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Developing an ANFIS-PSO Based Model to Estimate Mercury Emission in Combustion Flue Gases

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Abstract

Mercury content in the output gas from boilers was predicted using an Adaptive Neuro-Fuzzy Inference System (ANFIS). Input parameters selected from coal characteristics and the operational configuration of boilers. The ANFIS approach is capable of developing a nonlinear model to represent the dependency of flue gas mercury content into the specifications of coal and also the boiler type. In this study, operational information from 82 power plants has been gathered and employed to educate and examine the proposed ANFIS model. Resulted values from the model compared to the collected data, and it indicates that the model possesses an extraordinary level of precision with a correlation coefficient of unity. The MARE% for training and testing parts were 0.003266 and 0.013272, respectively. Furthermore, relative errors between acquired data and predicted values were between -0.25% and 0.1% which confirm the accuracy of PSO-ANFIS model.

Keywords: Flue gas; Emission; Mercury; ANFIS; PSO doi:10.20944/preprints201905.0124.v1

1. Introduction

Mercury contamination can cause significant ecological issues, and it has a considerable effect on human well-being around the world. As a lethal and exceedingly volatile metal, Mercury can cause contamination of both nearby and removed streams and lakes. It is the most dangerous hazard for babies and youthful kids as it influences the central nervous system, causing them utero and some other nasty illnesses. Nowadays, it is no longer in doubt that a substantial amount of mercury outflows to the earth comes from coal-consuming power plants. In 2010, roughly 2000 mg mercury outflows to the air from various sections worldwide(Amap/Unep, 2013). Coal burning had a share of 24% which is a relatively high share(Burmistrz et al., 2016). Power plants are in charge of around 33% Mercury outflows, and this type of emission caused by human beings (Alto, 2001) and Elemental mercury emission is about 20-50% of mercury emissions which originate from combustion of coal(Carpi, 1997; Srivastava et al., 2006). Nowadays mercury emission from coal consumption is a global concern. In 2006, total coal consumption in China was about 40.1% of the world consumption which is equivalent to 1238.3 million tons of oil (Zhang et al., 2008). Some studies predict that the amount of mercury emission is more likely to increase during the next years because of more uses in developing countries(Streets et al., 2009). The U.S. Environmental Protection Agency (EPA) distinguished this metal as one of the most dangerous air pollutants that must be dealt with under specific concern. In 1999, an approximated amount of 45 tons of mercury outflows from coal-consuming plants to the environment (Alto 2000). The developing worry of this contamination in the U.S has incited government and specialists to start endeavors to recognize, estimate and cut off on the anthropogenic emissions. As a result of the absence of cost-effective, promptly accessible and efficient practical control methodologies in the U.S, discharge of this dangerous contaminant from coal-consuming boilers are not basically under control. It gets worse when the greater of part power supply in a big country such as the United States originates from utility boilers that use coal (EPA 2001) and furthermore About 70% of electric power in China is produced by burning coal, in which 50% of this coal burned in coal-based power plants (Tian et al., 2012; Tian et al., 2011; You and Xu, 2010).

In 1998, Paying attention to the enormous potential for ecological dangers, EPA proposed a request in order to ask coal-consuming plants to publish information on the amounts of mercury contaminant outflows from their systems. This request was designed to gather information in three major parts precisely. The principal stage was intended to gather all standard data on coal-burning power plants around the U.S. afterward, analyzed feed data at the entrance of every plant during a year collected. Eventually, in the third phase, EPA chose 84 out of 1084 plants to gather data of mercury emission in some specified points within the selected plants. This selection was based on some statistic activities on the feed specifications and also the operational structure of each plant. Resulted in information from Stage III evaluated. Representing correlations were developed in order to predict the emission of mercury in each plant concerning coal qualities and operating conditions. It found that the best input data were characteristics of coal, for example, the concentration of mercury, heating value, chlorine sulfur, operating parameters such as temperatures and pressures and also yield parameters in boilers such as the amount of mercury oxidization. Beside abovementioned backgrounds, artificial intelligence approaches are powerful tools in order to forecast parameters by finding correlations between variables. This kind of networks are able to find the nonlinear relationship between parameters, so they are an valuable method (Baghban et al., 2015). Numerous investigations published in the literature regarding applications of artificial intelligence approaches. Computational intelligence approach can be used not only to predict the amount of mercury emission but also to reduce elemental mercury in outlet gas of boilers (Li et al., 2018a). Dragomir and Oprea (Dragomir and Oprea, 2013) present a multi-agent system for the operation of power plants. They used artificial neural networks (ANNs) to predict the amount of SO_2, NO_x, particulate matters (PMs) and mercury emissions. Jensen et al (Jensen et al., 2004) worked on the relationships between mercury in the flue gas and coal specifications and the type of boiler by a multilayer perceptron artificial neural network (MLP-ANN). They derived an accurate model with a correlation coefficient of 0.9750. Antanasijević t al (Antanasijević et al., 2013) developed a model to forecast the amount of PM10 emission by taking advantage of ANNs and genetic algorithm (GA). They conclude the estimation of PM10 emission up to two years made successfully and accurately. Zhao et al (Zhao et al., 2010) used support vector Machine to develop a model for mercury speciation in flue gases. They concluded that the SVM provides better prediction performances with a mean squared error of 0.0095 and the correlation coefficient of 0.9164. In 2016, Wang et al (Wang et al., 2016) worked on the application of GA-back propagation for predicting the amount of mercury component in flue gases of 20 different coal-fired boilers. Correlation coefficient training data points were as high as 0.895, and they showed that GA-BP is a promising method for this goal. Li et al. (Li et al., 2018b) employed computational intelligence approach to cut off on the elemental mercury in coal-fired boilers, and finally, they found that the increment of capture efficiency can approximately improve up to 15%.

In addition to the mentioned literature, a comprehensive literature review done. Adaptive neuro-fuzzy inference system (ANFIS) and also particle swarm optimization (PSO) were rarely used and needs to be investigated more in depth. The present study aims to find an reliable relationship between elemental mercury in the output gas, the specification of feed and the type of boilers by utilizing an ANFIS-PSO based approach.

2. Theory of Adaptive neuro-fuzzy inference system

A deep understanding of the power plant needed in order to control the amounts of mercury emissions. Therefore, an accurate estimation of emission is vital for engineers who want to control and reduce mercury emission (Song et al., 2017). The method of ANFIS proposed by Jang (Jang, 1991; Roger, 1993) and is a versatile and intelligent hybrid system. ANFIS approach can be expressed as a complete collaboration between computing activities and neuro-fuzzy system(Baghban, 2016). This method integrates natural and neural networks and uses their strength into its advantage. Such methodology exploits back-propagation calculation from the information gathering process to make the essential basics of the fuzzy system. Its framework is related to an arrangement of fuzzy IF-THEN rules which have learning ability to estimate nonlinear functions. Basics of ANFIS method are approximately similar to a fuzzy system developed by Takagi-Sugeno-Kang (Sugeno and Kang, 1988; Takagi and Sugeno, 1985). In reverse spread learning capability of the ANFIS method, which is based on the calculation of derivatives of squared errors in a backward manner form output nodes to the input ones, this method constructs and utilizes strong learning methodology based on gradient descent and least-squares methods. In order to determine the consequence factors in the forward section, the least square approach utilized. Then the preset parameters will reset by gradient descent in the regressive advance (Baghban et al., 2016a). The adaptive network constructed of five layers. Figure 1 shows these layers, their nodes, and connections with the assumption of two inputs expressed by “x” and ”y” to the fuzzy inference system (FIS) and a single output of “f”. As an explanation about the configuration of ANFIS, it noted that two fuzzy 'if-then' rules utilized which they follow sugeno FIS as:

$$f_1 = P_1 + q_1 y + r_1 \qquad \text{assume } x=A_1 \text{ , } y=B_1$$
$$f_2 = P_2 + q_2 y + r_2 \qquad \text{assume } x=A_1 \text{ , } y=B_1$$

Fuzzification layer which is the first layer of the structure produces all membership grades for each variable. Node functions in this layer can be defined as follows:

$$O_{1,i} = \mu_{Ai}(x) \qquad i = 1,2 \qquad (1)$$

$$O_{1,i} = \mu_{Bi-2}(x) \qquad i = 3,4 \qquad (2)$$

Memberships of a fussy set are (A_i, B_i) and $O_{1,\,i}$ represents the resulted value from i^{th} node of the first layer. The input signals are generated by the nodes of layer 2.

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi(x)} \qquad i = 1,2 \qquad (3)$$

The nodes of the third layer are used to compute the following parameter:

$$O_{3,i} = \bar{\omega} = \frac{W_i}{W_1 + W_2} \qquad i = 1,2 \qquad (4)$$

Where W_i is rule firing strengths of node i which has a normalized firing strength of ω_i. Results of layer 4 can be written as follows:

$$O_{4,i} = \bar{\omega} f_i = \bar{\omega} i (P_i + q_i y + r_i) \qquad i = 1,2 \qquad (5)$$

In this notation p_i, q_i, and r_i are called consequent parameters. Eventually, the general output can be defined as follows which calculated in the nodes of layer 5:

$$O_{5,i} = \sum_{i=1}^{2} \bar{\omega}_i f_i = \frac{\omega_1 f_1 + \omega_2 f_2}{W_1 + W_2} \qquad (6)$$

A considerable number of optimization methodologies, such as PSO, are available to reinforce the parameters and answers of ANFIS system(Baghban et al., 2016b). PSO is extraordinary compared to other approaches with the end goal of optimization. This study takes the benefits of this algorithm.

3. Model development

When there is not enough data on the detailed information of an operating power plant, it is tough to build up a precise model in order to estimate the amount of mercury outflow. In the present study, an endeavor has made to develop a model in order to predict mercury outflows from boilers at some specified testing locations. In this kind of locations, every single factor that may influence the mercury discharge considered and incorporated into the model. A total number of 82 data points were gathered from literature to train and evaluate the model (Jensen et al., 2004). The concentration of mercury in the inlet feed, ash content, chlorine content, the heating value of coal, sulfur content, and the temperature chosen as the most useful variables. This data bank comprises a total number of 82 data points, from which 75% used as training and the rest of them exploited testing samples. In the developed ANFIS model, six previously mentioned parameters considered as input parameters, and the elemental mercury emission selected as the target variable. Furthermore, PSO algorithm was used to find the optimized Gaussian membership function parameters of the proposed ANFIS model.

3.1. Fundamentals of Particle Swarm Optimization

Particle swarm optimization (PSO), inspired in the early 1990s from birds behavior seeking food (Chen et al., 2006; El-Gallad et al., 2002). In this model, particles update their places and pathways based on their and others information; so it was proposed that the particle possess a memory function. The optimization process is based on competition and collaboration between particles. When PSO is used to solve optimization problems, one can follow the particles state by their pathways, and velocities. Three vectors X_i, V_i, $Pbest_i$ are introduced to explain the properties of a particle: X_i is the current place; V_i the current speed; $Pbest_i$ the best spatial placement sought by the particle. The position and pathway of the particle will be updated gradually, based on the following formula:

$$v(k+1) = v(k) + c_1 rand(0,1) \times [pbest(k) - persent(k)] + c_2 rand(0,1) \times [gbest(k) - persent(k)] \quad (7)$$

$$\text{present}\ (k + 1) = \text{present}\ (k) + v\ (k + 1) \quad (8)$$

Where, $v(\ )$ is particle speed; $present(\ )$ is particle position; $c1$, $c2$ are learning coefficients and are greater than zero, and a random number between [0,1] is denoted using $rand(\ )$. Formula (7) represents the updating process of the particle's speed which includes particle's historical velocities and personal and global best positions (Meng and Pian, 2015).

4. Results and discussions

The amount of mercury emission was estimated using an ANFIS approach. Emission of mercury into the environment generally is an active function of mercury six previously mentioned variables. We used MATLAB software in order to construct our model. A Gaussian function was used to

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optimize the parameters. In addition to that, the total number of 10 clusters utilized in the ANFIS hybrid system. Optimization conducted on a total number of parameters that were determined by:

$$N_T = N_c N_v N_{mf} \tag{9}$$

Where the number of parameters for undergoing optimization is denoted by N_T, and N_{mf}, is used to show the number of Gaussian membership functions that used, N_υ and Nc show how many variables and clusters are used in the model, respectively. It is noteworthy to state that in this study, two membership functions, seven input and output variables, and 10 clusters used. Eventually, using a PSO algorithm, optimization was conducted for 140 tuning parameters. As is shown in **Figure 2**, in order to evaluate the functionality of PSO algorithm, a root means square error (RMSE) analyze used. Results show that in a total number of 1000 iterations, the minimum value of RMSE touched. **Figure 3** indicates train membership function parameters for each input variables. It is seen that the results of the presented model are in good agreement with the obtained data which is the result of great learning capability of the developed ANFIS model. **Figure 4** illustrates the obtained data of mercury emissions versus the test and training of ANFIS hybrid system. As is shown in **Figure 5**, actual and predicted mercury emissions are located on a straight line with an approximate slope of 1 (45^o line) which indicates that the obtained information and ANFIS predicted ones are in good agreement. The obtained cross-fit line in both test and training data sets have an R^2 equal to 1 which shows the accurateness of the model. In order to compare the results of mthe odel and evaluate its precision, the method of mean absolute relative error is used. For training and testing steps, using mean absolute relative error percentage (MARE %) method, percentage values of 0.003266 and 0.013272 are calculated, respectively. Resulted relative deviations are shown in **Figure 6**. Low relative deviations are observed due to accurately-predicted values. Different statistical analyses were also presented in **Table 1** for the suggested model.

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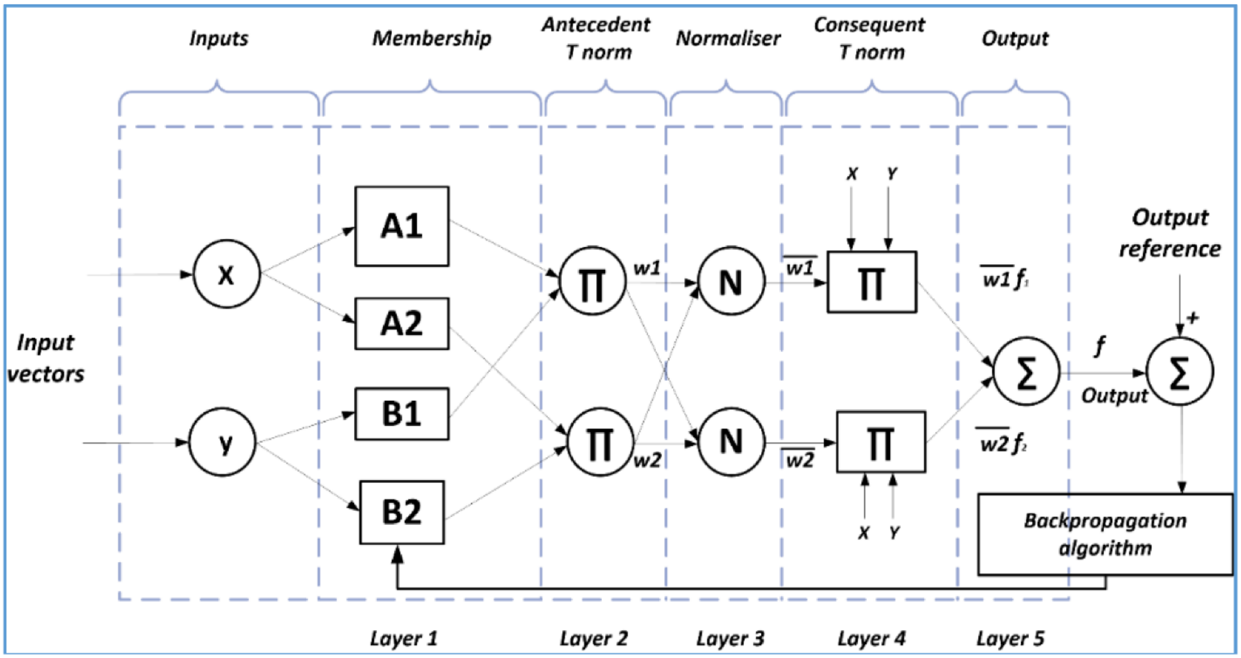

Figure 1. A schematic view of the ANFIS intelligent system.

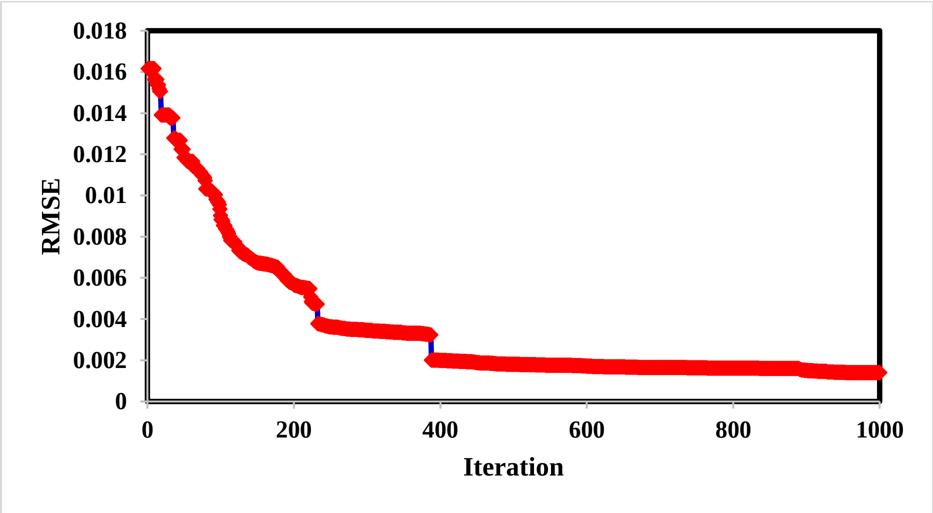

Figure 2. Root mean square errors versus a number of iterations.

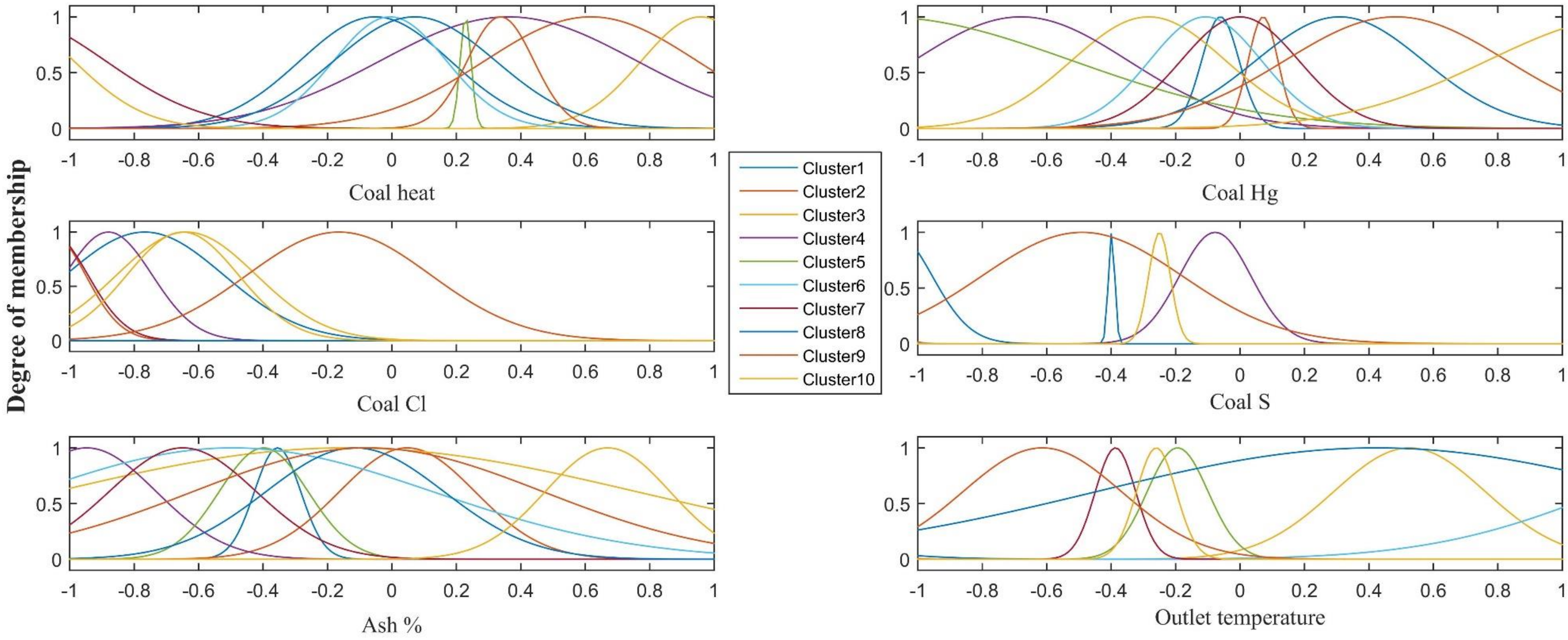

Figure 3. Trained membership function parameters

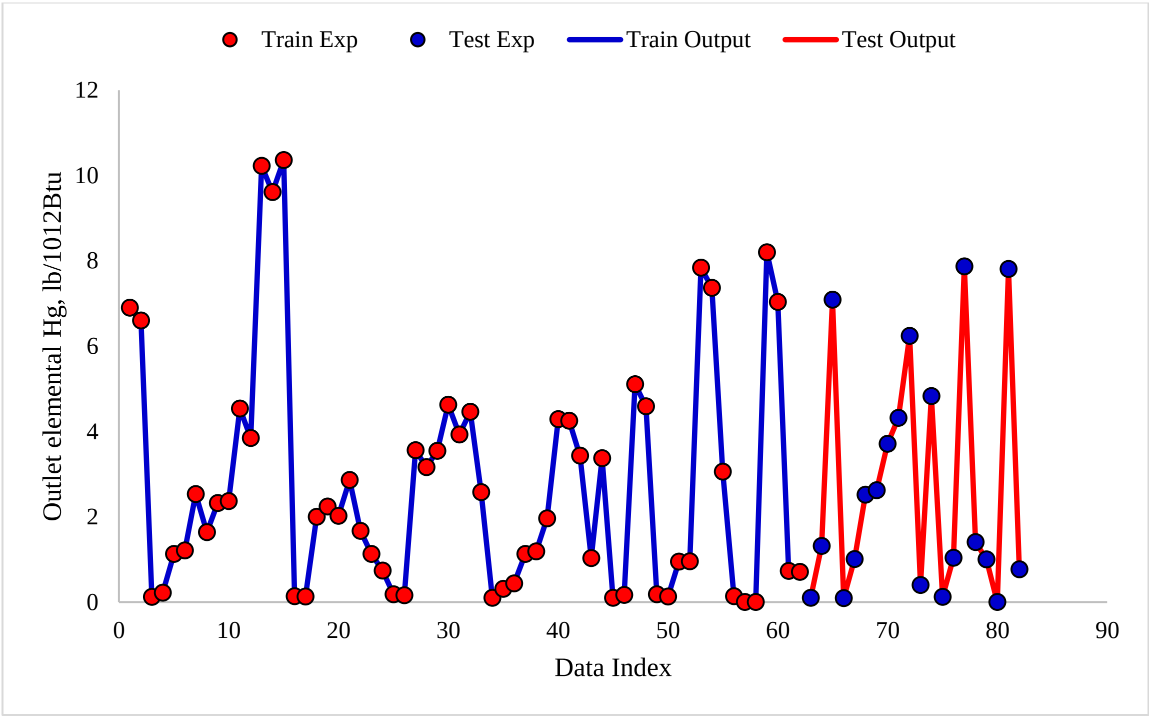

Figure 4. Obtained data from plants and ANFIS values for mercury emissions in the stages of training and testing.

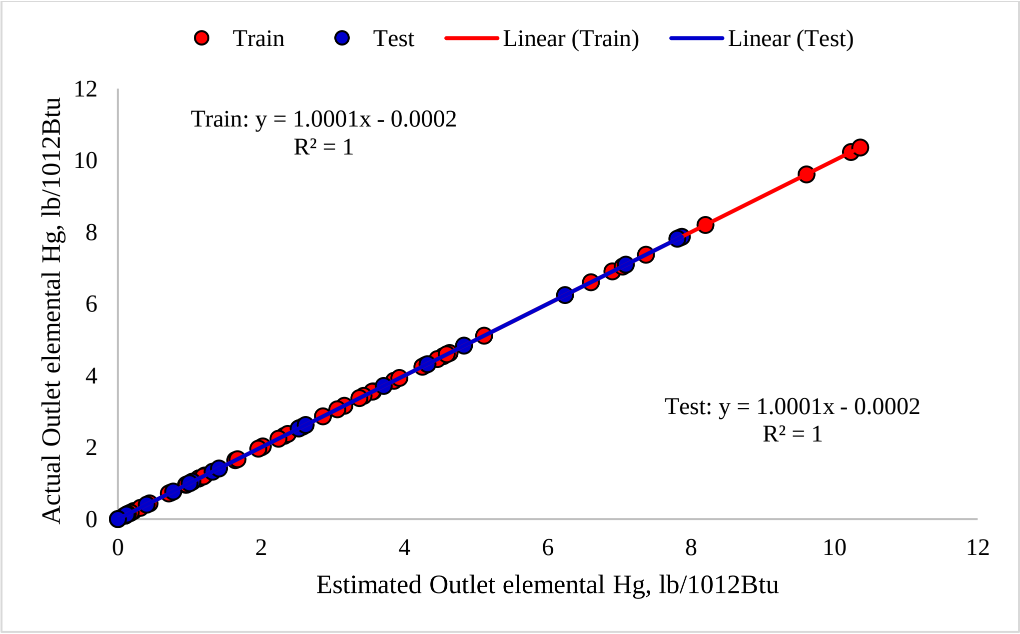

Figure 5. Regressions derived between estimated and collected data of mercury emissions.

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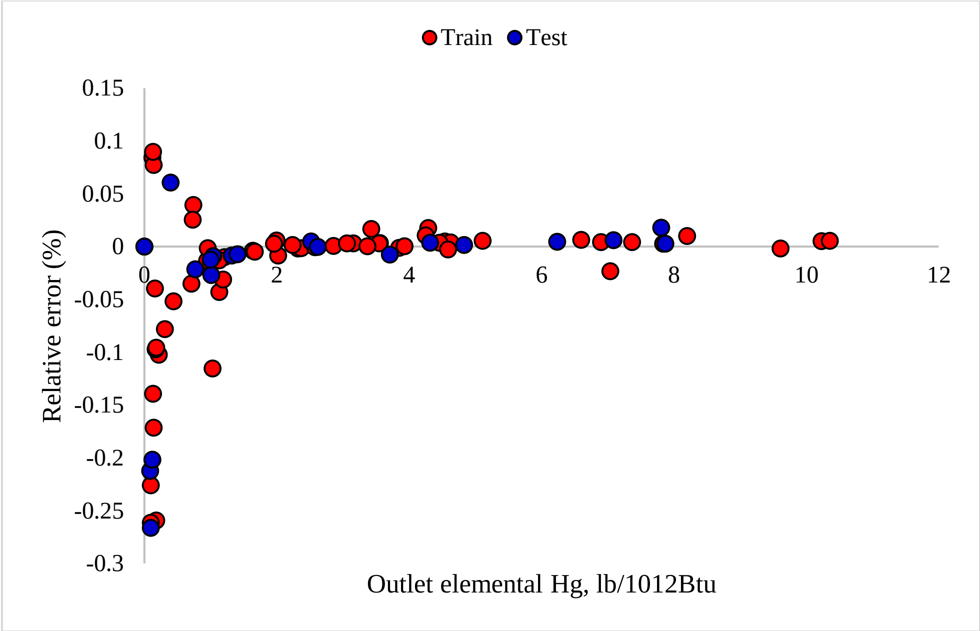

Figure 6. The deviation between the obtained data from plants and predicted mercury emissions.

Table 1: Statistical analysis of the model for all phases

	Train	**Test**
R^2	1.000	1.000
MSE	1.40E-07	1.39E-07
MRE (%)	0.037	0.044

5. Conclusions

Emission of mercury is known as one of the most perilous environmental contamination. In this study, a comprehensive literature review was done, and a predictive model was built to estimate the amount of mercury emission based on the characteristics of the coal supply, operational conditions, and so forth. The presented model is based on the ANFIS system which utilizes a PSO algorithm to estimate the amount of mercury emission to the environment. Data from 82 power plants have been used to train and develop the ANFIS model. The MARE% for training and testing parts were 0.003266 and 0.013272, respectively. Furthermore, relative errors between acquired data and predicted values were between -0.25% and 0.1% which confirm the accuracy of PSO-

ANFIS model. It is obvious that for both training and testing parts the coefficient of determination was calculated to equal to unity which reflects the accuracy of the proposed ANFIS-PSO based model.

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