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Optimal Decision Support System Using Multilayer Neural Networks for Incinerator Control

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Abstract—In the field of industrial control, there has been a significant increase in the use of AI based techniques. For various control problems there has been successful implementation of different Intelligent techniques like Fuzzy Logic, Artificial Neural Network and other Hybrids. One of the major byproducts recovered from crude oil is sulfur. Sulfur is recovered from crude oil using the Modified Clause process, upto 98 percent of the sulfur can be recovered by this method. The remaining 2 percent of the sulfur is one of the major constituents of waste gases and is released into the atmosphere. Waste gases cannot be directly released into the atmosphere as it has sulfur compounds and other harmful constituents. Oxidizing waste gases before releasing it into the atmosphere makes it safe for the environment. Oxidization of waste gases is done by the process of incineration. The incineration process requires fuel gas to achieve this. To use minimum fuel gas and to maximize oxidization, the incinerator needs to be optimized. This paper presents a neural network which is modeled for optimal control of incinerator in Sulfur Recovery Block of refineries. An Artificial Neural Network based Inverse Plant is modeled to achieve optimal control. The Neural Network model was developed by using the neural network tool box in MATLAB.

Keywords: Artificial Neural Networks, SRU, Incinerator

I. INTRODUCTION

Many of the useful daily products such as petrol, diesel, kerosene, Liquefied Petroleum Gas (LPG) are obtained by refining crude oil. One of the major byproduct of refining crude oil is sulfur. This sulfur is recovered by means of Sulfur recovery units. Tail gas is a stream of waste gas which is produced from the Modified Claus process in sulfur recovery units (SRU). One of the major constituents of tail gas are sulfur compounds which cannot be directly introduced into the atmosphere without treatment. The incineration process helps to destroy the harmful compounds present in the tail gas. Before releasing the waste gas to the atmosphere the tail gas is treated in Incinerator.

All the sulfur compounds in the tail gas are burned to SO_2 in the incinerator system and then this gas is discharged at a high elevation into the atmosphere. The incinerator is designed to limit total SO_2 emission consistently within 0.1 percent of unrecovered sulfur and to limit H_2S stack emissions to less than 10 ppmv.

The incinerator system includes four sections- incinerator, reduction furnace, waste heat boiler and vent stack. The fuel gas is burned to a temperature over 1650°C with excess air in the thermal oxidizer burner. The temperature is sufficient to heat the tail gas from TGTU to ~ 761°C in the thermal oxidizer mixing chamber and to oxidize the residual H_2S and sulfur compound to SO_2, while minimize SO_3 formation. To minimize NOx formation reduction furnace is used. To destroy NH_3 to N_2, the sour water stripper gas rich in NH_3 is fed to the burner along with required amount of air and fuel. The hot gas is directed into the incinerator. Schematic representation of the incinerator used in SRU is shown in figure 1.

The hot flue gas from thermal oxidizer mixing chamber is passed through incinerator waste heat boiler to recover heat from the gas. Steam is generated. The flue gas from incinerator waste heat boiler at 325°C is discharged to the incinerator stack. The stack height of 80 meters is set to ensure dispersion of SO_2 and to meet ground level concentration limits. Besides the oxidation of hydrocarbons to carbon dioxide and water, other oxidation reactions in the incinerator are as follows:

$$H_2S + 3/2O_2 \rightarrow SO_2 + H_2O$$

$$2COS + 3O_2 \rightarrow 2CO_2 + 2SO_2$$

$$CO + O_2 \rightarrow CO_2$$

$$CS_2 + 3O_2 \rightarrow 2SO_2 + CO_2$$

$$Sn + nO_2 \rightarrow nSO_2$$

The flow rate of fuel gas is controlled by the incinerator effluent temperature. This effluent temperature is maintained at desired operating temperature of ~ 761°C. The incinerator is refractory lined with an external thermal shroud to control the shell temperature. The shell temperature is monitored by skin thermocouples. The shell temperature is maintained between 149 to 350°C. The incinerator air blower is designed to ensure a minimum of 2 percent excess O_2 in the flue gas at the stack and flue gas temperature of ~ 761°C from the incinerator. Ambient air is drawn through the inlet filter to remove solid debris and to protect against water during heavy rainfall.

The reaction in the reduction furnace is as follows:

$$2NH_3 + 3/2O_2 \rightarrow N_2 + 3H_2O$$

Air and fuel flow is adjusted to ensure the destruction of ammonia to nitrogen. Formation of NO_x is caused due to excess air. The combustion air used in reduction furnace and the incinerator share the same air blower. The hot gas from the reduction furnace is directed into the incinerator. Waste Heat Boiler (WHB) cools the hot flue gas from incinerator. The heat from the flue gas is recovered by Incinerator Waste Heat Boiler and it generates Medium Pressure steam. Through the vent stack the flue gas is vented to the atmosphere at ~ 325°C. SO_2, O_2, NO_x and CO analyzers are provided in the stack to measure the SO_2, O_2, NO_x and CO in the effluent gas.

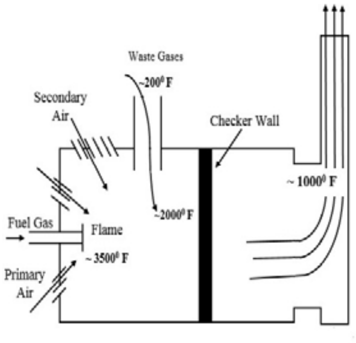

Fig. 1. Schematic representation of the incinerator

Suppose we know an input output relationship as described in equation (1). The inverse model is a function that produces the vector x for an input vector d. Equation (2) is the inverse model of equation (1). In an inverse plant model we construct a neural network approximation of $f^{-1}(\cdot)$ by using the data procured from the actual plant. The inverse plant model is shown in figure 2.

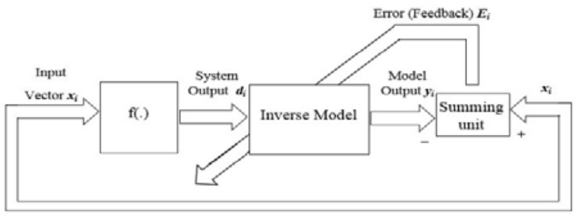

Fig. 2. Inverse Plant Model

$$d = f(x) \quad (1)$$

$$x = f^{-1}(d) \quad (2)$$

This paper is organized as follows: In Section II, the related work is discussed. The Neural network models and architectures are discussed in Section III. Section IV gives the problem definition and Section V discusses about the proposed methodology including preparation of training data and training the ANN. The performance analysis is discussed in Section VI. Conclusion and the further possible research directions are discussed in section VII.

II. RELATED WORK

Studies were initiated in 1973 to assure protection of the environment by determining if it was necessary to consume large volumes of fuel gas for the incinerator. Western Research carried out many laboratory and field investigations on the optimal use of fuel gas in incinerators. The result of these studies are shown in previous works [1-3]. One important conclusion drawn from these studies was that, there exists certain operating condition for a given incinerator which requires minimum fuel consumption and yet achieves satisfactory oxidization of harmful sulfur compounds. One other important outcome of these studies were that by operating the incinerator in the optimal operating range one could cut down fuel consumption to 60 percent. There exists different works which propose different methodologies and techniques for increasing the efficiency of incinerators by use of effective catalysts [4], modified design for tail gas cleanup process for Claus process [5][6].

Recently for adaptive control of nonlinear systems, artificial neural networks has been found to be very promising. The neural networks ability to model arbitrary nonlinear functions and their inverses is shown in [7-12]. The artificial neural networks has a generalizing capability to avoid the true analytical inverse requirement [9-11]. Various algorithms have been used for training neural networks and Levenberg Marquardt algorithm is found to be very efficient algorithm. It is considered to be the combination of steepest descent and the Gauss Newton method [13]. For non linear least squares problems Levenberg Marquardt is a standard iterative technique [14][15].

III. ARCHITECTURE

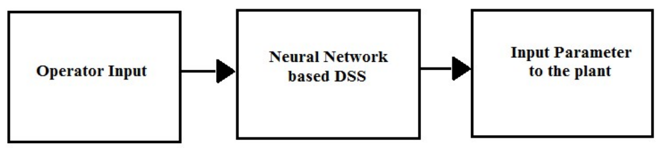

Fig. 3. Architecture of the proposed decision support system

The architecture of the proposed decision support control system as shown in the figure 3. In this model the operator inputs the desired output of the plant which are, Vent O_2 concentration, Vent SO_2 concentration, Temperature and Total flowrate of the flue gas. Based on the input provided by the operator, the neural network model predicts the input parameters for the incinerator which are fuel gas flowrate, air flowrate and O_2 concentration. These parameters ensure optimal control of the incinerator, that is the configuration in which he incinerator will consume minimum fuel and achieve the required oxidization.

Artificial neural network is a network of artificial neurons. One of the simplest forms of artificial neuron is the perceptron. Perceptron is modeled around McCulloch Pitts model of neuron. The input is applied to the perceptron in the form of an input vector. This input vector is multiplied with the weight vector and combined linearly with the bias. This is applied to the thresholding function to determine the neuron's output. The perceptron model is shown in figure 4.

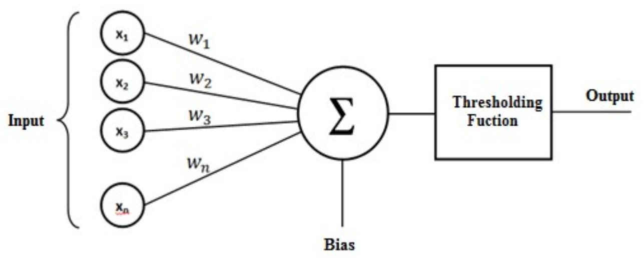

Fig. 4. Perceptron

$$v = \Sigma^{m}{}_{i=1} w_i x_i + b \quad (3)$$

$$y = \phi(v) \quad (4)$$

In equation (3) x_i is the i^{th} input vector and w_i is the i^{th} weight vector. b is the bias and v is the linear combiner's out-put. $\phi(.)$ is the activation function. An artificial neural network which is made of single layer of neurons is a single layer perceptron. To overcome some practical limitations another model known as the multilayer perceptron is used which has an input layers, n number of hidden layers and an output layer. A structure of a multilayer perceptron is shown in figure 5. In this paper an inverse plant is modeled by using multilayer perceptron.

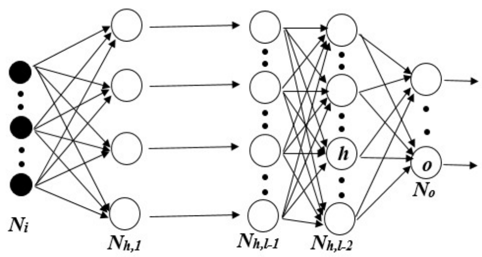

Fig. 5. Multilayer Perceptron

The initial weights for the model were found out by performing different runs using Bayesian regulation backprop-agation. These initial weights obtained by the trial and error method are provided to the Levenberg Marquard algorithm .

For training a neural network, Levenberg Marquardt (LM) algorithm is considered to be one of the best. This algorithm identifies the minimum of a function that is specified as the sum of squares of nonlinear functions. The combination of steepest descent and the Gauss Newton method is considered to be the Levenberg Marquardt algorithm 2. In this algorithm, the calculation of Hessian matrix is not required. Although in the case of Gauss Newton method the Hessian matrix is calculated. The Hessian matrix is approximated as the square of the Jacobian matrix which is given by the equation:

$$H = J^T J \quad (5)$$

The gradient of the error function is given by the equation:

$$g = J^T e \quad (6)$$

Here J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases and e is a vector of network errors. The standard backpropagation algorithm can be used for computing Jacobian matrix, instead of computing the Hessian matrix. Computation of Jacobian matrix using backpropagation is much more simpler. This approximation is used for the updation which is shown by the equation:

$$X_{k+1} = X_k [J^T J + I]^1 J^T e \quad (7)$$

When the current value of the solution is not at all close to the correct solution, the Levenberg Marquardt algorithm acts like steepest descent method. When the current value of the solution is close to the correct one, the Levenberg Marquardt algorithm acts more like Gauss Newton method. Thus the behavior of Levenberg Marquardt algorithm depends on the type of solution. The parameters of three layer perceptron artificial neural network developed for this project is shown in Figure 6.

IV. PROBLEM DEFINITION

The waste gases stream from a Sulfur Recovery Unit (SRU) contains a number of sulfur compounds that cannot be directly released into the atmosphere. The sulfur compounds present in the flue gas are removed by incineration. Incineration is the process of oxidizing the flue gases to render them safe to be discharged into the atmosphere. It is necessary to add fuel gas to the incinerator since the concentration of combustible compounds in waste gas are too low to support combustion alone. Thus to attain a temperature necessary for the oxidation of the compounds, fuel gas is added to the incinerator. The fuel gas needs to be optimally used to maximize the profits of the organization as it is a costly resource.

Decision support system is required to optimize the use of fuel gas as the optimal incinerator control can lead upto 40 percent savings on fuel gas [1]. This increases the efficiency of the incineration process. The output of the incinerator depends upon the various factors such as oxygen concentration, air flow rate, fuel gas flow rate etc. Thus for the optimal control of the incinerator, an inverse plant is modeled with the help of neural network. The neural network is then used by the plant operator in deciding the input parameters for the plant which will ensure the optimal.

V. METHODOLOGY

Following steps have been proposed to formulate the above said problem:

S.No	Paramaters	Values
1	Number of Layers	3
2	Neurons in input layers	4
3	Number of Neurons in first hidden layer	9
4	Number of Neurons in second hidden layer	13
5	Number of Neurons in output layer	3
6	Activation Function of input and hidden layers	Logsig
7	Activation Function of input and hidden layers	Linear
8	Training Algorithm	Levenberg Marquardt

Fig. 6. Parameters used in the model

1) Data points from modified Claus plant tail gas inciner- ator were collected.
2) The Data points acquired were plotted to understand the data graphically.
3) The optimal operating range of modified Claus plant tail gas incinerator was identified.
4) A training data set was prepared over different optimal operating ranges of the incinerator.
5) Multi-layer perceptron can be used to create a model which predicts the input parameters for optimal operation of the incinerator to meet the expected output. System can be simulated with the help of MATLAB/ SIMULINK.
6) Building a Multilayer Perceptron Neural Network where the operator enters the required plant output and the model predicts the input to the plant to meet the expected output.
7) The error histogram of the model is obtained to analyze the accuracy of the predictions.
8) The regression plot of the model is analyzed to under- stand the system performance.

A. Preperation of Training Data

Data points of modified Claus plant tail gas incinerator are collected using a simulator. These data points where graphically represented to understand the data. The relationship between the adiabatic stack temperature and fuel gas consump- tion is shown in Figure 7. From figure 7, it is observed that the curve is parabolic in nature. The curve shows that for optimal operation of the incinerator (less fuel more temperature) the data points should lie to the right of the curve.

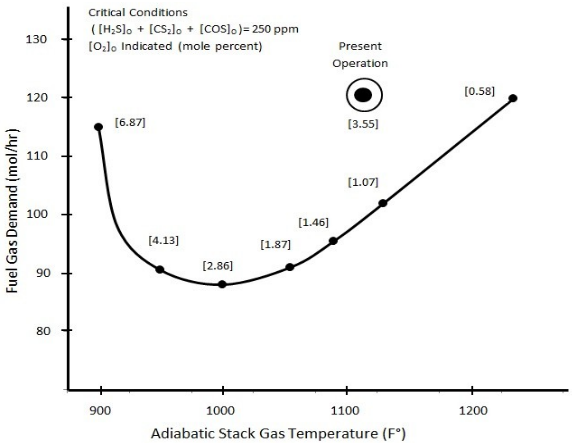

Fig. 7. Critical curve for incinerator operation

B. Neural Network Model

The proposed artificial neural network model have been simulated using neural networks toolbox in MATLAB. The model takes four inputs Vent O_2 concentration, SO_2 concen- tration, Temperature to be maintained in the incinerator, total flow rate of tail gas input into the incinerator. The Outputs of the network are control parameters of the process they are Fuel gas flowrate, Air flowrate and Oxygen concentration in the input air. The developed model is shown in figure 8. Figure 9 shows the GUI where the operator enters the required plant output and the model predicts the input to the plant to meet the expected output.

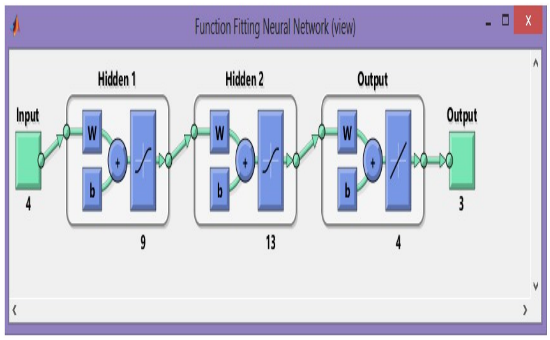

Fig. 8. Inverse Plant Model

C. Training of Neural Network

Many training algorithms have been developed for training of neural networks. All the training algorithm play a relevant and crucial role for the convergence of any particular problem. In this paper, Levenberg Marquardt Algorithm is used for training our multilayer perceptron. The Levenberg Marquardt algorithm was developed by Kenneth Levenberg and Donald

Fig. 9. GUI of the developed application

Marquardt. The Levenberg Marquardt method is a iterative technique used to solve nonlinear least squares problems and minimizes a nonlinear function. When the function is non linear in the parameters nonlinear least squares problem is occurred. The Levenberg Marquardt method involve an iterative improvement to parameter values. Thus the sum of the squares of the errors between the function and the measured data points is reduced.

The Levenberg Marquardt is a curve fitting method, which is actually a combination of two methods. It combines the gradient descent method and the Gauss Newton method. The fast convergence of Gauss Newton algorithm is combined with the stability of gradient descent algorithm. In gradient descent method, the parameters are updated to reduce the sum of the squared errors. The updation of the parameters is done in the direction of the greatest reduction of the least squares objective. In Gauss Newton method, the least squares function is assumed to be locally quadratic and the minimum of the quadratic is obtained. This assumption is made to reduce the sum of the squared errors. When the parameters are far from their optimal value the Levenberg Marquardt method behaves as gradient descent method. When the parameters are close to their optimal value the Levenberg Marquardt method behaves as Gauss Newton method. This algorithm is better and simpler than Gauss Newton, as the computation of hessian matrix is not required. It can solve the problems with error surface more than the quadratic approximation. Levenberg algorithm is superior to gradient decent algorithm as it converges the solution faster. The flow chart of the Levenberg Marquardt algorithm is shown in figure 10.

The training process using Levenberg Marquardt algorithm is as follows:

1) The initial weights are randomly generated to evaluate the Mean Square Error.
2) Use Weight updation formula to update and adjust the weights.
3) With the help new updated weights, again evaluate the Mean Square Error.
4) Due to weight updation, if the Mean Square Error is increased, reset the weight vectors and increase the coefficient by some factor. Repeat weight updation as per step 2.
5) Due to weight updation, if the Mean Square Error is decreased, accept the new weight vector and decrease the coefficient by the same factor as in step 4.
6) Repeat the same procedure from step 2 with new updated weights after every iteration until the current total error is smaller than the threshold limit value.

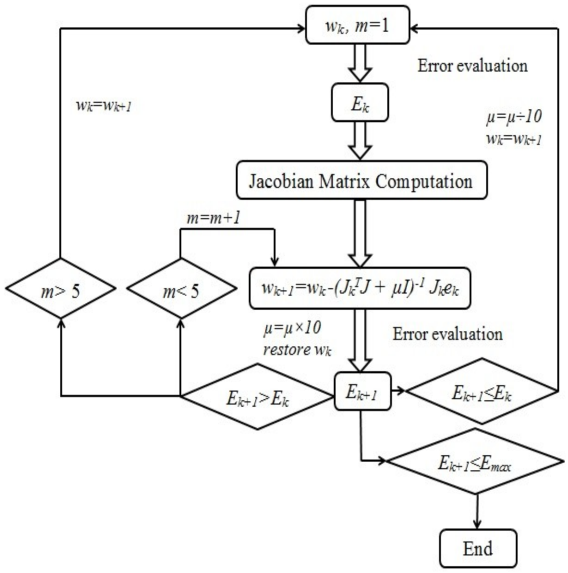

Fig. 10. Levenberg Marquardt algorithm

VI. PERFORMANCE ANALYSIS

A neural network was modeled to predict the input parameters for modified Claus plant tail gas incinerator. The predicted parameters are Fuel gas flowrate, Air flowrate and Oxygen concentration in the input air. Figure 11, shows the error histogram of the trained model. From the error histogram it can be the error range in readings are between -6.1 and 3.65. Figure 12, shows the regression plot. It can be observed that model has fit the data as well as all the points lie on the line inclined line.

VII. CONCLUSION

In this paper, a Neural Network based decision support system for optimal incinerator control is discussed. This paper proposes a decision support system by using an inverse plant model. The proposed model is built in MATLAB Simulink environment. It has been found that the model is able to successfully approximate the training data and generate the inputs for the plant for its optimal operation. The system can be extended by means of an Expert system so as to help the operator to make better decisions for optimal overall plant control.

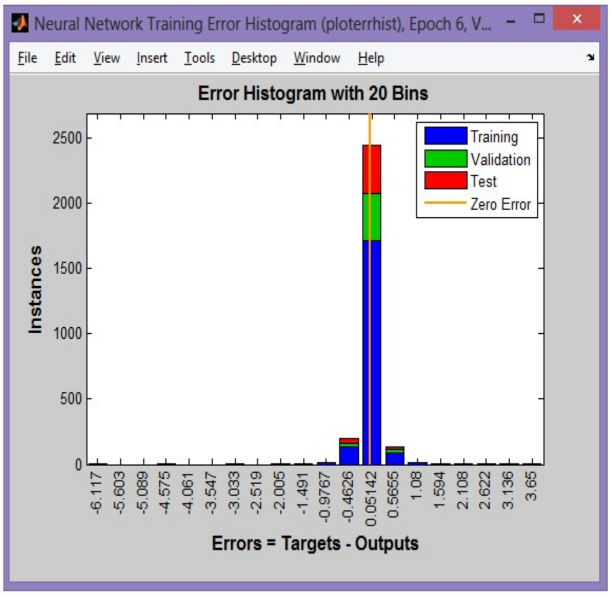

Fig. 11. Error histogram

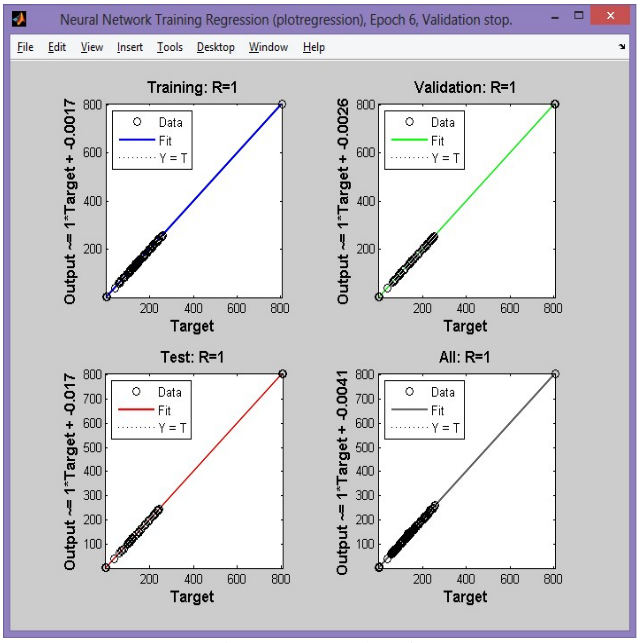

Fig. 12. Regression plot

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