Circuits and Systems, 2016, 7, 4046-4070
http://www.scirp.org/journal/cs
ISSN Online: 2153-1293
ISSN Print: 2153-1285

Fault Diagnostics on Steam Boilers and Forecasting System Based on Hybrid Fuzzy Clustering and Artificial Neural Networks in Early Detection of Chamber Slagging/Fouling

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How to cite this paper: Sathya Priya, M., Kanthavel, R. and Saravanan, M. (2016) Fault Diagnostics on Steam Boilers and Forecasting System Based on Hybrid Fuzzy Clustering and Artificial Neural Networks in Early Detection of Chamber Slagging/Fouling. *Circuits and Systems*, **7**, 4046-4070.
http://dx.doi.org/10.4236/cs.2016.712335

Received: May 4, 2016
Accepted: May 20, 2016
Published: October 31, 2016

Abstract

The slagging/fouling due to the accession of fireside deposits on the steam boilers decreases boiler efficiency and availability which leads to unexpected shut-downs. Since it is inevitably associated with the three major factors namely the fuel characteristics, boiler operating conditions and ash behavior, this serious slagging/fouling may be reduced by varying the above three factors. The research develops a generic slagging/fouling prediction tool based on hybrid fuzzy clustering and Artificial Neural Networks (FCANN). The FCANN model presents a good accuracy of 99.85% which makes this model fast in response and easy to be updated with lesser time when compared to single ANN. The comparison between predictions and observations is found to be satisfactory with less input parameters. This should be capable of giving relatively quick responses while being easily implemented for various furnace types.

Keywords

Steam Boiler, Fouling and Slagging, Fuzzy Clustering, Artificial Neural Networks

1. Introduction

The complex process of combustion for the purpose of energy production consists of consecutive reactions of both homogeneous and heterogeneous [1]. One of the common problems of fossil fuels is combustion deposits in the production of heat and electrical energy. During the complex process of combustion, the adequate amounts of mineral impurities present in fossil/biomass fuel are transformed into ashes and they are transported aerodynamically through the boiler as fly ash. The sediments accumulate as insoluble layers and the increase in deposits arrest and awkwardly corrupt pipes/other machinery in the hopper. Due to the discrepancy in deposition structures, two types of high temperature ash deposition schemes namely slagging and fouling are defined. The process generates a huge extent of ash that creates practical problems in boilers namely slagging, fouling, erosion, corrosion, abrasion, clinkering, sintering, and so on [2]. Especially, components in the boiler or the deposits on the heat transfer surface tubes that are regimented to convection are termed as fouling. While they are regimented to radiation are termed as slagging [3].

Thus slagging/fouling due the accession of fireside deposits on the steam boilers decreases heat transfer which is directly associated with reduction in boiler efficiency and performance degradation and in turn leads to unexpected shut-downs. Slagging/fouling not only impacts the steam production, but also outgrowth other relevant effects on boiler performance. The high development of incombustible volatiles associated to many fossil/biomass components due to the slagging/fouling is detailed [4]. The condensation vapours incombustible volatiles over the superheaters tubes forms a layer for the solid soot particles and this growth of the layer decreases heat transfer and obviously steam production and boiler efficiency [5] [6]. Thus the complete awareness of the complex combustion process is the primary step against the slagging/fouling. The survey shows various prediction models are proposed regarding statistic particle collision, slagging/fouling, ash melting and heat transfer through the layers. Ash formation, transport and slagging/fouling have been proposed [7]. They assimilate formation, boiler aerodynamics, transport systems and adherence of the particles deposited to the surface [8]. A deposit model based on Monte Carlo methods is detailed and simulated deposit growth under slagging/fouling circumstances [9]. A deposit model was developed at the University of Stuttgart. Recently, the nature of steam boilers shows a serious propensity to a slagging/fouling that reduce the boiler capacity [10]. Hence, serious action should be taken towards the development of boilers and the broad use of the fossil/biomass in the production of electricity. Due to the intrinsic complications of the slagging/fouling, the issue has not been wholly settled.

Primarily, fouling and slagging curtail heat transfer with the heat exchanger surfaces, and they stimulate corrosion and erosion on their surfaces. Thus decreased exchange efficiency and an increased maintenance costs of propensity results [11]. The major portion to fouling comes from the inorganic chemical composition of the fuel used in combustion. Empirical correlations are adapted to ashes behaviour within the boiler and as a consequence, the empirical correlations are developed for slagging/fouling based on its chemical analysis [12]. As part, the alkali index is employed to illustrate the fouling risk [13]. Yet, these correlations are not hypothesized for all types of biomass and do not take into account frequently other chemical components that increases the slagging/fouling trend. This is the reason, the empirical correlations are only recommended for fuel selection but not for slagging/fouling control. Hence the slagging/fouling aspects within the boiler are caused by other mechanism than coal [14]. In any circumstances, software is required externally for calculation and simulation. Commercial products are available boiler monitoring, particularly for slagging/fouling strategies [15], but there is a lack of knowledge about the internal behaviour of these applications. Essentially, alkali metals such as Na and K combined with Si, S, and Cl, are responsible for the above problems, and hence, they are a major portion of fouling. Calculation of different deposition indices based on the inorganic composition of the ash is one of the ways to resolve the fouling and slagging proficiency of a fuel. This is the fundamental step to removing them. Therefore Ash fouling of heat transfer surfaces is invariably one of the main viable affairs in coal-fired power plant utility boilers. The review shows that there are 1% of losses of energy efficiency and availability occurs in thermal power plants due to these problems [16]. The Electric Power Research Institute (EPRI) survey on ash fouling [17] showed 7% of units face continual fouling and 40% address random problems, by the whole of pulverized-coal utility boilers. In recent decades, there is extensive development of research proposed in this area. Consequently, there is still a lack of awareness about slagging/fouling nature in fossil/ biomass utilization, particularly in boilers [18]. So it is one of the signs to build up the technology and attain a broad development of fossil/biomass utilization. With this goal, the enthusiasm lies not only in the slagging/fouling mechanisms, but also in the impact of slagging/fouling in boiler operation and the tools to control and minimize the fouling effects.

A strain-gauge based measurement system is developed for slag deposits. It measures a load on the rods that suspend the pendant steam superheaters using strain gauges. The growth in deposits increases the weight and thereby the recorded strain increases [19]. Other strategies for monitoring and prediction of fouling in steam boilers are explained and they depend on the heat and material balances to implement heat transfer analysis in the furnace [20]. The calculated values needs to converge for the variation of the steam and its temperature, water flow rates, flue gas and the fouling level for a given steam boiler. Various researchers analyzed the slagging/fouling mechanisms in coal power plants including complex CFD simulations and chemical fuel analysis [21]. These traditional methods for steam boilers to reduce slagging/fouling are not applicable without an appropriate boiler evaluation. Large number of data is needed to develop correlations and to predict the desired parameters using mathematical methods like regression analysis. The Artificial Neural Network (ANN) model is capable to predict the new data with the help of reasonable set of given input data with high speed and accuracy. Recently, many researchers applied ANN to heat exchangers. The Neural Networks (NNs) are introduced recently to solve problems dedicated to system modeling, forecasting, identification, optimization, control, energy and power systems [22]. The application of the Neural Networks to renewable energies [23] and to the interpretation of slagging/fouling inside the boilers [24] also has been reported. But, not many researchers attempted ANN modeling in the determination of slagging/fouling using the fuel characteristics, boiler operating conditions and ash behavior. However, a hybrid control technique that assesses the above performance of boiler depending on slagging/fouling and technique to control slagging/fouling has not been already developed. This paper is perceived as a contribution to this inquiry.

The main goal of this paper is to present the application of a Hybrid System that combines NNs advantages with fuzzy clustering method to control slagging/fouling and optimize boiler performance, minimizing the effect slagging/fouling. Fuzzy cluster analysis finds its application in various engineering disciplines since it has great advantage of filtering outliers/noisy data. The author investigated transmembrane pressure data based on principal component analysis (PCA) and fuzzy clustering (FC) [25]. A fuzzy modeling strategy and predictive controller for boiler-turbine unit using fuzzy clustering and subspace identification (SID) methods was developed [26]. A probabilistic model to predict the effectiveness of soot-blowing based in Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference Systems was developed [27]. A novel method based on cluster analysis for industrial process control is developed [28]. A selective algorithm for constructing neural network ensemble based on clustering is proposed [29].

Many researchers used the hybrid method of fuzzy logic and neural networks to achieve the satisfactory results than the conventional statistical method and single ANN. But the concentration of slagging/fouling forecasting based on all the three factors such as the fuel characteristics, boiler operating conditions and ash behavior is not yet proposed. Hence the paper proposes hybrid method of fuzzy cluster and ANN for forecasting slagging/fouling. **Figure 1** shows the overview of slagging/fouling forecasting system in three phases of determination of slagging/fouling using 1) the fuel characteristics, 2) boiler operating conditions and 3) ash behavior. The proposed approach is established utilizing Fuzzy clustering method (using k-means and medoid) which allows every data to belong to every cluster to a valid degree. In addition, FC extracts the clusters membership levels of each normalized data in all the clusters and finally each cluster will be fed as input to ANNs. The employed FCANN allows the clusters to be larger which thereupon increases the accuracy of the proposed forecasting system. The simulation shows energy saving between hybrid FCANN outputs and real data obtained from steam boiler.

2. Brief Description of Methodology

This section briefs the ANN, Fuzzy clustering (FC) and hybrid FCANN used in this research to forecast the slagging/fouling level in bolier furnaces.

2.1. Fuzzy Clustering (FC)

Fuzzy clustering normalizes segregated clustering methods by admitting an individual object to be moderately classified into conjointly one cluster. Segregated/partition clustering methods are k-means and medoid. In fuzzy clustering, the membership is disseminated by all clusters. Here m clusters and a set of variables $x_{i1}, x_{i2}, \cdots, x_{im}$ are defined for classification. The variables $x_{i1}, x_{i2}, \cdots, x_{im}$ represent the probability that object

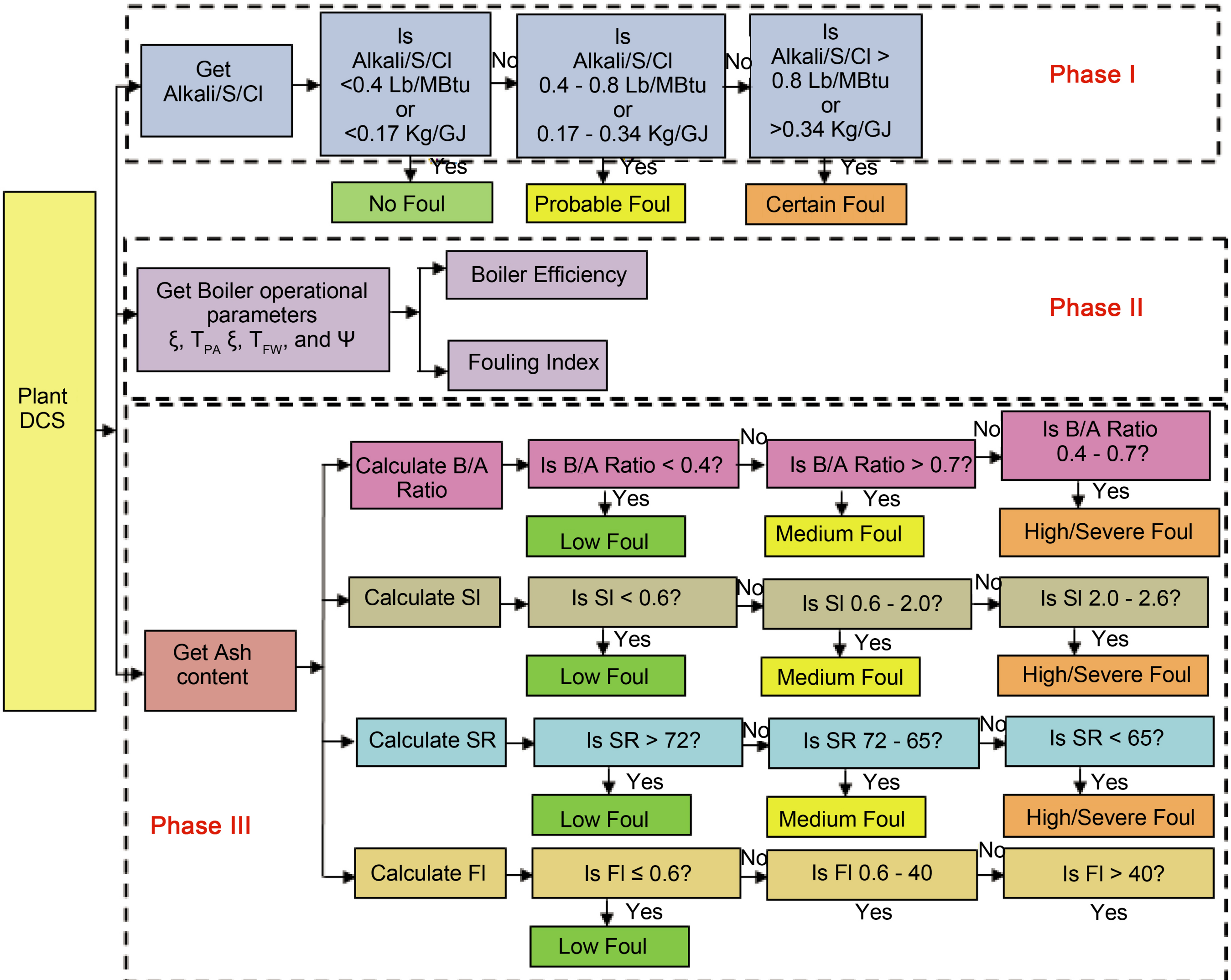


Figure 1. Overview of slagging/fouling forecasting system.

i is classified into cluster m. The variable x_{im} ranges between zero and one, with the restriction that the sum of their values is one. This denotes "fuzzification" of the cluster configuration. The advantage of fuzzy clustering is that it does not compel every object into a particular cluster. The fuzzy algorithm [30] claims to minimize the objective function, "O" given in Equation (1), made up of cluster memberships and distances.

$$O = \sum_{m=1}^{M} \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} x_{im}^2 x_{jm}^2 l_{ij}}{2\sum_{j=1}^{N} x_{jm}^2} \tag{1}$$

where x_{im} represents the unknown membership of the object *i* in cluster *m* and is the contrariety between objects *i* and *j*. The memberships are restricted to be non-negative and that the sum of memberships for a single individual must be one. Dunn's partition coefficient (D_{pc}) given in Equation (2) measures the closeness of the fuzzy response to the corresponding hard response (classify each object into the largest membership cluster) and thereby measures the "fuzziness" in a solution.

$$D_{pc} = \frac{1}{N}\sum_{m=1}^{M}\sum_{i=1}^{N} x_{im}^2 \tag{2}$$

D_{pc} ranges from $\frac{1}{M}$ to 1. D_{pc} is $\frac{1}{M}$ when all memberships are equal to $\frac{1}{M}$. D_{pc} may be normalized as in Equation (3) so that it varies from 0 (fuzzy) to 1 (hard cluster).

$$D'_{pc} = \frac{D_{pc} - \left(\frac{1}{M}\right)}{1 - \left(\frac{1}{M}\right)} \tag{3}$$

Another partition coefficient (P_c) [31] given in Equation (4) ranges from 0 (hard clusters) to 1-1/M (completely fuzzy). P_c may be normalized as in Equation (5).

$$P_c = \frac{1}{N}\sum_{m=1}^{M}\sum_{i=1}^{N}\left(g_{ik} - x_{ik}\right)^2 \tag{4}$$

$$P'_c = \frac{P_c}{1 - \left(\frac{1}{M}\right)} \tag{5}$$

Both D'_{pc} and P'_c provide a valuable implication of an admirable number of clusters. The cluster M should be chosen that D'_{pc} is large and P'_c is small.

2.2. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) is duplication techniques that recreate a few biological behaviors or mimic some human functions, *i.e.* training and course imitation. Simulation and prediction are contemplated as the best applications of ANN and therefore, they reduce the fouling problem. According to the particular type and objectives, ANN is built by a limited number of layers connected with distinct computing elements named neurons. The structure built is multilayer feed forward ANN having that the information is fed from the input layer to the output layer with intermediate layers in a single forward direction and there is no backward feeding. Intermediate/hidden layers incorporate sigmoid neurons with a view to conveniently reproduce non linear nature, and the output layer is formed with linear neurons to reproduce tasks without interruption. The number of neurons in the hidden layer is selected twice that of the number of input neurons in the input layer. Thus, n = 6, 10 and 2 respectively in **Figure 2**. A three-layer feed-forward neural network is constructed for this modeling. Initially, all data are normalized so that the size of data reflects the output; weights are randomly initialized before training the networks. The learning rate is set at 0.1 and momentum rates is also set at 0.1, and the iteration should be stopped when mean squared error reduces by less than 0.000001 or the model reaches 2000 iterations. As a result, the process gives information about significant rate of each input variable. Once the model has been satisfactory trained (no need of precise/noise-free data), the developed ANN

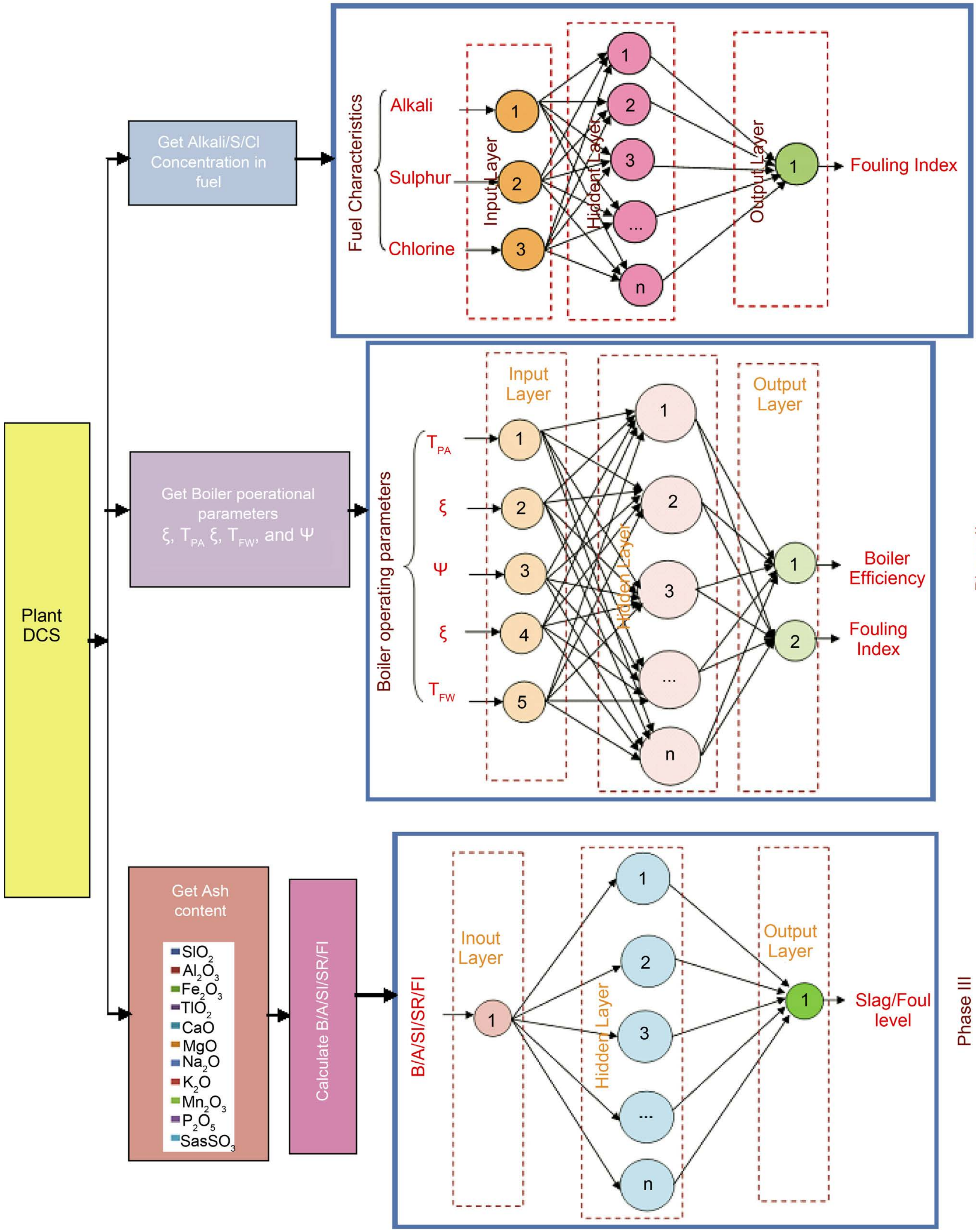


Figure 2. Block diagram of ANN model employed in three phases of prediction.

structure has been able to reproduce a boiler and monitoring fouling level of the heat exchanger. This ANN structure and input data mimics the authentic thermal simulation. The iterative process of training procedure ranks the most important variables focusing to minimize the number of input variables needed to reproduce a measured output. Comparisons of historical data of fouling level in super heaters with that of the predicted data ANN model shows good agreement with complex results of thermodynamic equations and the developed ANN reproduces satisfactorily the behavior of thermal boiler. Almost 70% of the data was used for training, and the rest 30% was used for testing. Figure 2 shows the block diagram of ANN models employed in three phases of determination of slagging/fouling using 1) the fuel characteristics, 2) boiler operating conditions and 3) ash behavior.

2.3. Development of FCANN Model

The proposed FCANN architecture is shown in Figure 3. The proposed approach is established utilizing Fuzzy clustering (FC) method (using k-means and mediod) and ANN which allows every data to belong to every cluster to a valid degree. In addition, FC extracts the clusters membership levels of each normalized data in all the clusters and finally each cluster will be fed as input to ANNs. The employed FCANN allows the clusters to be larger which consequently increases the accuracy of the proposed forecasting system.

3. Determination of Fouling Index (FI) in Three Phases

Ash formation in boilers is a very complicated problem. It requires the keen grasping of

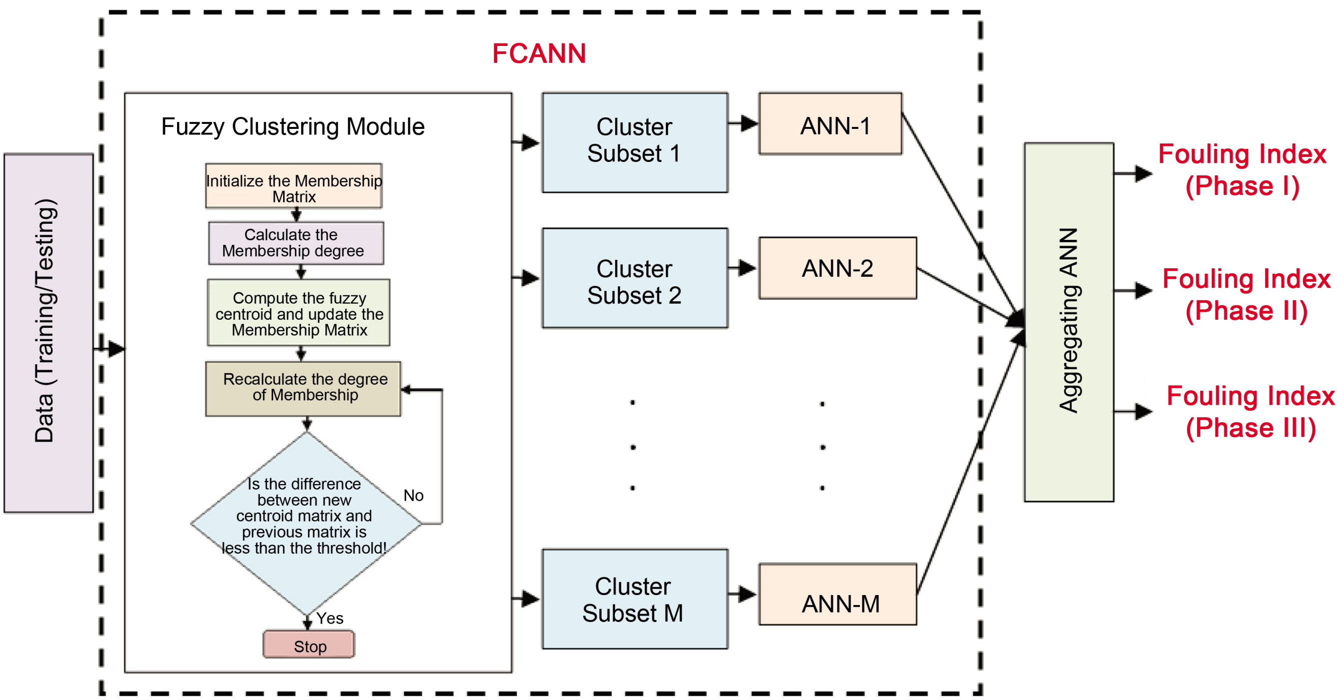


Figure 3. The architecture of FCANN model.

the cause of solid deposition which comprises the awareness of fuel characteristics, ash behavior, and boiler operating conditions. Therefore fouling index (FI) is determined in three phases using ANN involving 1) the fuel characteristics, 2) boiler operating conditions and 3) ash behavior.

3.1. Determination of Fouling Index Using Fuel Characteristics

Viscous temperatures of the ash/fly ash, alkali concentrations in the fuel, and sulfate formation propensity are some indexes of potential slagging or fouling problems. The fly ash ticklishness in a sulfur or chlorine-free fuel can be predicted by differential thermal analysis [31]. But sulfur is present in most biomass fuels. When they are fired, they are dependent upon physical state changes and post-combustion reactions and the melting temperatures cannot be predicted by laboratory enactment. Hence, it is essential to learn the elements in the fuel and their reaction in the boiler. various coals are classified proximate to fouling/slagging comprise the calculation of the weight in alkali oxides (K_2O + Na_2O) per heat unit, kg/GJ (lb./million Btu) in the fuel using the higher heating value (HHV). The detailed review based on plant expertise have shown that a risk of fouling/slagging increases above 0.17 kg/GJ to 0.34 kg/GJ (0.4 ib. to 0.8 1b. MMBtu). Above 0.34 kg/GJ (0.8 lb./MMBtu) the fuel is pretty near certain to slag and foul to a hysterical degree. Evaluation of the impact of a fuel on a particular boiler is done by combining field experience and boiler operating conditions with this information. fouling index of boilers which are co fired with bark, coal and oil is developed that indicates the tendency of fouling based on alkali and alkaline earths [32]. Alkali concentrations for many biofuels are shown in **Figure 4**. The proportion of water soluble sulfate forming compounds (CaO + MgO + Na_2O + K_2O) is represented as a percent of total ash in the fuel fed to the boiler. It is found that fouling tendency could be reasonable when sulfur is present in water soluble alkali. Since some straws have more chlorine than sulfur, chlorine content is also necessarily being intended as a reasonable measure of fouling tendency. Yet, the slagging tendency of a boiler cannot be predicted in terms of fuel properties only. While the slagging tendency commonly increases with alkali content, other inorganic components together influenced with boiler operating conditions and boiler design. The data in phase I prediction of slagging/fouling having Alkali, sulfur and chlorine concentration in fuel both in kg/GJ (lb./million Btu) are shown in **Figure 4**. The dataset shows twelve kinds of fuels namely Yard Waste, Wood-Straw, Wood-Almond, Wood-Ag Pit, Demolition, Urban waste, Forest Residuals, Wood-Ag Blend, Hybrid Poplar, Urban waste, WiIlow Butt and Red Oak respectively.

3.2. Determination of Fouling Index Based on Boiler Operating Conditions

Ash fouling of heat transfer surfaces enduringly has been one of the prime operational interests in coal-fired power plant boilers. Monitoring of ash fouling mainly requires learning the behaviors of the boiler. The boiler efficiency reduction is one of the paramount impacts of ash fouling. On-line computation invariably uses the conventional

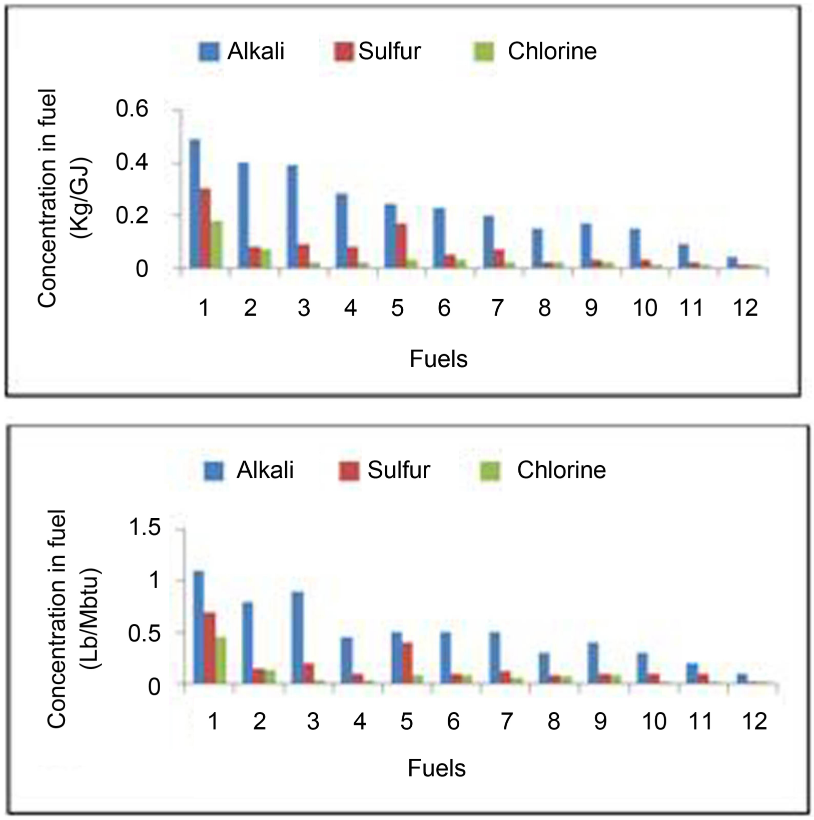


Figure 4. Data Records showing Fuel characteristics in Kg/GJ and lb./million Btu.

method (log-mean-temperature-difference approach [32]) for the calculation of the heat absorption of heat transfer surfaces. Commercial ash fouling boiler monitoring tools are also available, but the internal concerns of these functions are ambiguous. Furthermore, the internal concerns of ash fouling by means of fouling index (FI) measures the ash fouling degrees of heat transfer surfaces and thermal efficiency. A 300 MW coal fired utility boiler is considered for the analysis [33]. Sample data from the literature as shown in **Figure 5** is taken for forecasting in this section. In **Figure 5**, TPA denotes primary air temperature, ξ denotes secondary air flow rate, Ψ denotes coal mass flow rate, ζ denotes primary air flow rate, TFW denotes feed water temperature and FI denotes fouling index.

Comprehensive research is required to find out the cause-effect relation in boiler input and output variables. Required input parameters were initially selected on the basis of expert knowledge and previous experience for the ANN and FCANN model shown in **Figure 2** and **Figure 3** respectively. From the detailed review, it is noted that, the response of boiler is most sensitive to variations in the parameters of primary air flow rate ζ (m^3/h), coal mass flow rate Ψ (kg/s), and load demand (MW). From the expert knowledge, the variation of coal mass flow rate has the data of the changeable MW. It is also reviewed that the primary air temperature (T_{PA} (˚C)) is a significant factor affecting the combustion in furnace. Thus, boiler efficiency η (%) is obviously directly influenced

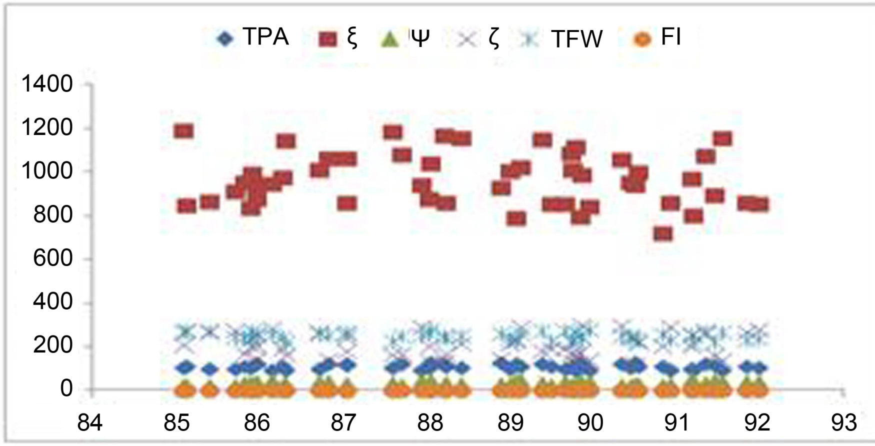


Figure 5. Data records of boiler operating parameters.

by T_{PA}, and it is also mostly influenced by the feed water temperature T_{FW} (˚C), primary air flow rate ζ (m^3/h) and secondary air flow rate ξ (m^3/h). Thus the fouling index of the heating surfaces is significantly influenced by ζ, T_{PA}, ξ, T_{FW}, and Ψ. The developed model is envisioned to be absolutely satisfactory more applicable for "on-line" applications and with less number of input parameters [33] in the determination of FI and boiler efficiency.

3.3. Determination of Fouling Based on Ash Behavior

Slagging and fouling are very complicated outcome which rely on many factors correlated with the nature of fuel, boiler operation and its design. In case of coal combustion the ash behavior in boilers is predominantly governed by coal minerals which go through in flame conversion and melting whereas for the biomass fuels, the ash-forming vapors are the main sources for slagging and fouling. The present section is focused on the forecasting fouling deposits produced during the combustion of coal in experimental boilers. The sample data with ash contents such as SiO_2, Al_2O_3, $Fe_2\ O_3$, TiO_2, CaO, MgO, Na_2O, K_2O, Mn_2O_3, P_2O_5, SO_3 and S taken for prediction is shown in **Figure 6**. The oxide ash content is a primitive measure of ash quality which confers the assessment of the composition of mineral content as well as approximates the slagging/fouling propensity of fuels with the employment of empirical correlations.

Indices used to predict slagging/fouling tendency of coals have been advanced since the 1960s. And they are normally constructed based on the analyses of the viscosity, ash fusion and ash chemistry. The most commonly applied indices are defined in Equations. Reviews on various ranges of these indices were carried out [34]. Most of the slagging/fouling indices have been carried out for coal combustion and are limited to the variety of coals considered. Several theoretical indices that predict fouling and slagging behavior of a fuel were calculated. The review shows that the sodium content in the coal was identified as the dominant factor influencing fouling (e.g. $(B/A) \times Na_2O$). And the sulfur content signals the quantity of pyretic iron in the mineral matter and it impacts the degree of oxidation of iron in the foul/slag, affecting its fouling/slagging tendency.

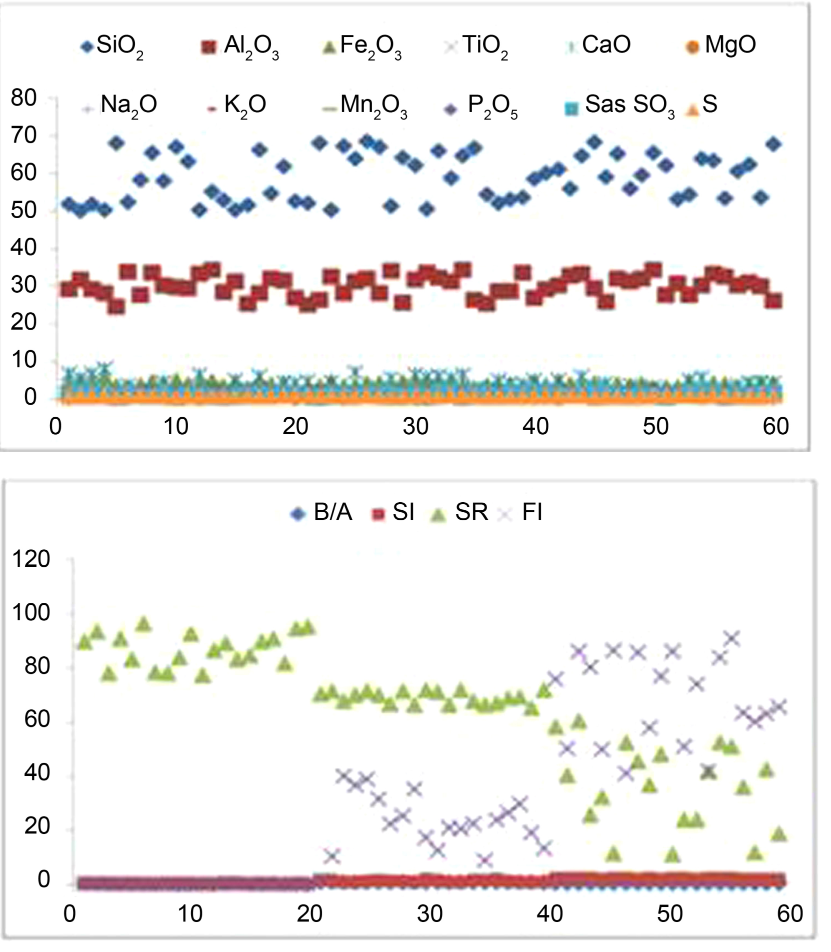


Figure 6. (a) Data records of Ash content. (b) Calculation of B/A, SI, SR and FI.

Increase in the basic oxides concentrations of iron, calcium and magnesium lower the ash viscosity and increase the slagging tendency. Generally the deposition behavior is predicted by the base-to-acid ratio B/A, where "Base" and "Acid" are directly the weighted sums of the percentages of the basic and acidic oxides (combining Equations (6) and (7) to obtain Equation (8)). It is also found that slagging or fouling tendency was low or medium when $B/A < 0.4$ or $B/A > 0.7$ and high or severe when B/A is 0.4 - 0.7 [33].

$$\text{Base} = \text{Fe}_2\text{O}_3 + \text{CaO} + \text{MgO} + \text{Na}_2\text{O} + \text{K}_2\text{O} \quad (6)$$

$$\text{Acidic} = \text{SiO}_2 + \text{Al}_2\text{O}_3 + \text{TiO}_2 \quad (7)$$

$$\frac{B}{A}\text{ratio} = \frac{\text{Base}}{\text{Acidic}} \quad (8)$$

Slagging index (SI) is given by $\frac{B}{A} \times S$ in Equation (9). It is also noted from literature that slagging propensity was low when SI < 0.6 or medium when SI is 0.6 - 2.0, high or severe when SI = 2.0 - 2.6 and extremely high when SI > 2.6. [35].

$$\text{Slagging index}\left(\text{SI}\right)=\frac{B}{A}\text{ratio}\times S \tag{9}$$

Slag ratio (SR) is given by equation 10. SR > 72 indicates low slagging, 72 ≥ SR > 65 indicates medium slagging and SR < 65 indicates high slagging.

$$\text{Slag ratio}\left(\text{SR}\right)=\frac{\text{SiO}_2\times 100}{\text{SiO}_2+\text{Fe}_2\text{O}_3+\text{CaO}+\text{MgO}} \tag{10}$$

Fouling index (FI) is given by Equation (11). FI is low when it is ≤ 0.6, high when 0.6 < FI ≤ 40, extremely high when FI > 40. FI > 40 tends to sintering of deposits.

$$\text{Fouling Index}\left(\text{FI}\right)=\frac{B}{A}\text{ratio}\times\left(\text{Na}_2\text{O}+\text{K}_2\text{O}\right) \tag{11}$$

The fouling phenomena caused by slagging and ash deposits are heavily affected by the variety of coal used. Which in turn affect the lifetime of the boiler superheaters. Therefore the determination of slagging/fouling in order to reduce its effect leads to reduction in emissions, operational and maintenance costs and increase in thermal efficiency. Prediction by numerical estimation and online detection of slagging/fouling assist to increase plant availability, optimize plant operation, and reduce the need for maintenance related action.

4. Results and Discussion

This section discusses the simulated results obtained using ANN and FCANN methods.

4.1. Simulated Results of FC Method

The clusters formed by FC method are given as input to the ANNs and finally the output responses are aggregated to get the predicted FI in all the three phases. Table 1 shows the summary of simulation results obtained in three phases namely fuel characteristics, boiler operation and ash content using FC method. From Table 1, the appropriate number of clusters are selected that maximizes the Average Silhouette and D'_{pc} while minimizing P'_c. From the thorough analysis of Table 1, it is seen that 2 clusters can be selected for Fuel Characteristics (Phase I) since the highest value of Average Silhouette is 0.85 and minimum value of P'_c is 0.02 (Table 1), 2 clusters can be selected for Boiler internal operation (Phase II) since the highest value of Average Silhouette is 0.45 and minimum value of P'_c is 0.35 (Table 1), 2 clusters can be selected for Ash Content (B/A) (Phase III) since the highest value of Average Silhouette is 0.89 and minimum value of P'_c is 0.02 (Table 1), 2 clusters can be selected for Ash Content (SI) (Phase III) since the highest value of Average Silhouette is 0.80 and minimum value of P'_c is 0.07 (Table 1), 2 clusters can be selected for Ash Content (SR) (Phase III) since the highest value of Average Silhouette is 0.71 and minimum value of P'_c is 0.10 (Table 1) and 2 clusters can be selected for Ash Content (FI) (Phase III) since the highest value of Average Silhouette is 0.80 and minimum value of P'_c is 0.12 (Table 1). In Table 1, Average Distance shown is the value of the average dissimilarity and Average Silhouette is the average of the silhouette values of all rows. The Silhouette statistic is

Table 1. Summary of FC simulation results obtained in three phases.

Number Clusters	Average Distance	Average Silhouette	D_{pc}	D'_{pc}	P_c	P'_c
Fuel Characteristics (Phase I)						
2	0.34	0.85	0.89	0.78	0.01	0.02
3	0.19	0.49	0.66	0.49	0.12	0.17
4	0.14	0.43	0.59	0.45	0.16	0.21
5	0.10	0.43	0.60	0.50	0.14	0.17
Boiler Internal Operation (Phase II)						
2	727.11	0.45	0.61	0.23	0.18	0.35
3	475.06	0.40	0.45	0.18	0.28	0.42
4	354.76	0.31	0.34	0.12	0.44	0.58
5	283.33	0.28	0.27	0.09	0.55	0.69
Ash Content (B/A) (Phase III)						
2	7.65	0.89	0.76	0.52	0.08	0.02
3	2.17	0.70	0.85	0.77	0.01	0.16
4	1.61	0.81	0.78	0.70	0.04	0.05
5	1.27	0.69	0.68	0.59	0.08	0.11
Ash Content (SI) (Phase III)						
2	10.07	0.80	0.77	0.53	0.09	0.07
3	4.61	0.76	0.76	0.64	0.06	0.09
4	3.00	0.64	0.73	0.65	0.05	0.19
5	2.57	0.53	0.63	0.54	0.15	0.18
Ash Content (SR) (Phase III)						
2	247.02	0.71	0.76	0.52	0.05	0.10
3	117.17	0.70	0.73	0.60	0.08	0.12
4	80.30	0.70	0.70	0.60	0.09	0.12
5	58.86	0.68	0.66	0.57	0.10	0.13
Ash Content (FI) (Phase III)						
2	247.13	0.73	0.80	0.60	0.06	0.12
3	135.66	0.65	0.73	0.59	0.10	0.16
4	81.71	0.70	0.72	0.62	0.09	0.13
5	59.15	0.70	0.70	0.62	0.10	0.13

used to aid in the search for the appropriate number of clusters by selecting the number of clusters that maximizes this value. Depending on D_{pc}, D'_{pc}, P_c, and P'_c, the number of clusters are searched that maximizes D'_{pc} and minimizes P'_c.

Simulation using fuzzy clustering (Table 2) gives the medoid of the nearest hard

Table 2. Cluster medoids in three phases.

Fuel Characteristics (Phase I)		
Variable	**Cluster 1**	**Cluster 2**
Alkali	0.49	0.17
Sulfur	0.30	0.03
Chlorine	0.18	0.02
Actual_foul	2	1
Row	1	9
Boiler Internal Operation (Phase II)		
T_{PA} (˚C)	106.15	121.54
ξ (m^3/h)	875.98	1081.76
Ψ (kg/s)	29.98	20.58
ζ (m^3/h)	200.92	167.97
T_{FW} (˚C)	262.27	250.39
Boiler efficiency	88.03	87.7
FI	0.55	0.06
Row	1	39
Ash Content (B/A) (Phase III)		
B_A_ratio	0.21	0.58
Level_of_fouling	1	3
Row	3	55
Ash Content (SI) (Phase III)		
SI	0.41	2.24
Level_of_fouling	1	3
Row	5	60
Ash Content (SR) (Phase III)		
SR	71.87	27.80
Level_of_fouling	2	3
Row	34	42
Ash Content (FI) (Phase III)		
FI	0.57	74.33
Level_of_fouling	1	3
Row	1	56

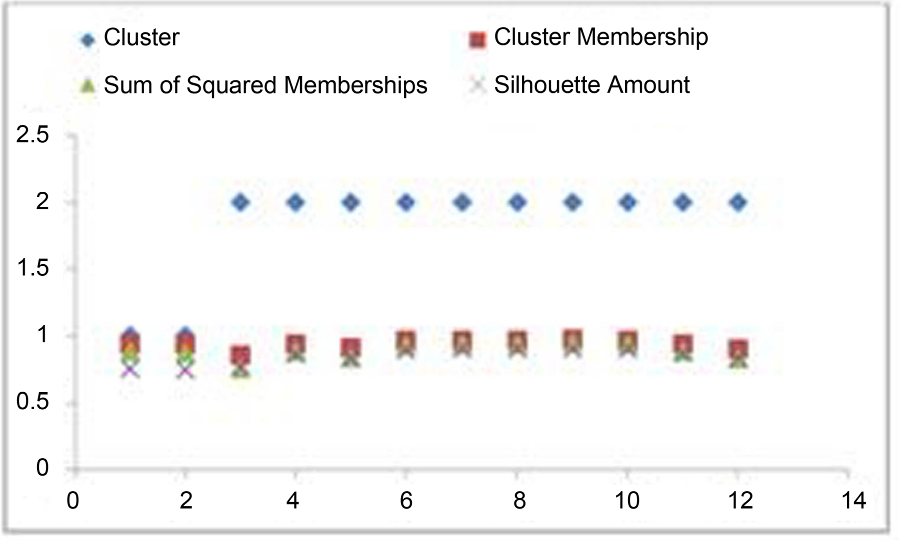
cluster configuration in all the three phases. Cluster medoids recognize and interpret cluster. The last row of the Table 2 gives the row number designated in the given database of the each cluster's medoid. Once the clusters are selected (Table 1), the corresponding cluster medoids in all the three phases for the given dataset are obtained

(Table 2). And the given dataset are grouped into selected number of clusters (Figure 7). Each row with the designated label of each individual database is sorted by Silhouette Value within cluster. Fuzzy clustering method (using k-means and medoid) allows every data to belong to every cluster to a valid degree. In addition, FC extracts the clusters membership levels of each normalized data in all the clusters. Cluster specifies the number of the cluster into which this row was classified. The outliers stand out on this report using Silhouette bar and are easily removed. Cluster Membership specifies is the maximum of the memberships. Sum of Squared Memberships specifies the square and sum of all memberships. Its value is one when a row is completely assigned to a single cluster and $1/M$ when the row is equally likely to be classified into each cluster. Hence, rows with high values here are near the center of a cluster. Rows with low values here are outliers. Silhouette Amount gives the value of the silhouette. Its value should be positive and most rows should be greater than 0.50. Figure 7(a) shows the Phase I simulation of given dataset shown in Figure 4. Figure 7(b) shows the Phase II simulation of given 52 dataset that includes TPA, ξ, Ψ, ζ and TFW and FI of Figure 5. Figure 7(c) shows the Phase III simulation (B/A) of given 60 dataset that includes ash contents shown in Figure 6(a) and corresponding B/A prediction shown in Figure 6(b). Figure 7(d) shows the Phase III simulation (SI) of given 60 dataset that includes ash contents shown in Figure 6(a) and corresponding SI prediction shown in Figure 6(b). Figure 7(c) shows the Phase III simulation (SR) of given 60 dataset that includes ash contents shown in Figure 6(a) and corresponding SR prediction shown in Figure 6(b). Figure 7(c) shows the Phase III simulation (FI) of given 60 dataset that includes ash contents shown in Figure 6(a) and corresponding FI prediction shown in Figure 6(b).

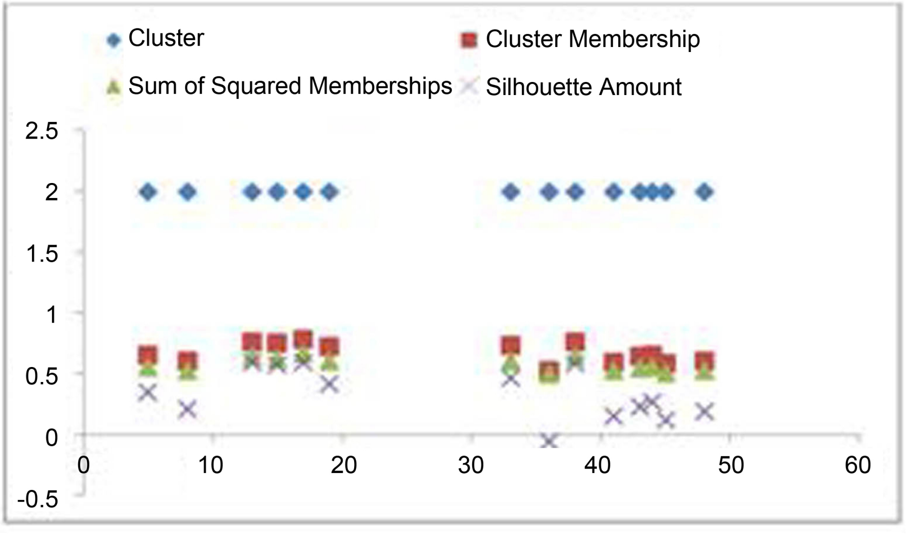
4.2. Simulated Results of ANN and FCANN Methods

Once the FC method (using k-means and medoid) is established, every data is allowed to belong to every cluster to a valid degree. Thus FC extracts the clusters membership levels of each normalized data in all the clusters and finally each cluster will be fed as input to ANNs. The employed FCANN allows the clusters to be larger which thereupon increases the accuracy of the proposed forecasting system.

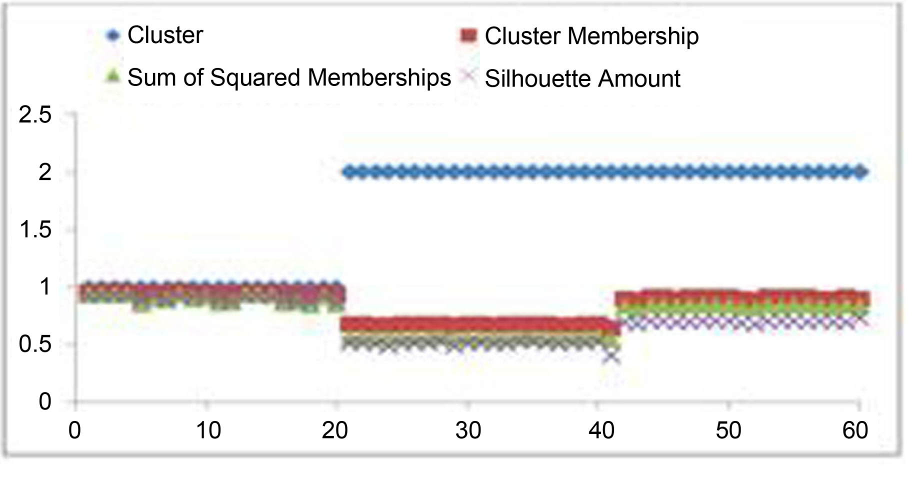
Figure 8 shows the simulation of FCANN and very good fitting with real data compared to single ANN method. Figure 8(a) shows the prediction of FI and thereby fouling level (FL) in phase I based on fuel characteristics shown in Figure 4 and according to Table 3. Figure 8(b) shows the prediction of FI and thereby fouling level (FL) in phase II based on boiler operating parameters shown in Figure 5. Figures 8(c)-(f) also shows the prediction of FL in phase III based on Ash contents and related calculations of B/A, SI, SR and FI are shown in Figure 6. Figure 8(c) show the prediction of B/A ratio, and its corresponding level of fouling (FL) predicted using both FCANN and ANN. Figure 8(d) show the prediction of slagging index (SI) and its corresponding level of fouling (FL) predicted using both FCANN and ANN. Figure 8(e) show the prediction of slagging ratio (SR) and its corresponding level of fouling (FL) predicted using both FCANN and ANN. Figure 8(f) show the prediction of fouling index (FI)


Cluster
Cluster Membership
Sum of Squared Memberships
Silhouette Amount
2.5
2
1.5
1
0.5
0
0
2
4
6
8
10
12
14

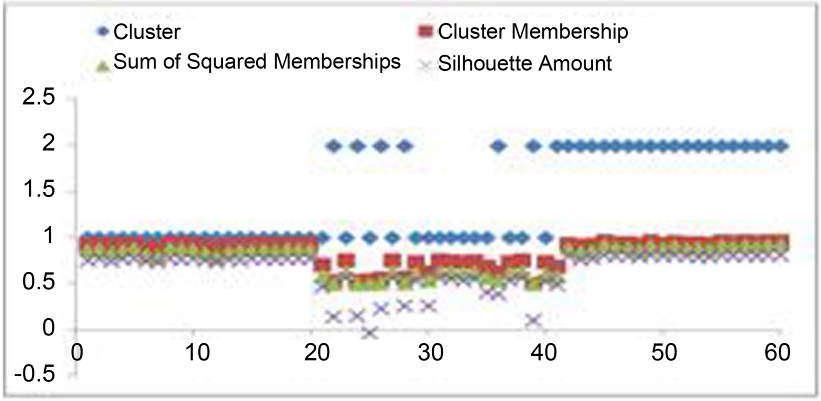
(a)


Cluster
Cluster Membership
Sum of Squared Memberships
Silhouette Amount
2.5
2
1.5
1
0.5
0
-0.5
0
10
20
30
40
50
60

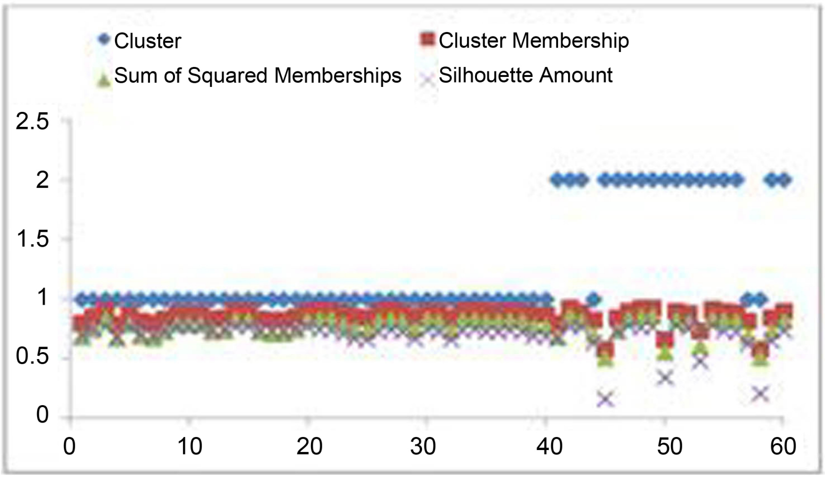
(b)


Cluster
Cluster Membership
Sum of Squared Memberships
Silhouette Amount
2.5
2
1.5
1
0.5
0
0
10
20
30
40
50
60

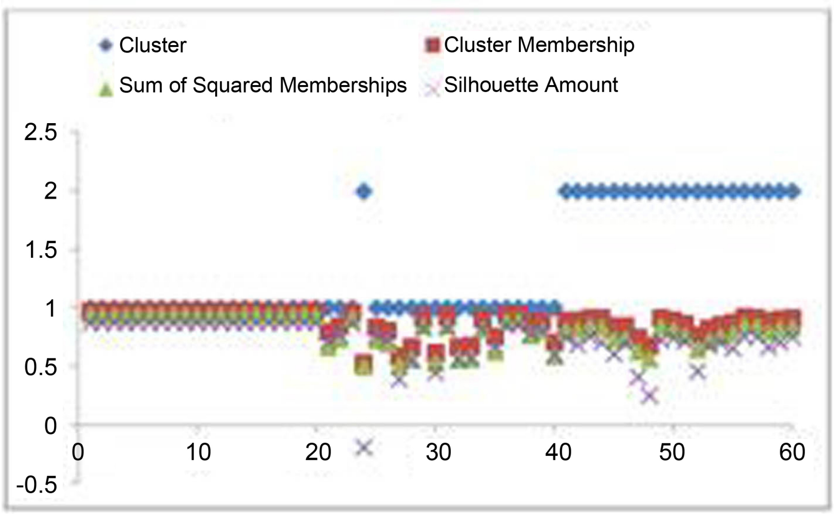
(c)



(d)

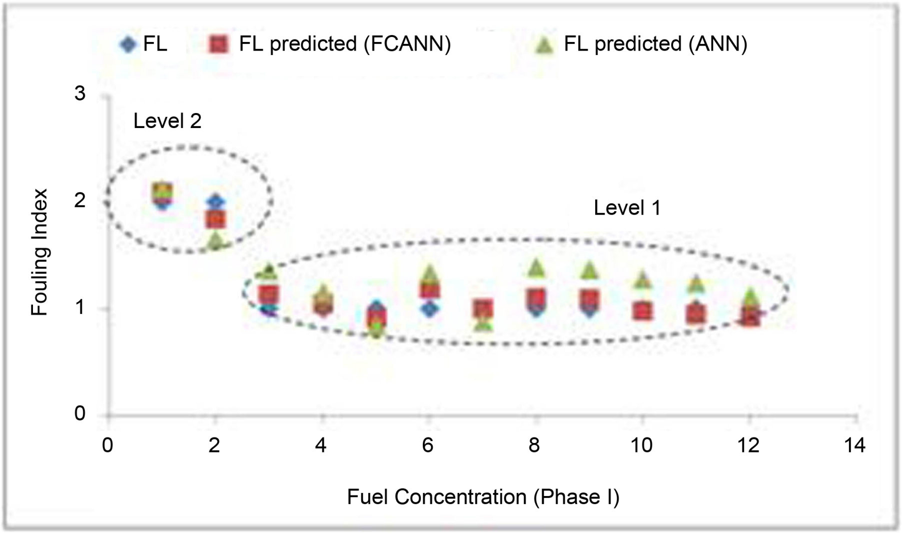


(e)

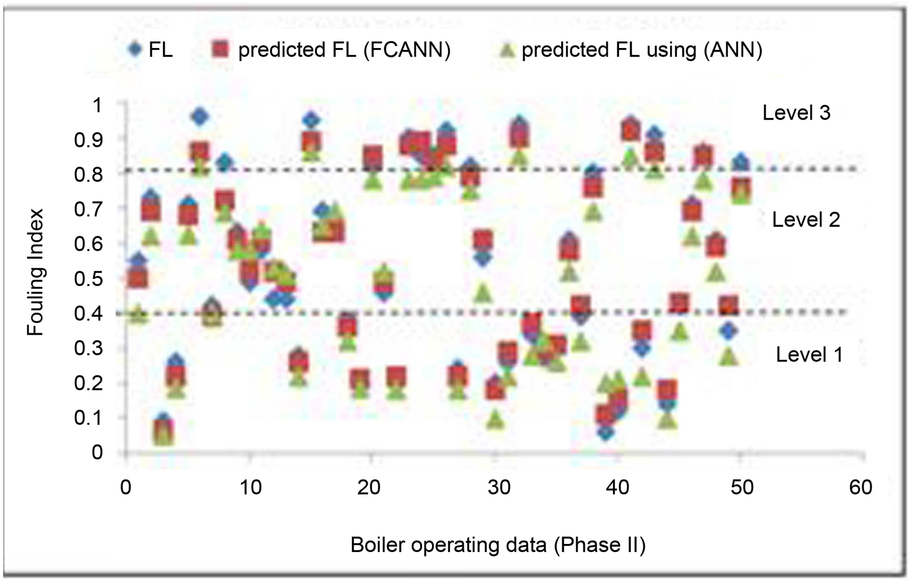


(f)

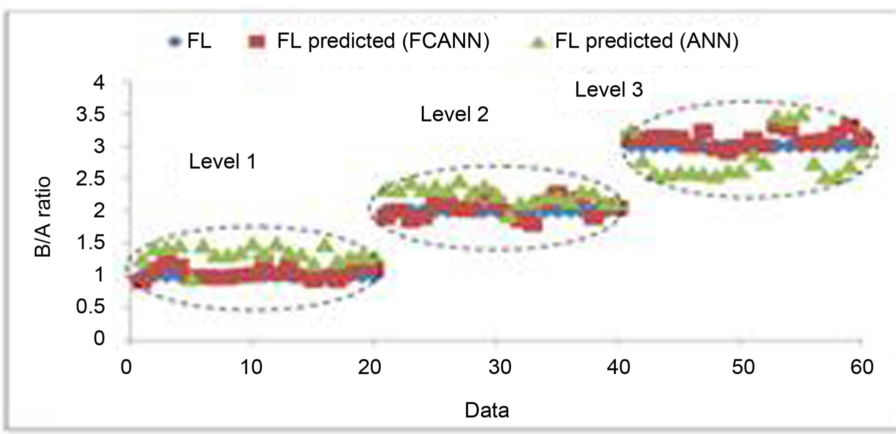
Figure 7. (a) Phase I simulation of given dataset. (b) Phase II simulation of given dataset. (c) B/A (Phase III) simulation of given dataset. (d) SI (Phase III) simulation of given dataset. (e) SR (Phase III) simulation of given dataset. (f) FI (Phase III) simulation of given dataset.


FL
FL predicted (FCANN)
FL predicted (ANN)
Fouling Index
Level 2
Level 1
3
2
1
0
0
2
4
6
8
10
12
14
Fuel Concentration (Phase I)

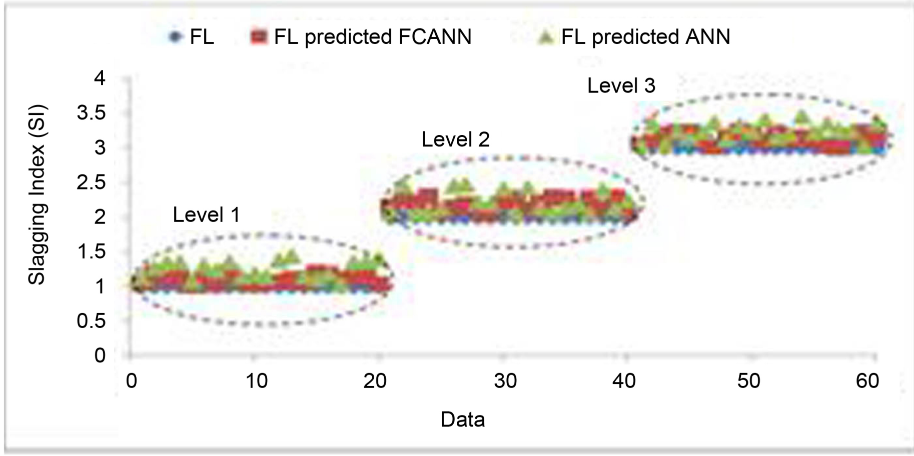
(a)


FL
predicted FL (FCANN)
predicted FL using (ANN)
Fouling Index
Level 3
Level 2
Level 1
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
10
20
30
40
50
60
Boiler operating data (Phase II)

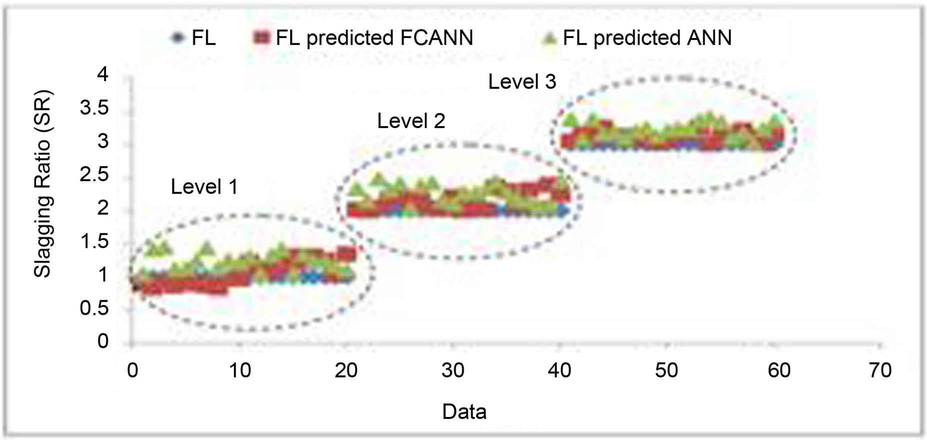
(b)


FL
FL predicted (FCANN)
FL predicted (ANN)
B/A ratio
Level 1
Level 2
Level 3
4
3.5
3
2.5
2
1.5
1
0.5
0
0
10
20
30
40
50
60
Data

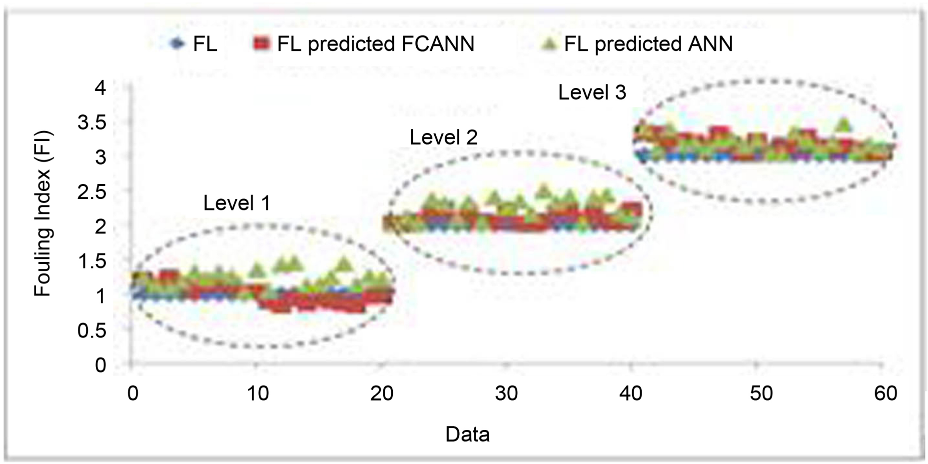
(c)



(d)



(e)



(f)

Figure 8. (a) Prediction of FL in phase I. (b) Prediction of FL in phase II. (c) B/A prediction of FL. (d) SI Prediction of FL. (e) SR Prediction of FL. (f) FI Prediction of FL.

and its corresponding level of fouling (FL) predicted using both FCANN and ANN. The simulation shows energy saving between hybrid FCANN outputs and real data

Table 3. Assignment of FI and fouling classification according to fuel concentration.

S. No.	Concentration in Fuel Lb/MBtu	Concentration in Fuel Kg/GJ	FL	FL Classification
1	Less than 0.4	Less than 0.17	1	No Foul
2	Between 0.4 - 0.8	Between 0.17 - 0.34	2	Probable Foul
3	Greater than 0.8	Greater than 0.34	3	Certain Foul

obtained from steam boiler.

4.3. Comparison of Results

In this section, the mean absolute percentage error (MAPE), the root mean square error (RMSE) for all the three phases and both the models ANN and FCANN are analyzed using the Equations (12) and (13). The simulated data are used to make comparison a between both the models ANN and FCANN. According to the prediction ability of the models the MAPE and RMSE using real plant data are analyzed and tabulated in Table 4. Where y_m is the experimentally measured value, y_c is estimated or calculated value, $e_t = y_m - y_c$, is the predicted error or residual used to analyze the accuracy of the estimates and n is the number of onsite experimental data.

$$\text{MAPE} = \frac{\sum_{i=n}^{n} \left| \frac{y_m - y_c}{y_m} \right|}{n} \tag{12}$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=n}^{n} \left| y_m - y_c \right|^2}{n}} \tag{13}$$

Fuzzy and neural network was performed to predict fouling in condenser [35]. Another work reviews the available techniques and methods for minimising deposition problems in boiler [36]. The Neurofuzzy technology was employed to relate process data to the cleanliness status of the boiler heat transfer sections [37]. An embedded based automation technique is designed in the laboratory using ARM7 platform with only stack temperature is used as the criteria for controlling the soot blower [38]. These works not concentrated on slagging/fouling forecasting based on all the three factors such as the fuel characteristics, boiler operating conditions and ash behavior.

From the previous results (Table 3), it is obvious that:

-FCANN model has smaller RMSE than ANN in all the three phases.

-FCANN model has smaller MAPE than ANN in all the three phases.

It is evident from the analysis that FCANN gives the minimum error amongst the two prediction models (ANN and FCANN) and hence it should be selected. The significance of using FCANN method mainly lies on predicting responses when inputs are bulky and multicollinear in nature. The goal of this study is to prove the enhancement in prediction by most appropriate FCANN method over the FC or ANN when adapted to predict the slagging/fouling in a steam boilers of any variable capacity.

Table 4. Performance indicator between ANN and FCANN models.

Methods		Performance Indicator	
		MAPE	RMSE
ANN (Phase I)		23.01	0.27
ANN (Phase II)		21.17	0.08
ANN (Phase III)	B/A	0.18	0.35
	SI	0.10	0.19
	SR	0.13	0.23
	FI	0.11	0.21
FCANN (Phase I)		7.84	0.10
FCANN (Phase II)		10.12	0.04
FCANN (Phase III)	B/A	0.06	0.13
	SI	0.08	0.16
	SR	0.09	0.17
	FI	0.07	0.15

5. Conclusions

The primary target of this paper was to develop a reliable slagging/fouling predictive tool which should facilitate in a comparatively short time the optimization of the coal/ biomass fuel blends, boiler operating conditions and ash behavior to minimize slagging/fouling.

- The simulation of proposed hybrid fuzzy clustering and artificial neural networks (FCANN) method has shown a good performance of the systems that characterize the above three factors, with satisfactory comparisons with experimental values compared to traditional, quantitative model-based approaches, yielding very good results with the accuracy rate of 99.85% in the pattern recognition used within the prediction paradigm.
- After attaining suitable training, the FCANN network is ready to be used on-line for diagnostic tasks which alerts operators budding anticipated fouling problem, identify conflicting practice of boiler firing that increases the fouling tendency, forewarns the variation of essential operational parameters to help in diagnostics of fouling event and keeps a historical record of forewarns for consequent analysis.

Irrespective of the selected method, an adequate format is needed in order to be read by a Graphical User Interface (GUI) which provides information about warning levels plots and diagnostic messages regarding slagging/fouling.

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