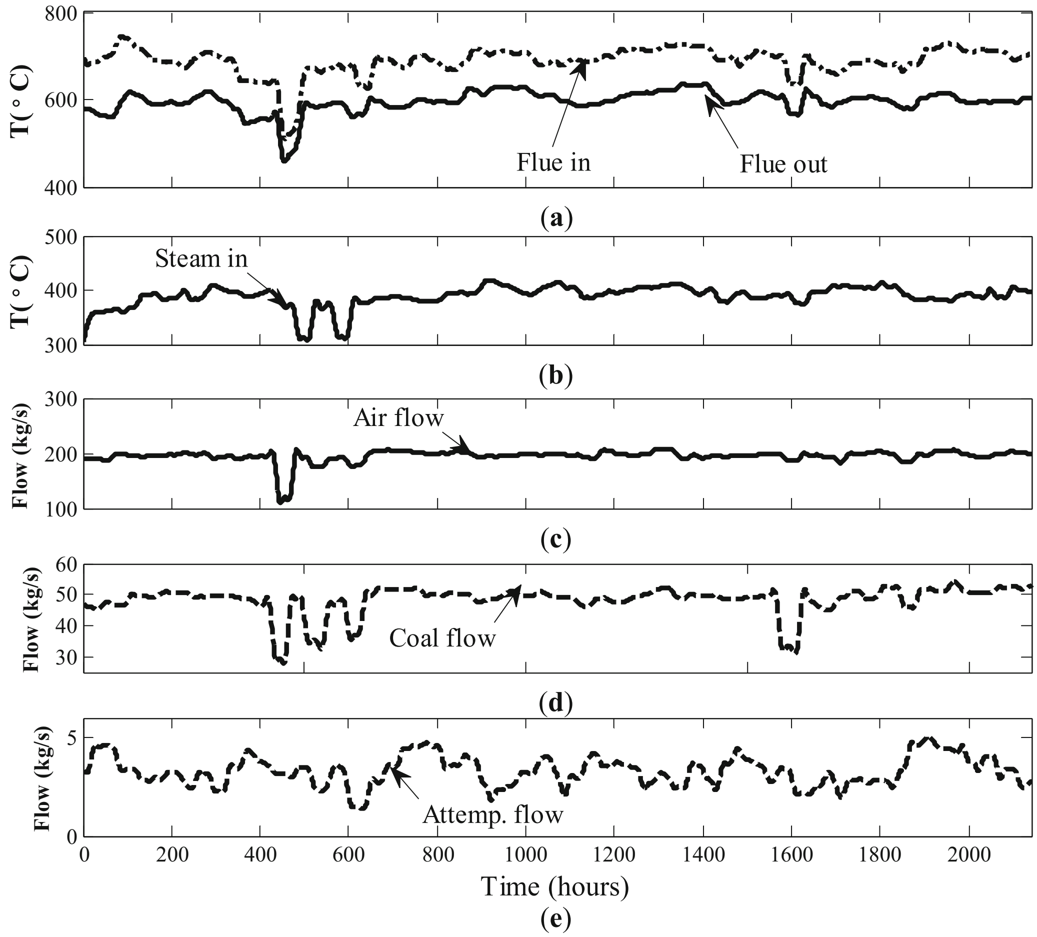

Figure 4. Power plant data (a) Flue gas input and output temperatures (°C), (b) Steam input temperature (°C), (c) Air flow (kg/s), (d) Coal flow (kg/s) and (e) Attemperator flow rate (kg/s).

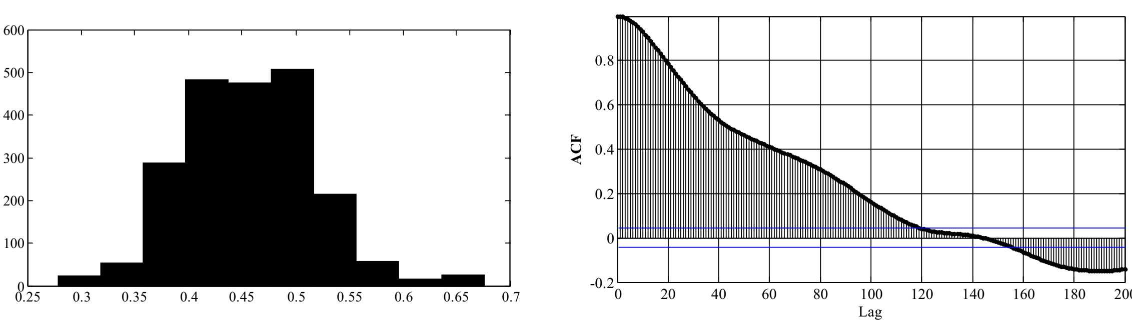

Figure 5. a) Histogram of CF and b) ACF of CF.

correlation plot is shown in figure 6. The ACF of the original and differenced series shown in figure 5b and figure 6b respectively are compared which shows that a first order differencing has eliminated the integrating effect as the ACF of the differenced series drop to zero relatively quickly while the ACF of the original time series decreases slowly. Similarly the optimal set of predictors is also differenced by an order 1 to make it stationary on mean.

The data involving four soot blow cycles is used for model development and the remaining data set is used for testing. Table 1 presents the summary of different ARIMAX structures that is analysed. The required number of lagged effects of the predictors is obtained by observing cross-correlation of each stationarized predictor variable with stationarized CF. The cross-correlation of the predictor variables fluein, flueout, steamin, attemperator flow,

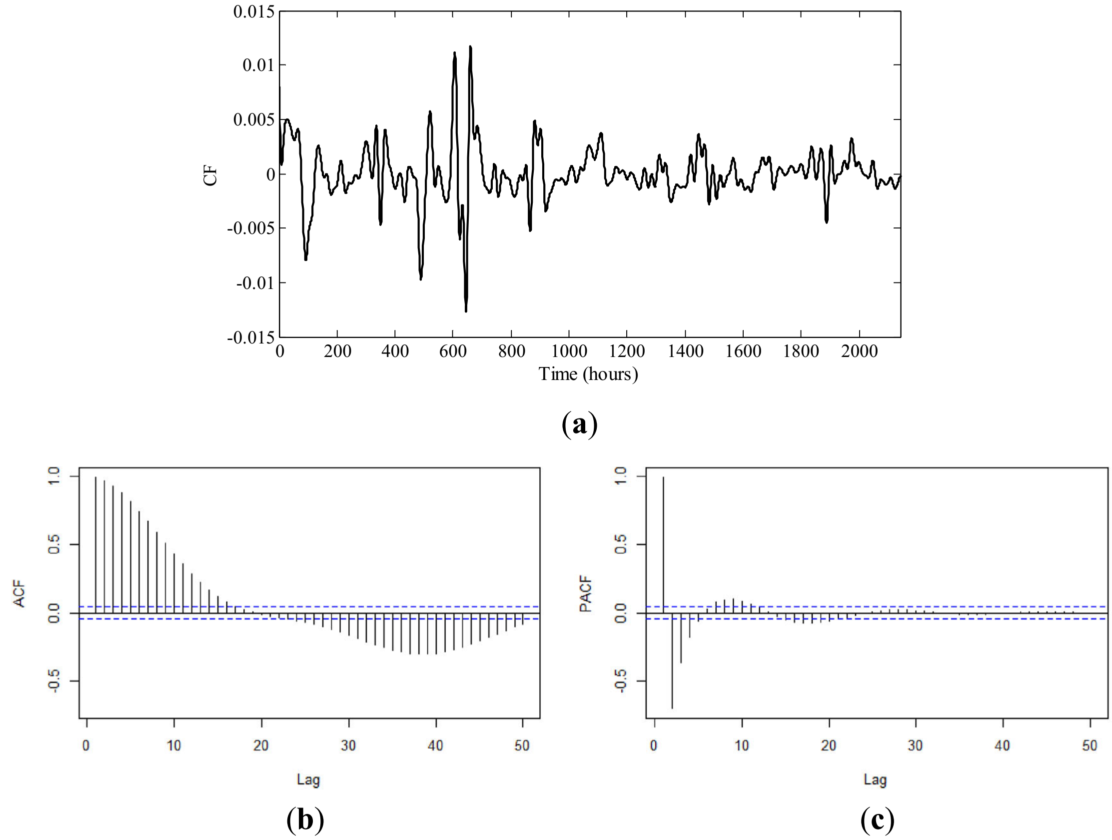

Figure 6. a) Differenced series of CF, b) ACF and c) PACF.

Table 1. Summary of ARIMAX model fitting parameters.

Model	Fit		Predictors	Coef	Z-value
	Testing RMSE	AIC			
ARIMAX(1,1,2)	0.78	−713.17	Fluein	2.65×10^{-3}	11.66
			Fluein(lag 2)	2.77×10^{-4}	1.28
			Flueout	-3.75×10^{-3}	−11.75
			Flueout(lag 2)	-7.78×10^{-4}	−2.63
			Steamin	1.34×10^{-4}	1.10
			Steamin(lag 2)	3.21×10^{-5}	0.24
			Air Flow	2.47×10^{-3}	11.24
			Coal Flow	2.63×10^{-3}	5.38
			Attemp Flow	3.39×10^{-3}	1.72
ARIMAX(2,1,1)	0.63	−719.21	Fluein	2.58×10^{-3}	11.71
			Flueout	-3.51×10^{-3}	−11.57
			Flueout(lag 2)	-3.89×10^{-4}	−3.05
			Air Flow	2.26×10^{-3}	11.46
			Coal Flow	2.58×10^{-3}	5.68
			Attemp Flow	4.57×10^{-3}	2.41

Table 1 continued

Model	Fit		Predictors	Coef	Z-value
	Testing RMSE	AIC			
ARIMAX(2,1,1)	0.07	−704.46	Fluein	2.64×10^{-3}	11.83
			Flueout	3.40×10^{-3}	−10.91
			Flueout(lag 1)	1.70×10^{-4}	2.23
			Air Flow	2.17×10^{-3}	10.99
			Coal Flow	2.51×10^{-3}	5.47
			Attemp Flow	5.36×10^{-3}	2.79
ARIMAX(2,1,1)	0.39	−698.88	Fluein	2.81×10^{-3}	11.24
			Flueout	-3.87×10^{-3}	−11.80
			Air Flow	2.20×10^{-3}	9.83
			Coal Flow	2.88×10^{-3}	5.58
			Attemp Flow	5.05×10^{-3}	2.29

coal flow with the dependent variable was significant at lag 1. The cross-correlation of air flow was found to be significant at lag 2. This suggests that fluein, flueout, steamin, attemperator flow, coal flow lagged by 1 period and air flow lagged by 2 periods would be a significant independent variable of CF. It was observed that all the selected model structures had uniform training error of 0.02. Whereas the testing RMSE is found to be minimum for ARIMAX(2,1,1) with Flue gas in, Flue gas out, Flue out with lag 1, air flow, coal flow and attemperator flow as predictor set. The estimated coefficients are given by Coef. The significance of each coefficient is tested using statistical Z-test. Z-value is

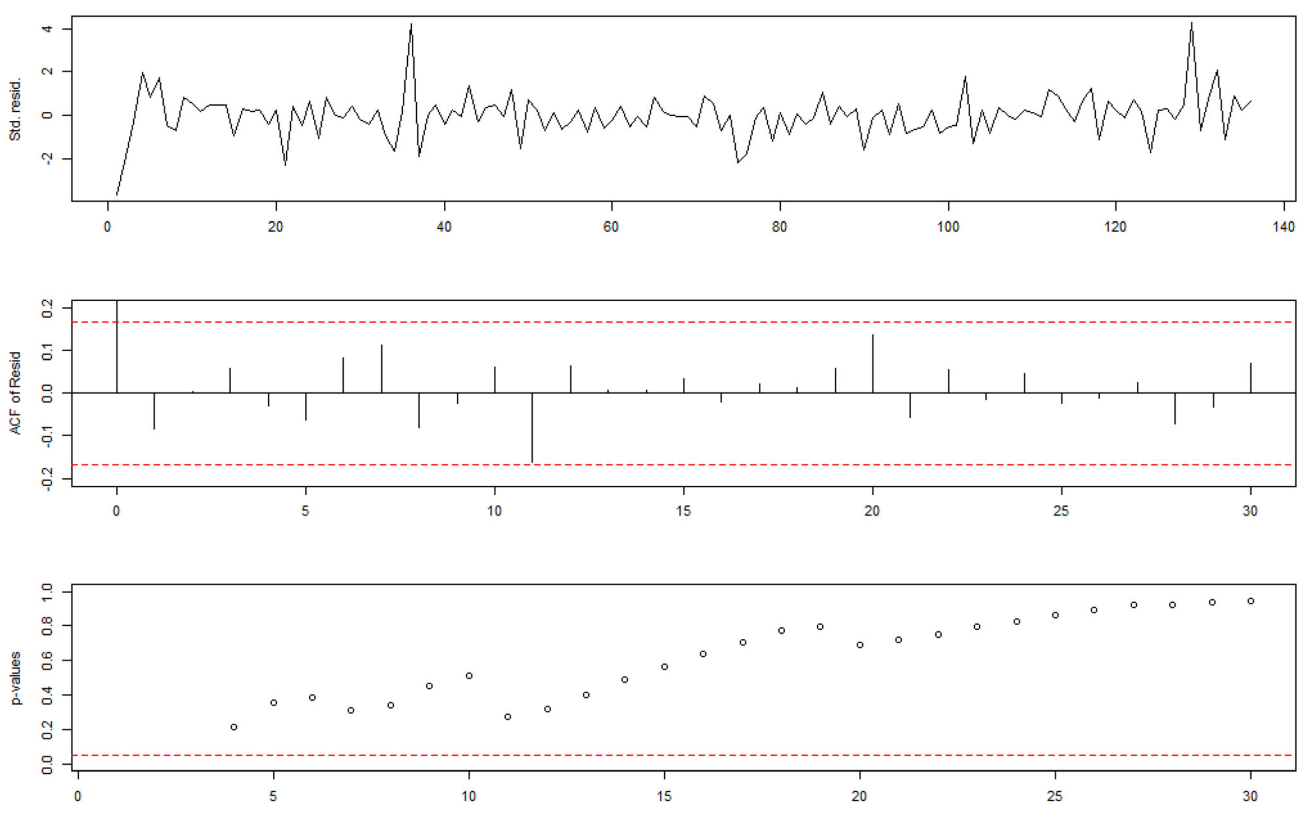

Figure 7. Residual Diagnostics plot.

the ratio between the estimated cooefficient and the standard error of the estimator. The larger the Z-value, less is the uncertainty of the related coefficient. The absolute value of Z-score is found to be greater than 2 which confirms the significance of the corresponding coefficient and hence the corresponding predictor. Akakie Information Criteria (AIC) is a better performance measure to determine which of multiple models is most likely to be the best model for a given dataset. Also, after considering the reasonably low AIC in comparison with the other models and the low RMSE during testing that model structure ARIMAX (2,1,1) with 6 predictors (Flue gas in, Flue gas out, Flue out with lag 1, air flow, coal flow and attemperator flow) is selected as the best fit. The estimated coefficients of the predictors, AR and MA terms of the best fit were also found significant using Z-test as tabulated in Table 1.

In time series modelling the residuals are assumed to be uncorrelated and normally distributed. These two conditions have to be satisfied in order to ensure that the identified model has captured all necessary information. The residual of the identified best fit ARIMAX (2,1,1) model is diagnosed and the results are shown in figure 7. The residual autocorrelation was obtained for 30 lags. It is observed that the autocorrelation coefficient from the residuals is well within the lower and upper significance level for all lags which confirms that the residuals are uncorrelated. Ljung-Box Q-test is applied to the residual to check the normality condition. The null hypothesis in the statistic test is that the residuals are normally distributed. The third plot in figure 7 shows that the p-value obtained is greater than the 5% significance level which accepts the null hypothesis.

4. Conclusion

In this work, ARIMAX model is developed which aids in online monitoring of the cleanliness factor of reheater using the optimal set of predictor variables to the model obtained by using cross entropy based aggregation algorithm. Taking the correlations between the ACF and p-value of the residual sequence, AIC and RMSE into consideration the preferred model of ARIMAX (2,1,1) was yielded with six predictors including flue gas input and output temperatures, flue gas output temperature with lag 1, air flow, coal flow and attemperator flow as a better fit for fouling monitoring. The identified ARIMAX structure can be highlighted in predicting the temporal trends of ash fouling which may act as the potential for initiating soot blow operation and hence prevent loss in thermal efficiency. The identified model that represents the dynamic behaviour of fouling can be used in scheduling of soot blow. As an extension of future work the consistency of the model has to be checked for other heat transfer surfaces and if possible at thermal power plants itself.

Abbreviations

ACF	Auto Correlation Function
ARIMAX	Autoregressive Integrated Moving Average with eXplanatory variables
CF	Cleanliness Factor
NLC	Neyveli Lignite Corporation
PACF	Partial Auto Correlation Function
RMSE	Root Mean Square Error

List of symbols

A	Heat transfer surface area (m^2)
c	Specific heat capacity (J/kg/K)
d	Number of differencing in ARIMAX
d	Heat exchanger tube diameter
h	Convective heat transfer coefficient (W/m^2K)
M	Mass of the fluid (kg)
$\dot{m}$	Mass flow rate (kg/s)
Nu	Nusselt number (dimensionless)
p	Number of autoregressive terms in ARIMAX
Pr	Prandtl number (dimensionless)
q	Number of moving average terms in ARIMAX
Re	Reynolds number (dimensionless)
R_f	Thermal resistance (W/m^2K)
T	Temperature of fluid (°C)
U	Overall heat transfer coefficient (W/m^2K)
{X}	Independent variables of ARIMAX
{Y}	Dependent variable of ARIMAX
α, β, τ	Model Parameters (dimensionless)
μ	Dynamic viscosity (kg/m/s)
ρ	Density of fluid (kg/m^3)
κ	Thermal conductivity of fluid (W/mK)
φ	Estimated coefficients of independent variable
δ	Estimated constant of ARIMAX model
θ	Estimated coefficients of moving average term
ξ	Estimated coefficients of autoregressive term

Subscripts

h	Hot fluid or flue gas
c	Cold fluid or steam
t	Time

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