Development of an Artificial Neural Network Based Model for Mimicking Combustion Tube Experiments for Heavy Oil Recovery

Y. Bansal[1,*], T. Ertekin[2] and M. Al-Wadhahi[3]

[1]ADNOC, UAE

[2]The Pennsylvania State University, USA

[3]Sultan Qaboos University, Oman

Abstract: Over the years, technologies for improved recovery of heavy oil have become an important part of the research efforts to meet the increasing demand for oil. Various methods are being developed for heavy oil recovery and among them in-situ combustion process has shown a good degree of potential in laboratory and pilot tests conducted in field. The in-situ combustion process needs to be studied further extensively because of the high degree of operational complexities involved in the process. Extensive laboratory studies have been conducted; however, a typical in-situ combustion tube experiment in the laboratory can be very costly in terms of its time, personnel and equipment requirements.

This work aims at reducing the number of laboratory experiments by developing an artificial neural network (ANN) that has the ability of emulating in-situ combustion tube experiments. An intelligent database was generated using commercial software to train the network within the parametric ranges adapted from previous experimental work. The ANN model was used to predict the cumulative production of oil, water and gas, peak temperature attained, location and velocity of the combustion front in the numerical combustion experiments mimicking the physical experiments. The proposed ANN model can be used to focus towards designing the experimental program within a rather small range of parameter variations resulting in more economical and focused analysis. Therefore, our methodology provides a unique and novel approach to understand in-situ combustion experiment.

Keyword: In-situ combustion, ANN, neural net, heavy oil.

1. INTRODUCTION

In-situ combustion is a process that involves igniting a portion of oil in the porous matrix of the reservoir to improve the recovery of oil. The heat produced as a result of combustion is utilized to reduce the viscosity of oil, vaporize formation fluids and to crack the heavy oil to form lighter components in the reservoir. The process can be classified as dry combustion if water is not injected with air and as wet combustion process if water is injected along with air. Wet combustion has further been classified as incomplete wet combustion, normal wet combustion and super wet combustion each of which refers to increased water-to-air ratios, respectively [1].

In-situ combustion process follows a complex reaction mechanism which requires an extensive study of parameters of reaction kinetics at reservoir conditions. It is also challenging to predict the sustainability and the propagation of the combustion front [2, 3]. In order to understand the process completely, typically several laboratory tests are conducted to find the amount of heavy oil that can be recovered in the process in addition to the relevant operational conditions. Looking at the number of tests required and the cost of each experiment to obtain results with scientific qualities, in-situ combustion experiments are considered to be cost intensive and complicated to [4, 5]. In addition to the oil recovered, the understanding of the process also includes determination of peak temperature, velocity and the location of the combustion front at various times.

This work aims at reducing the number of cost intensive in-situ combustion experiments by means of simulating laboratory experiments under a variety of conditions using an artificial neural network (ANN). ANNs are information processing models of human cognition of neural biological systems. Information is passed between neurons over connection links where each connection link has some weight and bias associated with it [6]. For a given problem a neural network contains one input layer, one output layer and one or more hidden layers while each layer contains different number of neurons. ANN applications have been successfully investigated widely in the oil and gas industry including predicting relative permeability characteristics for three-phase systems [7], enhanced oil recovery [8], history matching problems (Ramgulam,

*Address correspondence to this author at the PO Box 898, Abu Dhabi, UAE; Tel: +97126012192; Email: yogeshbnsl@gmail.com

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et al., 2007) [9], well test analysis [10], well performance predictions [11] etc.

Parameters that play an important role in combustion tube experiments are identified and their ranges are extracted from the literature. In this study a vertically operated adiabatic combustion tube is modeled using specifically designed artificial neural network architecture [12]. A finite-difference based hard-computing model was tuned by utilizing experimental data sets [13, 14] before generating the knowledge base for the proposed neural network. Dry combustion and wet combustion tube models were developed separately; but only wet combustion tube model is discussed in this paper.

2. DESCRIPTION OF THE POROUS SYSTEM

In the numerical experiments conducted, a 1.83 meters long combustion tube is used to simulate the in-situ combustion process. The tube is divided into 36 zones at which several probes are placed to measure the temperature of the combustion as a function of time (Figure **1**). Combustion zone thickness range is observed between 4.7cm to 8.9cm in the laboratory [15]. The grid block thickness in this study is the same as mentioned in Coates *et al*. [14]. Where, a history match was shown to match the numerical results with laboratory results using the same commercial simulator* as in this study. Moreover, a grid thickness within the specified range will be able to incorporate heat and mass transfers when the grid size is within range of reaction zone length scales [16].

In the numerical model, the system is treated as a one dimensional system flowing from top to bottom and the cartesian co-ordinate geometry is used with approximating the cylindrical system using a rectangular grid. The study considers Athabasca crude oil for which combustion reaction occurs in three stages: cracking, low temperature oxidation, and high temperature oxidation [17]. The reaction parameters for Athabasca crude is taken from the published literature [14] as shown in **Appendix A**. This work assumes that the crude concentration and composition ahead of the combustion front are constant and crude experiences the same reaction kinetics. Typically, the reservoir rock is crushed and mixed with desired concentration of heavy oil and water; which then is packed in the combustion tube and confined at the reservoir pressure. Therefore, rock and fluid properties are also assumed to be constant in generating the knowledge base.

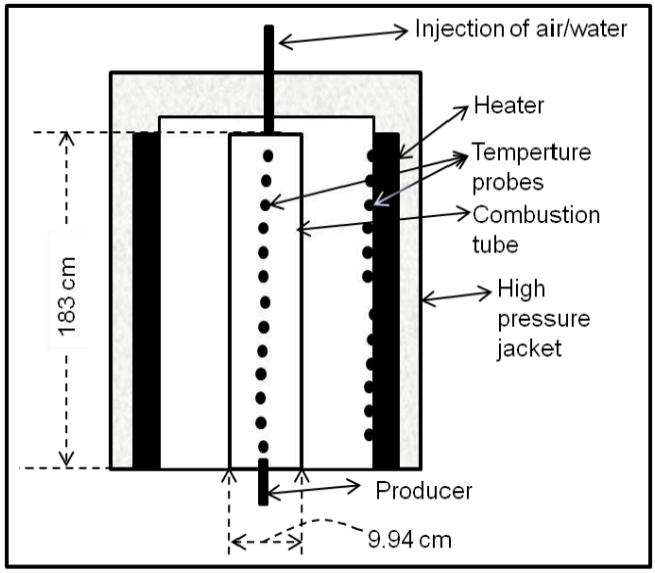

Figure 1: Schematic representation of the combustion tube considered in the study.

3. DATA GENERATION AND NETWORK TRAINING STRATEGY

For the above system, a list of parameters which are considered important in the process was prepared and the ranges of these variables were determined as shown in Table **1**. Different systems were studied with changing system properties and operating conditions within the parametric ranges given in Table **1**. All of these different scenarios were simulated using the numerical model and the results were extracted at uniform time intervals of 0.24 hours. The producing well is shut in when the temperature of the production well is observed to be 250°C or higher. The developed model predicts the cumulative production of oil, water, and gas at the end of simulation. In addition, peak temperature value, the velocity and location of the combustion front are also predicted at 25%, 50%, 75%, and 100% of the total production time. In this model, production time has been normalized for each case as the total production time differs for each combination of combustion tube properties and the operating conditions imposed on the combustion tube.

* CMG-STARS, version 2008.10
Paragon Center One
450 Gears Road, Suite 860
Houston, TX 77067

Before finalizing the training data set, cases involving the unexpected combinations were checked to decide whether they describe a realistic scenario or not. Using the list of parameters (Table **1**), a total of 2760 cases were considered and results of 2484 cases were shown to the network during the training phase of the development. The remaining 276 cases were reserved for testing (138 cases) and verification (138 cases) purposes. These cases were isolated from the training set used in building the ANN. Once the network was trained then the testing set was used to check the performance of the network. The selection of these three sets of data is made randomly by the artificial neural network software.

Table 1: Range of Parameters

Parameter	Lower Limit	Upper Limit
Porosity (ϕ,%)	20	40
Permeability (k,D)	3	12
Oil saturation (S_o,%)	30	90
Air injection ($Q_{a,i}$, m^3/hr)	1	3
Water injection(Q_{wi}, m^3/hr)	0.5	1
Heat rate (Ht_{in},J/d)	$1.1*10^5$	$2.2*10^5$
Duration of pre-heating (t_{heat},d)	0.15	0.2
Duration of air injection (t_{air},d)	0.15	0.3
Water to air ratio (WAR, m^3/sm^3)	0.001	0.006

Effective predictive capabilities of the network depend on a number of factors which include the architecture of the network; the number of hidden layers and the number of neurons in each layer, training and learning functions etc. There are no properly defined rules in designing a network to achieve a desired level of accuracy. The process of training the network follows a heuristic procedure. Accordingly, during the development phase of the study, different network architectures were tested. The term network architecture refers to number of hidden layers, number of neurons in each layer, transfer functions used between the layers of the network, training algorithm utilized, and functional links used in the input and the output layers. In most of the reservoir engineering applications, feed-forward back propagation networks are used which prove to be effective in this study as well.

4. STAGES OF DEVELOPMENT

Before developing the model for wet in-situ combustion process, different runs were conducted to perform a sensitivity analysis on the variables. A numerical model was structured to understand the effects of the reservoir properties in terms of porosity, permeability, and saturation of oil and water on the process. This paper reports the model developed for wet in-situ combustion processes studied in a combustion tube.

In this model, rock and fluid properties are confined to Athabasca crude and reservoir system with the specified combustion reactions. In order to achieve a better performance, the following functional links were added to the input layer.

- Ratio of porosity over saturation of oil,
- Square root of the ratio of permeability over porosity,
- Logarithm of the ratio of permeability over porosity,
- Total amount of air injected,
- Total amount of heat supplied (during the pre-heating cycle),
- Logarithm of total amount of heat supplied,
- Logarithm of water-to-air ratio.

Also, the product of peak temperature and distance to the combustion front was used as a functional link in the output layer. The final optimized ANN architecture for wet combustion tube model is shown in Figure **2**. These functional links significantly improved the learning ability of the network. These functional links were tested individually and in groups, and they were found to be more effective when all of them are used concurrently.

5. RESULTS AND DISCUSSIONS

Figures **3-5** provide comparisons between the values obtained from the numerical simulation studies and values predicted by the ANN for cumulative oil production, cumulative water production and cumulative gas production. Figure **6** compares peak temperatures of the combustion front obtained from the numerical model against the peak temperatures provided by the expert system at 25%, 50%, 75% and

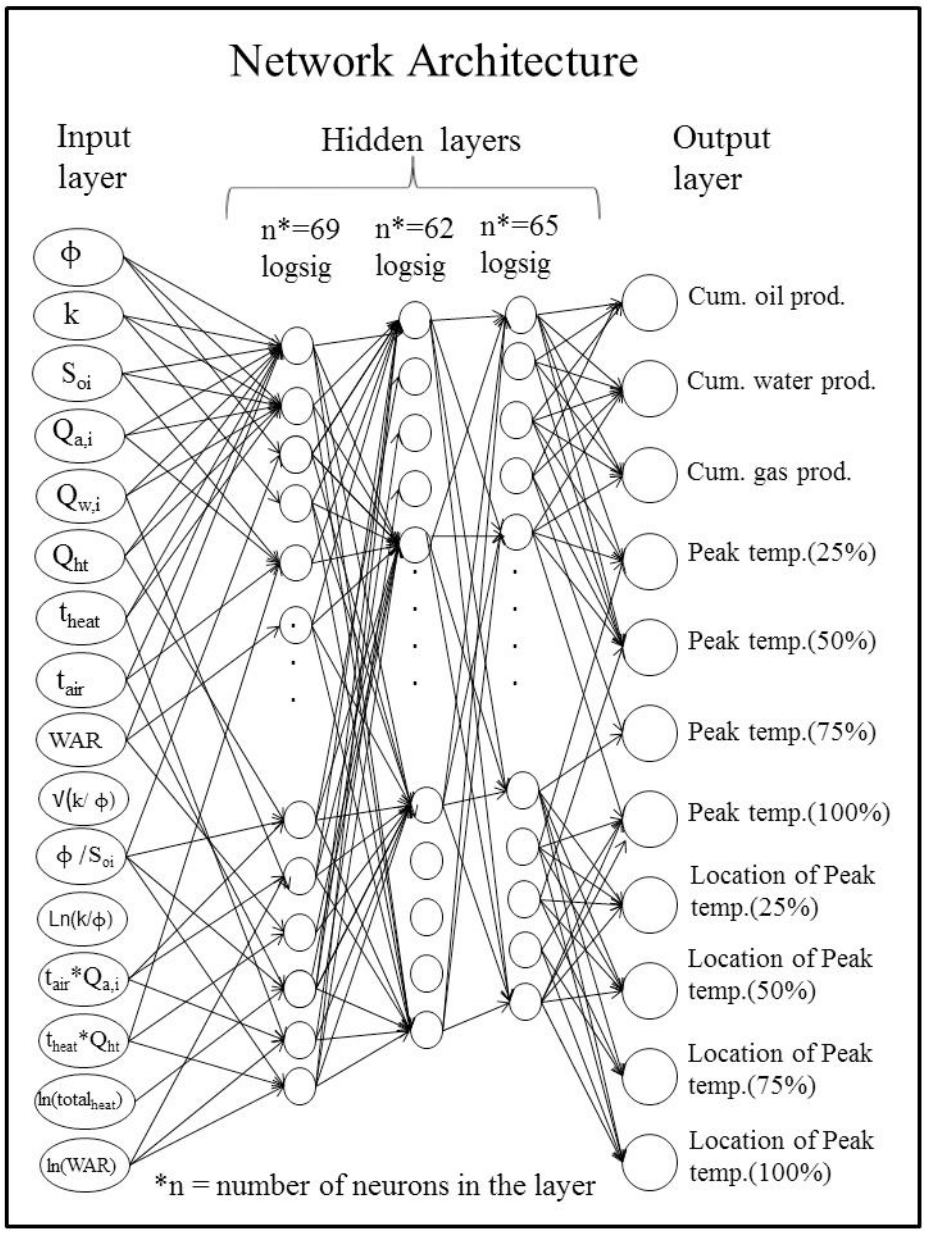

Figure 2: Network architecture of wet combustion tube model.

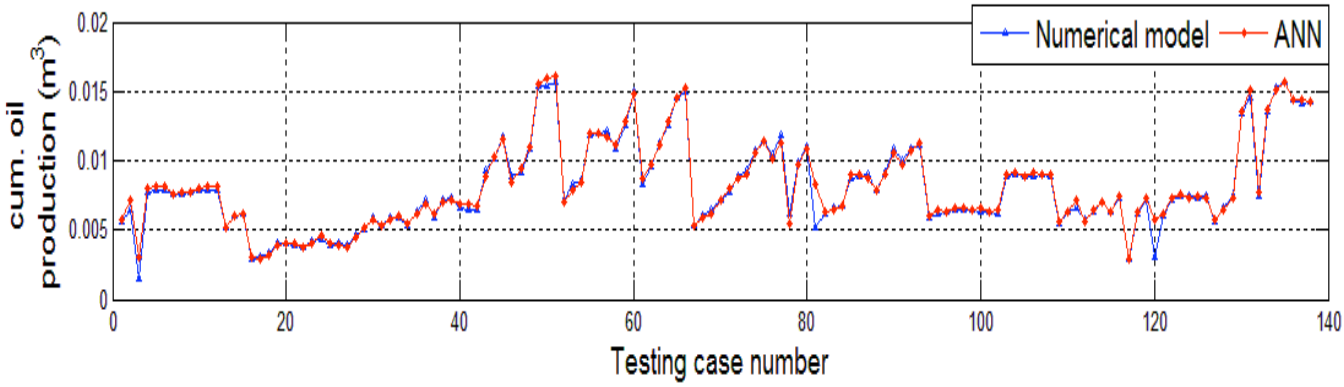

Figure 3: Cumulative oil production (m^3).

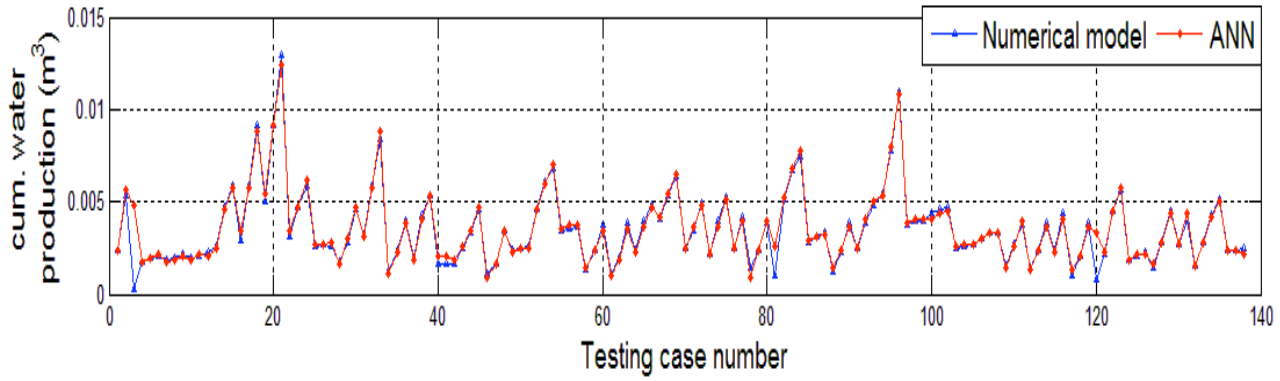

Figure 4: Cumulative water production (m^3).

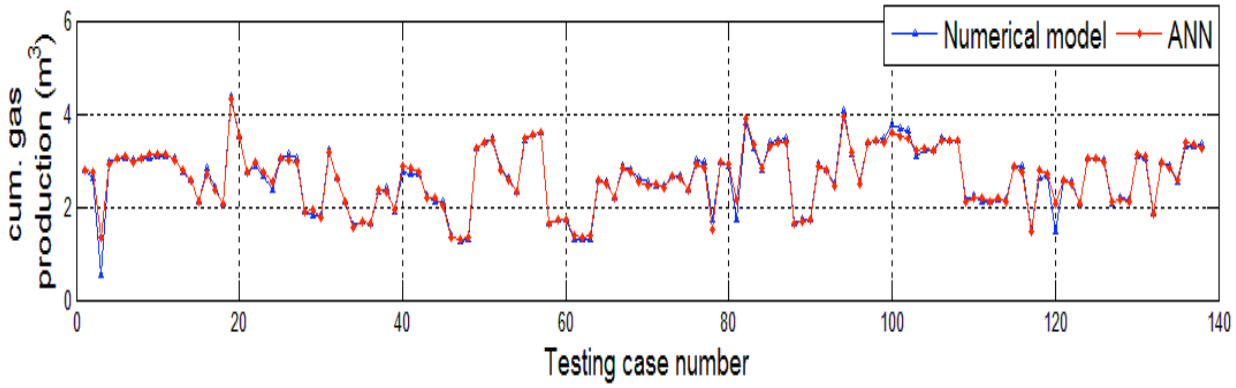

Figure 5: Cumulative gas production (m^3).

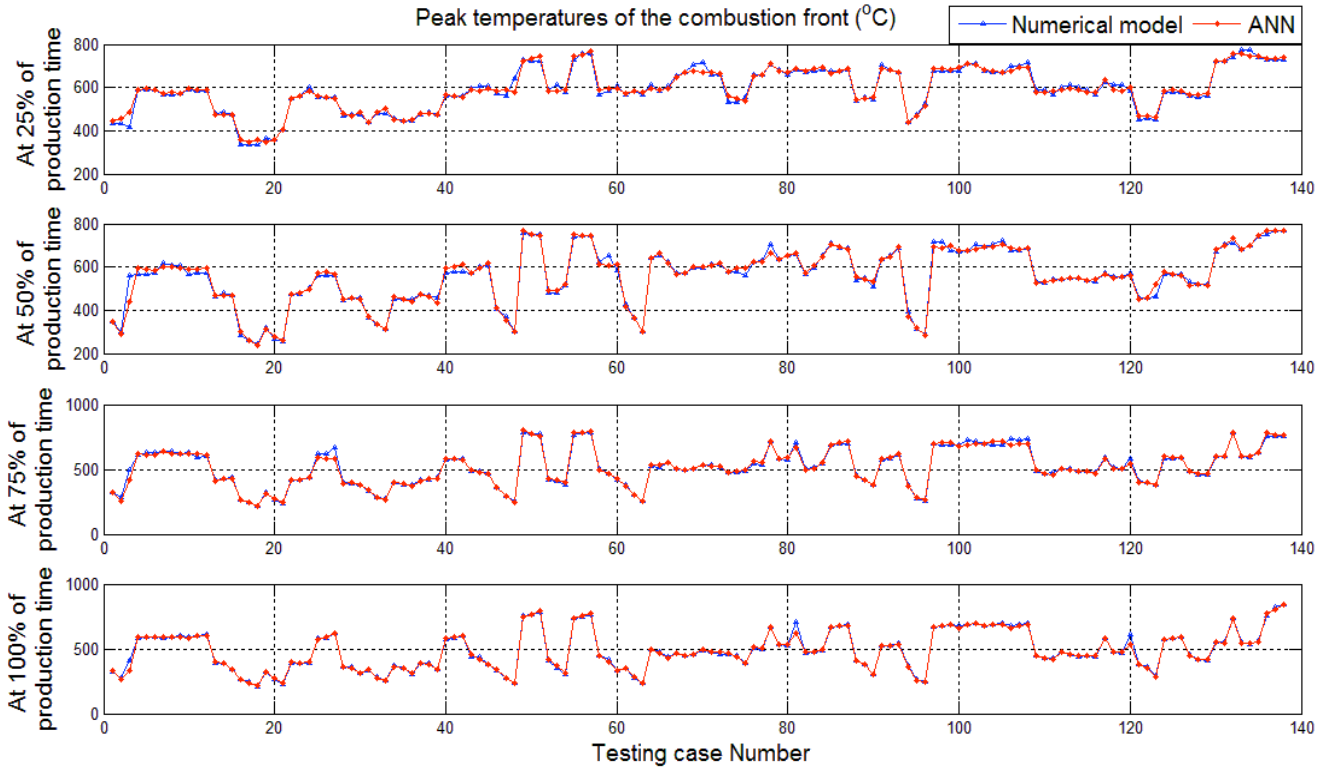

Figure 6: Peak temperature at the combustion front at various times.

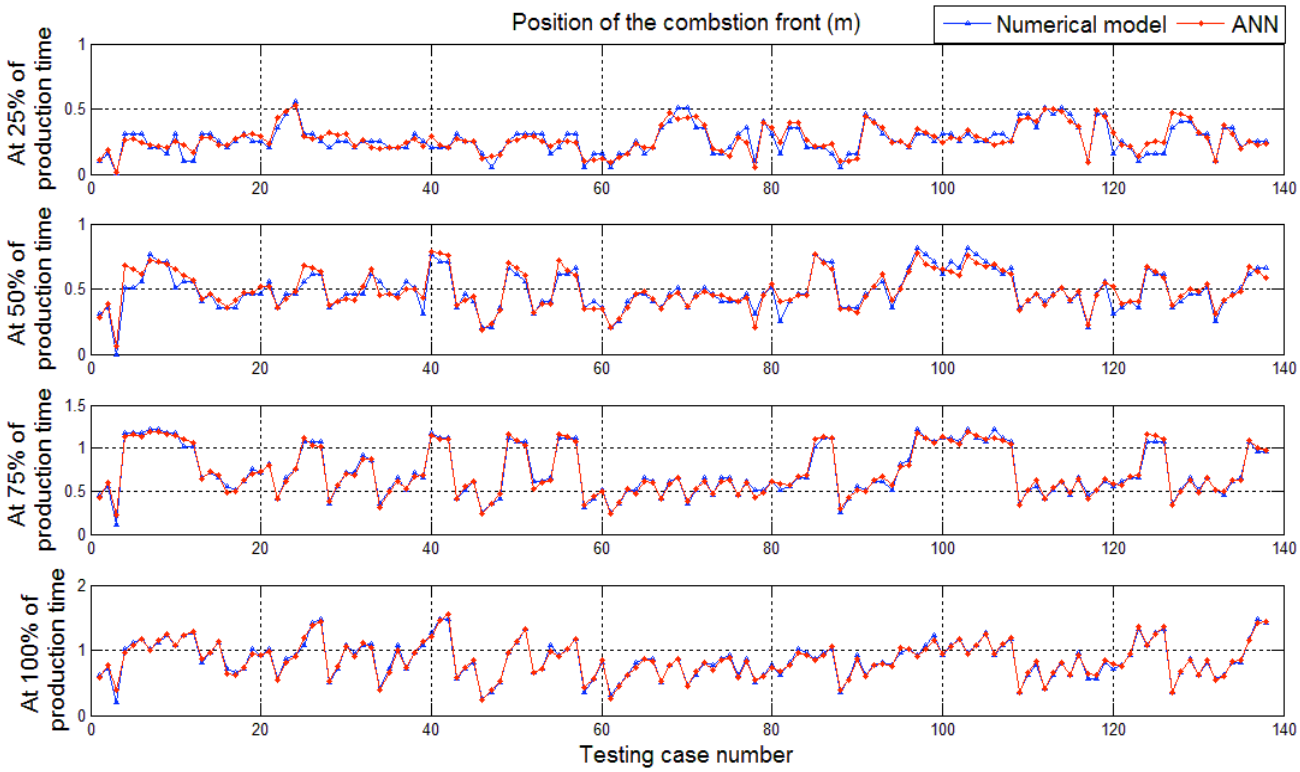

Figure 7: Distance covered by the combustion front at various times.

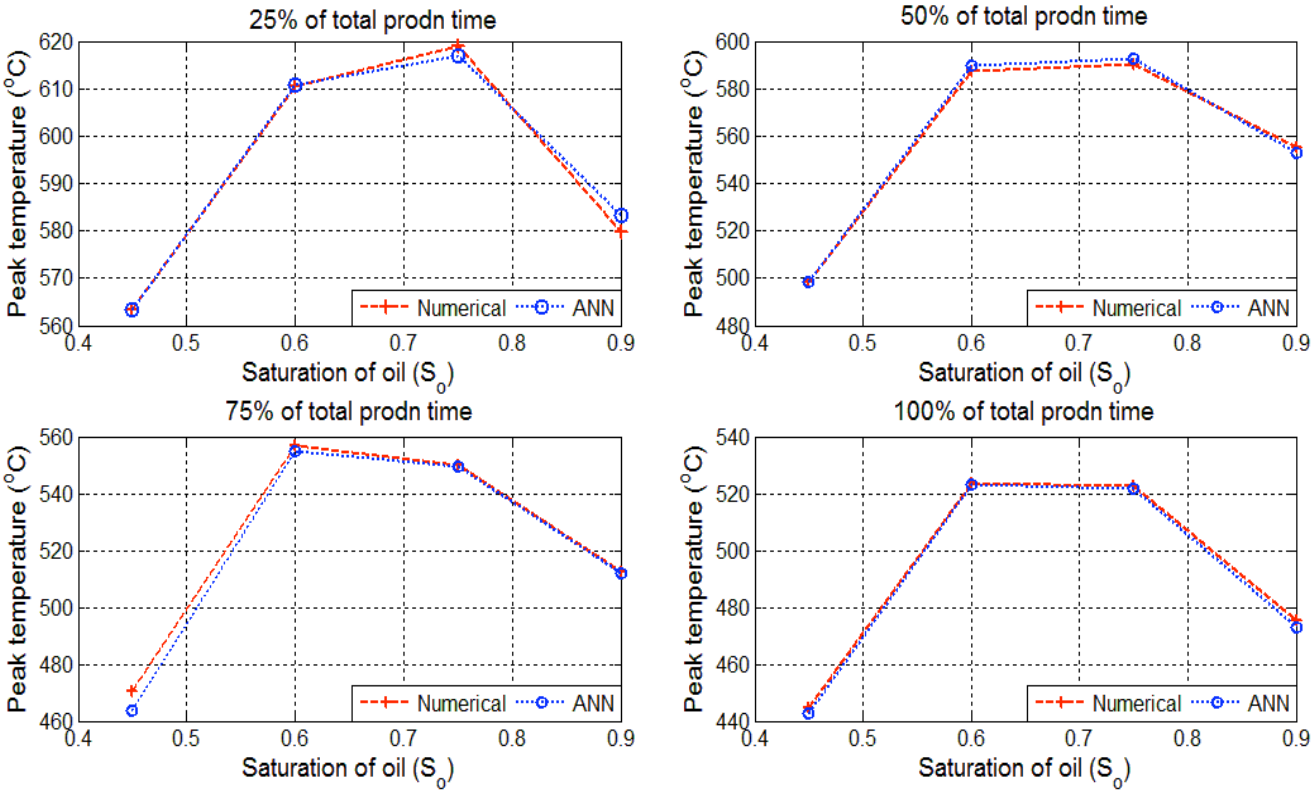

Figure 8: Variation of peak temperature with initial oil saturations at various times.

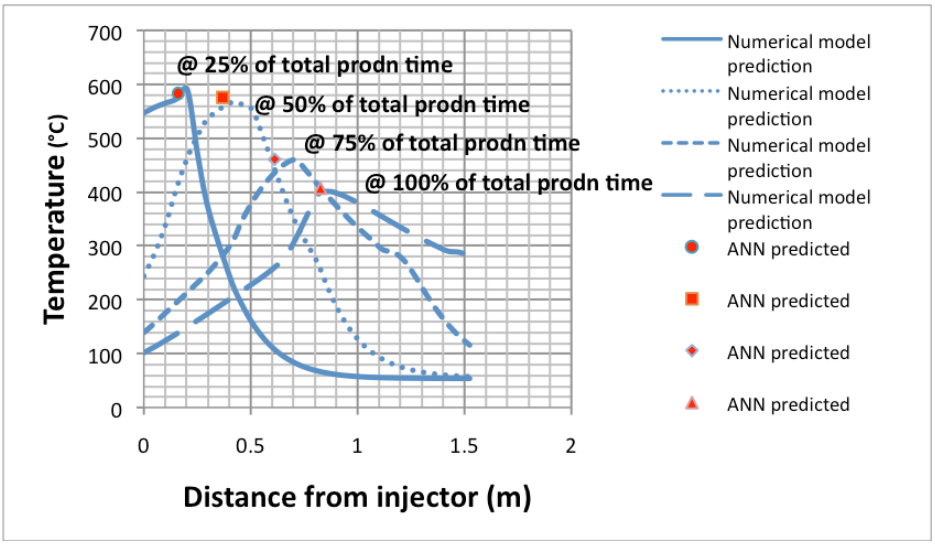

Figure 9: Comparison of peak temperature and their location at different times.

100% of the production time. Figure **7** shows a comparison between distances traveled by the combustion front obtained from the numerical model with the distances predicted by the ANN at different production times as shown on the ordinates of the each plot. Figure **8** shows that peak temperatures of the combustion front are higher for initial oil saturations ranging from 60% to 80% as closely predicted by ANN (a similar observation was made at the laboratory scale carried by Mamora [18]). Figure **9** shows the comparison of the peak temperature of the combustion front and its location in the combustion tube with respect to the temperature profiles calculated by the numerical model again at 25, 50, 75 and 100% of the total production time.

All of the results displayed in Figures **3-9** show good matches with an average error of less than 2% except for the position of the combustion front at the 25% of the production time where an average error of less than 6% was observed. In this exercise it is shown that ANN is able to map the combustion front movement dependence on the fuel content, porosity and permeability of the rock matrix, initial heating of the combustion tube, air injection rate and water-to-air ratio. During the early stages of the process, when the combustion front for a specific operational scenario moves more rapidly and as one of the aforementioned properties is changed then the movement of the front is significantly altered. Neural network sees an oscillatory profile of the distance covered and predicts the results within a slightly higher error margin (see first plot of Figure **6**).

A comparison is also made between the cumulative oil production by dry combustion and wet combustion tube models based on the predictions of the ANN (Figure **10)**. ANN is able to predict the improved oil

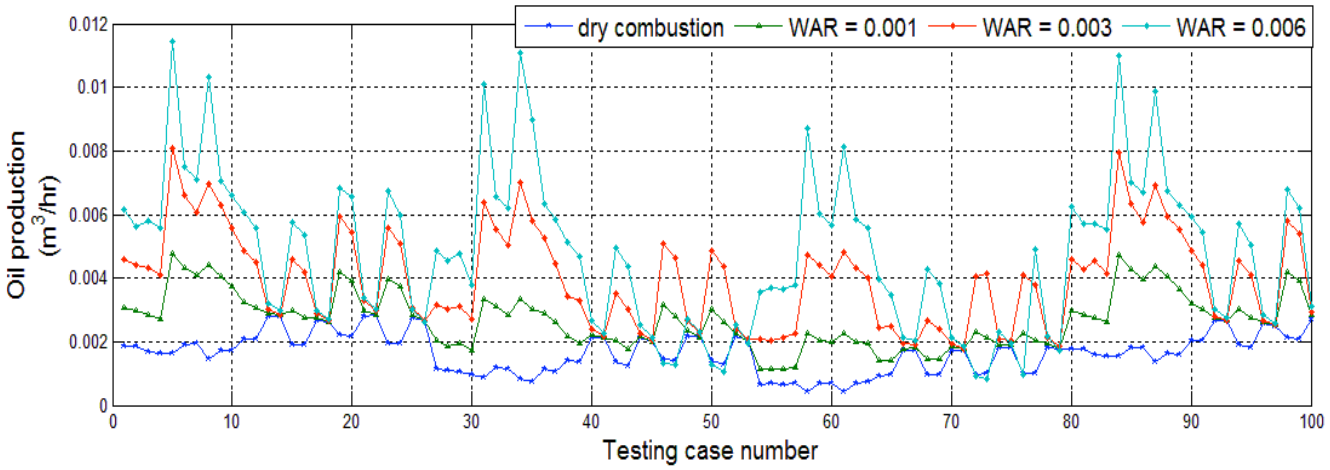

Figure 10: Comparison of cumulative oil recovery at different WAR (as predicted by ANN).

recovery of wet-combustion over dry combustion as suggested by Garon *et al*. (1974) [19]. In some of the cases, cumulative oil recovery with high water-to-air ratio (WAR) is equal or lesser than the cumulative oil recovered by dry combustion model. In these cases, the combustion front was quenched in the early phase of the process due to high water injection rate and low fuel content for combustion. Thus, the wet-combustion process performs similarly to water injection process resulting in lower oil recoveries.

It is recommended that any ANN should be broadly tested before implementing in a specific study. The network is broadly tested with varying conditions described in Table **1**. Where, the comparison shows a good quality match in predicting the cumulative productions and combustion front characteristics from the experiments. The network, described in the paper, is also tested for its structure where the functional links in the input layer and number of neurons in the hidden layer were added/removed from the network to compare the performance. Thus, the ANN developed in this study can easily be used in mimicking the laboratory experiments. However, the parameters like the tube length, combustion reaction mechanism, fuel type and the apparatus are assumed to be same. Therefore, the ANN will be useful for similar conditions of experiments. If the user wishes to change these parameters e.g. combustion reaction mechanism then the methodology discussed in the paper can be used to train the ANN.

CONCLUSIONS

Using some readily available information about the properties of the porous media, reservoir fluids, and its reaction kinetics, an ANN based screening tool is developed. The expert system proposed in this study is capable to predict the performance of in-situ combustion process in laboratory experiments in terms of cumulative production of oil, water and gas. The developed combustion tube laboratory experiment model can also predict the peak temperature of the combustion front, position of the front and its velocity at various production intervals. The movement of the combustion front is found to be highly sensitive of initial saturation of oil, porosity of the rock matrix, air injection rate, initial heating of the tube and water-to-air ratio. Results obtained in this study show that artificial neural networks can be developed as effective screening tools to predict the outcomes of a complex process such as in-situ combustion tube experiments designed for studying the efficacy of the process as an enhanced oil recovery scheme.

NOMENCLATURE

φ	Porosity
k	Permeability (Darcy)
S_o	Saturation of oil
$Q_{a,i}$	Air injection flow rate (m^3/hr)
$Q_{w,i}$	Air injection flow rate (m^3/hr)
Q_{heat}	Heat injection flow rate (J/days)
t_{heat}	Pre-heating time (days)
t_{air}	Air injection time (days)
A	Total air injected (m^3)
Ht_{in}	Total heat (J)
A_r	Frequency factor of reaction r
E_r	Energy of activation of reaction r (J/gmol)

APPENDIX A

Cracking reaction occurs in three steps and each reaction follows a first order rate reaction mechanism. (Belgrave JDM (1987) [20] and Adegbesan KO (1982) [17]). LTO reactions occur in two steps (Adegbesan KO 1982) [17]. In the first step, maltenes react with oxygen to produce asphaltenes and in the second step the asphaltenes reacts with oxygen with to form coke. In High Temperature oxidation (HTO), the coke obtained from the LTO reacts with oxygen to produce gas and water vapor (steam). This reaction occurs at the combustion front and during this reaction the temperature of the zone reaches around 600 °F–1500 °F (Adegbesan KO 1982) [17]. All the reactions are shown as follows:

Cracking Reactions:

$$\text{Maltenes} \xrightarrow{K_1} 0.372\ \text{Asphaltenes}$$

$$\text{Asphaltenes} \xrightarrow{K_2} 83.223\ \text{Coke}$$

$$\text{Asphaltenes} \xrightarrow{K_3} 37.683\ \text{Gas}$$

Low Temperature Oxidation Reactions:

$$\text{Maltenes} + 3.431\ O_2 \xrightarrow{K_4} 0.4726\ \text{Asphaltenes}$$

$$\text{Asphaltenes} + 7.513\ O_2 \xrightarrow{K_5} 101.539\ \text{Coke}$$

High Temperature Oxidation Reactions:

$$0.811\text{Coke} + O_2 \xrightarrow{K_6} 0.811\ \text{Gas} + 0.46\ H_2O$$

Reaction rate constants are temperature dependent terms and are described by Arrhenius type equation. This relationship can be written as:

$$K_r = A_r exp(-E_r / RT)$$

Where, K_r is the rate of the reaction, A_r is the frequency factor of the reaction, E_r is the activation energy of the reaction, R is universal gas constant and T is the temperature of the reaction. Published values of reaction parameters are used in data file prepared for the numerical model and the values are represented below (Coats, R., Lorimer, S., Ivory, J. (1995) [14]).

Rate Constant Parameters

r (Reaction)	Reactant	A_r	E_r (J/g mole)
1	Maltenes	$7.86*10^{17}(d^{-1})$	$2.347*10^5$
2	Asphaltenes	$3.51*10^{14}(d^{-1})$	$1.772*10^5$
3	Asphaltenes	$1.18*10^9(d^{-1})$	$1.763*10^5$
4	Maltenes	$11.1*10^9(d^{-1}Kpa^{-1})$	$8.673*10^4$
5	Asphaltenes	$3.58*10^9(d^{-1}Kpa^{-1})$	$1.856*10^5$
6	Coke	$150.2(d^{-1}Kpa^{-1})$	$3.476*10^4$

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