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DEVELOPMENT AND TESTING OF AN EXPERT SYSTEM USING ARTIFICIAL NEURAL NETWORKS FOR A FORWARD IN-SITU COMBUSTION PROCESS

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Abstract

The main topic of the research is the enhanced oil recovery (EOR) method of forward dry in-situ combustion (ISC). ISC is an EOR method used to produce heavy oils with high viscosity levels that are either infeasible or not economical using other EOR methods. The ISC process is a thermal recovery method that initiates when hot air is injected into the injection well to create heat inside the reservoir, which will in turn create a burning front moving from the injection well toward the production well. During this process, some of the reservoir's oil will be utilized as fuel by the process of in situ oil burning. The fuel that is produced by this process will support the combustion front. Once the heat is generated steadily by the continuous injection of hot air, the oil viscosity in the reservoir will be decreased which allows the new less viscous oil to flow to the producer. The project's goal is to create an expert system for forward in-situ combustion that has the ability to predict similar outcomes to those obtained by a thermal recovery simulator[1]. The predicted outcomes are the oil production, the gas production and the abandonment time of the project. In order to develop the expert system, relevant output results of oil production, gas production and abandonment time of the project need to be obtained using a thermal simulator for three field patterns with varying sizes ranging from five acres to 25 acres. The numerical simulator uses ten input variables including field properties and design parameters. Such examples of these inputs are porosity, permeability, injection rate, oxygen content of injection, thickness of the reservoir, initial temperature and pressure of the reservoir and the initial oil and water saturation. Due to these different variables, it is expected that the

[1] The thermal simulator STARS from CMG was used for this work.

output from the simulations will have a large range and wide scope, which will help in developing a useful and flexible expert system.

The simulations generated data for three different sized patterns ranging from five to twenty five acres. The next objective in the project was to create an expert system for each different pattern using artificial neural networks (ANN)[2]. ANN is a tool that functions like the human brain. It is a mathematical model that uses an inter-connected set of neurons that is able to adapt itself depending on the data fed to the system. Because of the characteristic of continuous adjustment, ANN is called an adaptive and a non-linear system. The ANN, when modeled correctly to fit a specified set of data, will be able to spot trends in the data when going through the learning process. If the learning process is successful, the ANN system will be able to predict the simulated data within a certain level of accuracy. The targeted level of accuracy for this work was five percent error or lower. The process meeting this target is called the validation process and in this project the average error of the ANN system is found to be below five percent, which deemed the expert system to be successful.

[2] The software NeuralPower 2.5 was used for the development of the expert system in this work.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Chapter 1

Introduction

The production of heavy oil is one of the challenges in the petroleum industry today. There have been projects that have used carbon dioxide injection, steam injection, in-situ combustion, water flooding and polymer flooding. Once the primary and secondary recovery has been exhausted, the last step of oil extraction is the tertiary recovery. Typically, in heavy oil reservoirs, primary recovery uses standard procedures in oil extraction and will produce less than ten percent of the oil in place. Secondary recovery, which usually uses the water-flood technique, will produce 30 to 45 percent of the oil in place. EOR processes or tertiary recovery, if run successfully, can produce up to 70 to 80 percent of the oil in place. All of the processes mentioned above have the same general goal in mobilizing the oil by lowering its viscosity in reservoir conditions. This work will concentrate on the production of heavy oil recovery using the in-situ combustion process.

There have been many studies of the in-situ combustion process using laboratory tubes, which are then scaled up to field scale. In this study, no laboratory experiments were used but instead the study directly analyzed the different scenarios of the field scale. The first order of work was to generate data using the numerical simulator and the in-situ combustion process for fields of sizes five acres, 15 acres and 25 acres. In the simulation portion of the work, many input variables were incorporated to yield widely varying output results. For each pattern, approximately 400 data points were generated by simulation so that it could give ample and diverse data to train the expert ANN system. There were three categories of variables in this simulation experiment. The first part was the reservoir properties (permeability, porosity, reservoir thickness, etc). In the second part, there were design decisions that were included in the simulation work such as injection rate and oxygen injection content. The third part is the production output of oil production, gas production and length of the project.

After the simulator generated the output data, the last procedure was to use the output data to train and build an artificial neural networks (ANN) or the expert system. ANN is a tool that is able to spot trends in a set of input and output data and build a system using those data that will then be able to predict an output given a set of inputs. For each of the three patterns, an ANN expert system was developed using the data generated. Eighty-five percent of the data was used in the training of the neural networks and the remaining 15 percent of output data was used to validate the system. The goal of the ANN expert system is to have the capacity to predict an output, which closely resembles the output generated using the simulator. An error of five percent is the target between the simulator output and the expert system output.

Chapter 2

Literature Survey

In-situ combustion (ISC) process is an enhanced oil recovery (EOR) method that has not been used extensively in the industry. There are some reasons for ISC's lack of popularity such as the lack of extensive study on the subject and the lack of field data of the in-situ combustion process. Another reason for ISC's lack of use in the industry is its requirement of high investment which discourages many companies from utilizing it as a viable method. There are several types of in-situ combustion processes including dry combustion, wet combustion, forward combustion and backward combustion. This work solely concentrates on the forward dry in-situ combustion process. There are many factors that will determine the success and feasibility of the process such as the type of in-situ oil, the thickness of the formation, the porosity of the reservoir, etc. In-situ combustion is typically used for heavy oil reservoirs with medium to high permeability. There have been some projects that used in-situ combustion for light oil reservoirs, but in general light oil is matched better with carbon dioxide injection and other EOR processes. Other variables that need to be studied in the field scale are the initial oil saturation, the porosity of the reservoir and the thickness of the reservoir and the injection rate needed to sustain the combustion front in the reservoir. This chapter will discuss the different types of in-situ combustions and the general description of artificial neural networks (ANN).

2.1 In-Situ Combustion

The general premise of in-situ combustion is to have hot air injected into the injection well to create heat inside the reservoir by the ignition of the in situ oil. The burning of the oil will then form a combustion front that travels from the injection well to the production well. The fuel burned is the result of the cracking and distillation of the in situ oil. Naturally occurring coal can also be another source of the fuel that is needed for the combustion front. When the air is injected, vapors will form, which will attach to the liquid and condense in the colder zone ahead of the combustion zone. The combustion zone will reach temperatures ranging from 700 F to 1500 F. At this temperature cracking of the heavy oil will take place in the hydrocarbon zone. The cracking of the heavy oils will generate the coke, which is needed to sustain the combustion front propagation. This process will continue to occur until the oil is displaced from the injection well to the production well to be extracted. Figure 2.1 on the next page illustrates the general in-situ combustion process.

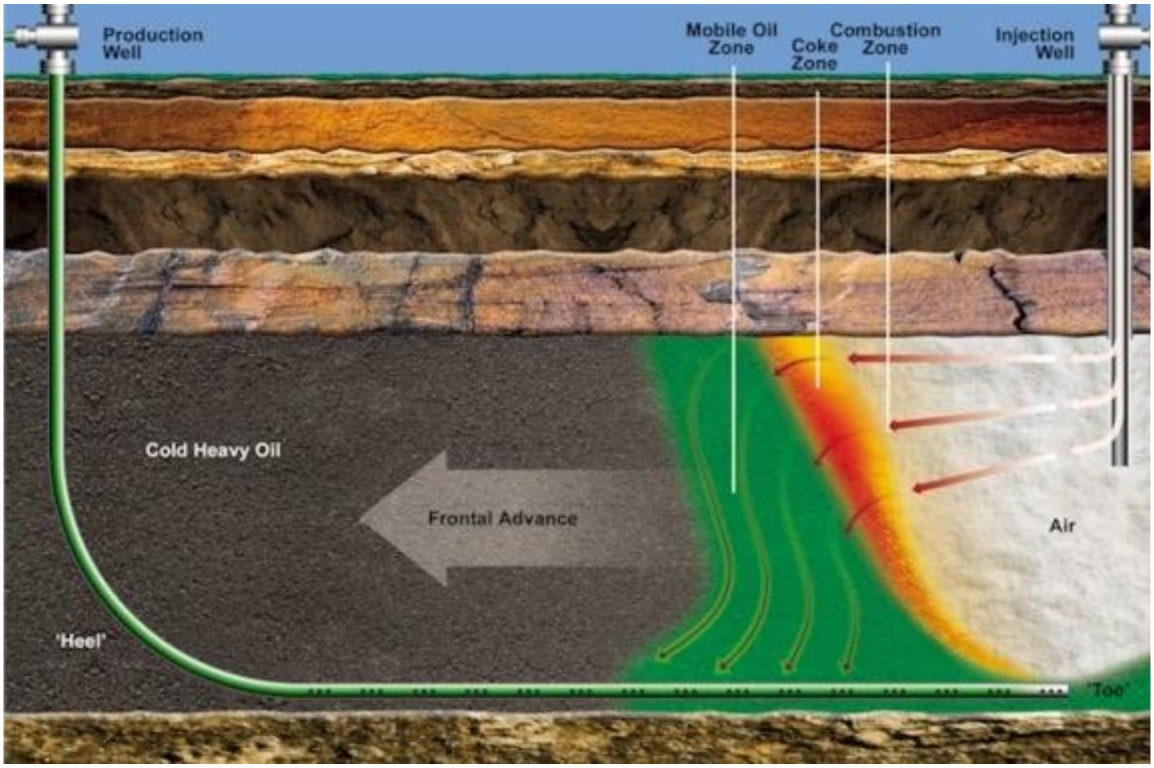


Fig 2.1- General set up of an in situ combustion project.

(http://www.heavyoilinfo.com/feature_items/thai/thaiprocesss.jpg)

From the figure above, one can see that there are a number of different zones in the in situ combustion process. Each zone has its functions in the complex behavior of an in-situ combustion process. The zones to be discussed next are the burned zone, the combustion zone, the cracking zone, the evaporation zone, the steam plateau, the water bank, the oil bank and the initial zone.

A) The Burned Zone- Oil in this zone has been burned due to hot air injection and in turn has created the fuel to be later supplied for the combustion front. This zone is filled with air and is the first zone subjected to the air injection from the injection well. Due to the exposure of high temperatures, mineral alterations in this zone are possible.

B) The Combustion Zone- The zone of the highest temperature is found here.In this region oxygen combines with fuel and high temperature oxidation occurs. Water and carbon dioxide are the products of this combustion reaction.

C) Cracking Zone – In this zone fuel is found. The fuel is formed due to cracking and pyrolisis which is deposited in the rock matrix.

D) Evaporation Zone- Oil that remains in this zone is oil left behind the steam plateau. The composition of the in situ oil is modified in this zone due to the high temperatures of the combustion zone; the lighter ends vaporize and move ahead to mix with the original oil while the heavy ends pyrolize and deposit as fuel on the rock. The heavy ends are the undesirable compounds that contain sulfur and metals.

E) Steam Plateau- Most of the oil is displaced ahead of the steam plateau and in this zone the immobile oil undergoes steam distillation. The original oil will undergo thermal cracking and the magnitude of cracking that occurs depends on the temperature. The thermal cracking causes the oil's viscosity level to decrease.

F) Water bank- This zone forms due to a decrease of temperature.

G) Oil bank- This area contains the oil displaced and the light ends that were formed due to cracking.

H) Initial zone- This zone is the unchanged portion of the reservoir that is yet to undergo a process of combustion.

The two main parts of the chemical reactions in the in-situ combustion process are pyrolysis due to an increase of temperature and oxidation, which occurs in the presence of oxygen. The two types of oxidation reactions encountered are low temperature oxidations (LTO) and high temperature oxidations (HTO). LTO occurs when oxygen that is mixed with the oil to form oxidized hydrocarbons such ketones, alcohols and peroxides. LTO will generally raise the oil viscosity. When oxygen contacts the oil at higher temperatures (HTO), water and carbon dioxide are formed. Pyrolysis is the alteration of chemicals due to increase of heat. With pyrolysis, usually at temperatures above 500 degrees Celsius, light hydrocarbons and coke-like residue are formed.

LTO reactions are the only reactions in the in situ combustion process that raises the viscosity of the oil. With proper air injection, the LTOs will be minimized and the ISC process will deliver higher quality produced oil at lower viscosities and higher API oil gravities.

2.2 Forward and Reverse Combustion

a) Forward combustion

The forward combustion process is the most typical. The combustion front moves from the injection well towards the production well. The process starts with the preheating of the oil near the injection well. Then, air is injected into the injection well to start the combustion front which will then move towards the production well. As more air is injected, the temperature inside of the reservoir will also increase, which will lower the viscosity of the oil in place promoting improved flow conditions, which will yield oil production at the producer.

b) Reverse Combustion

In reverse combustion, air is injected into the injection well, but the combustion front starts at the production well and flows counter to the air flow. The combustion front then will move due to an increase of temperature caused by air injection and coincidental to these high temperatures, the in-situ oil will be cracked: light ends vaporize and the heavy ends will turn to residue (Prats et al, 1985) and coke, which will be the fuel for the combustion front. The problem with reverse combustion is that it is difficult to sustain the combustion front because of low oxygen levels. Also, since more burning will take place in this process, there will be less oil to recover in comparison to forward combustion. This method is recommended for very high viscosity oils (Prats et al, 1985).

2.3 Dry and Wet Combustion

a) Dry Combustion

Dry combustion is the type of in-situ combustion where the injection exclusively involves air. There is no water involved in the process hence the term “dry”. The initial step is to preheat the reservoir until a minimum temperature is reached to start the ignition. Next, the injection of air (oxygen) will follow to start the combustion front. If the air injection is too high, the combustion front will move too fast and burn unnecessary in-situ oil in the process yielding a lower output of oil. Conversely, if the air injection is too low, the combustion front will not be sustained and failure of the procedure is imminent. The range of temperature for dry combustion is from 700 F to 1500 F. If the temperature levels are very high, the combustion zone is rather thin. The disadvantage of dry combustion is that the heat capacity of the injected air is too low, which creates very high temperatures in the burned zone (Prats et al, 1985). Sometimes the use of water injection is used to address this problem.

b) Wet Combustion

Wet combustion is another type of in-situ combustion that uses water to aid in the heat transfer of the process. Also, wet combustion can help with the efficiency of the reservoir since there will be less oil burned due to a decrease of temperature when the water is injected. Usually, the process of wet combustion uses an alternate method of injecting of air and water instead of injecting them both simultaneously. The key factor in wet combustion is the water/air ratio, which is closely monitored to see how this ratio affects wet combustion front movement. In a laboratory study (Coates et al,1995), it was shown that wet combustion can produce more oil in comparison to dry combustion if the process is commenced before the sand pack is depleted. Not only this, another advantage of wet combustion is that it lowers the fuel consumption of the oil in place resulting in a higher cumulative oil production.

2.4 Artificial Neural Networks (ANN)

An artificial neural network (ANN) is a mathematical model that has the ability to learn trends in a set of data that uses a set-up that mimics the human brain. The neurons in the ANN are each inter-connected with links and each link has a specific weight value. A neural network always contains one input layer and one output layer. In between, there are hidden layers with some neurons. The size of the hidden layer and the number of neurons are dependent of the design of the neural network. The input layer is used for the input variables to the neural network and the output layer is the layer that will yield the results predicted by the neural network.

The input layer is dependent on how many input variables are being tested by the ANN and the output layer is determined by how many output results are being predicted. The hidden layers and the number of neurons are the most determinant factor in the ANN. In each hidden layer, a transfer function needs to be selected for the network. There are many choices for the transfer functions for the hidden layers such as the sigmoid, the tan-sig, and the purelin transfer functions. A learning rate will also be selected for the ANN. If the learning rate is too high or too low the ANN architecture will suffer. If the learning rate is too low, the synaptic weights of each link will change slower over time, which will make the learning process much too slow. On the other hand, if the learning rate is too high, the system will become unstable (Haykin et al,2009).

One of the most important features of an ANN system is that it is a non-linear adaptive system. The system parameters are being continuously changed during the training phase of the operation, which makes it adaptive .The nonlinear aspect of ANN gives the system a significant amount of flexibility to achieve any desired input and output map. An input is presented to the neural network and a corresponding desired or target response set at the output (when this is the case the training is called supervised). An error is composed from the difference between the desired response and the system output. This error information is fed back to the system and adjusts the system parameters in a systematic fashion (the learning rule). The process is repeated until the performance is acceptable. It is clear from this description that the performance hinges heavily on the data used. If one does not have data that cover a significant portion of the operating conditions or if they are noisy, then neural network technology is probably not the right solution. On the other hand, if there is plenty of data and the problem is poorly understood to derive an approximate model, then neural network technology is a good choice. This operating procedure should be contrasted with the traditional engineering design, made of exhaustive subsystem specifications and intercommunication protocols. In artificial neural networks, the designer chooses the network architecture, the performance function, the learning rule, and the criterion to stop the training phase, but the system automatically adjusts the parameters. Therefore, it is difficult to bring a priori information into the design, thus, when the system does not work properly it is also difficult to incrementally refine the solution. Nevertheless, ANN-based solutions are extremely efficient in terms of development time and resources. In many difficult cases artificial neural networks provide performance that is difficult to match with other technologies.

The goal of the neural network developed in this work is to be able to predict similar outcomes when compared to the simulator used to obtain the production output data. If the results are within five percent, the neural network is complete and can be considered an expert system for the particular data set. Two types of the neural network will be developed. The first will be a forward path neural network where the inputs will be the reservoir properties and design decisions to predict production output. The second type will be an inverse model of the ANN where the input variables will be the reservoir properties and production output and the design decisions will be the output of the ANN. The forward model of the neural network developed will have the capabilities to forecast production outputs in oil and gas production as well as predicting the abandonment time of the project. The criterion to stop the project is either when the production well reaches 550 F to prevent well damage or if the project has run its course of 10 years. The second stage of the expert system development is the inverse model. Instead of forecasting production output and abandonment time, the inverse model's task is to predict the design decisions needed to be made to reach the specified goal of production values and abandonment time. Later, this development will be helpful to create an optimization model or an economical analysis to be applied for this work. The inverse model is a more challenging task since the solutions provided by the expert system will not be unique unlike the solutions provided by the forward path network.

2.5 Successful Applications of the ISC technique

Since there have not been much data and enough experiments to fully understand the ISC procedure, the use of in-situ combustion is not as prevalent as carbon dioxide and steam injection in the tertiary stage of production. However, there have been some fields that have been produced successfully after implementing the ISC process. The Suplacu field in Romania, both the Santhal field and Balol field in India and South Belridge in California are all good examples of successful in situ combustion projects (Gadelle et al.1990). In each of these fields, the production from using ISC was higher than the expected production if those said fields used a different enhanced oil recovery technique. The similarities between these fields is that their permeability is usually on the high end ranging from 500 mD to 2000 mD, the formations are not too thick ranging from 50 feet to 150 feet and the porosity levels of these fields are usually from 0.20 to 0.40.

In-situ combustion is also an option for a field which has been unsuccessfully exploited by other types of EOR processes. For example, if a steam injection or a carbon dioxide process was used and was not successful in oil exploitation, ISC could be used to continue the production of the reservoir's oil. Also, if well equipment is lacking in number and if there is no steam generator in the area for use of the steam injection method, ISC techniques could also be applied.

Chapter 3

Data generation via numerical data simulation

In order to train an expert system via artificial neural networks, an ample amount of data of high quality must be generated. The simulator, which covers thermal recovery and in-situ combustion, was used for this purpose. This chapter will discuss and describe the numerical model used for this project.

3.1 Data file description

A) Grid and Reservoir Definition

In this portion of the numerical simulator, the size and geometry of the pattern are defined. The model for this project has 400 grid-blocks total in the shape of a square with 20 blocks on each side. The pattern is homogenous with constant porosity and permeability. Porosity and permeability values are also specified in this section. Reservoir thickness is another variable set in the initial part of the data file.

B) Fluid Definitions

The second part of the data file deals with the fluid in place in the reservoir. The composition of the oil and its properties such as viscosity, critical pressures and temperatures of the compositions and the kinetic reactions are listed here.

C) Initial Conditions

This portion of the data file controls the initial conditions of the simulation. Things such as initial temperature, initial pressure, oil saturation and water saturation are specified.

D) Well Specifications

The last part of the data file controls the specifications of the injection well and the production well. The user can specify the design characteristics of the injection well such as the diameter size. In addition to that, the reservoir production designs can be specified in this section such as well configurations of a five-spot or even a nine-spot well configuration. For this project a five-spot design was used. The injection well is placed in the middle of the pattern and four production wells are placed in all the four corners of the pattern. The injection rate and the injection content (oxygen percentage) values are also specified in this section. The total amount of time the simulation is to be run is also specified along with increase of injection rates in following years.

3.2 Input parameters used in the simulation

Table 3.1 below shows the list of input parameters used to run the numerical data simulator and which input parameters were variables and which were constant throughout each simulation run.

Table 3.1- Reservoir variables for the simulations.

Pattern acreage	Constant
Porosity	Variable
Thermal conductivity of the rock	Constant

Initial pressure	Variable
Initial temperature	Variable
Initial oil saturation	Variable
Heat capacity of the rock	Constant
Thermal conductivity of water, oil and gas	Constant
Permeability	Variable
Oil API	Variable
Oil viscosity	Variable
Critical Temperature of fluids	Constant
Critical Pressure of fluids	Constant
Solid density of the coke	Constant

3.3 Reservoir properties effects

There are many reservoir properties that affect the final outcome of production in an in-situ combustion project or in any oil extraction projects. The studies of reservoir properties are significant because they are essentially the determinants of whether a reservoir will be economically sustainable. The correct estimation of a particular reservoir's properties is paramount to the success of that project economically.

3.3.1 Pattern Acreage

One of the reservoir properties studies in this work was the acre size of the pattern. Extensive simulations were run for patterns of five acres, fifteen acres and twenty five acres. Naturally speaking, a pattern with a larger pattern will yield a higher cumulative oil production. However, it does not necessarily mean it is the most profitable. A reservoir field of 100 acres can be divided into four sections of 25 acre patterns or 20 sections of five acre patterns. The more profitable of these two decisions depend on the cost of each procedure, which will take time, equipment, drilling of wells, amount of air injected, oxygen content in injection and other factors into consideration.

3.3.2 Porosity and oil saturation

Porosity is one of the biggest factors for overall cumulative production since the larger the porosity, the more oil in place will be available for the production. The range for porosity in the simulations is from 0.25 to 0.40. In-situ combustion reservoirs are recommended for reservoirs with least a porosity of 0.20, since anything lower would not be worth the effort and over-pressuring may occur due to the air injection.

Oil saturation is also important in determining if a project is worthwhile to pursue. The higher the oil saturation, the more oil is in the system, and this fact will let the reservoir engineers be more flexible with the type of methods to recover the oil. For example, a reverse combustion method can be used in a high oil saturation pattern since more oil is afforded to be burned for the fuel. In lower oil saturated fields, using reverse combustion would not be ideal since the oil production would be diminished. In real life oil extraction projects, the prediction of a reservoir's initial oil saturation is extremely important work and is one of the initial steps to determine if a reservoir is economically attractive to undergo production. A reservoir's initial oil saturation can be over-estimated or under-estimated by a company and both have negative effects. If a company has predicted that initial oil saturation of a given reservoir is significantly higher than the actual oil saturation of the reservoir, the oil production project can net a heavy loss economically. On the other hand, if a company predicts the oil saturation of a given reservoir is lower than the reservoir's actual oil saturation, a great opportunity of oil production will be ignored and ultimately a loss in profit will also occur.

3.4 Design parameters effects

Like reservoir properties, design parameters play an integral part in the results of an in-situ combustion project. Unlike reservoir properties, these factors are controlled by the project design engineers who are working on the project. The role of air injection and oxygen content in injection are two of the most important factors in in-situ combustion project. Generally, the higher the injection rate, the faster the combustion rate will be. However, if the combustion rate is too fast, too much oil is burned and production values are going to be lower. Not only this, a higher injection rate will be costlier.

The next design decision that is crucial to in-situ combustion is the oxygen content of the injection. The higher the oxygen content (oxygen enriched), the faster the combustion process will be and like injection rate an over use of oxygen content can be detrimental to the project, since enriching the oxygen is expensive and it does not necessarily mean better production. Enriched-air injection is more needed in reservoirs of heavy oils when compared to light oils. The use of enriched-air has its economical advantages also since it can be used for large scale operations requiring high pressures (Petit,H.J.M et al, 1987). It also has some advantages in the technical aspects of a project. The production of carbon dioxide produced by the combustion downstream from the burned zone is another advantage of using enriched-air in the injection process since the carbon dioxide will increase sweep efficiency. On the following page, Table 3.2 lists which design parameters were kept constant and ones that were varied for the simulations.

Table 3.2- Design variables of the simulations.

Injection Rate	Variable
Concentration of air in injection	Variable
Time of Air injection	Constant

As mentioned before, the injection rate of oxygen and the oxygen content of the injection are crucial to the success of an ISC project. An ISC project is more economical when compared to other popular methods such as steam injection. According to Lorimer, the energy required to supply heat to the reservoir compares favorably with steam injection. The estimated cost to place 1 GJ of energy in a 7 MPa reservoir is 2.6 to 4.4 dollars in steam and only 1 dollar in in-situ combustion. This is due to the fact that ISC is not compromised by large heat losses due to overburden and underburden in thin formations. However, ISC projects have been less successful than steam injection projects because of the difficulty of maintaining the combustion front in in-situ combustion. Sometimes, the injection rate is too small to maintain the combustion and even if the injection rate is thought to be sufficient and not excessive, the direction of the front will inexplicably become erratic. This erratic behavior will create problems such as increasing the oil saturation which will then immobilize the oil even further. This is why the injection rate and frequency of injection are paramount to the success of ISC projects.

3.5 Sample simulation runs and analysis

The next segment of this chapter shows preliminary tests of the project by running a few sample runs and exhibiting how reservoir properties and design decisions affect the shape of a simulation run. It is also a test to see if the input ranges to be used in the thesis is well within the realistic boundaries of practical use of this technique:

In situ combustion (ISC) is a type of enhanced oil recovery (EOR) technique that has been studied extensively for the past 50-60 years. The general process is that oxygenated air is injected into the well to create a burning front which is produced by burning of some of the original oil in place. In ISC, heat is generated through igniting the formation oil and then propagating a combustion front through the reservoir. The fuel that is used in this process is supplied by the coke that is embedded in the sand grains ahead of the combustion front. Consequently, the oil in the reservoir will have its viscosity lowered and will be able to flow to the production well to be produced. ISC is feasible for all three types of oil which are heavy, medium and light oil. In this section, there will be two ISC sample projects discussed simulating the ISC process of a heavy oil reservoir. The constraints that will stop the projects are if the projects reach 10 years (87600 hours) or if the producer temperature reaches 550 F. There were two simulations runs both with every input variable held constant except the nature of the injection process. The first sample employs an injection rate that is constant throughout the simulation from the beginning until the end. The second simulation run incorporates a technique of an incremental increase of injection rate per year and continually increased throughout the simulation.

Table 3.3 lists the input parameters that were used for both experiments:

Table 3.3: Sample runs set-up.

Porosity	0.325
Permeability	1000 Md
Oxygen content	25 %
Initial temperature	102 F
Initial pressure	2470 psi
Reservoir thickness	120 ft
Initial injection rate	984,000 SCF/day
Oil saturation	0.61
Water saturation	0.39
Acre of pattern	15
Oil viscosity	1113 cp

For each of these two simulation runs the output results that are of the main focus are the oil production rate and the cumulative oil production. Surely, the design parameters of the project and the reservoir properties will play a role in these results which will also be discussed. The obvious variables which will enhance oil production are porosity, reservoir thickness, oil saturation and permeability. The two design techniques that will be looked into in this discussion are the injection rate and the oxygen content of the injection and how they both affect the combustion front and in turn the overall oil production profiles. These two design parameters also need to be considered because some reservoirs that cannot handle high injection rates or high oxygen content will show some fracturing. Even if the reservoir could handle higher injection rates and oxygen contents, it might not be economically feasible even if the project time is be shorter. There are high operating costs for using high injection rates and high oxygen contents and these costs could offset negatively the saved costs of having a shorter project time gained by having those high injection rates with high oxygen content.

The injection rate is a very important design parameter for in-situ combustion because this is the driving force to supply oxygen to maintain the combustion front. Sample one and sample two runs' initial injection content are the same (980,000 SCF/day). The difference between the two runs is that sample two has an incremental increase of injection rate of 600,000 SCF/day per year which is done to aid in the combustion front movement. According to a study (Coates et al,1995), "Air is injected through the formation through a slot and as the combustion front expands outward radially, the injection flux needs to be continuously increased to supply sufficient oxygen to sustain combustion."

That is the main difference in sample one and sample two. Where sample one has a constant injection rate, sample two will feature an increase of injection rate as time goes on. The oil rate profile is altered greatly using these two techniques.

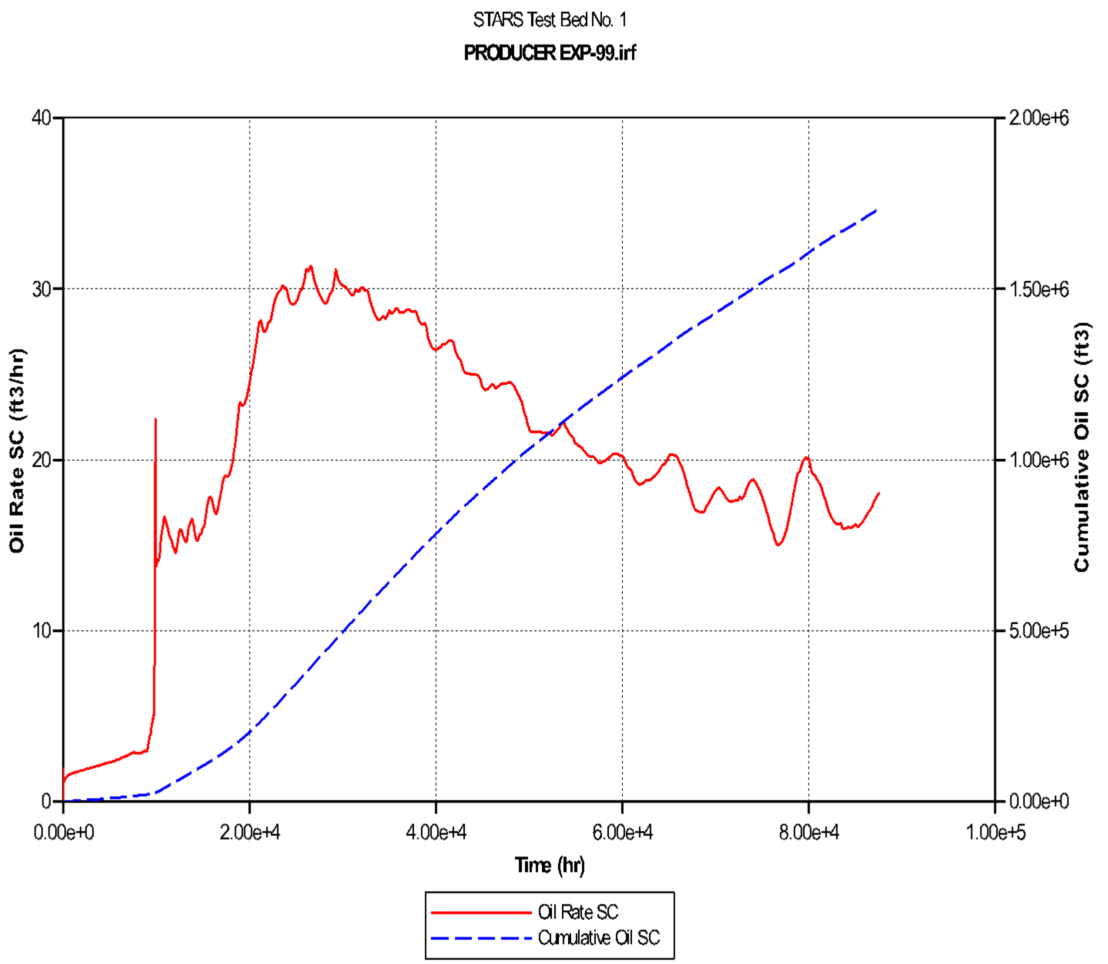


Figure 3.1: Oil production rate and cumulative oil production for sample one (constant injection rate).

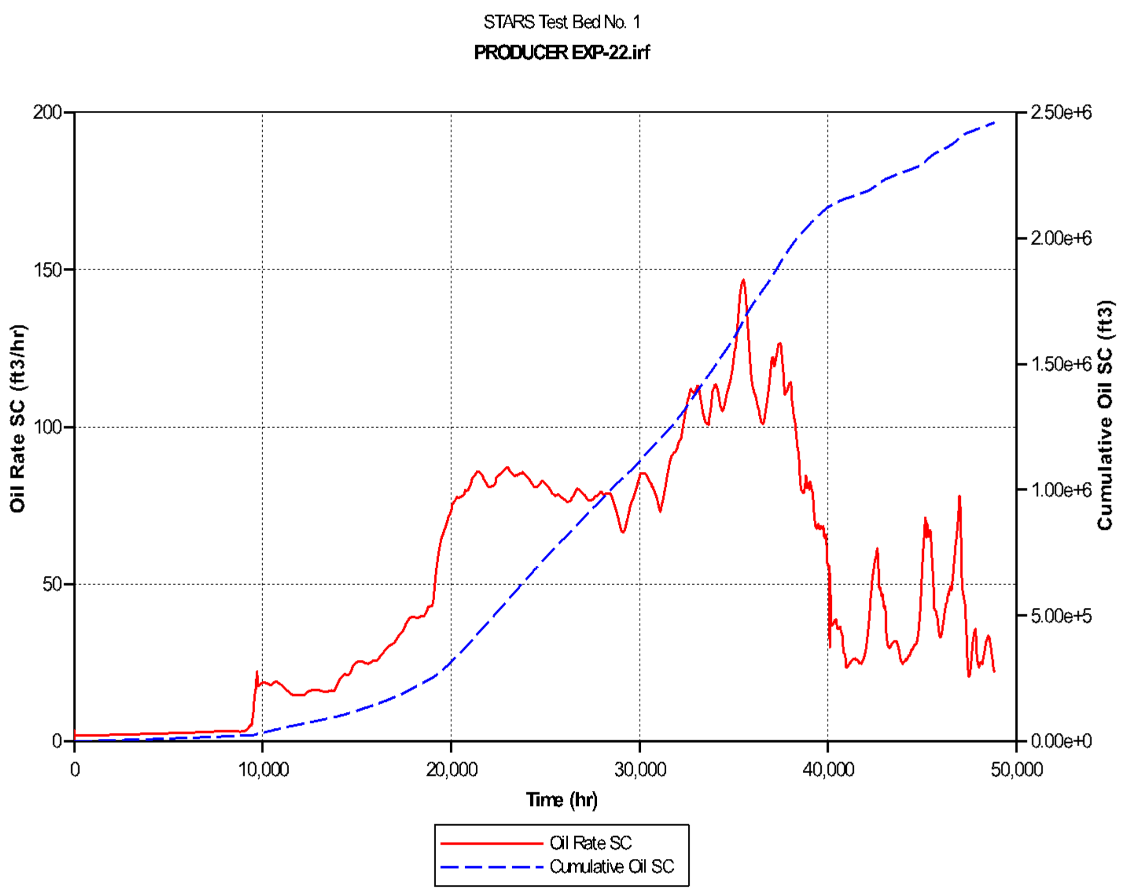


Figure 3.2: Oil production rate and cumulative oil production for sample two (incremental increase in injection rate).

The figures of 3.1 and 3.2 on the previous page show that using a constant injection rate will yield a good initial oil rate, but as the combustion front increases in radius, this injection rate is not enough to sustain combustion. After one year (8760 hours) of the project, the oil rate will stay stagnant at around the same level. In contrast, using an incremental increase of injection provided better results for the oil rate. In this case, when the oil rate reaches a plateau after one year, there is an increase of injection rate to aid the combustion front movement which will in turn increase the oil rate. As mentioned above, there are associated operating costs of using a higher injection rate. However, when the discrepancy of oil rate is as significantly high as between these two examples, it is beneficial to use a higher rate of injection. The oil production rate and cumulative oil production graphs for sample one and two are found on the next page.

This can also be seen through the temperature profiles provided for the two runs. At 24,000 hours and 35,000 hours the front is more advanced for sample two when compared to sample one due to the increase of injection rate.

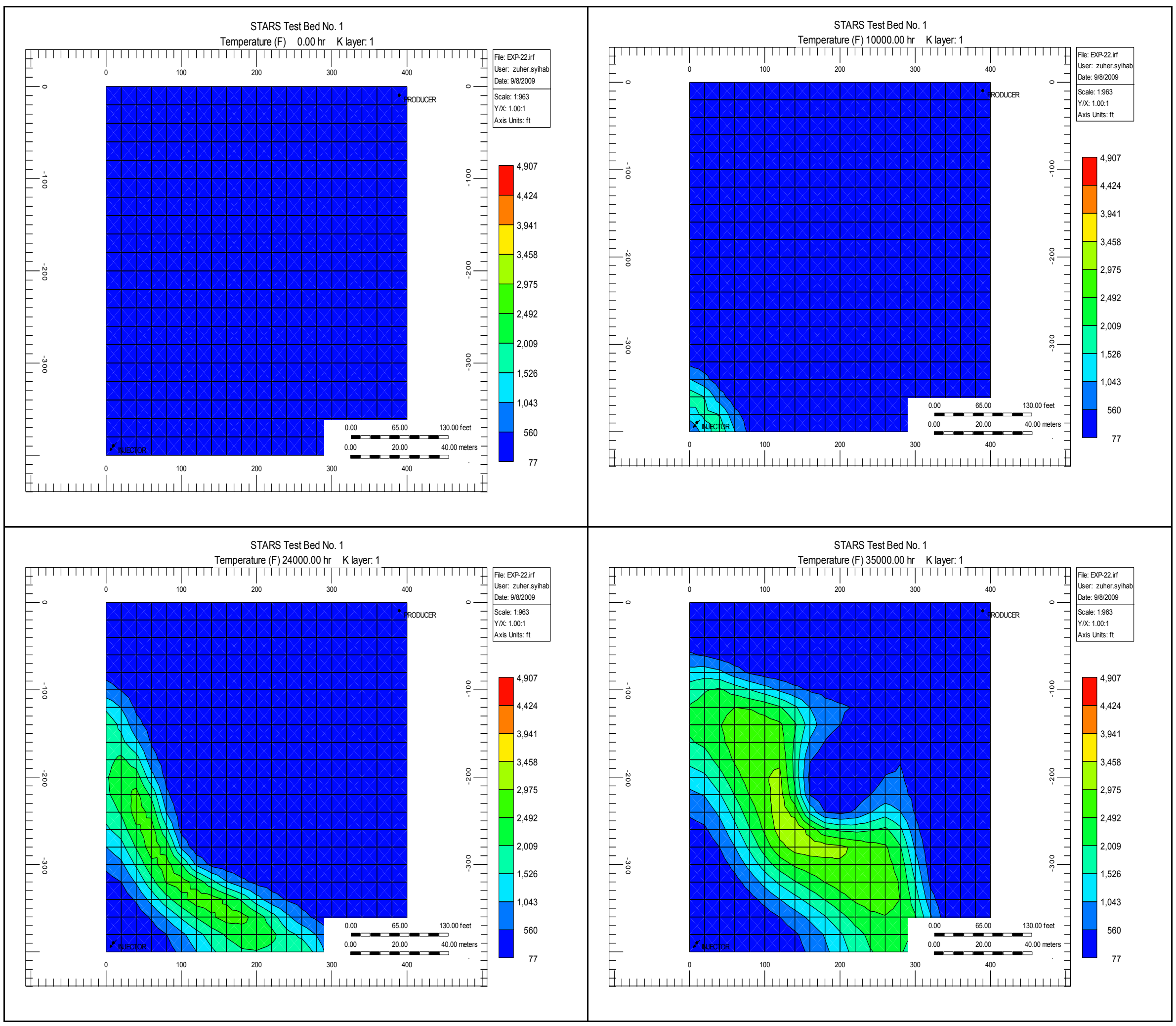


Figure 3.3: Temperature profile for sample one (constant injection).

When comparing figure 3.3 with figure 3.4, the simulation run associated with incremental increase of injection rate, it is evident that the temperature increases at a much slower rate. The combustion front can be concluded to move at a slower pace which will prolong the project time.

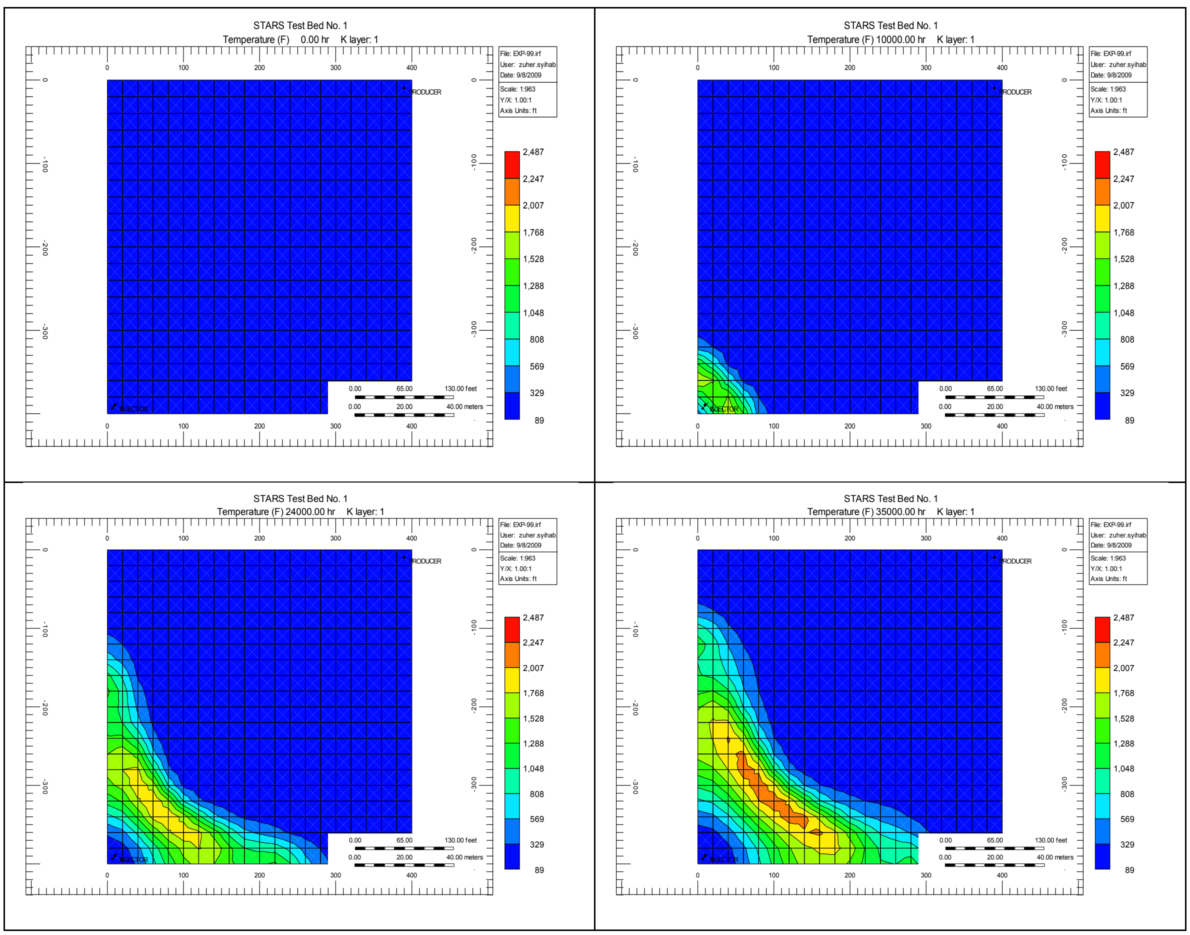


Figure 3.4: Temperature profile for sample two (incremental increase of injection).

From viewing figure 3.4, it is clear how an increase of injection rate could aid the combustion front in a positive way which will increase the oil production rate and shorten the length of time of the project.

The next set of figures shows that the ISC process is functioning appropriately. The decrease of the oil saturation in the figures representing each simulation run shows that the oil production has taken place in the production well.

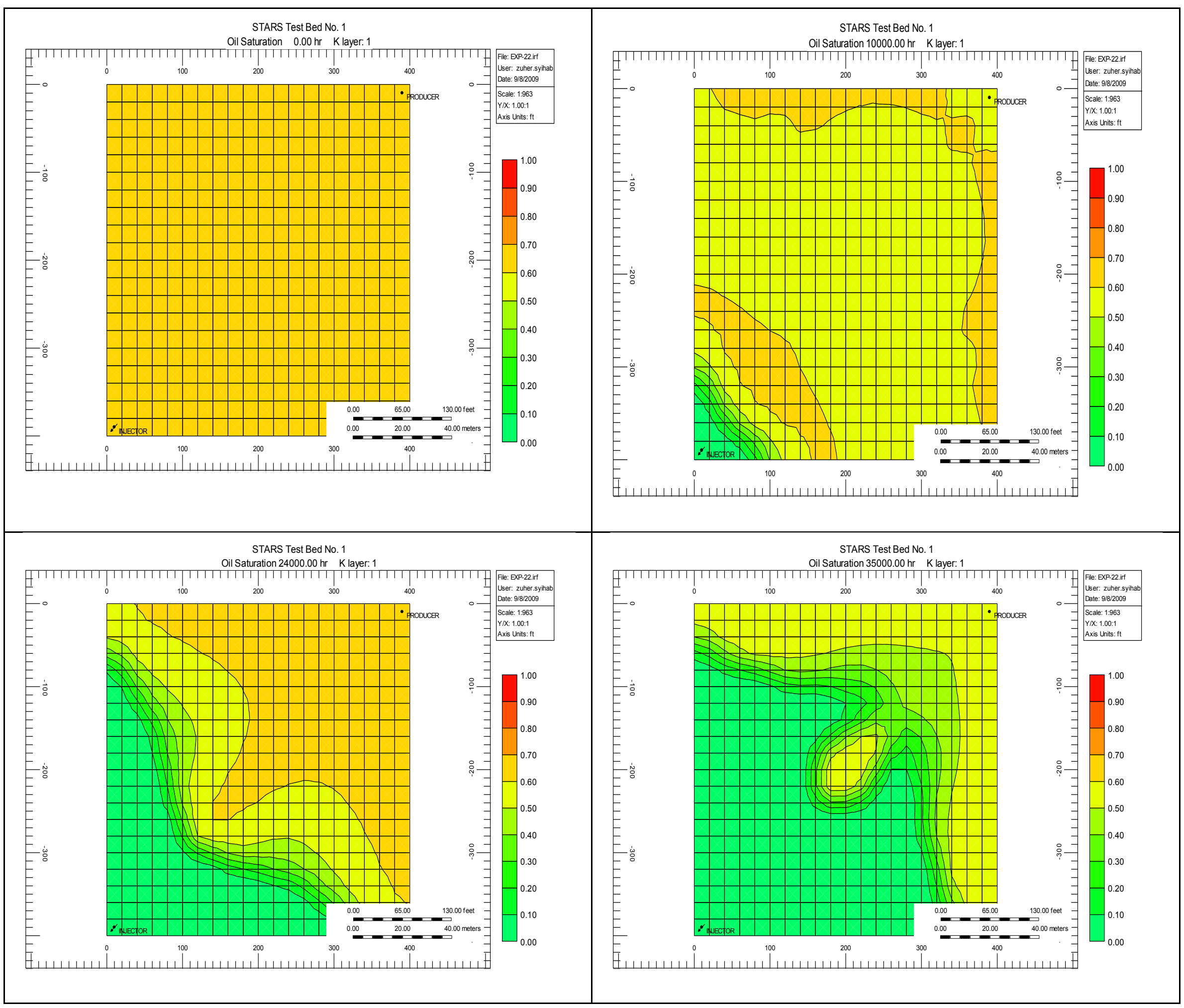


Figure 3.5: Oil saturation profile for sample two (incremental increase in injection).

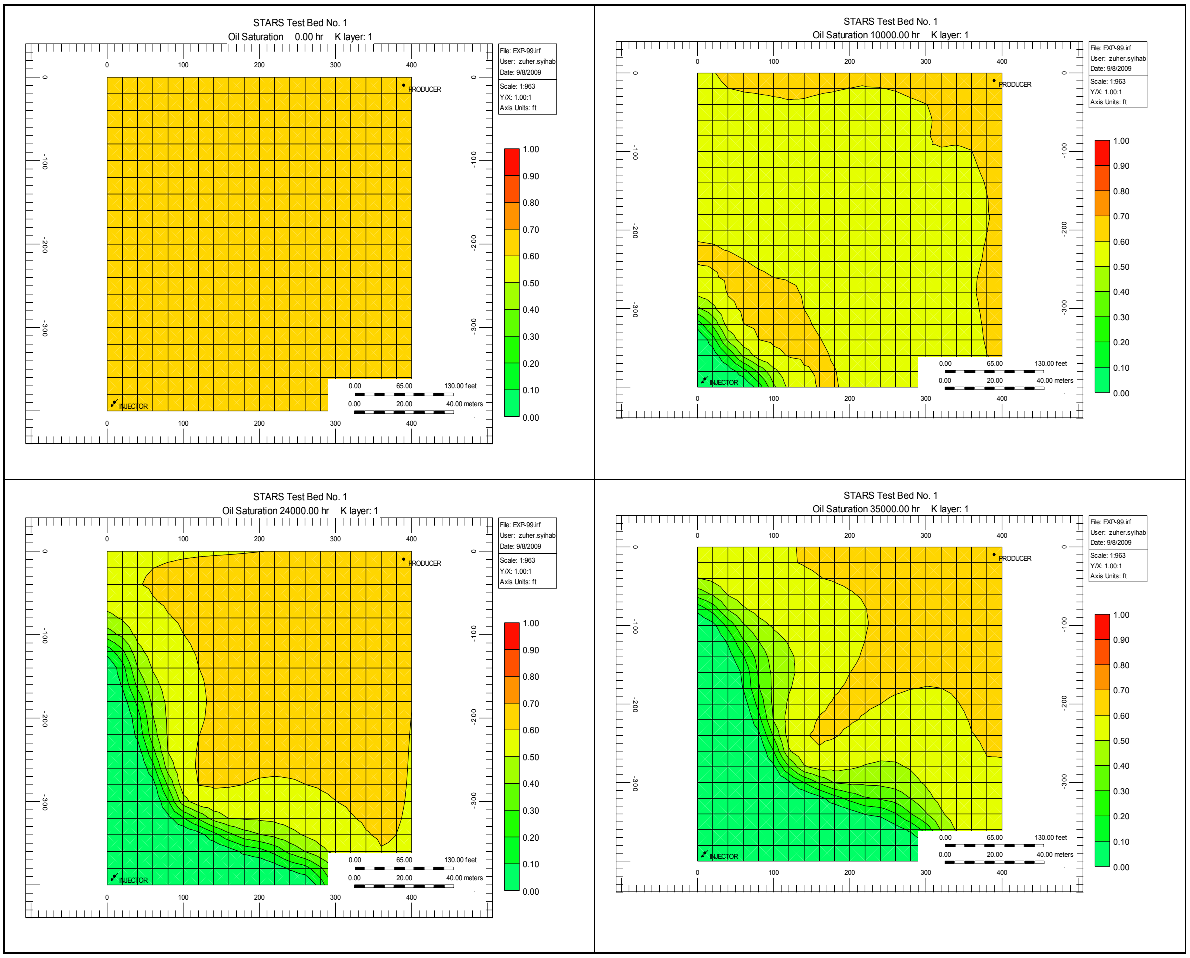


Figure 3.6: Oil saturation profile of sample one. (constant injection).

Again, it is evident that the oil saturation in sample two decreases faster due to the faster oil production which was caused by the different techniques of injection rate applied to these two sample simulations.

Next, are the figures of the oil viscosities of each of the two sample simulation runs. The viscosity property is important as its reduction is the main purpose of an EOR project. It is vital to decrease the oil viscosity so the oil resistance to flow decreases leading to more efficient oil production. Not only this, a decrease of oil viscosity will result in the production of higher quality crude oil with a higher API. Just like the oil saturation, the oil viscosity of sample two decreases at a faster rate when compared to sample one and that can be seen by the figures below.

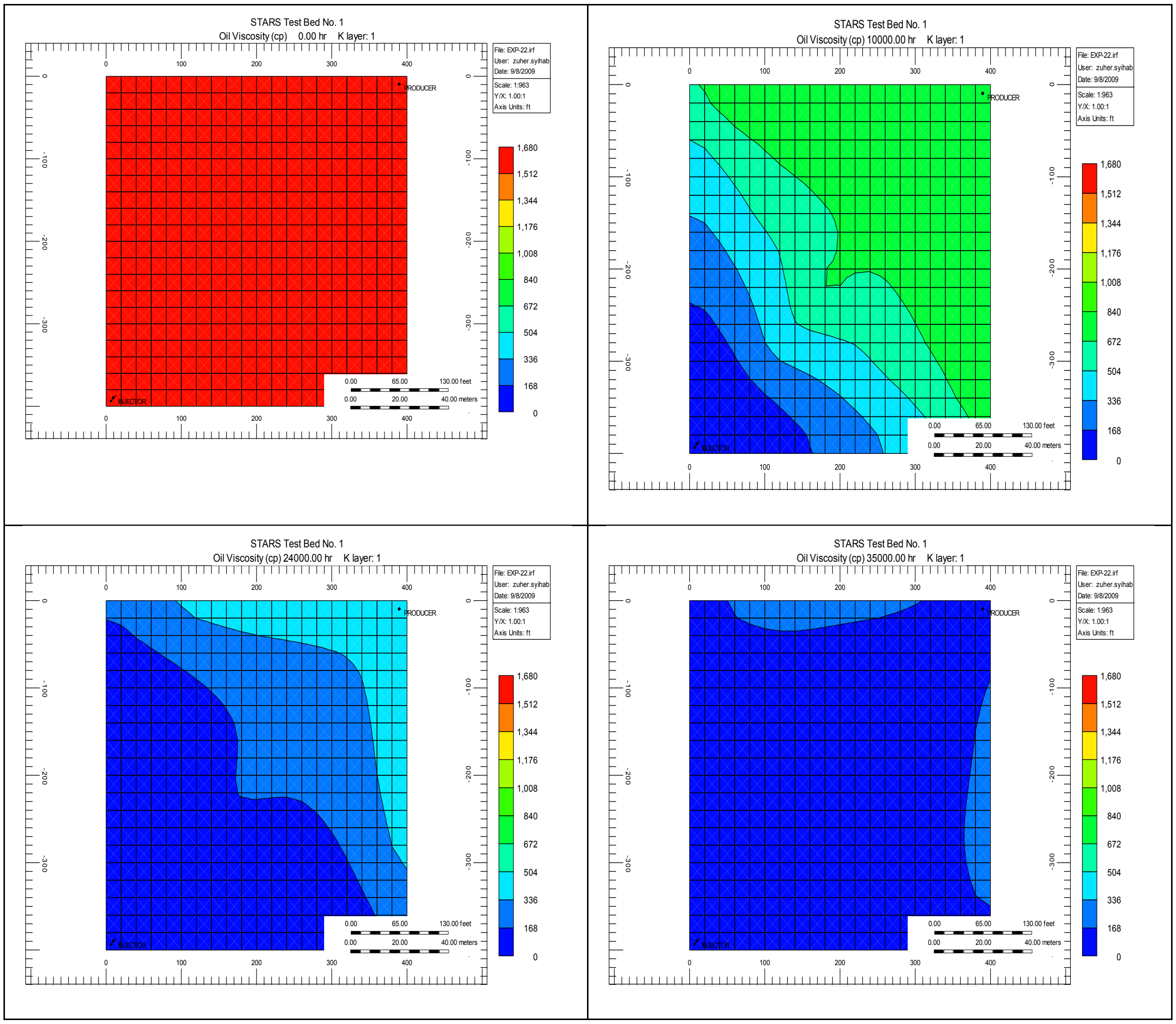


Figure 3.7: Oil viscosity profile for sample two (incremental increase of injection).

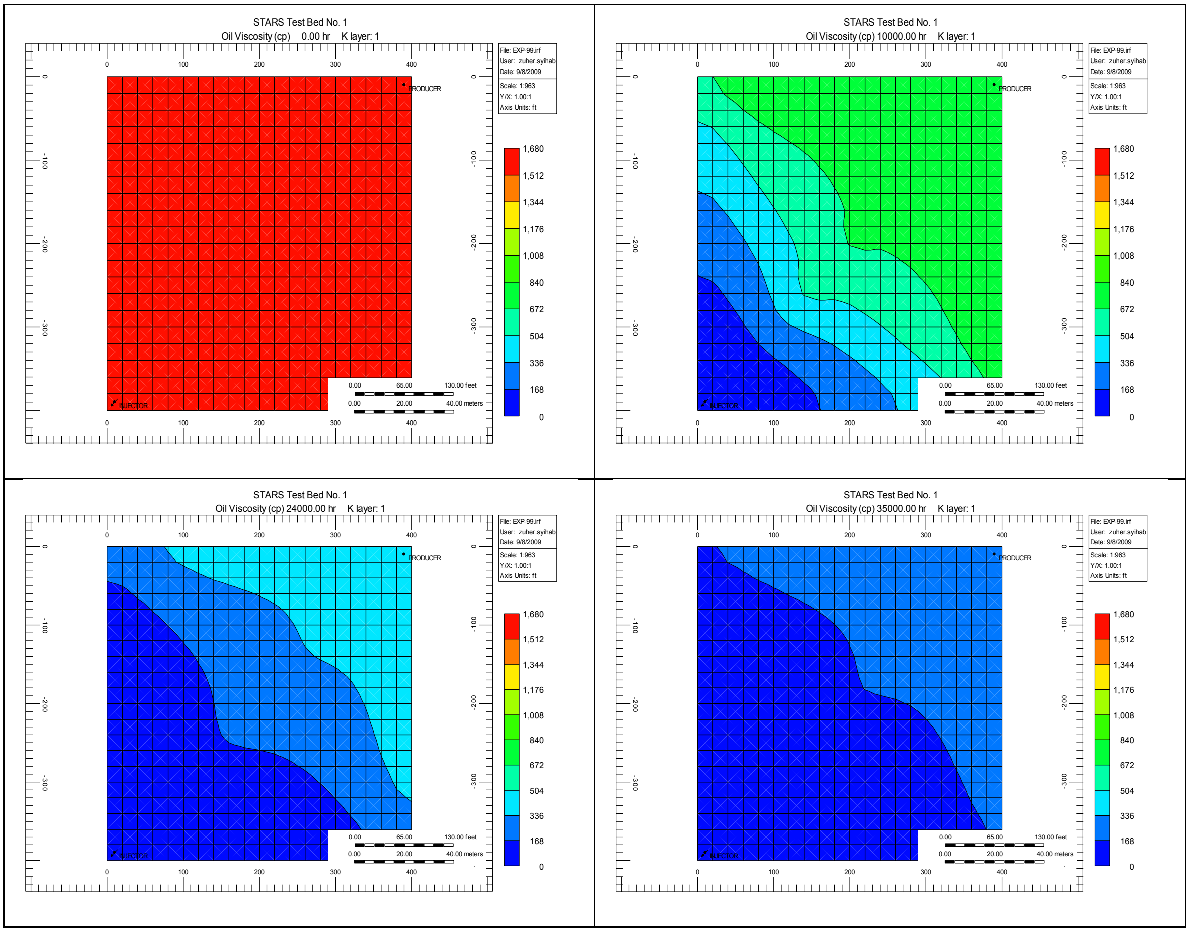


Figure 3.8: Oil viscosity profile of sample one (constant injection).

Another very important design parameter in ISC is the oxygen content of the injection process. To show the effects of an increase of oxygen content, another sample was run. The last sample run has the exact reservoir and design parameters as sample one, except the oxygen content of the injection is raised from 25 % to 50 %. On the next page are the two oil production rate and cumulative oil production figures (fig 3.9 and 3.10) of sample "1" and sample "1A" to show the differences in oil flow rate and cumulative oil production just by raising the oxygen content of the injection.

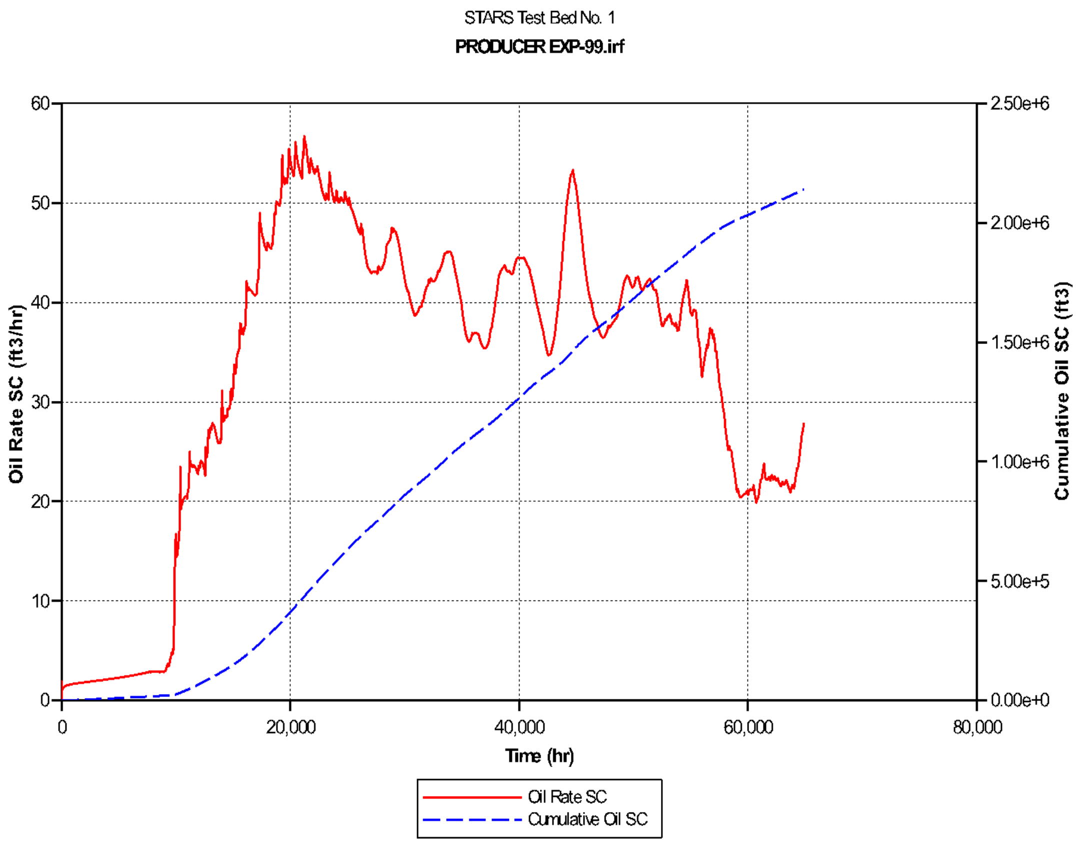


Figure 3.9: Oil production rate of sample one with 50 percent oxygen content in injection.

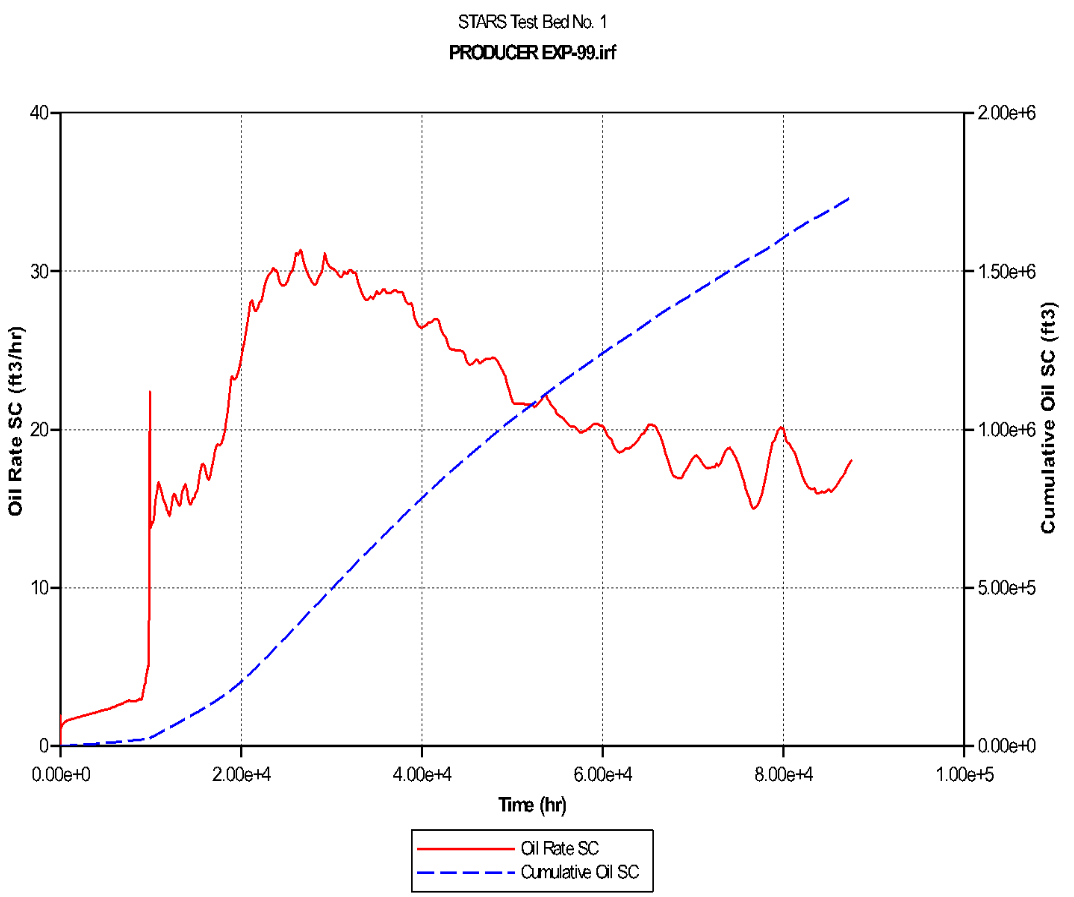


Figure 3.10: Oil production rate of sample 2 with 25 percent oxygen content in injection.

3.6 Sampling method and its use in preparing data files to be simulated

These types of simulation runs are performed for each pattern that ranges from five to 25 acres. Most of the simulation runs included above were done on the medium scale of pattern size (15 acres) but if simulations are done for the larger pattern (25 acres), the initial injection is raised to help sustain the combustion front for that particular pattern. For each pattern there are approximately 400 simulations done to ensure that all input parameters are scattered and not just centrally located in one area. For example, the range of porosity used in the project will be between 0.25 and 0.40. If 450 runs are made and 375 of those experiments used the range of 0.25 to porosity to.30, it means the project does not cover a large enough range of possibilities to generate varied output data that can be used for the development of the artificial neural networks.

When all of the simulation runs are completed, the final step of the study is the training and the validation of the expert system using the output data procured via the numerical simulator. The goal of the expert system is to be able to predict outcomes similar to those predicted by the simulator. The explicit objective is to reach an error difference of five percent or lower. However, before the numerical simulations are run, the 400 data files need to be generated. It can be generated manually (picking and choosing random input variables to be used in the runs), but this method can create problems such as overuse of time, overlapping data files and random manual technique has the possibility of not covering the whole scope of the project since the large spectrum of input variable possibilities are not covered. Due to these reasons, the bootstrap sampling method was implemented for the project.

In this project, there were a total of ten input variables and three output variables. Each input variable had its ranges, for example porosity's range was from 0.25 to 0.40. Initial temperature range was from 100 F to 200 F, etc. Since the range is wide and the number of input variables is not small, the total number of possibilities for the input data set is huge reaching hundreds of thousands total possibilities (total population). The challenge was to draw a sample from this population which will represent each area and scope of the total population. In this work, only 1200 total combinations of input data files were used. However, those input samples did cover the scope of the total number of possibilities and represented the population well. To put it in simple terms, consider a government election polling from the state of Pennsylvania. Imagine the total votes reached five million people, and a news agency wants to see the trend of the poll in the early hours after the votes have been made to see which candidate will win. They decide to take 50 thousand votes from all counties in Pennsylvania. If those 50 thousand votes were taken only from two or three counties in the state, the wrong result might be predicted since it does not represent the total population well enough. On the other hand, if those 50 thousand votes covered all of the counties in Pennsylvania, the prediction of a correct result is much likelier since the sample does represent the whole state of Pennsylvania. It is the same idea in theory with the sampling used for this work. If of the 1200 total input data samples, the porosity used for the simulation runs was in the range of 0.37 to 0.40, the project's output results are not wide enough to be used for a neural network model training nor is it realistic enough to produce an expert system. No engineer will ever consider a system close to being adequate if only 10 to 15 percent of real-life range is analyzed. That is why before the simulations were run, it was vital to verify that the data files do cover the entire spectrum for input variables.

The sampling method used for this thesis is called the bootstrapping sampling method. Bootstrap is a simple and powerful type of Monte Carlo sampling method used to assess statistical integrity or estimate distribution from a sample's statistics. The two assumptions of the Bootstrap Method are:

1) The sample or the ranges are a valid representation of the whole population
2) Bootstrap method will take sampling with replacement from the sample. Each sub-sampling is independent. It means that the method assumes the sub- samples come from the same distribution of the population, but each sample is drawn independently from other samples.

Some examples of the uses of bootstrap method are when a user has a small sample of data that he is not sure of its theoretical distribution. Bootstrap method can estimate variance and mean average of the sample. Also, bootstrap can check if two samples come from the same population.

The bootstrap algorithm for this project was implemented in code for MS-Excel. The program will first ask all input variables, ranges and distribution. Uniform distribution was selected. Next, the user will input the total number of samples he wants from the program. After a click of button, all the samples will appear in the Excel spreadsheet. Figure 3.11 on the following page shows the set up of the selection of the input variables and their ranges. After they have been selected, a number of sample data files will be generated depending on the amount that the user requested.

Name	Distribution	MIN	MAX
Oxygen content	Uniform Uniform	0.21	0.50
Permeability		500	2500
Porosity	Uniform	0.25	0.40
Oil saturation	Uniform	0.5	0.7
Water saturation	Uniform	1-oilsat	1-oil sat
Initial temperature	Uniform	100	200
Initial pressure	Uniform Uniform Uniform	1000	2500
Thickness		100	150
Area of pattern	Uniform	5	25
Injection rate	Uniform Uniform	30000	75000

Figure 3.11: Data Samples.

Figures 3.12 to 3.15 will illustrate how the simulations cover the whole spectrum of the ranges of the input variables. There was no bias in the sampling method that would result in the use of a specific area such as areas of the low range, middle range or the high range. All areas are evenly distributed to achieve complete coverage of these input variables. All variables and their ranges were well represented after using the bootstrap method. The figures will have two axes each showing an input variable. For example, the figure 3.12 represents the sampling variables of oxygen content and permeability. The range for permeability was from 750 mD to 2500 mD. The range of oxygen content was from 0.21 to 0.50. The figure shows that every corner of the ranges of these two input variables has been covered. The figures on the following pages show similar results when checking the coverage area of other input variables.

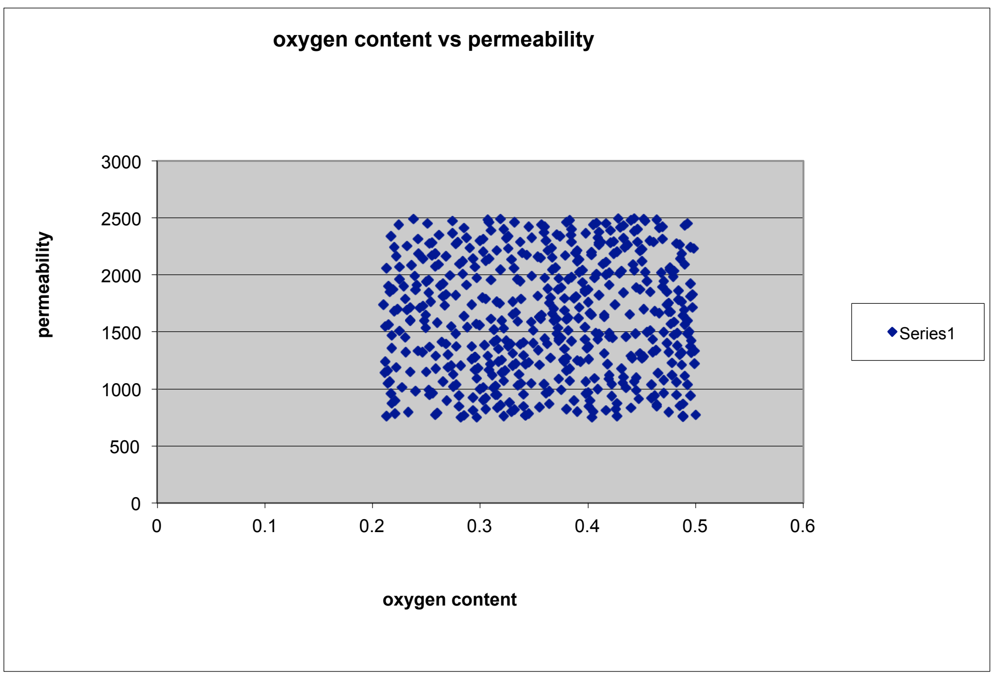


Figure 3.12: Oxygen content vs permeability input variable map.

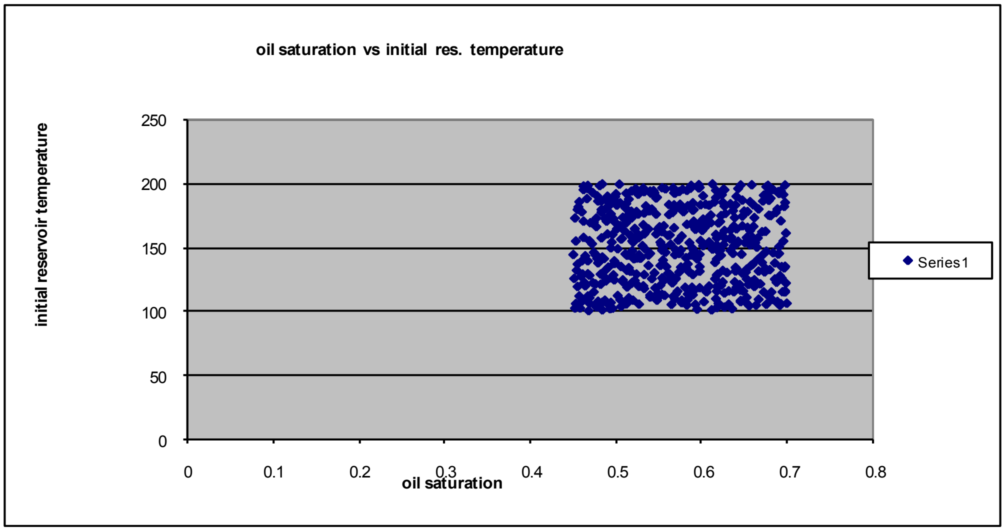


Figure 3.13: Oil saturation vs initial reservoir temperature input variable map.

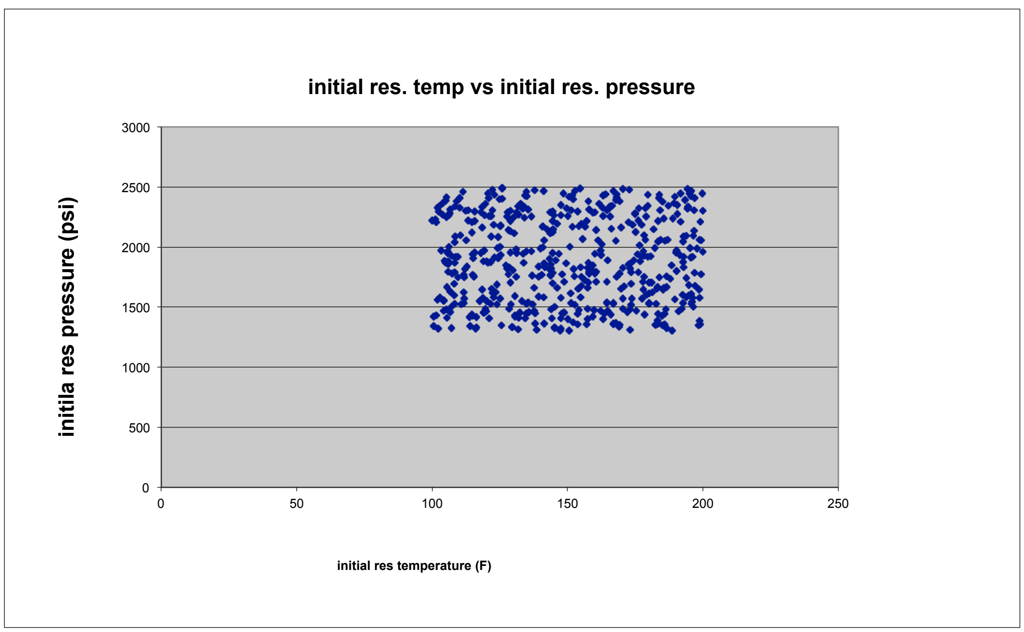


Figure 3.14: Initial reservoir temperature vs initial reservoir pressure input variable map.

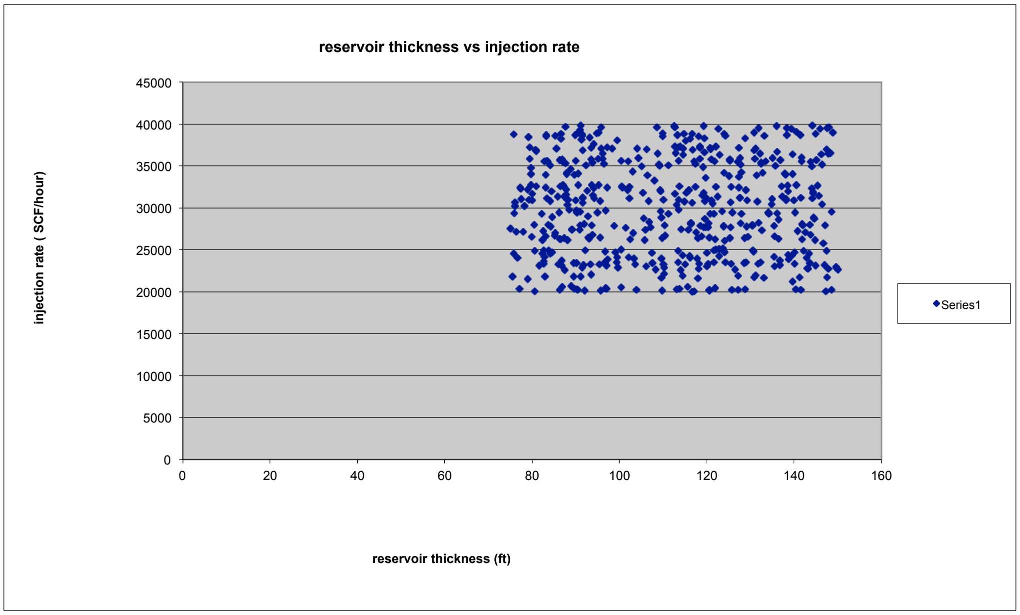


Figure 3.15: Reservoir thickness vs injection rate input variable map.

These figures do clearly illustrate that the bootstrap sampling method did its job in preparing the input data for the simulations that were ran by the numerical simulator. After the simulations have been run, the data obtained by the simulator will be used to train the expert system until it learns the trends of the data and can then predict similar outcomes compared to those predicted by the numerical simulator.

Chapter 4- Development of the ANN expert system

The development of the ANN expert system involves a basic understanding of neural networks. There are some rules of thumb that are important for the network such as the more varied and higher quality data you feed to the network for training, the quicker and more efficient the network will learn trends in the data to make accurate output predictions. However, the quality of data is much more significant in order to achieve success in building an expert system. Like the previous chapter mentioned, if an ANN system is given a large number of data for training, but the scope of the data covers only one side of the spectrum range of the input variables, the network will not properly learn all trends and in turn will make inaccurate final output predictions. Thus, the three initial steps taken in this work to ensure that the data were of good quality were:

1) Ensuring that the data covered all the ranges of the input variables properly.
2) Verifying that the data generated by the simulator were of good quality and were sufficient in number.
3) Observing which simulation runs contained low quality results. After each simulation process was finished, one could check the material balance error of that particular run. A simulation run that finished with a material balance error of less than one percent was deemed to be of high quality. This was a challenge in the smallest pattern of five acres because it was rather sensitive to the injection rates. For example, if the injection rate for a five acre pattern was high and the oil saturation and permeability were on the lower end of the spectrum range, the pressure in the system would rise above realistic levels and cause a low quality result when verified at the end via the material balance error. In addition, the simulation would sometimes experience unrealistic behaviors and crash.

Thus, it was important to eliminate these low quality data from the data pool that were to be later used in the training and development of the expert system.

Topological characteristics now have to be considered to build an ANN system. The total number of hidden layers, number of neurons, transfer functions, learning rate and momentum are the most important aspects of developing an ANN system. Also, the number of samples to be used from the data pool for training and validation needs to be determined. For each acreage pattern, the total number of samples ran were approximately 400 each. Initially, it was only 150 each, but as mentioned previously, a lower number of data samples would give bigger challenges in developing the expert system even if those 150 samples are of high quality and cover a wide range.

4.1 Expert system coverage

The expert system to be developed will specialize in predicting three output values (oil and gas production and abandonment time) using ten input values in a field application of an in-situ combustion project. The ANN expert system will focus on fields that have medium permeability (500 mD) to high permeability (2000 mD). Typical porosity values will be tested from 0.25 to0.40 porosity. ISC has been utilized for the production of light oil reservoirs, however this work focuses on the production of heavy oil that employs the ISC technique. One of the main objectives of this neural network development is to gauge the importance of oxygen-enriched air in the injection process as well as the incremental increase of injection rates for all three different sized patterns. Most laboratory studies have focused on constant injection rates throughout the simulations, however for this work, the injection rates were increased after a set period of time to aid in the movement and velocity of the combustion front.

Oxygen enriched air is sometimes used in ISC projects that deals with low permeability, but this work will only study the effects and predict outcomes of production using varying degrees of oxygen enriched air in a medium to high levels of permeability. The range for the oxygen content of the injection is from 21% oxygen (air humans breathe) to 50% oxygen (enriched air).

4.2 Initial steps in development of the forward model of the expert system

The feed-forward backward propagation algorithm was used to train the expert system using the data generated by the numerical simulator. The output is calculated in the forward direction and the error is counted backwards. The number of neurons in the input layer represents the total number of inputs of the system (ten inputs) and the number of neurons in the output layers represents the total number of output values (three outputs). The number of hidden layers and the number of neurons in those layers are the most important in making an ANN expert system. The issue of overtraining and under-training is often caused by using too many or too few hidden layers and neurons. For a rough estimate this equation was used:

Number of hidden neurons = (SQRT(total of data samples) + (total inputs + total outputs))

Another feature of the back-propagation algorithm is the transfer functions. Transfer functions are the basic equations that calculate the output, errors and weights in this algorithm. They are the links for the relationship between inputs and outputs.

The three typical transfer functions used for this algorithm are the logsig, the tansig and the purelin functions. The next section focuses on the training of the expert system and the steps taken to ensure that the system could make accurate predictions.

4.3 Training of the forward expert system

The art of an ANN development also relies on trial and error. So, the first model was started with three hidden layers with 25, 15 and 20 neurons respectively. At this point of the training, the variable of learning rate was focused on. Learning rate in neural networks is a constant used in error back-propagation learning and other artificial neural network learning algorithms to affect the speed of learning. The mathematics of the back-propagation algorithm is based on small changes being made to the weights at each step. If the changes made to weights are too large, the algorithm may "bounce around" the error surface in a counter-productive fashion. In this case, it is necessary to reduce the learning rate. On the other hand, the smaller the learning rate, the more steps it takes to get to the stopping criterion. The stopping criteria for all the expert system training in this work was set at 0.99 in correlation factor. Initially, the learning rate was set at 1.5, and the system was training rather quickly. The correlation factor reached an average of 0.85 for the three outputs after only fifteen minutes of training and it was approaching the stopping criteria of 0.99. However, when the correlation factor reached higher levels, the training system started to "bounce around" exactly as predicted by the theories of artificial neural networks. The next step consequently was to lower the learning rate to see its specific effect on the system with all other variables (hidden layers, neurons, and momentum) held constant. The learning parameter was lowered to 0.5 and the training system took a much slower approach in its learning process. While a learning rate of 1.5 reached a correlation factor of 0.85 after fifteen minutes, using this new learning rate took a significantly longer time to reach that point. This process was too slow so a good learning rate could be found between 0.5 and 1.5. A momentum variable was also added for the training process to alleviate this possible problem with the learning rate.

Another challenge for the training process was that there were three data samples for the three different sized patterns to consider. So, an expert system that might be developed properly for the smaller sized pattern might not work for the largest sized pattern. This was encountered several times in the training process and expected from very early in the work.

Since, the number of input and output variables were not overwhelmingly wide (ten inputs and three outputs), the three hidden layers were changed to two hidden layers to see if the new architecture could improve the final predictions. After more trial and error and adjustments, a final architecture was reached for all three different sized acre patterns. The system contains 2 hidden layers with 18 and 13 neurons respectively and a learning rate and momentum of 0.8. Figure 4.1 on the following page is the graphical representation of the final architecture for the forward expert system.

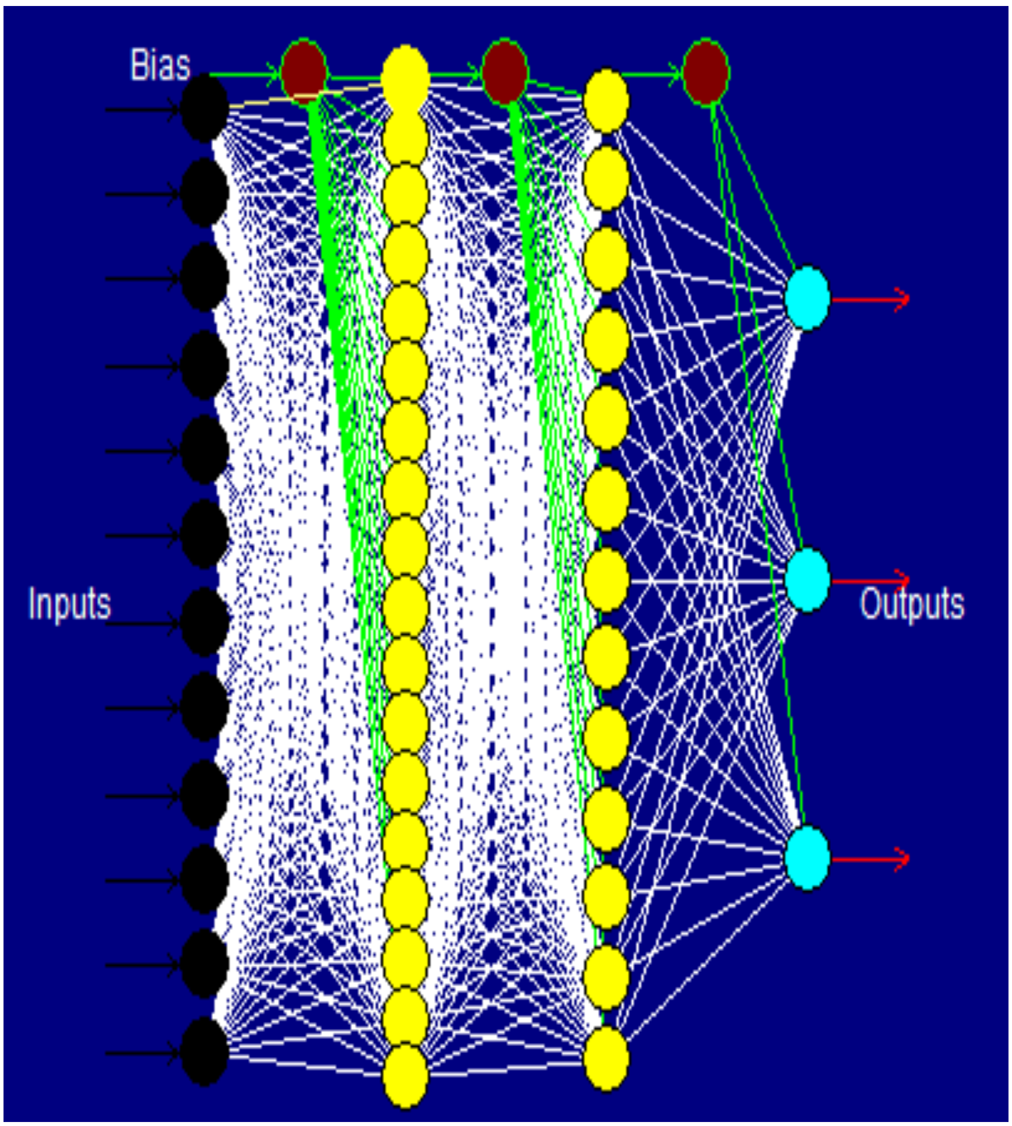


Figure 4.1- The final architecture for the forward model of the expert system.

Once this final architecture of the ANN was finalized, there needed to be a final stage of testing to make sure that the system provided good predictions because it properly learned the system instead of memorizing it. If the system memorized the data instead of learning the data, the "expert" system will only be valid for that particular set of data and cannot be used for any other sets of data. That is why this final testing stage is crucial in determining the quality of an expert system.

There were 400 samples and the first 340 samples were used for training and the last 60 samples for validation. To ensure proper learning and not memorization, the architecture was tested using the first 60 samples for validation and the last 340 for training. If the result predicted here were satisfactory, the next stage of testing was to pick out 60 random samples from the whole population of 400 and use them as a validation set and the rest of the samples were for training the expert system.

The final architecture predicted the simulator results within the five percent error target and could be said as an expert system for this specific area of a forward dry in-situ combustion field project. The following pages will contain illustrations of the training results obtained for all three outputs (abandonment time, oil and gas production) for all three different sized reservoir patterns for the forward direction neural networks.

4.4 Visual representation of the training of the forward expert system

Figures 4.2 to 4.7 show the training process of the forward expert system. The goal of the training process was to reach a correlation factor of at least 0.99 and for each of these training figures, that goal was reached.

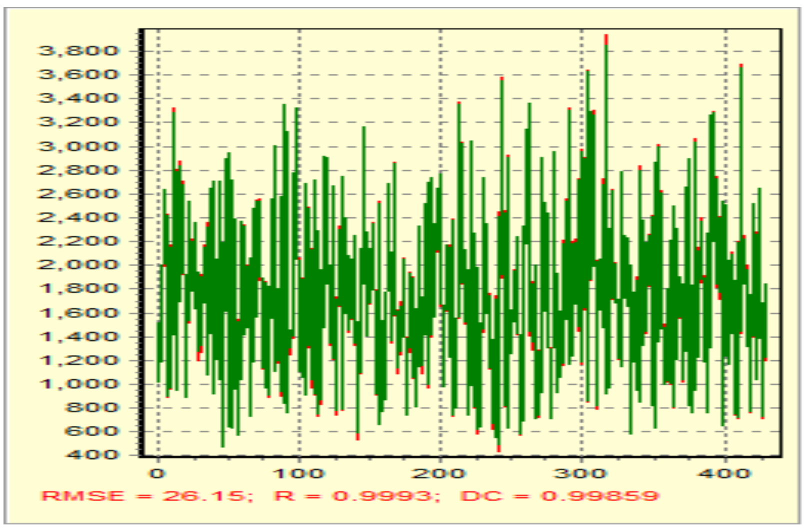


Figure 4.2- Training the expert system for the cumulative gas production in MMSCF in the five acre pattern.

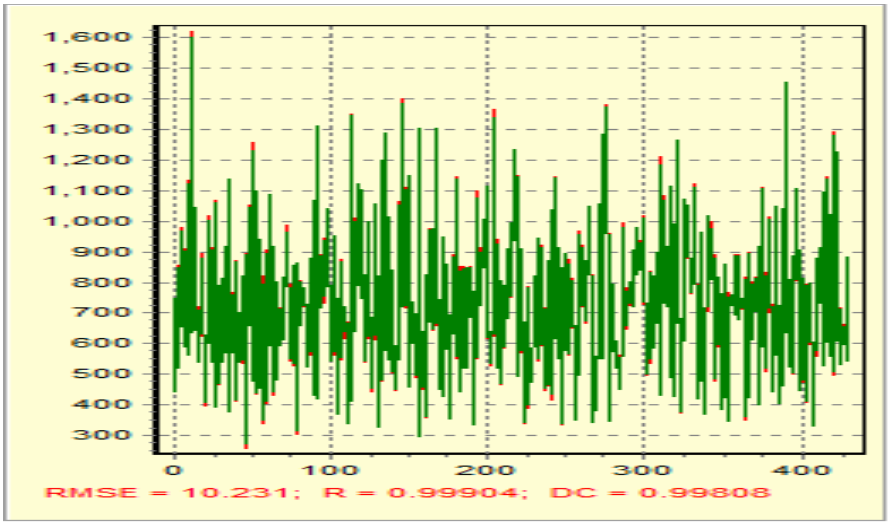


Figure 4.3- Training the expert system for the cumulative oil production in MSCF in the five acre pattern.

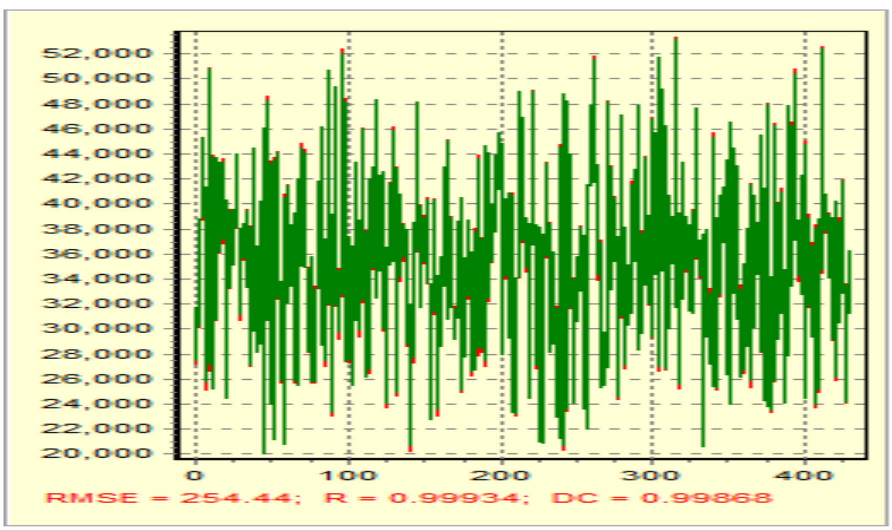


Figure 4.4- Training the expert system for the abandonment time in the five acre pattern.

Figure 4.5- Training the expert system for the cumulative gas production in MMSCF in the 15 acre pattern.

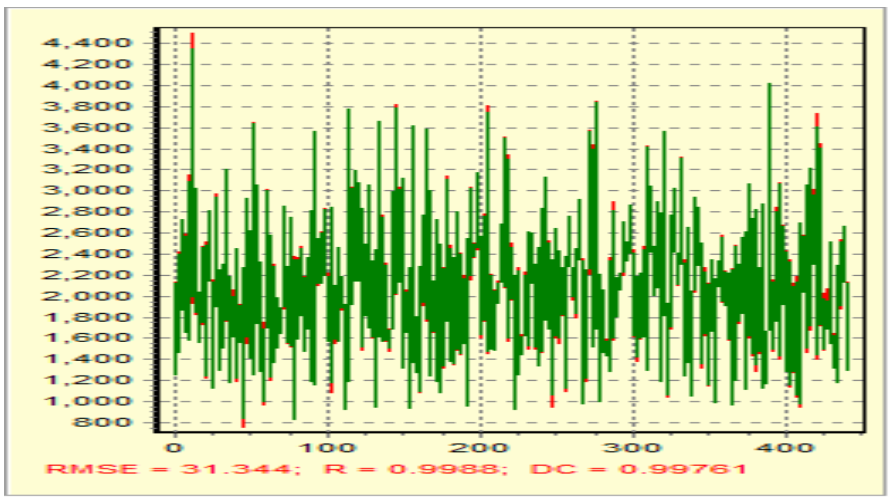


Figure 4.6- Training the expert system for the cumulative oil production in MSCF in the 15 acre pattern.

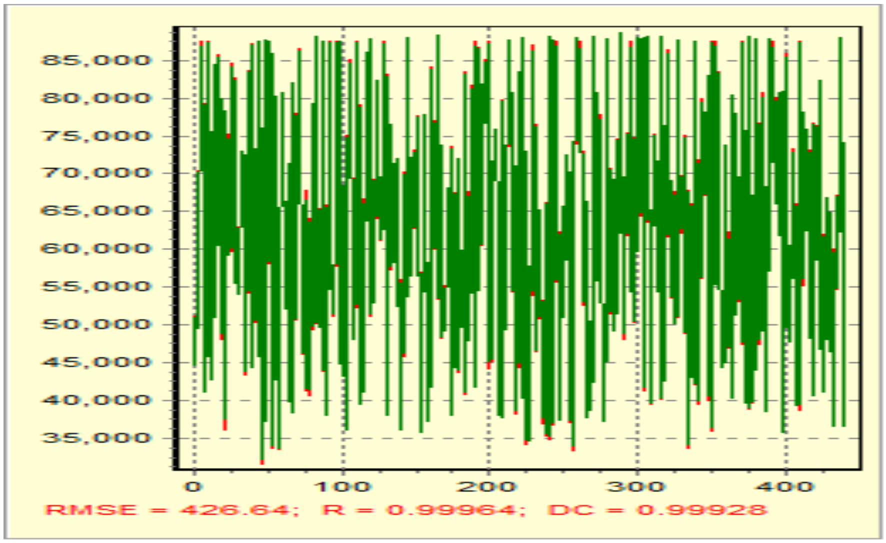


Figure 4.7- Training the expert system for the abandonment time in the 15 acre pattern.

4.5 The inverse model of the expert system

The forward model of the expert system was able to predict outcomes in reservoir production and abandonment time given a set of reservoir properties and crucial design parameters. The inverse model's aim is to predict what design decisions should be taken to reach a specified production target.

For example:

1) In a five acre pattern with a given set of reservoir properties, what should be the injection rate be if the target production for oil in that pattern is 20 thousand barrels?
2) What should be the oxygen content of the injection in a given reservoir if the maximum time that could be spent in production is eight years?

These are all questions that should be able to be answered if one develops an inverse model for the expert system. Since most projects are oriented to reach certain goals, this optimization tool is a more valuable technique in real world applications. While the forward model lets the user understand how reservoir properties and design parameters affect the production outcome, the inverse model will show what design decisions need to be made to reach specified production goals and time constraints. The main difference between the forward and the inverse model is that the forward version of the expert system provides a unique solution to each problem while the inverse is not unique. For example, a reservoir with its embedded field properties will be produced using an initial injection rate of one million SCF/day and an oxygen content of 0.25. With these design configurations, the forward model of the network will give one set of solution of abandonment time and oil and gas production. For the example above, the oil production will be 50,000 barrels with an abandonment time of 7 years. When the process is switched to an inverse model and the goal of the project is to reach 50,000 barrels of oil produced and an abandonment time of 7 years, either the initial set up (an initial injection rate of 1 million SCF/day, an oxygen content of 0.25) or a new set up with different design decisions can provide the same results.

The inverse model of the expert system can also be used for an economical analysis of an in-situ combustion project. A higher injection rate and higher oxygen content in the injection will be costlier, but with the inverse expert system, the ANN will be able to show how these design decisions affect the final outcome of the project and the user will be able to analyze further the economic gain or repercussions of those decisions.

4.6 Development of the inverse expert system

The idea of the inverse model is to use the reservoir properties and the production results obtained from the numerical simulations to be used as the input of the ANN expert system, and the design parameters to be the output of the ANN expert system. Initially, the same architecture for the forward model was used for the inverse model but that attempt failed since the prediction results with that architecture had too many errors. The goal was the same as the forward model so that the ANN predictions could be five percent over or under the numerical simulations. A different ANN architecture needed to be constructed so that the inverse model could function properly. Another challenge was that one architecture had to be constructed that would apply to all three different sized patterns. Like the forward model, if an ANN architecture functioned properly for the five acre pattern, it does not necessarily mean that it would work for the other sized patterns. The key guidelines were followed in building the inverse model just like it was followed constructing the forward model and the final architecture of the inverse model was two hidden layers with 36 and 30 neurons respectively, with a learning rate and momentum of 0.8 and stopping criteria of 0.99 in the correlation factor. Figure 4.8 on the following page is a graphical representation of the final architecture for the inverse expert system:

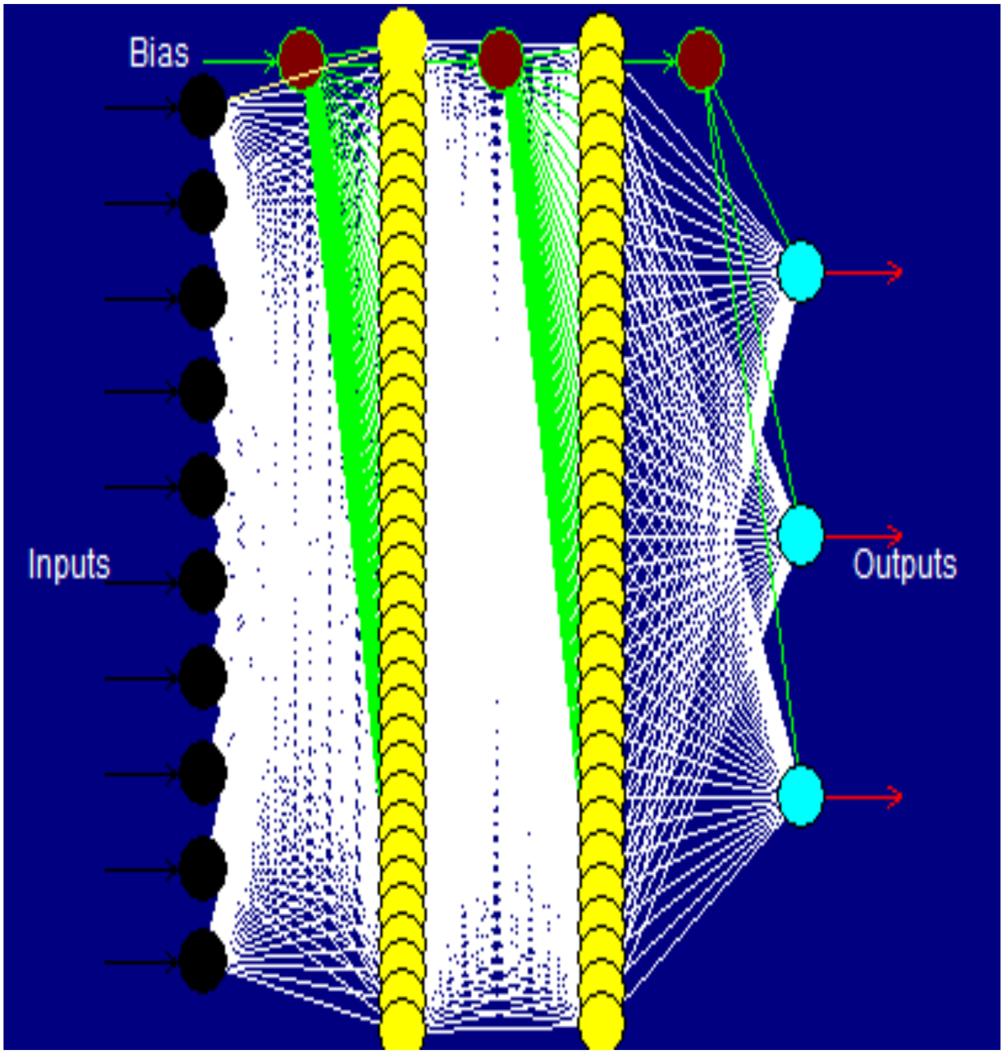


Figure 4.8: Final architecture for the inverse model.

4.7 Visual representation of the training of the inverse expert system

The figures 4.9 to 4.11 show the training configurations of the reverse model for two different sized acreage patterns (five and 15 acres) and the two design decisions of the project (injection rate and oxygen content in injection). All trainings were stopped when a correlation factor of 0.99 was reached.

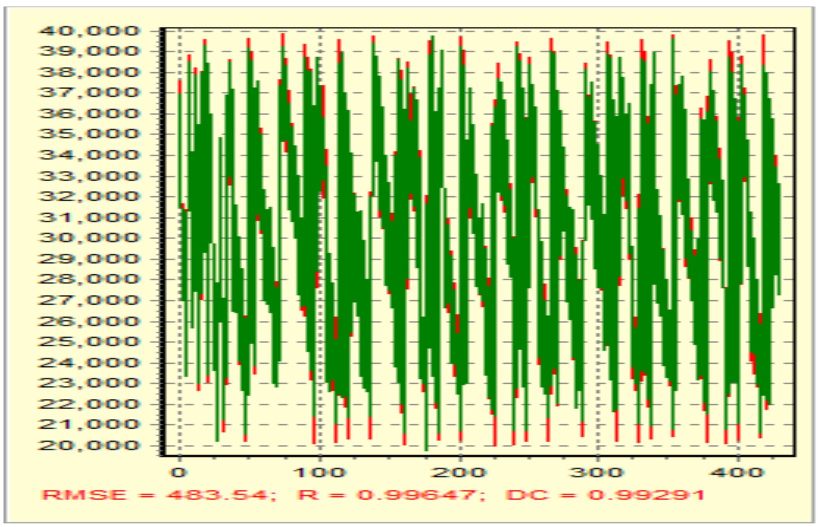


Figure 4.9- Training of the initial injection rate in the five acre pattern.

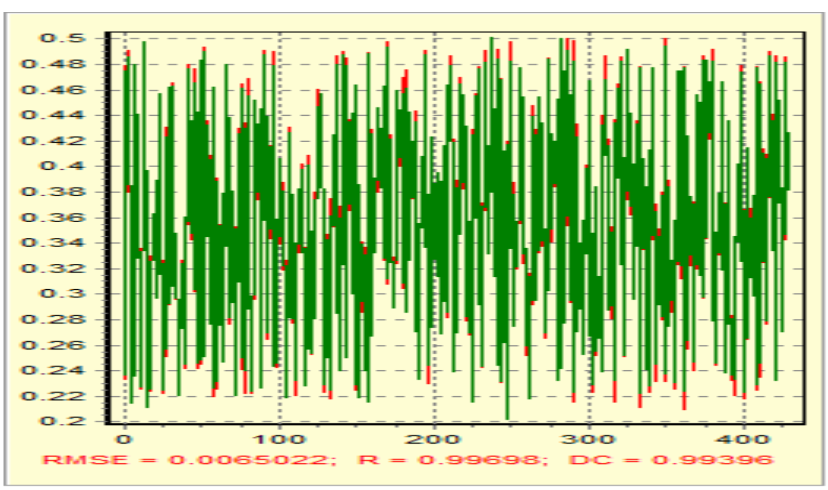


Figure 4.10- Training of the oxygen content in the five acre pattern.

Figure 4.11: Training of the initial injection rate in the 15 acre pattern.

Chapter 5

Results and Discussion

After all the training was performed for both the forward and the inverse model, the results predicted by these expert systems were compared to those results predicted by the simulator. The main objective is to have the expert system's output predictions within five percent of the output obtained via the numerical simulator. This chapter will display those results as well as discuss how greatly the variables from reservoir properties and design parameters affect an actual in-situ combustion project.

5.1 Sample compilation of the results obtained by the expert system

Table 5.1 below presents the results of the forward model of the neural networks in the five acre pattern compared to the results of the simulator with the predictions of the expert system. The goal of the forward neural network was to predict three production values using given reservoir properties and a few design parameters. The focus of Table 5.1 is solely on the oil production of the five acre pattern. From Table 5.1, the reader can understand where the ANN vs simulator figures shown later in the chapter was drawn from. This is one such example.

Table 5.1 Oil Production results for the five acre pattern.

CMG (MSCF)	ANN(MSCF)	Percent error
612.3400	612.088	0.041177
574.9000	571.6871	0.562012
483.2700	481.3927	0.389964
441.9900	447.6606	-1.26673
768.3700	739.8034	3.861372
784.8100	842.8161	-6.88242

669.7100	665.1587	0.684243
904.2500	909.0428	-0.52724
969.8600	965.0507	0.498349
574.4000	561.9175	2.221417
460.4750	450.3656	2.244703
708.6100	723.8886	-2.11062
585.3200	594.9556	-1.61955
565.7400	556.2779	1.700963
864.5600	856.0879	0.989636
766.6700	765.7743	0.116963
573.8200	579.1794	-0.92535
549.6200	550.5023	-0.16027
773.1000	751.1012	2.92888
1037.8000	1028.408	0.913295
958.7900	967.4208	-0.89215
942.7300	941.3574	0.145809
862.8500	865.1783	-0.26912
576.2500	579.6248	-0.58224
769.8700	762.2113	1.004803
735.5400	754.2821	-2.48476
678.7300	685.1519	-0.93729
672.1100	686.9076	-2.15424
889.1700	872.4052	1.921678
739.9500	740.624	-0.091
1295.0800	1267.078	2.209958
533.0330	525.8835	1.359525
809.3500	786.8874	2.854617
604.6400	596.7169	1.327784
561.9200	551.2528	1.935091
1125.4700	1133.368	-0.69683
1329.4800	1284.611	3.492808
608.8800	607.3914	0.245084
606.5200	608.795	-0.37369
868.6400	876.6224	-0.91058
1010.8700	984.2297	2.706712
468.2900	470.5176	-0.47344
430.0450	425.2285	1.13268
821.1900	841.0715	-2.36383
1059.9300	1094.535	-3.1616
533.1850	525.0016	1.55874
663.9400	627.893	5.740946

By observing Table 5.1, the accuracy of the forward model for the five acre pattern predicting oil production is accurate. The biggest prediction error in the table is at 6.83 percent which means the average error for this expert system is well below five percent. From this table, this compact ANN figure was created. All ANN figures use the blue to denote the numerical simulation and the red to denote the ANN predictions):

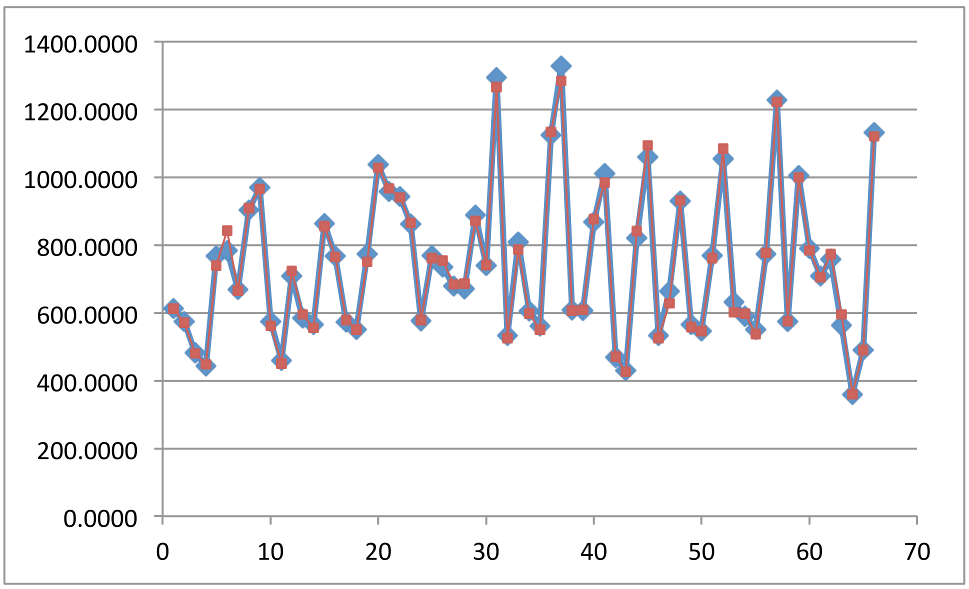


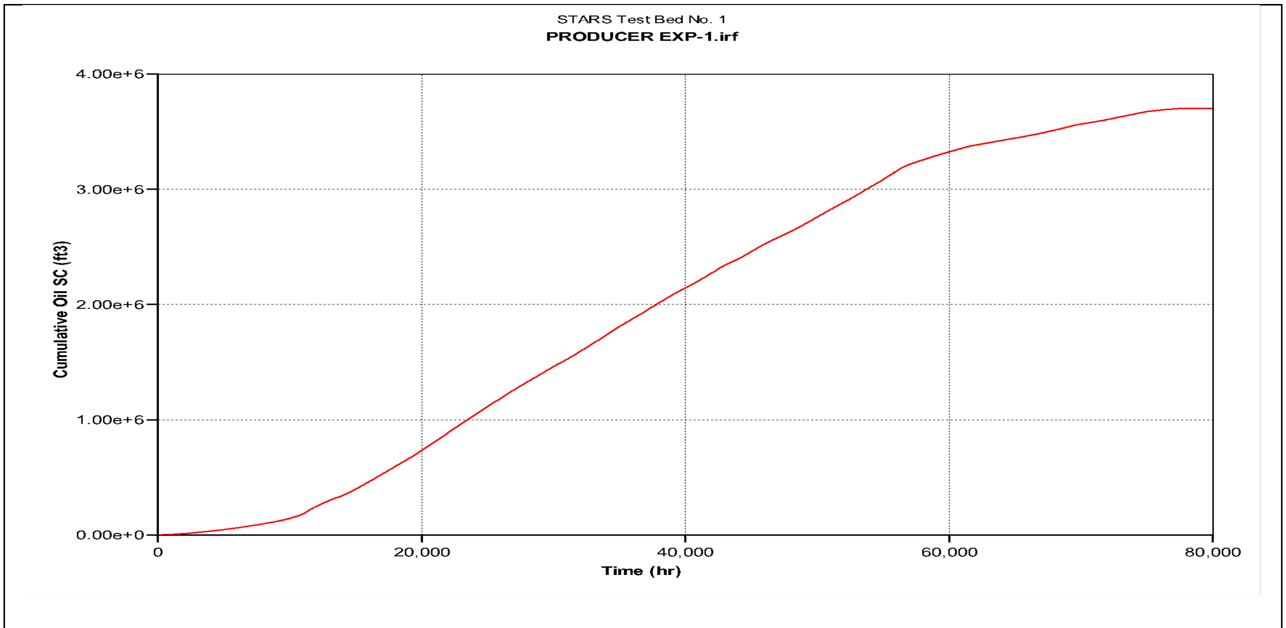
Figure 5.1: Oil production (MSCF) vs number of validation data.

This is just one figure showing the accuracy between the numerical simulation and the ANN predictions. From Figure 5.1, one can see the accuracy of the expert system when compared with the numerical data simulation. The remaining ANN vs simulator figures will be presented later in the chapter to show the accuracy of the expert system, however, a discussion on the effects of reservoir properties and design parameters will be presented first to give a better understanding on their role in the process of dry forward in-situ combustion.

5.2 Reservoir properties effects on ISC projects

There are many factors that affect the oil production for an in-situ combustion project. The main reservoir properties that affect oil production are the oil saturation, the porosity and the thickness of the reservoir. These three properties are the more important factors when an in-situ combustion project is considered.

The figures 5.2 to 5.4 on the following pages show how these three factors can affect oil production. As mentioned before, these three reservoir properties are some of the first few reservoir properties to be inspected before a decision on a production product is made since they are vital to a project's success.



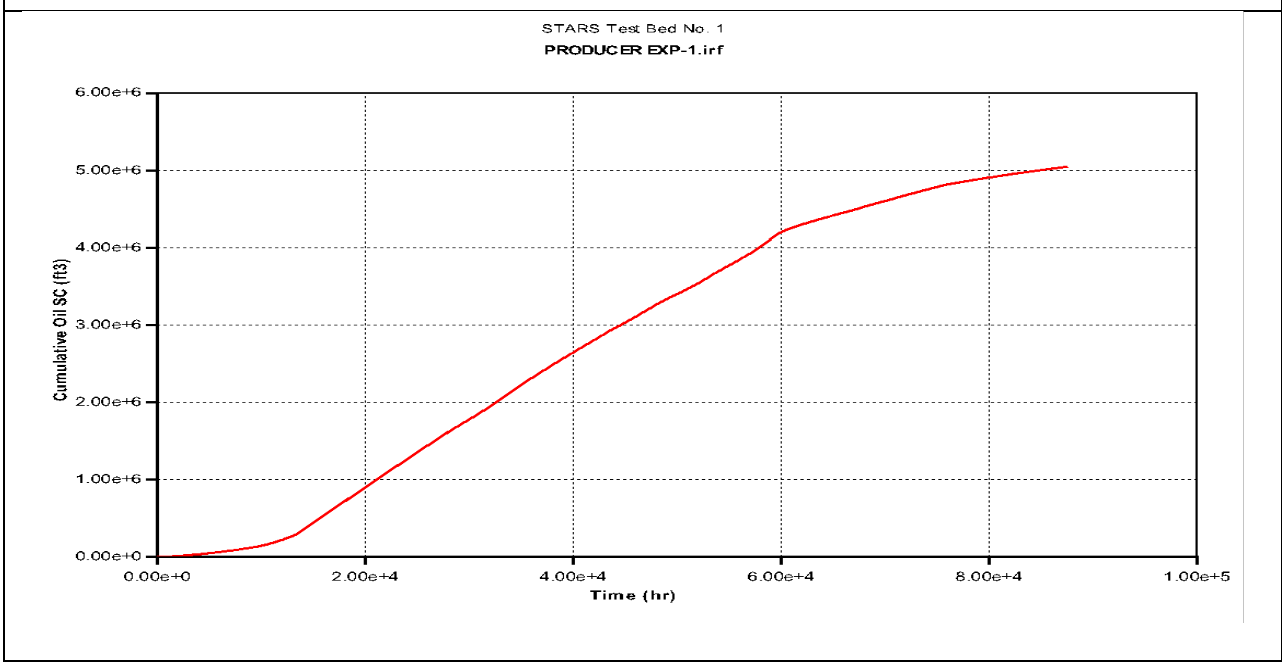


Figure 5.2- Effects of porosity on oil production. The top graph had a porosity of 0.25 and the bottom graph a porosity of 0.30.

Figure 5.2 shows how the results for oil production will be different with each variable held constant except porosity which was raised from 0.25 to 0.30. The difference of oil production is more than one million MSCF.

Figure 5.3 on the next page shows how oil saturation can affect oil production:

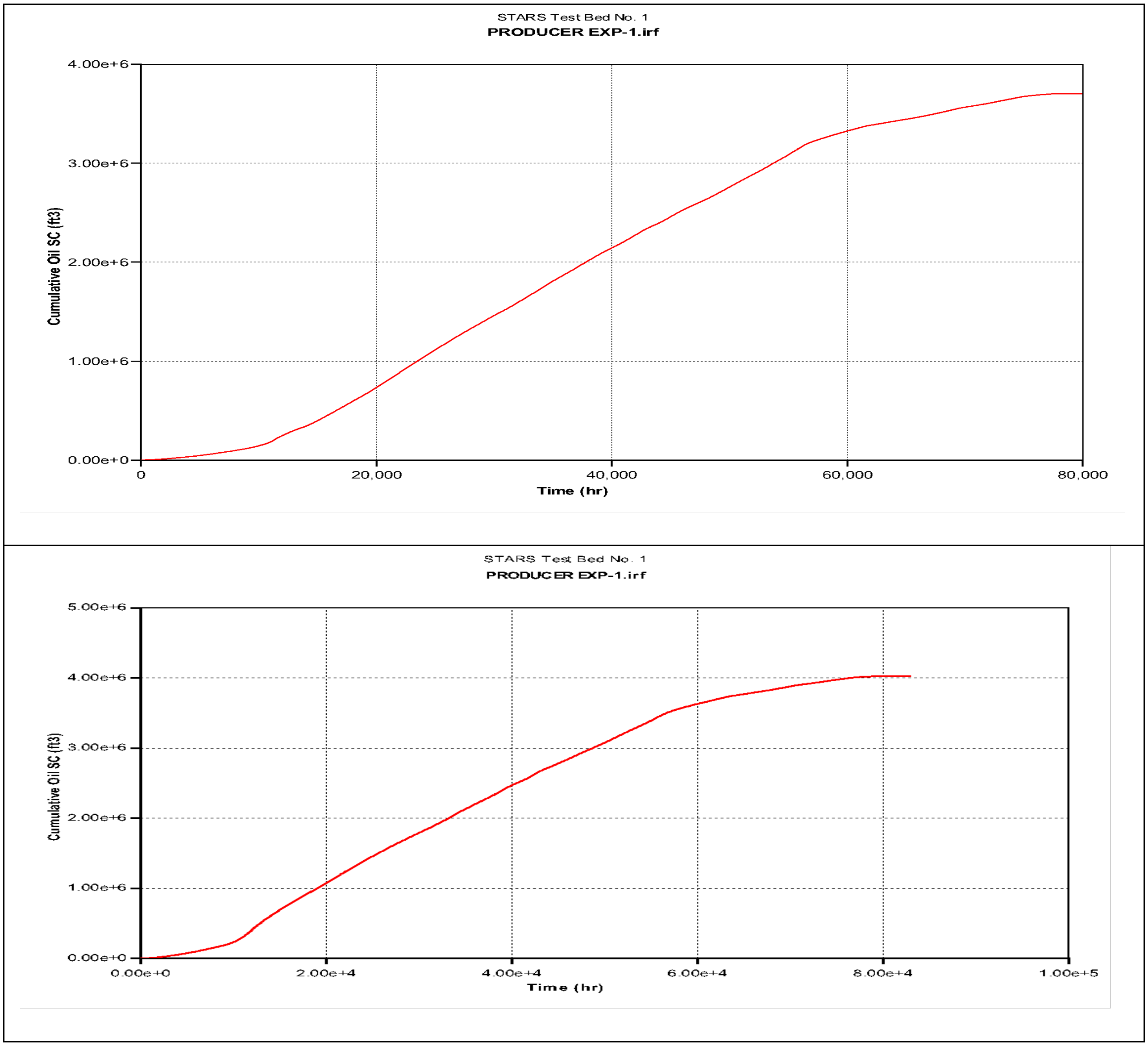


Figure 5.3- when oil saturation was raised from 0.65 to 0.70. The top graph has an oil saturation of 0.65 and the bottom graph has oil saturation of 0.70.

Just by raising the oil saturation by 0.05, an extra 200,000 SCF of oil would be produced. Another obvious reservoir property that affects oil production is the thickness of the formation. The thicker the formation is, the more oil in place (OOIP) the reservoir has. These three reservoir properties were arbitrarily selected for this project but in real life projects the reservoir thickness is one of the first things a reservoir engineer looks for as they are critical in the determining the success of an oil production project.

Permeability is the next reservoir property variable to be examined. From the simulations performed for this work using a permeability range of 500mD to 2500 mD, permeability has a role in the abandonment time of the project and also the economics. If the permeability is too low, it has to be offset with a higher injection rate and possibly more oxygen content to aid in the combustion movement in the reservoir which will in turn make the project more expensive. Since the stopping criteria for the simulations is if the producer well reaches 550 degrees F, a low permeability in the reservoir will take longer to reach that threshold than a reservoir with a higher permeability. Consequently, if a 25 acre pattern is designated to be produced in only 10 years and no more, and the economic constraints do not allow a higher injection rate nor a high oxygen content of the injection, the combustion front will not reach that 550 degree threshold and will decrease the overall production in the reservoir since the combustion was not maximized.

Another way to view the situation is what happens when two reservoirs with differing permeability reach the threshold temperature of 550 degrees in the production well with every reservoir property and design parameter held constant. The overall cumulative oil production will stay the same, but the production rate will be higher since the reservoir with the higher permeability will reach the production well threshold of 550 degrees F quicker. On the next page is an illustration of how permeability alone can affect the shape of the production and how fast it can be done. Overall production is more or less the same, but the time that it takes to produce theoil is different. The first graph is a production profile of a reservoir with permeability of 1000 mD and the second graph is the same reservoir in terms of all the properties and design decisions, except this time, the permeability was raised to 1500 mD.

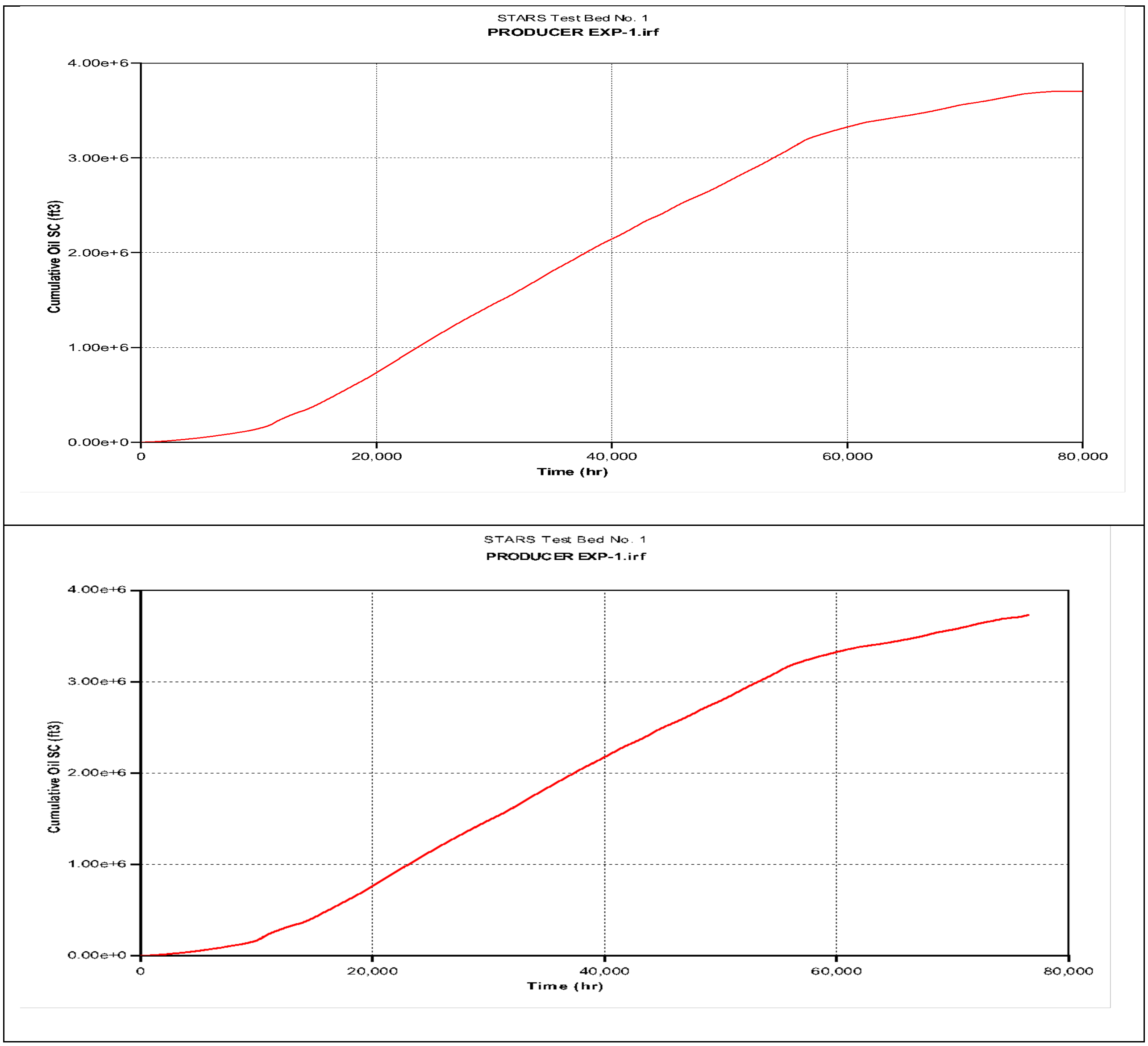


Figure 5.4- Permeability effects. The top graph used a permeability of a 1000 mD and the bottom graph used a permeability of 1500 mD.

From looking at the figures of the permeability effects, the difference in abandonment time is not too significant but it is present. The first graph with 1000 mD finished overall production in 80,000 hours or 9.20 years while the second graph with a permeability of 1500 mD finished producing after 74,000 hours or 8.44 years.

5.3 Design parameters affecting ISC projects.

Permeability is a reservoir property that affects the speed of the oil production; however, it is not as influential for the role of production speed when compared to either injection rate or the oxygen content of the injection. Again, this is a give and take situation since increasing injection rate and oxygen content in the injection will speed up the production process but, unlike permeability, these two design parameters come with a cost. It is not necessarily beneficial to neither maximize the oxygen content nor the rate of injection due to this reason. For example, an oxygen content of 0.50 will make the project time shorter while producing a similar amount of oil when compared to the slower process of 0.21 oxygen content. But will the saved time in the project cover the cost of the higher oxygen content usage? That question could be answered with an economical model that studies these two decisions. So, for a given reservoir, it is conceivable that the ideal solution to maximize profit could either be the minimum oxygen content in injection and injection rate, the maximum or somewhere in between. This work does not focus on the economic model of the reservoirs, so the next set of figures will only show how injection rate and oxygen content of injection will affect abandonment time and production rate. To demonstrate the effects of the oxygen content, the first graph is a simulation run with an oxygen content of 0.23 and the second graph is a simulation run using 0.50 oxygen content. Both figures (will be shown on the next page).

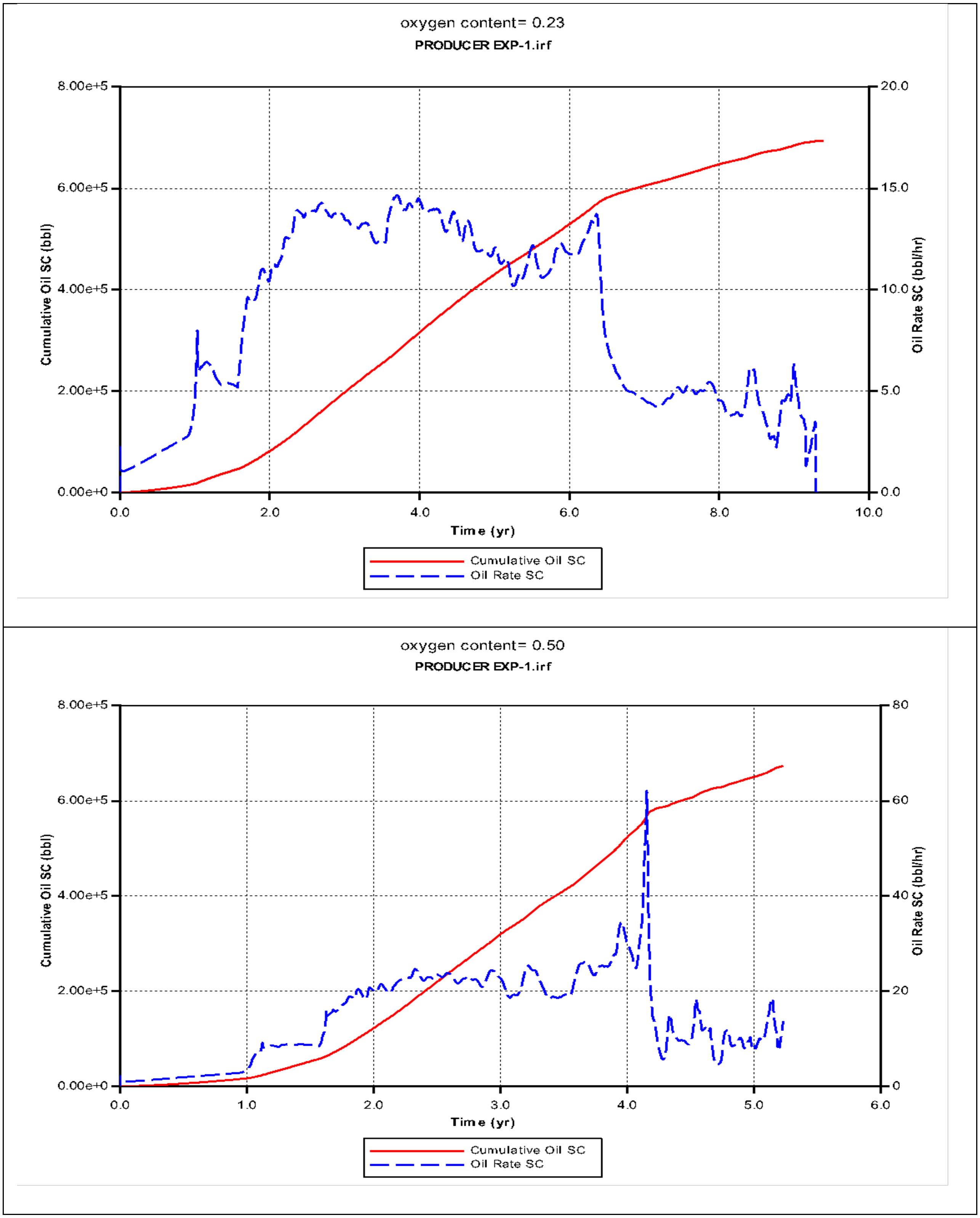


Figure 5.5 – Oxygen content effects on oil production. The top graph uses 0.23 oxygen content and the bottom graph uses an oxygen content of 0.50.

One can see the effects of using higher oxygen content in this example. The oil flow rate using lower oxygen content was significantly lower than when using higher oxygen content. This is due to the slower combustion front movement when using lower oxygen content. Also, using lower oxygen content in injection made the project approximately three years longer when compared to the simulation that used a higher oxygen content of injection. In accordance with an ISC study (Adewusi et al,2002), the increase of injection rate will yield an earlier time of oil production when compared to regular air injection processes. Not only that, the oil produced will have lower viscosity and a higher API gravity level due to the faster velocity of combustion.

The next area to be examined is the injection rate and how it affects the oil flow rate and abandonment time. One thing to consider is that this work deals with three different sized acre patterns. So, the injection rate was adjusted for each pattern. Each pattern features an initial injection rate and naturally the bigger patterns have the largest initial injection rate. Furthermore, the simulations used the technique of the incremental increase of injection for each simulation run. The rate of increase of the injection rate also differed when performing a simulation run of a bigger pattern size. For example, for the smallest pattern of five acres the initial injection rate was 150,000 SCF/day and used an incremental increase of 250,000 SCF/day per year. The 25 acre pattern used an initial injection rate of 300,000 SCF/day while using an incremental increase of 500,000 SCF/day per year. If the incremental increase was kept constant for all the patterns, the largest pattern would suffer in its production due to its larger radius of the combustion front. Thus, an adjustment was made to make the incremental increase of injection rate bigger for the bigger sized pattern due to this logic. Most laboratory tests have used constant injection rates to study the behavior of in-situ combustion projects and some runs of those types were made for comparison purposes. Figure 5.6 on the next page show how production rate and abandonment time are affected when both techniques are used (constant injection and incremental increase of injection rates.

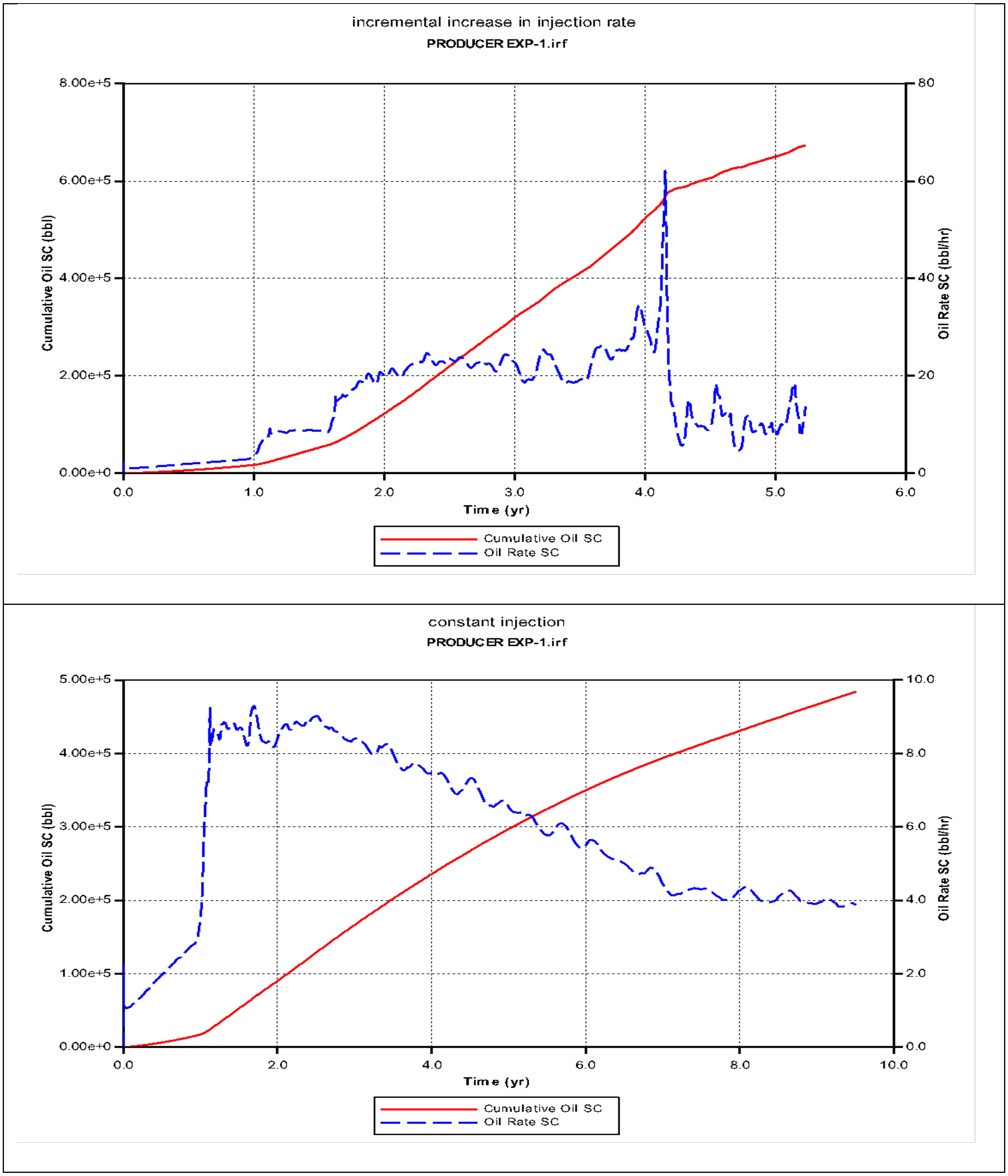


Figure 5.6 – Incremental increase in injection effects on oil production. The top graph uses the incremental increase of injection rate while the bottom graph uses constant injection.

If the incremental increase in injection rate is kept constant for all the different sized acres, the production in the larger sized patterns will surely suffer as the combustion front movement in the larger pattern will not be fast enough. Since the larger patterns cover a larger space, with a lower rate of injection, the combustion front will not move as well and affect oil production. If the incremental rate of injection rate is too high for the smaller sized patterns, too much of the oil in place will be burned and it will also affect the oil production adversely. In addition, the operational costs with those higher injection rates will rise. Thus, it is important to have different initial injection rates and also differing incremental increases in the injection rates for different sized patterns with the larger patterns obviously having a larger initial injection rate and a larger gap between their periodical increases in injection rates.

The last variable to be discussed is the size of the pattern in which in-situ combustion will be used in. If a reservoir engineer decides to use a series of small patterns, there will be a need to use more injection and production wells over the whole field than if using a larger sized pattern. Again, this is where economic analysis can show which technique would maximize profit. The high costs of using more wells (injector and producer) will be offset by the shorter abandonment time when using those smaller sized patterns. There will be less worry about increasing interest rates, damage of equipment when compared with projects that have a longer project time. Another advantage of lowering the abandonment time is that a reservoir engineer can more quickly evaluate the project's success rate, another important aspect of the economics of petroleum. A shorter abandonment time will allow the reservoir engineer to know if the remaining prospect of the project will be profitable. The figures on the next page show the production profile when using three different sized patterns of five acres, 15 acres and 25 acres respectively.

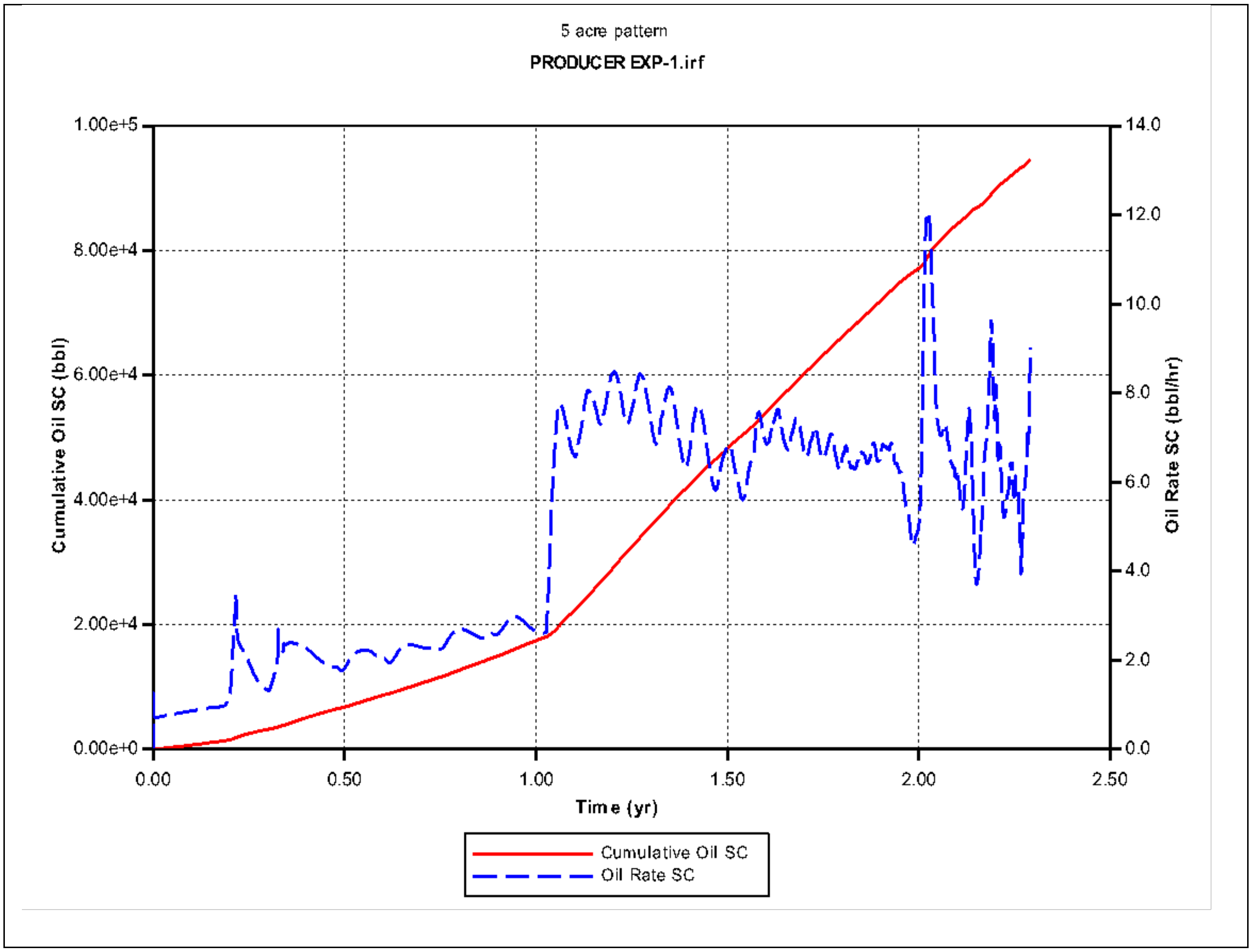


Figure 5.7 – Pattern size effects on oil production (five acre pattern).

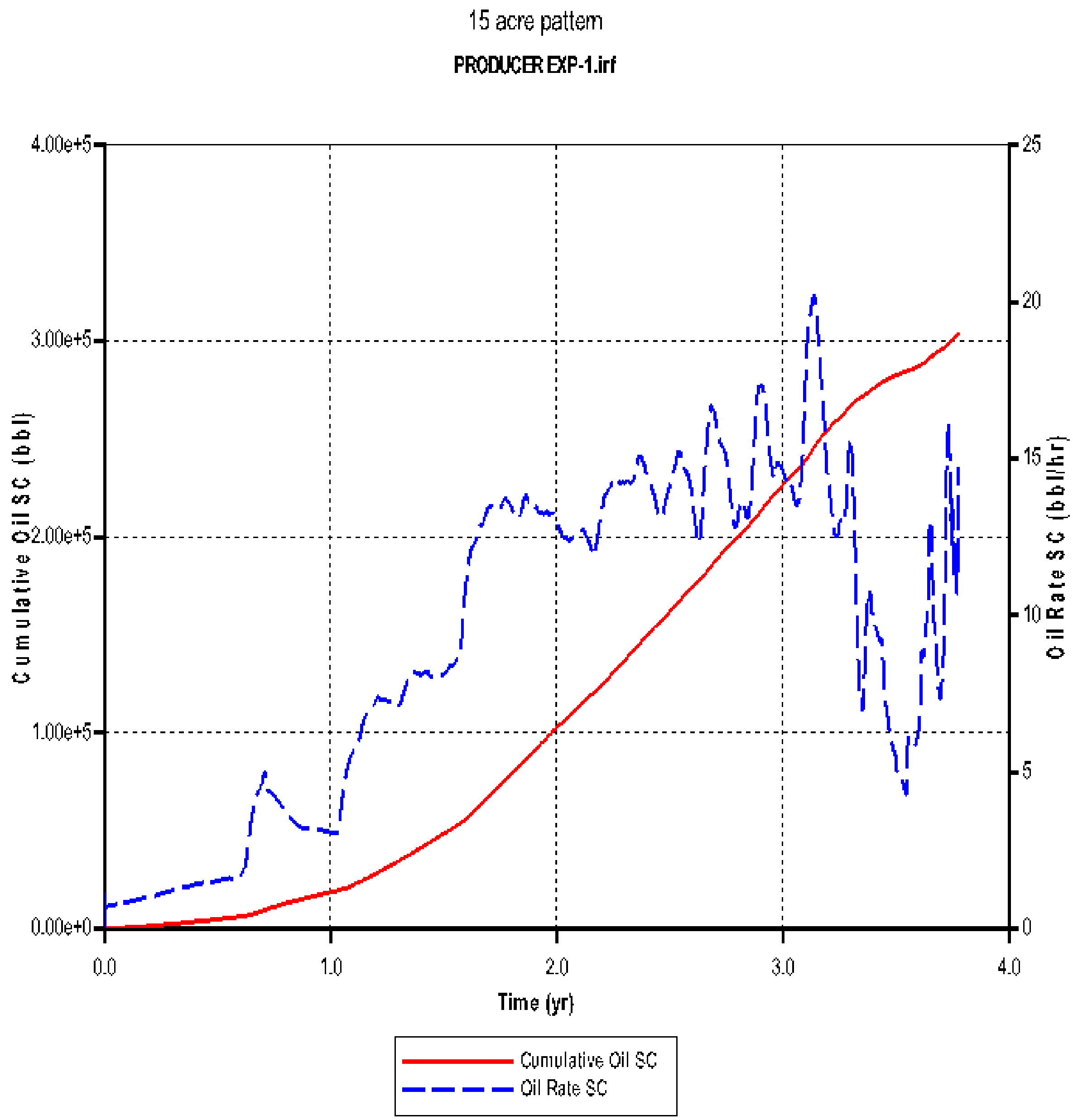


Figure 5.8: Pattern size effects on oil production (15 acre pattern).

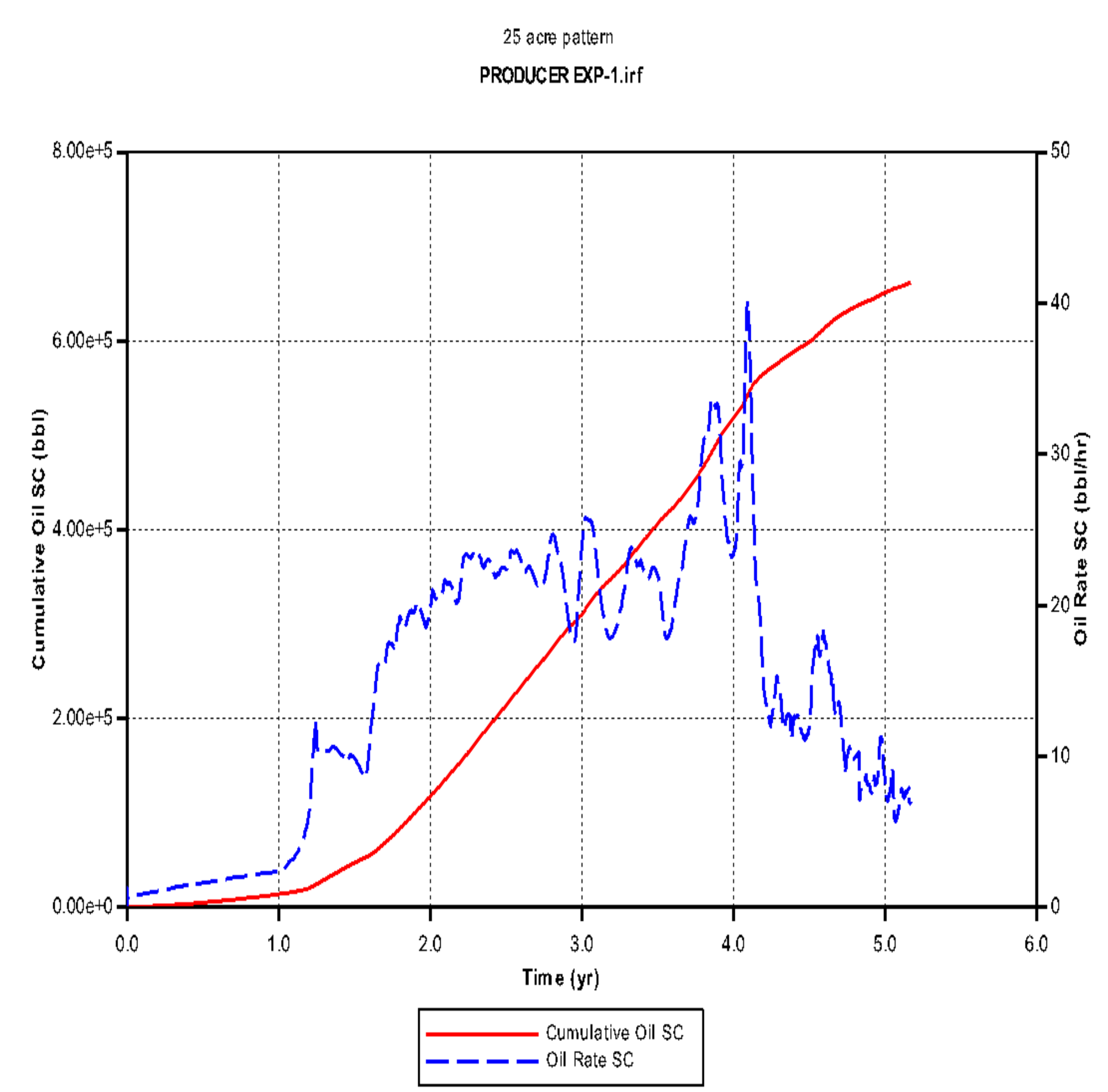


Figure 5.9:Pattern size effects on oil production (25 acre pattern).

5.4– Neural network results.

Now that the reader understands how the factors predicted in the expert system affect the general ongoing of an in-situ combustion project, this section will provide graphs to show how the expert system was able to function and predict the rest of the variables and design decisions in all the different sized patterns

5.4.1 Results of the forward model of the expert system

These figures on the following pages are results of the validation data for the forward ANN developed for the five acre 15 acre and 25 patterns. They all use two layers in the architecture with 18 and 13 neurons respectively and a learning rate and momentum of 0.8. The transfer function used for both layers was the sigmoid transfer function. The stopping criterion was when the correlation factor reached 0.99.

Figures 5.10 to 5.12 represent the validation data results for the five acre pattern. The blue lines represent the results from the CMG simulation and the red lines represent the data predicted by the ANN.

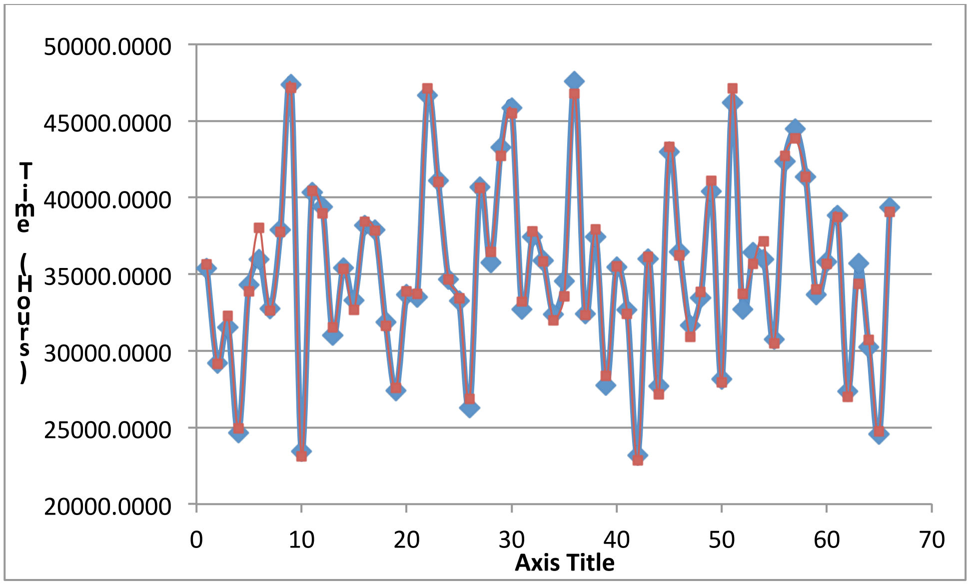


Figure 5.10: Total time of project (hrs) vs the number of validation data.

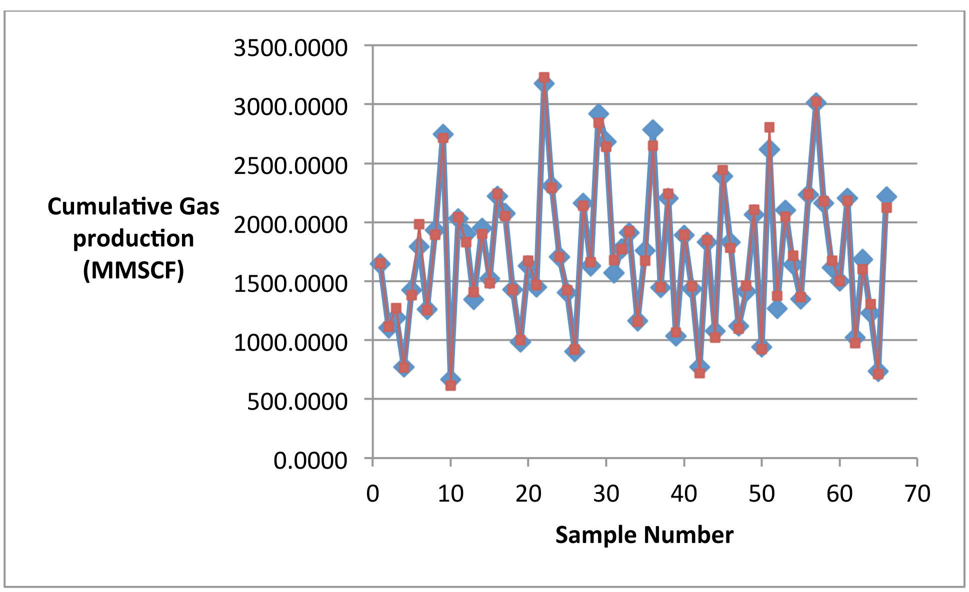


Figure 5.11: Cumulative gas production(MMSCF) vs number of validation data .

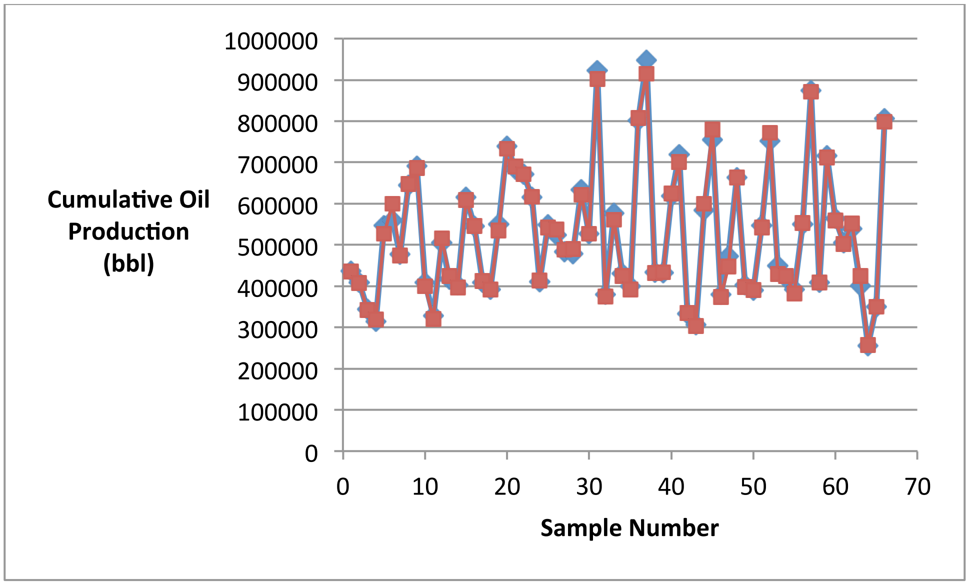


Figure 5.12: Cumulative oil production (bbl) vs number of validation data.

The next set of figures of 5.13 to 5.15 represents the validation data for the 15 acre pattern of the project still predicting the three outputs of oil production, gas production and abandonment time.

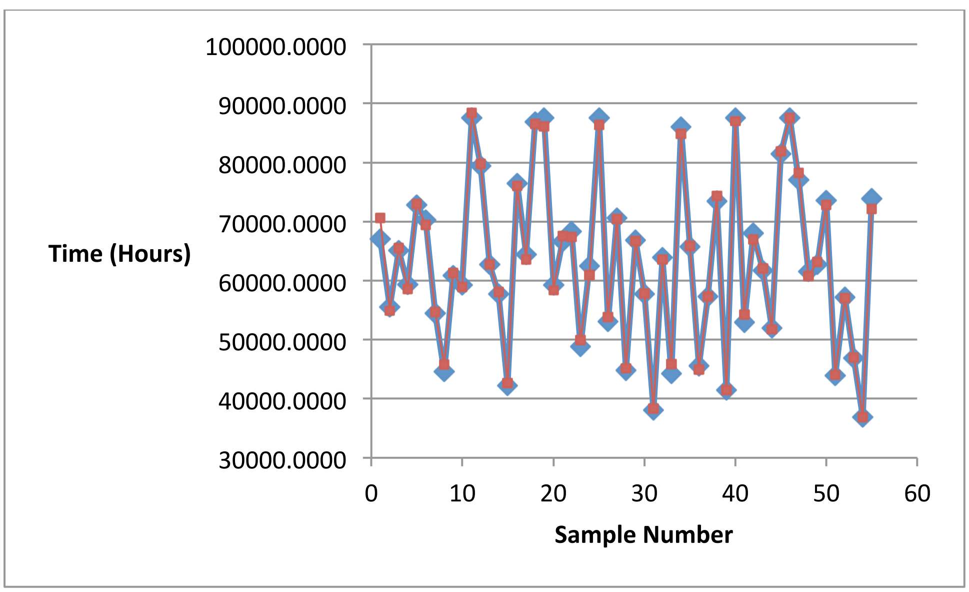


Figure 5.13: Total time of project (hrs) vs number of validation data.

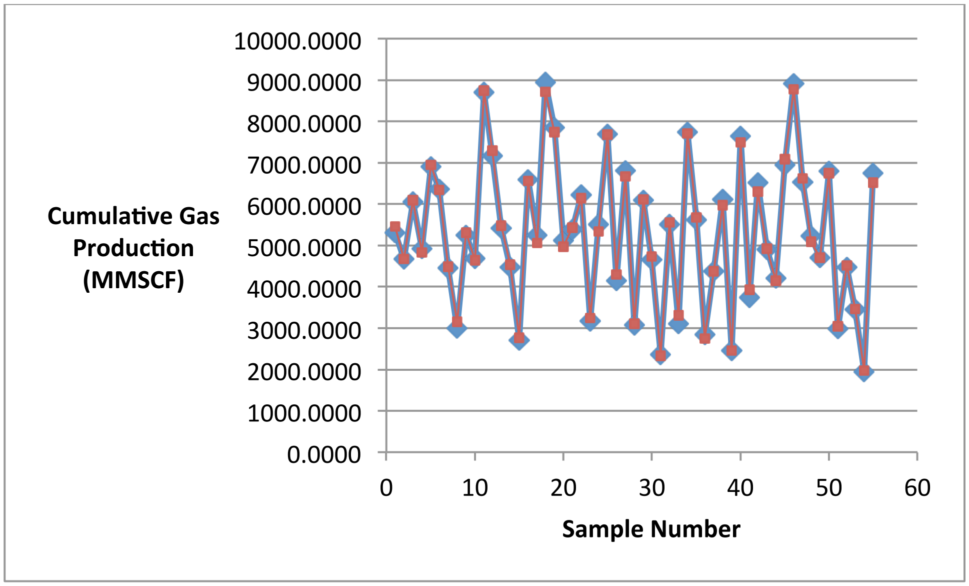


Figure 5.14: Cumulative gas production (MMSCF) vs number of validation data.

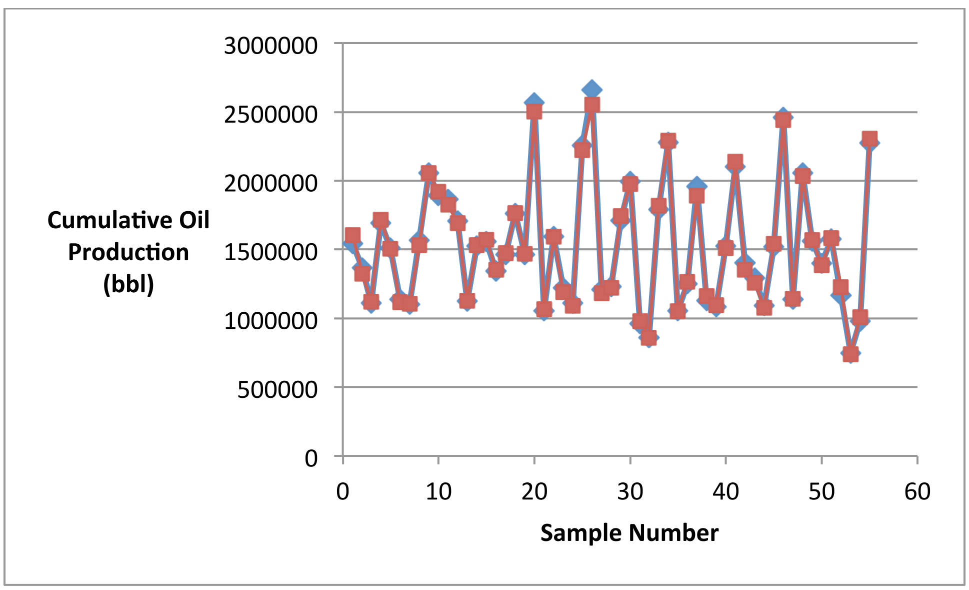


Figure 5.15: Cumulative oil production (bbl) vs number of validation data.

Now for the 25 acre pattern and its three output results of oil production gas production and abandonment time represented by figures 5.16 to 5.18:

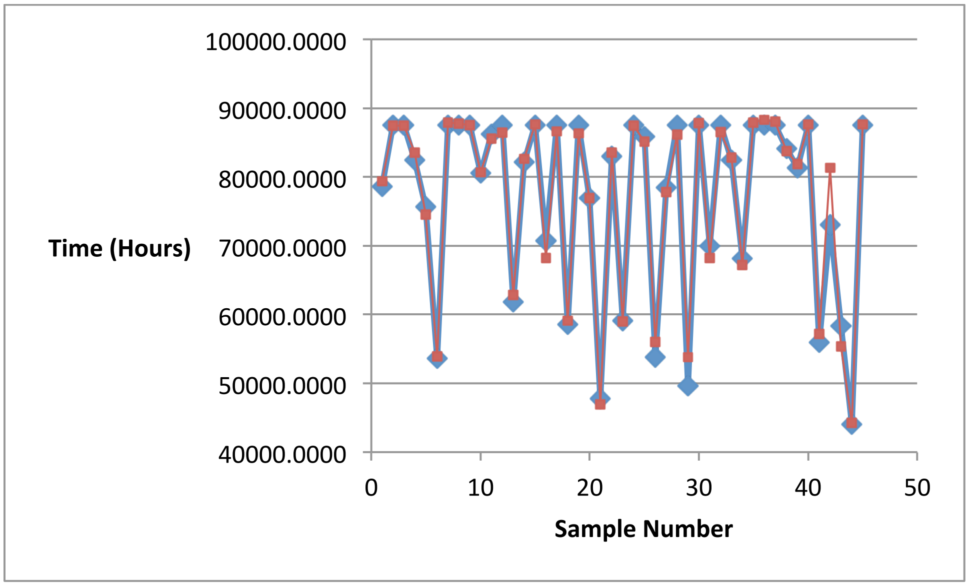


Figure 5.16: Total time of project (hours) vs number of validation data.

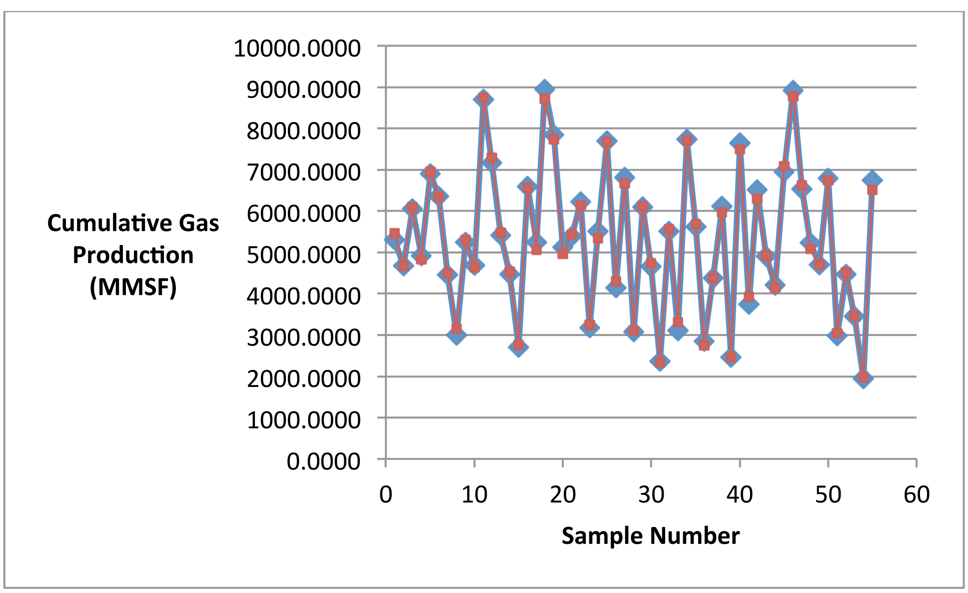


Figure 5.17: Cumulative gas production (MMSCF) vs number of validation data.

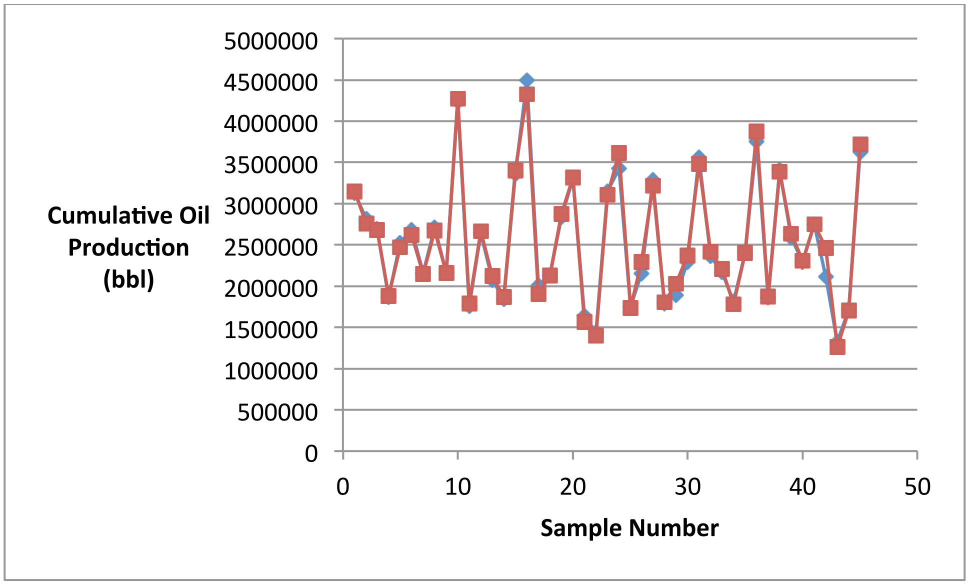


Figure5.18: Cumulative oil production (bbl) vs number of validation data.

For the forward model and the three different acreage sizes, the results showed that the architecture was stable. The largest error for the forward model was just over seven percent and the average error for each pattern was below five percent. Due to these statistics, the development of the forward model was finalized and the focus was shifted into checking the more challenging inverse model results.

5.4.2 – Results of the inverse model of the expert system

The next set of figures from 5.19 to 5.24 represents the validation data for the inverse model of the ANN for the five, 15 and 25 acre patterns. The design decisions to be predicted were initial injection rate and oxygen content of injection in the producer. The architecture used for the inverse model was different. It used the same two layers but the number of neurons for each layer was 36 and 31 respectively. A learning rate and momentum of 0.8 were used along with the stopping criteria of 0.99 correlation factor. The transfer functions used for each hidden layer were also the sigmoid function.

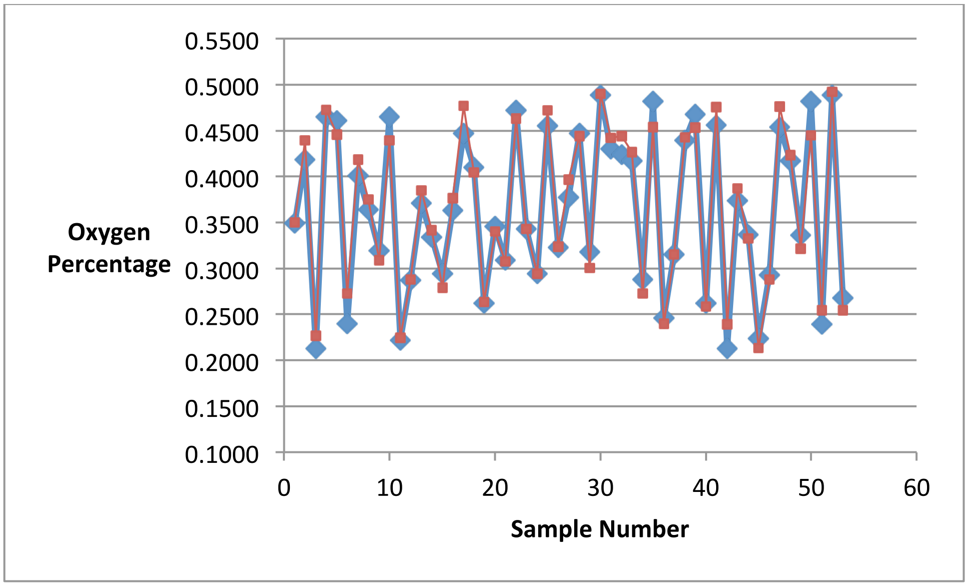


Figure 5.19: Oxygen percentage in injection (pct) vs number of validation of data.

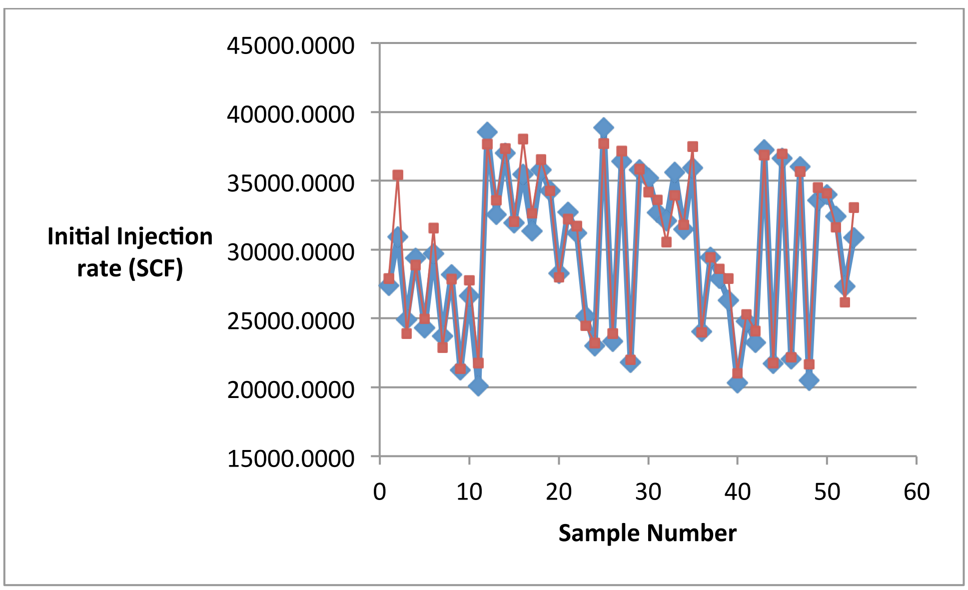


Figure 5.20: Initial injection rate (SCF) vs number of validation data.

Now for the 15 acre pattern:

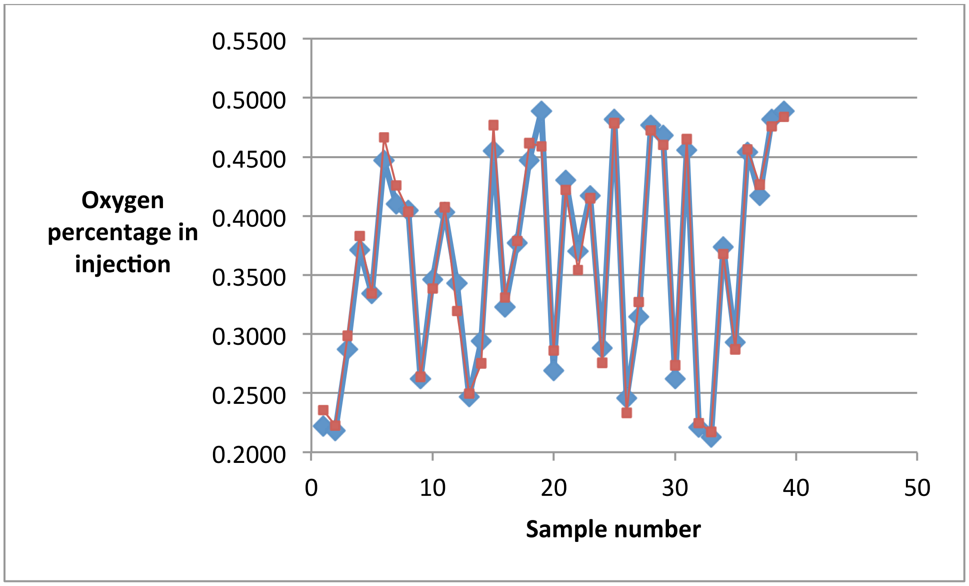


Figure 5.21: Oxygen content of the injection vs number of validation data.

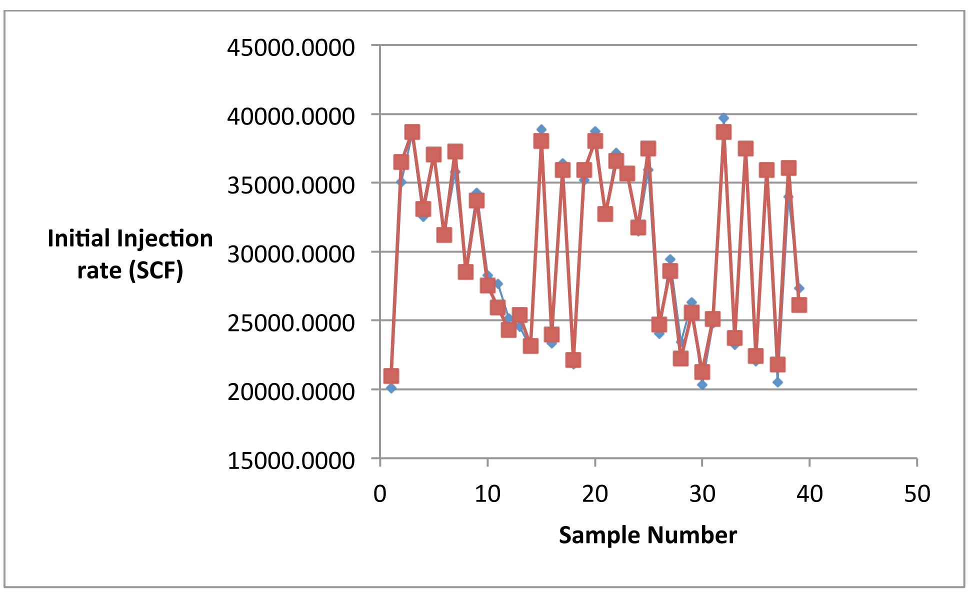


Figure 5.22: Initial injection rate (SCF) vs number of validation data.

Now for the 25 acre pattern:

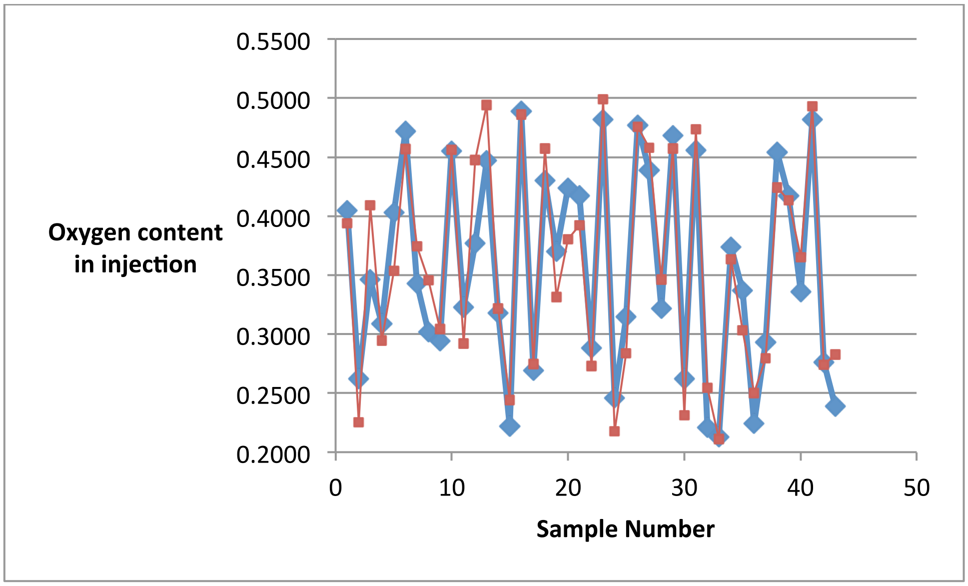


Figure 5.23: Oxygen content in injection vs number of validation data.

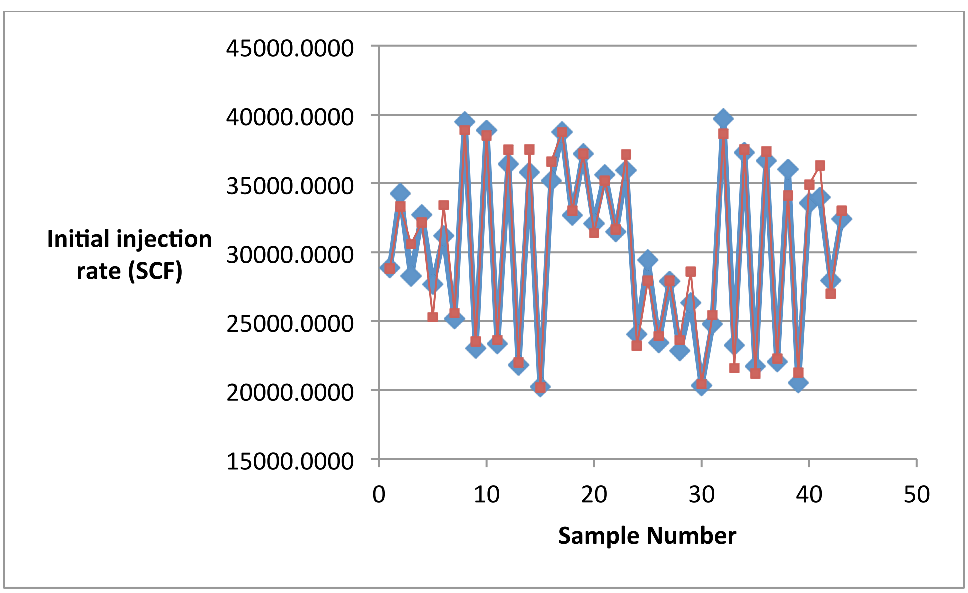


Figure 5.24: Initial injection rate (SCF) vs number of validation data.

As one can see, the accuracy of both forward and inverse expert systems was sufficient. The forward model was more accurate because the neural network predicts a unique solution while for the inverse model, the solution is not unique. Also, since the solutions are not unique for the inverse model, some the results were then fed back to the simulator to verify if the production and abandonment time matched the expected values. Just by verifying the statistics of the inverse model, for all the three different sized patterns, the largest error was at 12 percent. However, the average error was still below the target of five percent. The final statistics also reinforced the fact that the inverse model is a more challenging task to complete. The average error for the forward model was well below five percent, but the average error for the inverse model just was below the five percent target.

Conclusions

In this study, the importance of several reservoir properties in the in-situ combustion process has been established. Furthermore, it is seen that ISC processes are driven by the injection parameters of the project such as the injection rate and the oxygen content of the injection. A total of 1200 reservoir systems were ran via a thermal simulator and its results of oil and gas production as well as their abandonment time were used for training and validating of the expert system.

Due to the large number of data and its wide scope of range, the forecasting of results of production that was obtained via the development of the expert system needed to be tested even more. This was done by testing the expert system against randomized input variables that were within the original range of each input variable but with a combination that the expert system had never seen before. After obtaining the results via the numerical simulator, the predictions of the expert system were very similar to those simulator results.

The inverse model was also developed for this in-situ combustion project predicting what design parameters injection rate and oxygen content of injection) needed to be taken to reach a specified production goal. This aspect of the expert system is imperative for later development of an optimization model and a detailed economical analysis for this particular work. The following conclusions were reached after studying the forward in-situ combustion process of heavy oils of medium to high permeability:

1) Oil saturation, formation thickness, and porosity are the most important reservoir properties for production since it indicates how much oil/gas is inside the system initially.
2) Permeability plays a decent role in speeding up the process of production and will save time for the project to enhance profit.
3) Injection rate and the oxygen content of the injection are the most influential design parameters in an in-situ combustion project. Too high of an injection rate will burn too much of the oil in place and not enough injection rate will stunt the movement of the combustion front. Both problems will lead to inefficient production.
4) Building the expert system for both the forward and the inverse models required testing the output results so that the system did not over/under-train. Therefore, the selection of the number of hidden neurons is crucial. The wrong choice will lead to over or under-training. Firstly, the samples to be run need to cover both extremes of the spectrum of the input variables' range and secondly, the expert system needs to be validated by checking its output prediction capabilities with randomized input data. It ensures that the expert system does not only memorize a particular section of the data field but the whole area of the field.
5) The forward model of the ANN provides a unique solution in the prediction while the inverse model does not.
6) There needs to be an adequate economical analysis to determine which combination of variables provides the most profitable solution. For a specific field, a five acre pattern configuration could be the best, while for some other fields a 25 acre pattern configuration is most efficient.

7) Incremental increase of the injection rate should be used due to the continually increasing radius of the combustion front. If the injection rate is constant throughout and it is too high at the start, too much oil could be burned which will reduce the overall oil production, but if the injection rate is not sufficient, the combustion front will be slowed down significantly in the later stages of the project and will negatively impact the production of the reservoir as well.
8) This work lays the base foundation for future work in this area. By reading this thesis, one should understand the main factors that affect the ISC process as well as how inputs and outputs need to be used to create an accurate expert system.

Limitations and future work possibilities

1) The expert system developed is for one type of heavy oil. A study could be made for various fluids in reservoirs ranging from light oil to medium-heavy oil.
2) The study concentrated on reservoirs of medium to high permeability and a study can be extended in inspecting reservoirs with low permeability.
3) The reservoirs studied were of the constant porosity type. Perhaps, another study could be done for reservoirs with variable porosity levels.
4) No economical analysis was done for this work, however the foundations to building an economical analysis model were made after developing the inverse expert system. Economical analysis is a key component of the reservoir engineer as financial support is the backbone of any EOR processes and especially for in-situ combustion since not many field scale projects have been done using this technique when compared to steam or CO2 injection.
5) The well configurations could also be added for future studies. In this work, a conventional five spot setting was used with one injector in the center and four producers on the corners. A nine spot pattern could be added for study as one of the design parameters of an in-situ combustion project.

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