CANDIDATE SELECTION PROCESS FOR POLYMER GEL APPLICATION BY USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

CANDIDATE SELECTION PROCESS FOR POLYMER GEL APPLICATION BY USING ARTIFICIAL NEURAL NETWORKS

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Rapid increase in water-oil ratio has been one of the most important challenges of the oil companies that are producing from the mature oil fields. For this reason, various studies have been conducted to diminish the excessive water production. One of the most widely used chemical shutoff technique, polymer gel treatment, involves injection of different polymers into the production wells in order to plug the easy flow pathways of the excessive water.

For the successful application of the polymer gel treatment, selection of the candidate wells is crucial. Consequently, this study aims to find a methodology that would be helpful during the candidate selection process and investigate the parameters dominating the successful applications. In this study, MATLAB® codes are developed in order to get benefit from the Artificial Neural Network technique for the candidate selection process and production data of the 60 wells are used for the simulations.

Throughout this study, data pre-processing is applied to the available dataset in order to obtain more utilizable dataset. Here, some inconsistent field data is eliminated. Then, by using the dataset some success criteria that represent the success rate of the treatments are determined and calculated. Before performing a neural network analysis, Principal Component Analysis (PCA) is performed and dominating well parameters in the data set are identified. Then correlation analysis is performed and some of the irrelevant parameters are excluded from the neural network analysis. Finally, by combining the PCA and correlation analysis different scenarios are developed for each success criterion and 450,000 different neural network structures are developed for the entire study. For each success criterion, the most successful neural networks are selected and their error levels are also presented.

Keywords: Polymer gel treatment, Water shutoff, Production trend, Heavily fractured reservoir, High water cut.

ÖZ

YAPAY SİNİR AĞI KULLANILARAK POLİMER JEL UYGULAMASI İÇİN ADAY SEÇİMİ

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Su-petrol oranındaki ani yükseliş olgun sahalardan petrol üretimi yapmakta olan petrol şirketleri için en büyük zorluklardan birisidir. Bu nedenle, aşırı su üretimini azaltmak amacıyla çeşitli çalışmalar yapılmıştır. En çok kullanılan kimyasal su kesme yöntemlerinden birisi olan polimer jel enjeksiyonu; farklı polimerlerin, aşırı suyun geldiği kolay yolları tıkamak amacıyla üretim kuyusuna basılmasından ibarettir.

Başarılı bir polimer jel uygulaması için, aday seçimi kritik önem arz etmektedir. Sonuç olarak, bu çalışma aday seçimi konusunda yardımcı olacak bir yöntem geliştirmeyi ve başarılı uygulamaları yönlendiren unsurları incelemeyi amaçlamaktadır. Bu çalışmada, aday seçimi konusunda, Yapay Sinir Ağı yönteminden faydalanılabilmesi için MATLAB® kodları oluşturulmuş ve 60 kuyunun üretim verisi simülasyonlar için kullanılmıştır.

Bu çalışma süresince, daha kullanılabilir veri seti elde edebilmek için veri çeşitli işlemlerden geçirilmiştir. Burada, bazı tutarsız saha verileri elenmiştir. Sonra, veri seti kullanılarak uygulamanın başarı oranını gösteren bazı başarı ölçütleri oluşturulmuş ve hesaplanmıştır. Yapay Sinir Ağı analizinden önce, ilk olarak temel bileşenler analizi yapılmış ve başarı oranını domine eden parametreler tespit edilmiştir. Daha sonra, korelasyon analizi yapılarak başarı ölçütleri ile anlamlı bir korelasyona sahip olmayan parametreler Yapay Sinir Ağı analizinden çıkarılmıştır. Son olarak, temel bileşenler analizi ve korelasyon analizi birleştirilerek her bir başarı ölçütü için farklı senaryolar oluşturulmuş ve çalışma süresince 450,000 farklı yapay sinir ağı yapısı oluşturulmuştur. Oluşturulan bu yapılardan en başarılı yapay sinir ağları seçilerek hata oranları ile birlikte sunulmuştur.

Anahtar Kelimeler: Polimer jel uygulaması, Su kesimi, Üretim eğrisi, Yoğun çatlaklı rezervuar, Yüksek su oranı.

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CHAPTER 1

INTRODUCTION

1.1 General Background

In general, oil companies produce unwanted water in addition to hydrocarbons. Water cut levels increase as the oil field gets mature and eventually these high water cut values may impair the revenues of the oil companies. Some major problems associated with the excessive water production are; costs of processes like production, separation, injection and corrosion problems on pipes, pumps and other surface equipment. Also, increase in water cuts may increase the tendency to form emulsion; therefore, it could become necessary to treat produced fluids with emulsion breakers.

In literature, both mechanical and chemical water shutoff techniques are proposed to mitigate excessive water production. Among these techniques, polymer gel injection is widely used as it offers cost effective, environmentally friendly and safe solution to the excessive water problem. Raman field, which is a naturally fractured limestone reservoir located in the southeastern part of Turkey, has been struggling with the high water-oil ratio problem especially for the last decade. In order to relieve the high water cut trends in the Raman field, cross-linked polymer gel (polyacrylamide-chromium gel) treatments have been applied and promising results were obtained. However, in some applications, poor treatment outcomes are obtained that may stem from the inaccurate candidate selection.

Based on the available literature review, so many aspects should be reviewed before selecting the candidate well for the water shut-off treatments (Kabir et al., 1999). According to Kabir et al. (1999), as much of the following data as possible should be considered before determining the candidate wells; production history, well history (workover, perforation etc.), wellbore schematics, well logs (open hole and cased hole), reservoir and fluid properties, core reports and petro physical data, depositional environment and geology, fluid contact (OWC / GOC) movement and pressure history, structural maps and cross-sections, stick diagrams showing relative depth of perforations by reservoir, drive mechanism and depletion strategy, reserves information, simulation results, water control diagnostic plots. Also they stated that, if it is possible further diagnosis should be performed like fluid contact logs, water movement detection logs, production logging combination tools, cement bond log, noise logs, pressure build-up tests, tracer tests, downhole video camera and 4-D seismic results. However, generally, candidate well selections are performed based on the anecdotal screening guidelines or the past experience of the company, which often results in inconsistent treatment outcomes (Seright et al., 2003).

Researchers have been investigating the effect of different type of rocks, fluids, wells and gel properties over the production response of a well that was treated with polymer gels. Liang et al. (1993), suggested a mathematical model in order to resemble gel placement in producer wells. Based on this approach different authors, (Caicedo et al., 2005; Marin et al., 2002; Seright et al., 1998) have put forward advanced theoretical models to simulate gel behavior in the porous media and some approaches aim to estimate well productivity index. Parameters considered in these models are as follows; initial well producing rates, permeability, porosity, water and oil saturation near wellbore region, gel volume, percentage of basic sediments and water (BS&W), reservoir fluids characteristics, gel blocking characteristics, which is residual resistance factor to oil and to water.

Some other researchers have focused on the parameters like, well liquid rate, rock consolidation, lithology, rock wettability, reservoir fluids viscosity and salinity of the water in the reservoir (Prado et al., 2009; Llamedo et al., 2005; Pérez et al., 2001; Seright and Liang 1994; Seright 1992).

Once the effect of individual parameters over the polymer gel injection process is known, reservoir simulation can be used for the candidate selection in order to predict the performance of well after the treatment by evaluating the well data prior the treatment. However, reservoir simulation models demand extensive information about the reservoir such as rock and fluid properties, historical production data, geological reservoir model that are not always available for mature oil fields (Barati et al., 2006). Also, reservoir simulation models require detailed knowledge about processes such as gel chemical reaction and gelation time which adds a lot of uncertainty in the modeling of polymer gelation kinetics.

The basic idea behind this study is the extraction of the information from the previous treatments in order to make better candidate selections for the future treatments. Once the relationship between the well parameters and success rate of the gel treatments is obtained, it can be used to predict potential outcomes of the polymer gel application on the other wells. Artificial neural network (ANN), a kind of Artificial Intelligence system, could be used to extract and store experimental knowledge gained from the previous treatments. ANN’s are able to model both linear and non-linear problems; therefore, they have been used in many areas of science and engineering. ANN's are the computational structures which are constituted to generate, or at least mimic, intelligent behavior. These artificial systems are typically organized in layers, which are made up of large number of very simple and highly interconnected nodes (artificial neurons). Inputs are presented to the network by means of input layer, then they are processed at the hidden layers via weighted connections. Then the processed information sent to the output layer, where the inputs and corresponding outputs are compared and the weights of the connections are modified according to the learning rule (Kay, 2001).

Consequently, during this study, various scenarios are constructed by using the information obtained from the statistical analyses, namely principal component and correlation analyses. Then, MATLAB® codes are developed to construct artificial neural network structures for the candidate selection process and production data of the 60 wells from the Raman field are used for the simulations. Then various network structures are generated by using different training and verification sets and it is observed that success rate of the candidate wells could be estimated via this technique. Moreover, sensitivity analysis is also performed to see the effects of each factor on each success criterion and it is observed that total rate before and after the treatment are the well parameters that dominate the success rate of the polymer gel application. Furthermore, statistical analyses like correlation and principal component analysis are performed to analyze the relationship between the well parameters and success criteria. From these analyses, it is concluded that parameters like ratio of total rate after and before the treatment, thickness of Mardin perforation, cumulative oil production, and average salinity have little impact on the first principal component and they do not have significant correlation with the success criteria; therefore, they are excluded from the neural network analysis. In addition, thickness of Garzan perforation is also eliminated as it does not show significant correlation with any of the success criteria. Moreover, correlation matrix is constructed to observe the degree of correlation between well parameters and significant correlations are discussed. Finally, the terms like cleanup time and effectivity index are introduced for the first time in this study to ease the evaluation of the process. Detailed description and examples about these terms are explained in Chapter 7, but for the sake of completeness, brief information is provided here. After polymer gel treatment, cumulative oil production (N_p) versus cumulative water production (W_p) plots could be prepared. In these plots, most of the time, production data of the wells show a curvature trend that is caused by the decrease in water production as a result of gel treatment. Generally, slope of the data points is maximum immediately after the treatment and it decreases as the time passes. However, after a certain period of time, data points may begin following a straight line with a constant slope. The formation of the straight line suggests that most of the injected gel has been subjected to the syneresis process. Once the production data starts following a straight line, after a certain period of time, trend line can be plotted to fit the straight line part of the production data and can be extrapolated towards Y-axis. It is suggested that, cumulative oil production value, where the trend line crosses Y-axis represents the additional oil recovery by means of polymer gel treatment. It is also proposed that the point, where the production data deviates from the trend line shows the cleanup time and effectivity index could be calculated by dividing the additional oil recovery at the cleanup region to the cleanup time.

1.2 Scope of the study

This study focuses on the following topics:

i. Use of artificial neural networks for the candidate well selection,
ii. Analysis of the influences of different parameters on the success of the treatments,
iii. Analysis of the post treatment performances,
iv. Statistical analysis of parameters that may influence the success of the treatments.

The research results are organized in the following chapters:

Chapter 2 is a review of the literature on the polymer gel application.

Chapter 3 is a review of the literature on the artificial neural networks.

Chapter 4 is a review of the literature on the design of artificial neural networks.

Chapter 5 describes the problem and the proposed strategy.

Chapter 6 describes the proposed methodology for the solution of the given problem.

Chapter 7 summarizes the results of the statistical analysis and neural network analysis obtained through this study and discussions related to these results.

Chapter 8 concludes the whole study.

Chapter 9 provides information about the recommendations for the future works.

CHAPTER 2

POLYMER GEL APPLICATIONS

2.1 Polymer Gels

Polymer gels can be used to diminish the excessive water production during oil production. Polymer and cross-linker are injected from the surface together and hopefully mixed at the reservoir rock and polymer gel begins to form within the fractures at reservoir temperature. In a successful treatment, it is expected that the formed gel to coat the flow pathways of the reservoir fluid (especially fractures or fissures in fractured rocks, such as carbonates). Therefore, treatment reduces the flow of water into the well while leaving the oil flow rate essentially unchanged. This phenomenon results from the fact that gel decreases the relative permeability of water more when compared with the relative permeability of oil.

After gelation, gels take place an intermediate state between a liquid and a solid; therefore, they have cohesive forces like solids, while being mobile like liquids. The polymer structure holds certain amount of liquid that prevents the whole network from collapsing (Molloy et al., 2000; Horkay et al., 2000; Young et al., 1989). Also, polymer structures have the ability to swell or shrink depending on the state of the external media and they are sensitive to acidity, temperature and salinity of the environment (Cohen 1996; Molloy et al., 2000; Horkay et al., 2000).

Al-Sharji et al. (2001) experimentally proved that, the water flows through the pores between the polymer molecules in the same way that water flows through the pores between sand grains in a reservoir rock, but they also stated that increased flow rates enlarge the flow pathways within the gel by elastic deformation. On the other hand, they argued that the oil flow occurs through the gel in form of droplets or filaments by establishing a pathway through the gel-filled pores. Also, Avery et al. (1988) stated that due to its hydrophilic nature, gel solution preferentially settles in the zones of high water saturation and high water permeability.

The fundamental mechanisms that may occur during the treatment are as follows; redistribution of fluids around the wellbore leads to segregation of oil and water within the porous medium (Liang et al., 1995), injected polymer diminishes the pore wall roughness of the solid matrix via its lubrication effect (Zaitoun and Kohler, 1988), enhancement of water wettability due to adsorption of hydrophilic molecules (Barreau et al., 1997[b]), increase in the capillary pressure due to the reduction of the pore diameter that results from the adsorption of polymer molecules (wall effect) (Barreau et al., 1997[a]).

2.2 Gelation time

Gelation time is a crucial parameter as it determines the injection period and distance of gel penetration. Gelation process begins slowly and viscosity stays almost constant for a period of time, then rapid increase in viscosity is observed. Therefore, gelation time is defined as the time at which rapid increase in viscosity is observed. For the estimation of the gelation time Arrhenius equation (Equation 2.1) is used. According to the collision theory, transition state theory, or just common sense, the temperature and reaction rate are directly proportional and this relationship is quantitatively determined by the Arrhenius equation.

$$k = Ae^{-E_a/(RT)} \tag{2.1}$$

At higher temperatures, the probability that two molecules will collide is higher and high collision rates lead to higher kinetic energy which influences the activation energy of the reaction. Therefore, activation energy could be defined as the amount of energy required to ensure that a reaction happens. Arrhenius equation gives the dependence of the rate constant k of a chemical reaction on the absolute temperature T (in Kelvin), where A is the pre-exponential factor (or simply the prefactor), E_a is the activation energy, and R is the universal gas constant. As the equation implies, gelation time is a function of activation energy, gas constant and temperature (Laidler, 1987). Also gelation time is inversely proportional with the polymer concentration. Gelation time decreases with an increase in polymer concentration. (Arjmand et al., 2003).

2.3 Determination of Gel Treatment Volume for Production Well

Determination of the optimum treatment volume to be injected is an important consideration for the successful gel treatment application. Small amount of treatment volumes may decrease the chance of filling the fractures, whereas relatively large amount of treatment volumes may increase the possibility of matrix invasion. Also, larger treatment volumes are generally unfavorable due to increase in operational expenses. Several different strategies have been proposed by various researchers; however, Portwood (1999) stated that, it is always better to consider all available approaches before making a final decision;

- The first approach is based on minimum gel treatment volume. According to this approach, daily production capacity of the well is determined in a pumped off condition and the obtained daily total volume indicates the minimum treatment volume. In literature, it is stated that this approach gives better results for naturally fractured wells, especially when 2 or 3 times of the minimum gel treatment volumes are injected.

- The second approach is based on distance from the wellbore. In this approach, treatment volume is calculated by means of radial flow calculations. Experiences indicate that 50 to 60 feet of radius from the origin of the wellbore may be used for the treatment volume estimations. Another method suggests the use of minimum 50 and maximum 200 barrels of gel per perforated feet depending on the well productivity index.
- The third approach is based on well response. In this method, treatment pressure is constantly monitored and instant changes in the design may be implemented if necessary. If the treatment pressure remains low or increases gradually during the treatment, initial treatment strategy may be applied without changes. However, rapid increase in the treatment pressure may indicate that high permeability zones have been filled and no more gel is required.
- The last approach is based on experience in a given field. In this technique, field data from the previous treatments are evaluated by considering the treatment volume, corresponding pressure, fluid production rate, fluid level and modification or improvement may take place depending on the experience.

2.4 Gel Strength

Polymer gels should have certain amount of strength in order to withstand the flow of water. Strength of the gel in the reservoir is related to three factors; polymer adsorption on rock surface, gel resistance to shear (elasticity), and polymer concentration. However, gel strength is generally represented by its concentration (Avery et al., 1988). Additionally, Bartosek et al. (1994) indicated that, cross-linker concentration in the injected solution may decrease significantly as a function of the distance from the wellbore, since the porous medium could retain the heavy metal cross-linker (like chromium). For this reason, gel strength may also depend on the penetration distance.

Llamedo et al. (2005) argued that flow of formation water through the gel depends on the salinity of the formation water. If the formation water is more saline than the water inside the polymer, polymer is more resistive to the flow of reservoir water as the tendency to reach an ionic equilibrium will prevent the intrusion of the reservoir water to the gel structure. They also stated that, if the formation water is less saline than the water inside the polymer, water can enter into the polymer gel more easily as the ionic equilibrium supports this flow direction.

It is stated that, there exists a minimum pressure gradient that must be achieved to extrude a given gel through a fracture. Once this gradient is exceeded, the pressure gradient during gel extrusion is insensitive to the flow rate. This behavior is attributed to a strong “slip” effect exhibited by the gel (Seright 1995; Seright 1999). In an ideal situation, not only permeability reduction but also long term resistance to extrusion is expected from the polymer gel application. Several researches have been conducted to investigate the behavior of polymer gels in porous media under stress (Sydansk and Southwell, 2000; Van Hoek et al., 2001; Zitha et al., 2002; Vasquez et al., 2003). In these experiments, first polymer gel is injected into a core sample until a uniform distribution is reached. Then, core holder is shut-in to allow polymer gel to take its final form. After that, brine is forced through the core at a constant flow rate to observe the blocking ability of the gel. During these experiments, first an increase in pressure drop over time is observed at the initial stage of the experiment. Then, researchers observed that this period of pressure drop either continues with the plateau or continues to grow for a short time until it reaches a maximum beyond which, it decreases towards a plateau. According to Zitha et al. (2002), initial increase in pressure drop is due to the elastic compression of the gel and the porous medium. After that, gel micropermeability begins to influence the behavior. If the gel micropermeability is large, micro-flow forces the pressure drop to follow a plateau, without gel rupture. On the other hand, if the gel micropermeability is low, critical rupture pressure of the gel is achieved causing the macroscopic brine-gel displacement. After breakthrough of brine, the macroscopic displacement will have little effect on the pressure drop; hence the final pressure drop will tend to follow a plateau (Muntasheri 2008).

In general, higher polymer concentrations are used in reservoirs that have highly conductive water bearing fractures, and lower polymer concentrations are used in reservoirs that are extensively producing from the matrix. If the excessive water production mechanism is obscure, it is recommended to begin treatment with small amount of lower polymer concentration gels. In the early stage of the treatment, well response dictates the remaining treatment strategy. If the injection of low polymer concentrations at the beginning of the treatment results in vacuum or low pressure at the wellhead, concentrations can be increased in subsequent stages. However, if well responds with a sudden increase in pressure at the early stage of the injection, it may become necessary to reduce the polymer concentrations. Generally, final part of the treatment includes relatively low volume of high polymer concentrations to provide the necessary strength to withstand the high differential pressure at the near-wellbore region (Portwood 1999).

2.5 Gel Syneresis

Researches showed that polymer gels have tendency to expel water in the long term; this phenomenon is called as syneresis and diminishes the stability of the gel as the time passes. Effects of gel syneresis vary depending on the field conditions, nonetheless gel syneresis is thought as an inevitable part of any gelation process (Vinot et al., 1989). As the syneresis process proceeds, permeability of gel-treated porous medium will increase and treated well may regain its original productivity. At this stage, gradual increase in the total production rate can be considered depending on the water cut.

At the end of polymer gel injection process, after some time, injected gel eventually reaches its final form and the remaining cross-linker start to react with formation water. This process results in shrinkage of polymer gel and expulsion of water which is captured by polymer particles. Syneresis effect increases with time and the volume of expelled water may reach 95% depending on the conditions. Factors that may affect the degree of syneresis are silicate/polymer and gelation agent concentrations, temperature, salinity and divalent cations (Bryant et al., 1996). Moradi-Araghi (2000) stated that, temperature plays a crucial role on the hydrolysis process and he argued that at reservoir temperatures of 100 to 150 ^{o}C the amide groups on the polyacrylamide (PAM)-based polymer undergo accelerated hydrolysis. Also, hardness of brine may accelerate the syneresis process as the high Mg^{+2} and Ca^{+2} content may result polymer precipitation. This process is explained by the interaction between the negatively charged carboxylate groups on the partially hydrolyzed polyacrylamide (PHPA) chains with the positively charged divalent cations (Moradi-Araghi and Doe, 1987).

On the other hand, Krishnan et al. (2000) argued that, although syneresis effect depends on several parameters, the "rigidity" of the gel, the position and configuration of the gel in the reservoir are crucial.

Degree of syneresis plays an important role during the choice of gel system. A gel system that may lose 95% of its original volume would not be a favorable system for water shut-off applications. However, experiments indicated that presence of syneresis in a bulk gel has little effect on the permeability reduction ability of the polymer gel system. Also, it is stated that the extent of syneresis is similar for bulk and core samples, but the rate can be significantly slower in cores (Bryant et al., 1996). On the other hand, Usaitis (2011) stated that, evaluation of the gel syneresis on bulk samples may give misleading results and core experiments should be performed to obtain more accurate results.

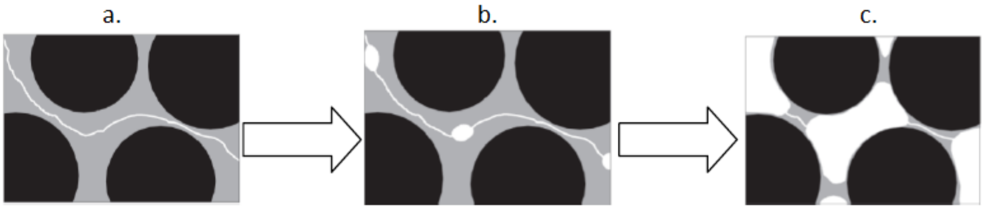

Figure 2. 1 Syneresis of polymer gel (Usaitis, 2011)

Figure 2.1 represents the development of the syneresis process. In this figure, thin white line indicates a possible flow pathway for the reservoir fluid. Figure 2.1 c. shows high degree of syneresis; however, thin layers of the gel still hinder the flow of fluid.

Seright (1999, 2001) stated that, polymer gel lose water through fracture faces as it is forced through the fractures. However, as the dehydration proceeds remaining polymer gel in the fractures becomes more concentrated and more resistant to being breached than the initially injected gel (Seright 2003). During the polymer gel treatment, depending on the treatment volume or treatment duration, polymer gel injection and deposition of concentrated gel may occur simultaneously. In this case, freshly injected gel may flow thorough the small wormholes taking place on the concentrated gel. Wormholes of the concentrated gel that are filled with freshly injected gel are perhaps the weakest part of the polymer structure and they may provide possible flow pathways for first breaching of gel by brine (Seright 2003).

In Raman field, sometimes, wells that have high injectivity values and that are vacuuming the polymer gel throughout the whole injection period, are treated in two stages. In these cases, after routine treatment procedure, well is shut in for approximately 10-20 hours and then treated again. By using the argument proposed by Seright (2003), it can be stated that, during the first stage of the treatment injected polymer may become concentrated and wormholes may eventually form during the shut in period. Then, the second stage aims to fill the wormholes on the concentrated gel; therefore, polymer gel that is formed by using inadequate water can be used during the treatment in order to mimic the concentrated gel.

2.6 Cleanup Period

After polymer gel treatment, productivity of the well varies in time, this phenomenon has been reported as cleanup period and it is observed in field applications, especially during the first weeks after the treatment. Cleanup period mainly results from the redistribution of fluids around the wellbore region. Seright (2005) stated that, cleanup time directly related with the cube of distance of gel penetration and it is inversely related with the pressure drawdown and permeability to water at residual oil saturation in the gel treated zone.

2.7 Permeability Reduction Mechanisms Related to Gel Application

In literature, it is stated that polymers are able to adsorb onto the pore surface and reduce selectively the permeability to water (Mennella et al., 1998). The mechanism of selective permeability reduction, sometimes called as disproportionate permeability reduction, is a debatable issue and for this reason various hypotheses have been proposed to clarify the subject.

In polymer gel applications, adsorbed polymer layer forms at the pore scale and this polymer layer is crucial for the permeability reduction process. For this reason, selected polymers should display strong attractive interactions with the rock surface in order to maximize adsorption and layer stability. According to Mennella et al. (1998), two fundamental interactions play a crucial role on the adsorption process. First one is the dispersion interactions (London van-Der-Waals) that are generally attractive and controlled by the polymer structure and molecular weight. Second one is the electrostatic interactions between the polymer/brine and rock/brine interfaces. Research conducted by Mennella et al. (1999), showed that adsorption onto quartzite is increasing while passing from the anionic hydrolyzed polyacrylamide (HPAM) to the weakly-anionic polyacrylamide (PAM) to the cationic polyacrylamide (CAT).

Another parameter that influences the adsorption process is the amount of clay contained in the host rock. Clays are expected to affect the adsorption process by means of their high surface area and negative charge. Adsorption researches performed by using cationic polyacrylamide (CAT) onto a clay mineral (Wyoming montmorillonite) and onto a mixture of quartzite (92%) and clay (8%) proved that clay content directly increases the thickness of the adsorption layer. Therefore, it can be argued that presence of clay minerals may lead to non-uniform polymer layer thickness both at the pore scale and within the volume of rock treated during the field applications (Mennella et al., 1998; Chiappa et al., 1998).

Several researchers argued that aqueous gelants preferentially enter into the pore channels mostly filled with water due to their natural affinity. For this reason, injected gel molecules restrict the flow of water more when compared with the flow of oil. Seright et al., (2001) observed this phenomenon by using X-ray microtomography before and after polymer gel injection. Studies also indicated that, selectivity increases as the oil saturation increases (Liang and Seright 1997; Nilsson et al., 1998).

Other researchers claimed that, disproportionate permeability reduction is related with the ability of oil to channel through polymer gel by deforming it elastically. In their coreflood experiments, they observed increase in oil permeability with time and flowrate (Willhite et al., 2000; Seright 2005). On the other hand, Krishnan et al. (2000) observed in their laboratory work that the gel is also permeable to brine. In the light of above information, it can be argued that, both oil and water may channel through polymer gel by deforming it elastically, or by following the flow paths that may be formed due to gel syneresis (expulsion of water or solvent). During flow of reservoir fluid through polymer gel, disproportionate permeability reduction may occur due to the physical or chemical differences between the oil or water molecules.

Prado et al., (2009) stated that disproportionate permeability reduction directly increases with increase in oil viscosity, they explained this phenomenon as follows; as the oil viscosity increases, gelant invasion into the oil bearing pores decreases and this results in disproportionate permeability reduction. Moreover, increase in oil viscosity increases the drag capacity of the oil, that is, ability of oil molecules to elastically deform the gel is enhanced.

CHAPTER 3

ARTIFICIAL NEURAL NETWORKS

3.1 Definition

An artificial neural network (ANN) is a system that relies on the operational principles of the biological neural networks; therefore, it can be defined as a replication of biological neural systems. ANN's are the computational structures which are constituted to generate, or at least mimic, intelligent behavior. Computational units of the ANN's, the nodes, are responsible for receiving, processing inputs and finally giving the corresponding results. In general, ANN’s are composed of large number of very simple and highly interconnected nodes operating in parallel. The connections between the nodes enable the flow of information between the nodes. The flow between the nodes can be unidirectional; the information flows only in one direction, and bidirectional; the information flows in both directions. The interactions of the all nodes through the connections establish the behavior of the network. ANN’s offer an alternative method of approach for problems, where the algorithmic and symbolic approaches are not suitable. ANN’s have successfully been constructed and applied for solving pattern recognition, capacity planning, business intelligence, robotics, or intuitive problem related aspects. Also, ANN’s have become very popular over the past few years especially in areas such as forecasting, data analytics and data mining.

3.2 Model of a biological neuron

Human brain is made up of a complex network of neurons. Figure 3.1 illustrates the typical structure of a biological neuron. A typical neuron collects signals from others through a hair like structures called dendrites, which surround the soma. Then the neuron sends out spikes of electrical activity through a long cable-like structure, axon, which splits into thousands of branches. At the end of each strand of the axon, a structure called a synapse converts the activity from the axon into electrical effects that can increase or decrease depending on its strength of connection and causes excitation or inhibition in the connected neuron. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes (Medsker and Liebowitz 1994).

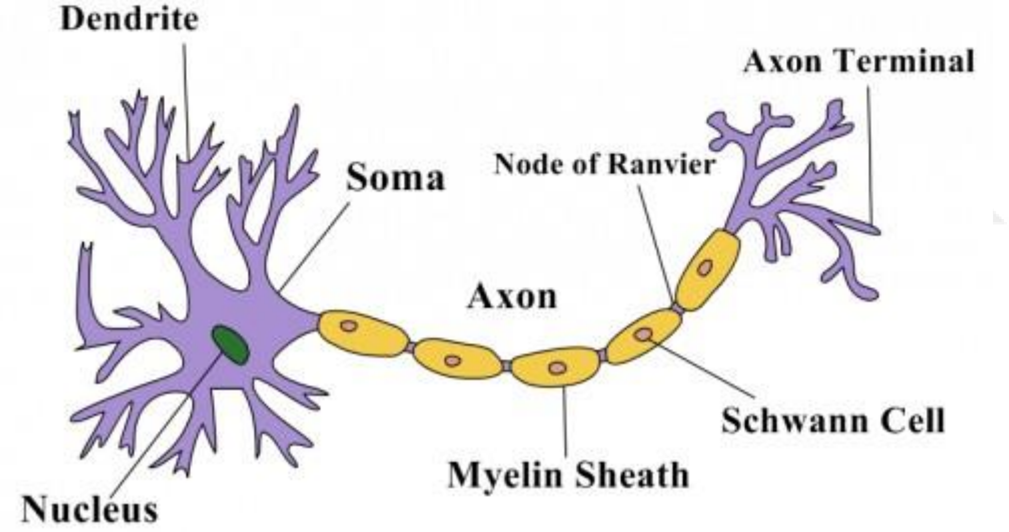

Figure 3. 1 Typical biological neuron

3.3 Model of an artificial neuron

A neuron is a unit of the structure that processes information for the operation of the neural network. Figure 3.2 shows the structure of an artificial neuron. As can be seen from the figure, a typical neuron has several properties:

- A number of input signals,
- A weight factor that is applied to each input signal,
- An activation and transformation function,
- An output signal,
- A learning algorithm.

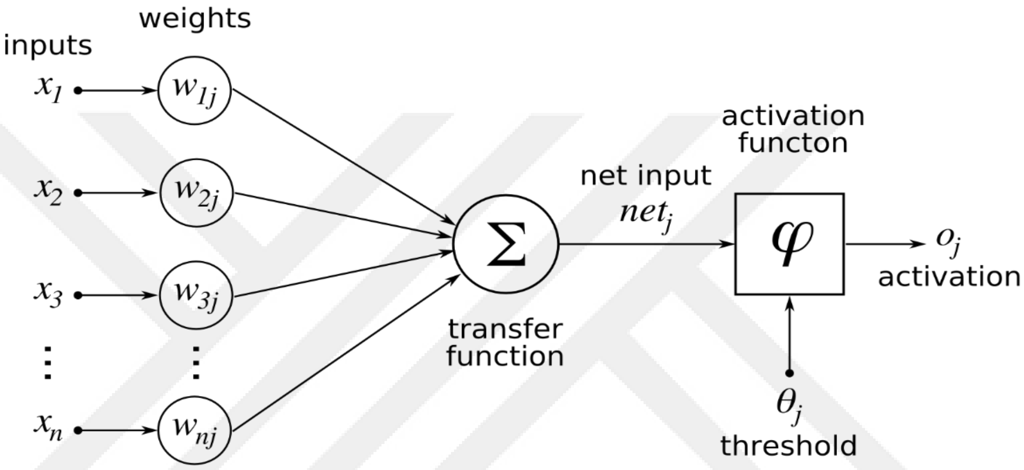

Figure 3. 2 Typical artificial neuron

3.4 Types of neural networks

3.4.1 Feed-forward networks of layered neurons (FANN)

A feed-forward neural network is an algorithm that consists of interconnected layers of neurons, organized in layers. Elements in each layer have connections with the previous layer and by means of these connections inputs are fed forward. During this algorithm, inputs enter the first layer of the network and then pass through the network layer by layer. During this operation, neuron on the first layer is able to feed a neuron on the third as well as the second layer. However, during normal operation, feedback does not take place, for this reason, these types of networks are called feed-forward neural networks (Priddy and Keller 2005).

3.4.1.1 Single-layer perceptron (SLP)

Single-layer perceptron network is the simplest form of a layered network that consists of one or more artificial neurons in parallel. As can be seen from the Figure 3.3, each neuron in the layer provides one network output and is usually connected to all of the external (or environmental) inputs.

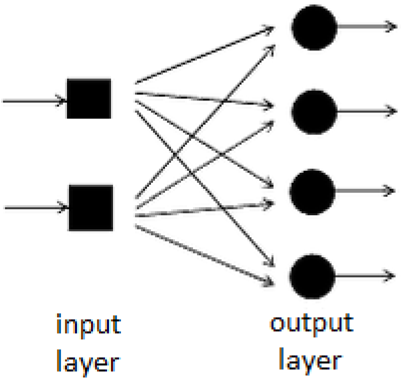

Figure 3. 3 Single-layer network

3.4.1.2 Multilayer perceptron (MLP)

A multilayer perceptron (MLP) is a feed-forward artificial neural network model that consists of one or more hidden layers that are fully connected to the next one. The function of hidden layer is to transform the inputs into something useful that the output layer can use. Hidden layers are used to increase the expressiveness of the network. Number of hidden layers in the network is directly related to the complexity of the network. Addition of hidden layer increases the capability of network to perform higher-order statistics. Figure 3.4 shows the network with a single hidden layer.

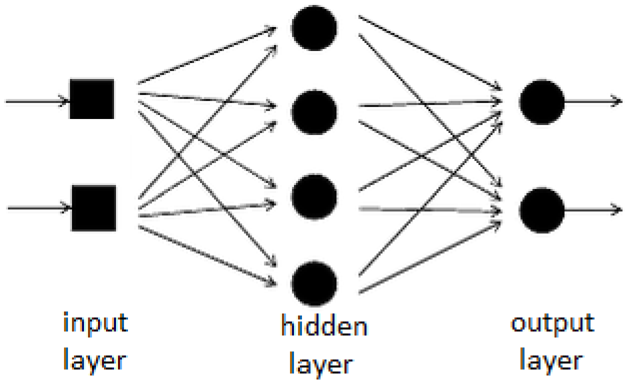

Figure 3. 4 Multi-layer network

3.4.1.3 Functional Link Networks (FLN)

The functional link artificial neural network (FLN) is a class of network that was designed to overcome the complexities related with multi-layer neural network. Although single layer neural networks can be considered as an alternative approach, due to their linear structure they often fail to establish complex nonlinear problems. Consequently, in order to bridge the gap between the linearity and the complexity, the FLN architecture is suggested and has been successfully used in many applications such as identification, classification, pattern recognition and prediction (Pao 1993).

3.4.1.4 Radial Basis Function Networks (RBFN)

Radial basis function network (RBFN) is a class of network, whose activation function is selected from a class of functions called basis functions. Some of the most commonly used basis functions are; Gaussian Functions, Multi-Quadric Functions, Generalized Multi-Quadric Functions, Inverse Multi-Quadric Functions, Generalized Inverse Multi-Quadric Functions, Thin Plate Spline Function, Cubic Function and Linear Function. Main features of the RBFN networks are;

- They are two-layer feed-forward networks,
- The hidden nodes implement a set of radial basis functions,

- The output nodes implement linear summation functions as in the case of MLP,
- The network training is divided into two stages: first the weights from the input to hidden layer are determined, and then the weights from the hidden to output layer,
- The training/learning is very fast,
- The networks are very good at interpolation.

3.4.1.5 Learning Vector Quantization Networks (LVQN)

The learning vector quantization network (LVQN) is a neural network that uses a competitive (winner-take-all) learning strategy. The LVQN consists of two computational layers: a competitive layer (Kohonen layer) and an output layer. While former is responsible for detecting regularities and correlations in the input vectors and assigning them subclasses, latter is responsible for transforming these subclasses into target classes.

3.4.2 Recurrent neural networks (RNN)

A recurrent neural network (RNN) is a class of artificial neural network whose neurons send feedback signals to each other. The basic feature of RNN is that it has at least one feedback loop. By means of this loop, networks exhibit dynamic temporal behavior.

3.4.2.1 Elman networks

An Elman network is a class of recurrent neural networks that consists of four layers: an input layer, an output layer, a hidden layer and a context layer. This context layer is responsible for feeding the output from the hidden layer. The Elman network keeps the values at the context layer and outputs them on the next run of the neural network. These values are then sent, using a trainable weighted connection, back into the hidden layer. Elman neural networks are very useful for predicting sequences, since they have a limited short-term memory.

3.4.2.2 Hopfield networks

The Hopfield type network is a multiple-loop feedback neural computation system. The neurons in this network are connected to all other neurons except to themselves, which means there are no self-feedbacks in the network. Main characteristics of the Hopfield networks are;

- All neurons are input as well as output neurons,
- There are no hidden neurons,
- Each neuron receives input from all other neurons,
- A neuron is not connected to itself.

3.4.3 Self-organizing maps (SOM)

The Self-Organizing Map (SOM) is a class of artificial neural network, which uses a competitive learning technique to train itself in an unsupervised manner. Unsupervised manner means that, human intervention is not required during the learning and little needs to be known about the characteristics of the input data. The basic idea behind the SOM is that, it uses a neighborhood function to preserve the topological properties of the input space and represents multi-dimensional data in much lower dimensions (usually one or two dimensions), which simplifies complexity and reveals meaningful relationships. SOM architecture is suggested and has been successfully used in many applications such as clustering, prediction, data representation, classification, visualization, etc.

3.5 Activation functions

The activation or transfer function is an important part of an artificial neural network which is required for the process of the hidden layer and the output layer. The fundamental role of the activation function is that, it determines the magnitude of the response that the neuron may form. Activation function limits the amplitude of the response by squashing the amplitude range of the output signal to some finite value. As a result, activation function brings specification and simplification to the problem that the neuron is attempting to solve (Hagan and Demuth 2002).

There are number of common activation functions in use with neural networks. Eight types of activation functions are commonly used that are listed in Table 3.1. Depending on the type of the problem, particular activation function may work best; however, it should be stated that, linear transfer functions are generally used for inputs and outputs and nonlinear transfer functions are used for hidden layers. Schematic representation of these functions can be found in Figure 3.5 and Figure 3.6.

Table 3. 1 List of Activation Functions

Activation Function	Equation	Range of Mapping
Logistic	$f(x)=1/(1+e^{-x})$	0,1
Linear	$f(x)=x$	0,1 or -1,1
Tanh	$f(x)=\tanh(x)$	-1,1
Tanh 1.5	$f(x)=\tanh(1.5x)$	-1,1
Sine	$f(x)=\sin(x)$	-1,1
Symmetric Logistic	$f(x)=(2/(1+e^{-x}))-1$	-1,1
Gaussian	$f(x)=e^{-x^\wedge 2}$	0,1
Gaussian Complement	$f(x)=1-e^{-x^\wedge 2}$	0,1

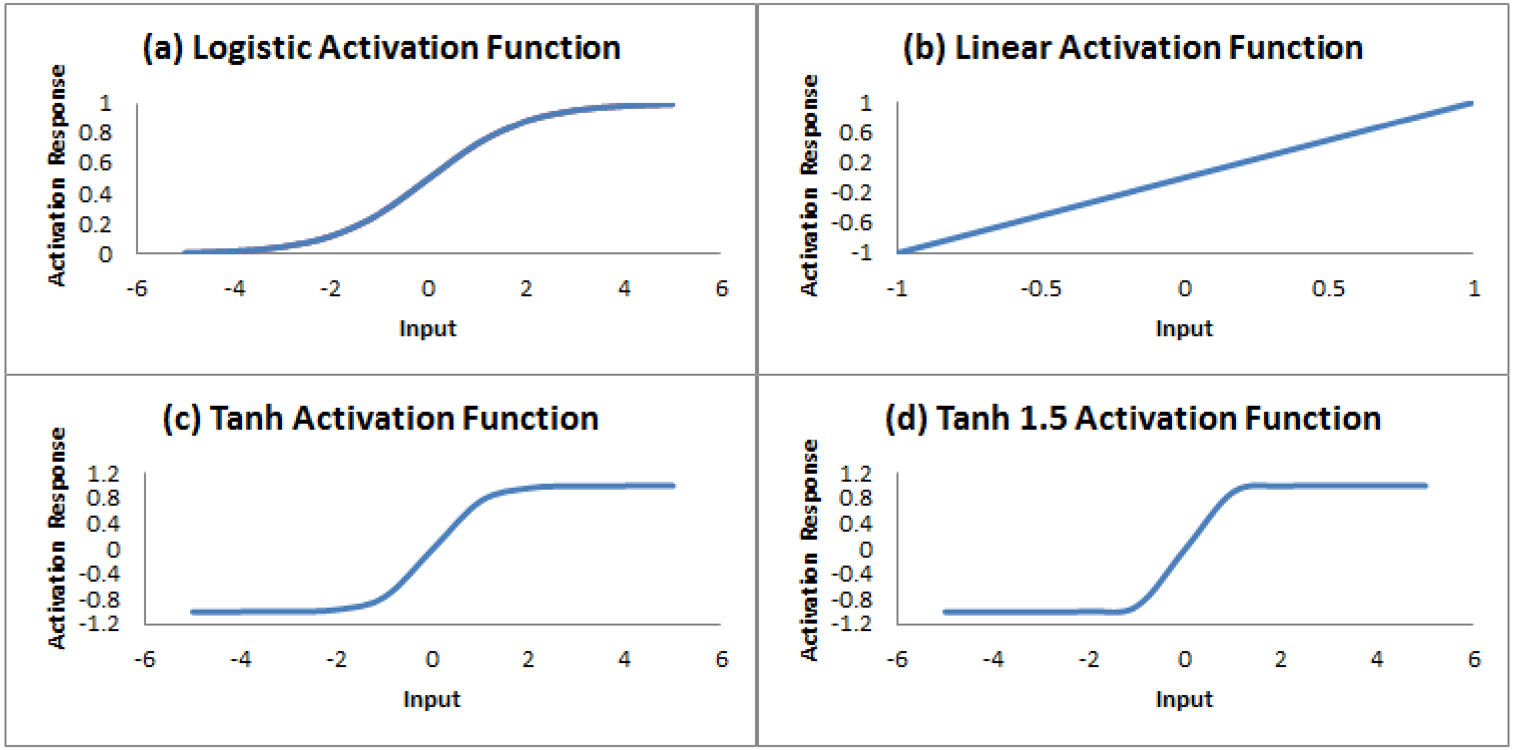

Figure 3. 5 (a) Logistic, (b) Linear, (c) Tanh, (d) Tanh 1.5. Activation Functions

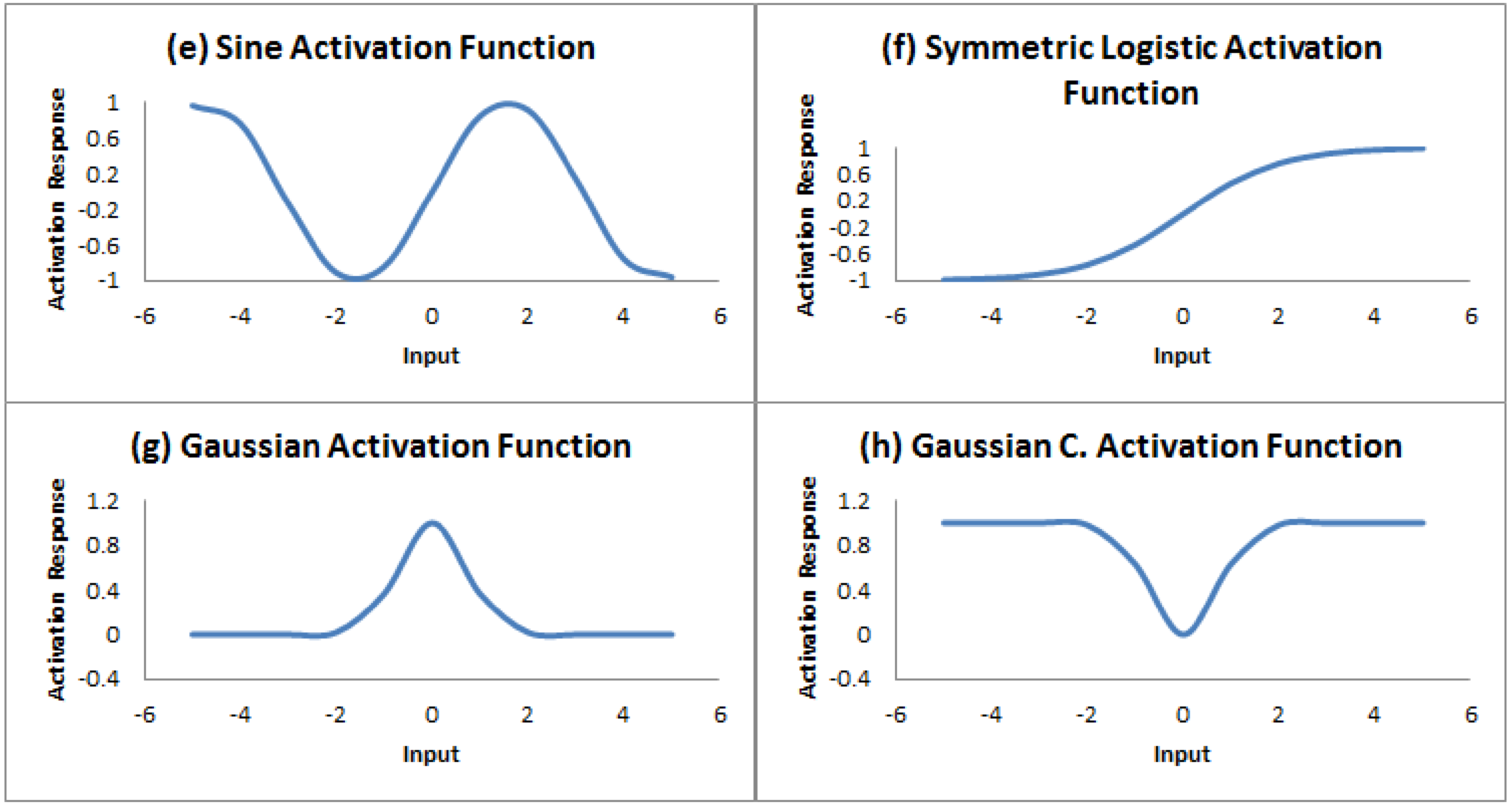

Figure 3. 6 (e) Sine, (f) Symmetric Logistic, (g) Gaussian, (h) Gaussian C. Activation Functions

CHAPTER 4

DESIGN OF ARTIFICIAL NEURAL NETWORKS

4.1 Data pre-processing

In general, databases are composed of noisy, missing and inconsistent data. For this reason, before training the data, pre-processing should be performed to obtain representative data set. If the dataset includes irrelevant, unnecessary, noisy or unreliable data, then it is difficult to extract knowledge during the training step. Data preparation and filtering steps can take considerable amount of time. Data pre-processing methods are divided into following categories;

- Data cleaning,
- Data integration,
- Data transformation,
- Data reduction.

4.1.1 Data cleaning

Data cleaning is a process performed to clean the data by filling in incomplete values, smoothing noisy (containing errors) data, identifying or removing outliers (deviated from the expected values), and resolving inconsistencies. Incomplete data may stem from the human/hardware/software problems; noisy data may occur during collection, entry or transmission parts; inconsistent data may result from the data coming from different data sources. To clean the data, algorithms may be formed to fill the missing values, identify outliers and smooth out noisy data, correct or erase inconsistent data.

4.1.2 Data integration

Data integration is a process that involves the merging of the data from multiple data stores. Analyst should be careful while collecting data from different data stores, especially for the data that are derived by using the data coming from different data stores.

4.1.3 Data transformation

The basic idea behind the data transformation is manipulation of the distribution of input variables, so that they can better match outputs. Data transformation involves the following steps;

- Normalization; Scaling attribute values to fall within a specified range,
- Smoothing; Removing the noise from data by using binning, clustering and regression,
- Aggregation; Aggregation or obtaining the summary of the data,
- Data reduction; Replacing the low level data with the high level data.

4.1.4 Data reduction

Data reduction techniques are applied to obtain a representative data with a small amount of volume. Data reduction involves the following steps;

- Reducing the number of attributes; principle component analysis,
- Reducing the number of attribute values; clustering, aggregation, generalization.

4.2 Creating network structure

4.2.1 Structure selection

Building and processing neural networks requires several steps such as; data preprocessing, structure selection and network sizing. However, during these steps, selection criteria are not well established; therefore, the designer should find a methodology to measure the performance of neural networks and should pick the most suitable one.

4.2.2 Sizing the network structure

Some important considerations while sizing the network structure are as follows;

- Layers of neurons,
- Number of input nodes,
- Number of neurons in the hidden layers,
- Number of neurons in the output layers.

However, there is no guideline that can be followed during sizing of the network structure and most of the time, selection procedure depends on the rule of thumbs combined with trial and error.

4.3 Training (learning) the network

Training is one of the fundamental processes of artificial neural networks. Training is an iterative action of weight and bias adjustments. During each iteration, network gains more information about the given problem. First of all, network is simulated by the given input parameters, then the weights are adjusted and neural networks give better response at each iteration as a result of its adjusted weights.

Training procedure can be classified as supervised and unsupervised. Supervised training is an algorithm that uses a known dataset (desired inputs and outputs) to make predictions. By using the dataset, supervised training algorithm tries to construct a model that is able to make predictions for a new dataset. Unsupervised training is an algorithm, in which the network has to make sense of the inputs without external help (Medsker and Liebowitz 1994).

4.3.1 Supervised training

In the supervised training algorithm, network is fed by set of input and output parameters. Training vector and the expected response are introduced to the network. Then the network parameters are adjusted depending on the input parameters and error values. Adjustment is performed with an iterative procedure with the aim of obtaining a network which is able to simulate the actual behavior of the given problem.

4.3.2 Unsupervised training

In the unsupervised training algorithm, learning procedure takes place with the absence of examples and the algorithm tries to represent the particular input patterns in a way that reflects the statistical structure of the overall collection of input patterns. The most common unsupervised learning method is cluster analysis, which is used for exploratory data analysis to find hidden patterns or grouping in data. The clusters are modeled using a measure of similarity, which is defined upon metrics such as Euclidean or probabilistic distance.

4.4 Error Functions

Error functions are used to compare the system output to the desired output value. Typical error functions used include;

- Mean Absolute Error,
- Mean Squared Error,
- Sum Squared Error.

Generally, the training process terminates when;

- A pre-defined, arbitrary error level has been achieved,
- The maximum number of calculations has been reached.

4.5 Backpropagation algorithm

Back propagation is a widely used algorithm which trains the given feed-forward multilayer neural network for a given set of input patterns with known classifications. In order to use back propagation algorithm, an artificial neural network must have at least three layers; input, output and hidden layer. The back propagation algorithm functions as follows;

- Weights are randomly assigned to input parameters,
- After calculations, network produces an output by using the neuron inputs, input weights, and the transformation functions,
- The output is then compared to the target output and the error is calculated using the corresponding error function,
- Then backpropagation occurs through the network by changing the input weights depending on the calculated error,
- This process repeats until the error reaches the desired value or the maximum number of iterations is performed.

Some of the well-known types of backpropagation algorithms are as follows;

- Gradient descent backpropagation; a training function that updates weight and bias values according to gradient descent,
- Gradient descent with adaptive learning rate backpropagation; a training function that updates weight and bias values according to gradient descent with adaptive learning rate,

- Gradient descent with momentum & adaptive learning rate backpropagation; a training function that updates weight and bias values according to gradient descent momentum and an adaptive learning rate,
- Levenberg-Marquardt backpropagation; a training function that updates weight and bias values according to Levenberg-Marquardt optimization (Demuth and Beale 2008).

CHAPTER 5

STATEMENT OF PROBLEM

Excessive water production due to channeling, coning or cusping is a problem of central importance for oil companies. Especially, rapid increase in water-oil ratio and corresponding decrease in oil production due to excessive water production may decrease the profits of the oil company dramatically. Raman field, which is a naturally fractured limestone reservoir located in the southeastern part of Turkey, has been struggling with the high water-oil ratio problem especially for the last decade. In order to relieve the high water cut trends in the Raman field, cross-linked polymer gel (polyacrylamide-chromium gel) treatments have been applied and successful results were obtained. Although the polymer gel application gained wide acceptance from the operator of the field, topics like candidate selection, treatment design and performance evaluation still remain controversial. Consequently, main aim of this study is to propose a methodology for the selection of the candidate wells for the gel treatment using artificial neural network. The candidate well selection procedure will be designed as process-oriented, since the results-oriented selection procedure may result in missing the important learning opportunities. Besides candidate selection, developing a strategy for the evaluation of post treatment production performance and analyzing the contribution of different well parameters on the success rate of the treatments are aimed in the scope of this study.

CHAPTER 6

METHODOLOGY

As it was stated, main aim of this study is to propose new candidate wells for the future polymer gel applications by using the knowledge gained from the previous applications. Prediction of the response of a treated well by using the pre and post treatment data of the other treated wells can be considered as a pattern recognition problem. In literature, it is stated that neural networks are capable of solving pattern recognition problems and finding the highly complex relationship within the huge amounts of data (Ali 1994; Mohaghegh 1995; Ahmed et al. 1997). Once the relationship between the well parameters and success rate of the gel treatments is obtained, it can be used to predict potential outcomes of the polymer gel application on the other wells. However, before performing the neural network analysis input parameters representing the state of the wells before the treatments and success rate of the treatments representing the response of the wells to the treatments should be well established. In this part of the study, methodology for the determination of the input and output parameters and their utilization via neural network analysis are defined.

6.1 Determination of the Input Parameters

In this study, selected input parameters are; cumulative oil and water production, injectivity at 500 psi, perforation thicknesses, average water cut before the treatment, oil rate and total rate before the treatment, total rate after the treatment, ratio of total rate after and before the treatment, average salinity before the treatment, productivity index of oil and water before the treatment. Productivity index of oil and water is calculated by multiplying the productivity index of well with oil cut and water cut respectively (Liang et al., 1993; Seright et al., 1998). Almost all of the available parameters are included while determining the input parameters. It is thought that appropriate combination of these parameters could be used to represent the state of the well before the treatment. However, it should be mentioned here that, total rate after the treatment is also included in the input parameters. Although this parameter is not known before the application, small changes in this parameter cause large deviations on the response of the well especially at the cleanup region. In general, oil companies have a rough estimation about the total rate after the treatment before the application and these estimations could be used during the neural network analysis. Also, several scenarios could be generated by varying these estimations; therefore, best, worst and average case scenarios could be obtained.

Other parameters that could be included during the analysis are related to the application of the polymer gel treatment. In this case, polymer gel volume and concentration could be used during the analysis. At first glance, one may consider these parameters as controllable and it could be thought that they are decided by the company; however, most of the time, this is not the case. Suppose that injection strategy of the oil company consists of 1,000 bbl 5,500 ppm, 1,000 bbl 7,000 ppm, 1,000 bbl 8,500 ppm and 1,000 bbl 10,000 ppm. However, in general, initial injection scheme is modified depending on the response of the well. If the wellhead pressure dramatically increases at the beginning of the application, it would not be possible to follow initial injection scheme. In this case, application could be terminated after injecting 1,500 or 2,500 bbl of polymer gel. For this reason, operational parameters are not controllable and including these parameters on the analysis may give inconsistent results.

In order to select most effective and related input parameters for each success criterion, statistical analyses, namely principal component analysis and correlation analysis are performed.

6.1.1 Principal Component Analysis

Principal Component Analysis (PCA) is a variable reduction procedure and it is aimed to find the most powerful parameters in the dataset by using this technique. Also, some ineffective parameters can be identified and eliminated from the neural network analysis. Therefore, more scenario could be simulated within a shorter period of time and better neural network structures could be obtained as a result of the use of relevant parameters. In this study, principal component analysis is performed for each success criterion and well parameters; therefore, parameters that are thought to dominate the success of the treatments are identified for each success criterion. Furthermore, parameters that have less influence on the principal components are eliminated from the analysis especially if they do not have a correlation with the success criterion.

6.1.2 Correlation Analysis

Correlation analysis is performed to observe the correlation between the well parameters and success criteria; therefore, parameters that have correlation with success criteria are also identified and utilized during the neural network analysis. Here parameters that are obtained from correlation analysis are used as a complementary to the parameters obtained from principal component analysis. After performing statistical analysis, input parameters that will be used during the neural network analysis are determined and different scenarios are constructed.

6.2 Determination of the Output Parameters

Output parameters that reflect the success rate of the treatments are assigned as oil rate one year after the treatment, additional oil production one year after the treatment, profit one year after the treatment, additional oil production at the cleanup region and effectivity index. Here, five different output parameters (success criteria) are assigned as the company policy may vary. For example, some companies may prefer longer cleanup times, others may want to increase the effectivity index, others may want to diminish the water production dramatically and some others may want to increase the oil rate and do not take the water production into consideration. It should be mentioned that, terms like cleanup time and effectivity index are introduced for the first time in this study to ease the evaluation of the process and diversify the success criteria. In order to estimate the profit obtained from the whole treatment, one should know how long the effect of treatment lasts on a treated well and this duration could only be obtained from the cleanup time approximations; therefore, for the successful economic evaluation of polymer gel treatments, oil companies should have certain approach for the cleanup time estimation. Detailed description and examples about cleanup time and effectivity index introduced in this study are explained in Chapter 7, but brief information is provided here.

After polymer gel treatment, cumulative oil production (N_p) versus cumulative water production (W_p) plots could be prepared. In these plots, most of the time, production data of the wells show a curvature trend that is caused by the decrease in water production as a result of gel treatment. Generally, slope of the data points is maximum immediately after the treatment and it decreases as the time passes. However, after a certain period of time, data points may begin following a straight line with a constant slope. The formation of the straight line suggests that most of the injected gel has been subjected to the syneresis process. Once the production data starts following a straight line, after a certain period of time, trend line can be plotted to fit the straight line part of the production data and can be extrapolated towards Y-axis. It is suggested that, cumulative oil production value, where the trend line crosses Y-axis represents the additional oil recovery by means of polymer gel treatment. It is also proposed that the point, where the production data deviates from the trend line shows the cleanup time and effectivity index could be calculated by dividing the additional oil recovery at the cleanup region to the cleanup time. Figure 6.1 shows the schematic representation of the estimation of the cleanup region from the cumulative production data. In this plot, blue line indicates the cumulative production data and orange dashed trend line shows the fitted trend line. Also, estimation for the cleanup region and additional oil recovery at the cleanup region are illustrated on the plot.

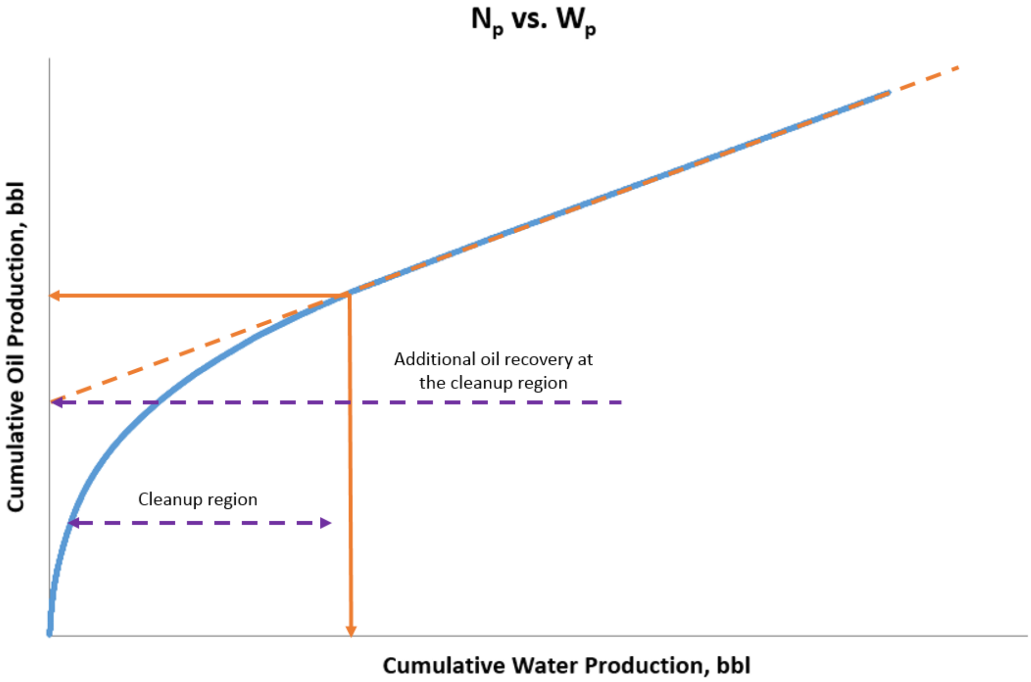

Figure 6. 1 Estimation of the cleanup region from the cumulative production data

6.3 Neural Network Analysis

After identifying the parameters that are used during the neural network analysis, next step is the normalization of these parameters for the neural network analysis. In the process of training neural networks it is customary to preprocess the data since the input values may include extremely low, high or nearly identical values.

During this study, Equation 6.1 is used to normalize the data and normalization constant (norm) is selected as 0.01. X_{min} and X_{max} represents the minimum and maximum values in the dataset for the parameter that is aimed to be normalized. For example, while normalizing the water cut values; X_{min} is equal to 78.5% (lowest water cut value in the dataset) X_{max} value is equal to 100% (highest water cut value in the dataset). Suppose that one of the wells from the dataset has a water cut value of 90%, then its normalized value could be calculated as 0.625.

$$\mathrm{X_{normalized}} = (1 - 2 * \mathrm{norm})\left(\frac{\mathrm{X} - \mathrm{X_{min}}}{\mathrm{X_{max}} - \mathrm{X_{min}}}\right) + \mathrm{norm} \qquad (6.1)$$

After normalization procedure, next step is the construction of different data sets that will be used during training, testing and validation steps as the structure of the networks and error levels may change dramatically depending on the characteristics of the wells on different steps. For example, suppose that, all the successful wells are reserved for the training step, in this case, neural network structure may have tendency to overestimate the predictions for the candidate wells. Selection process may be performed randomly or one can manually select the samples that are used during the training, testing and validation steps. As it was stated before, data of the 60 wells are available and they are sorted in descending order based on well numbers, then the rows are replaced randomly and 100 different data sets are generated from the original data set. During the neural network analysis, wells at the first 30 rows are assigned for the training step, second 15 rows are assigned for the testing step and last 15 rows are assigned for the validation step. Therefore, for each data set wells at the training, testing and validations steps are randomly assigned.

Next step is the determination of the structure of the neural networks. In this study, a multilayer perceptron (MLP) type neural network structures are used during modelling. These structures include two layer, a hidden layer and an output layer.

In literature, it is stated that network structure consists of a hidden layer with a sigmoid transfer function and an output layer with a linear transfer function could be used as general function approximator. It could be used to estimate any function with a finite number of discontinuities arbitrarily well, as long as adequate number of neurons are provided in the hidden layer (Demuth and Beale 2008). For this reason, logsig transfer function is utilized for the first layer and purelin transfer function is utilized for the second layer. Logsig and purelin transfer functions are introduced in previous parts. Table 3.1 shows the algorithms of the corresponding transfer functions while Figure 3.5 (a) and Figure 3.5 (b) illustrate the plots of logsig and purelin functions respectively. The performance of a neural network during training is measured based on the mean squared error. Also, mean absolute errors (MAE), root mean squared errors (RMSE) and regression values (RRV) are used while evaluating the performance of different models.

Network parameters and developed MATLAB® codes in this study are given in Appendices and the whole application can be summarized as follows. First of all, data is randomly arranged on a MS Excel spreadsheet. Then, it is transferred to a text file named as GELWELLS1.txt. Test.m opens the text file and takes the field data in a vector form. Then normalization process takes place and whole data is updated to normalized values varying between 0.01 and 0.99. Then available 60 well data is separated into three as 30 for training, 15 for test, and 15 for validation parts. As it was stated before, satisfying number of neurons should take place at the hidden layer. For this reason, number of neurons at the hidden layer is varied between 1 and 100. Network performance measuring function is selected as mean squared error and the training algorithm is trainlm. Mean squared error is the average of the squares of the errors and it indicates the minimum distance between the fitted line and data points. Trainlm is a network training function that updates weight and bias values by means of Levenberg-Marquardt optimization. This function is often regarded as the fastest backpropagation algorithm and it is highly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms (Demuth and Beale 2008). During the training procedure, default parameters are selected for the trainlm function. Then training is performed and corresponding outputs are generated for each neuron at the hidden layer. After that, outputs are back-normalized and mean absolute errors (MAE), root mean squared errors (RMSE) and regression values (RRV) are calculated for each neuron at the hidden layer. Then the same procedure is repeated with different data sets. Here the wells are randomly distributed between training, test and validation sets. As a result, 100 different data sets are simulated for 100 different neuron numbers at the hidden layer for each success criterion.

After obtaining satisfying error levels, corresponding training, test, validation sets and the number of neurons at the hidden layer are noted in order to form the neural network structure with these parameters. Then, Form.m is operated to construct the desired neural network structure. Structure of the Form.m is very similar to the Test.m; however, Form.m does not have a loop in its hidden layer as the optimum number of neurons are already found while operating the Test.m code. At the end, Form.m generates the desired network structure named as net.mat.

Then, Simulate.m is operated to get outputs from the formed network. First of all, data of the candidate wells are arranged on a MS Excel spreadsheet. Then, it is transferred to a text file named as CANGELWELLS.txt. Simulate.m opens the text file and takes the candidate well data in a vector form. Then candidate well data is simulated and outputs are saved to a file named as Outputs.dat.

CHAPTER 7

RESULTS & DISCUSSIONS

7.1 Statistical Analyses

This part of the study aims to select most effective and related input parameters for each success criterion by using the principal component analysis and correlation analysis. In this way, irrelevant input parameters could be excluded from the neural network analysis and margin of error could be diminished. Also, principal components could be compared with the sensitivity analysis results of the neural network analysis in order to check the reliability of the neural network analysis. Furthermore, by analyzing the results of the statistical analysis one can better understand the relationship between input parameters and success criteria; therefore, one may have more clear vision about how the treatment mechanism works in a given field.

Consequently, principal component analysis is performed in order to observe the patterns in data and highlight the similarities and differences and then the correlation analysis is performed to observe the degree of the correlation between the parameters.

7.1.1 Principal Component Analysis

Principal Component Analysis (PCA) is generally treated as a variable reduction procedure. Datasets may include some variables that are correlated with one another, possibly because they are measuring or representing the same or similar property. Therefore, it is possible to reduce observed variables into smaller number of principal components (artificial variables) that will account for most of the variance in observed variables. Aims of the PCA could be summarized as follows;

- Extracting the important information from the data set,
- Compressing the size of the data set by eliminating the less important information,
- Simplifying the data set,
- Analyzing the structure of the observations and the variables (Abdi and Williams, 2010).

The PCA method is applied by utilizing the eigenvectors and eigenvalues of a matrix. In this method, covariance matrix is calculated to reduce redundancy and maximize the variance. Mathematically, PCA could be defined as an orthogonal linear transformation with the assumption that all basis vectors are orthonormal matrix. Therefore, aim of the PCA is calculating the variances and coefficients of a dataset via eigenvalues and eigenvectors (Jolliffe, 2002). In this study, PCA is performed by using the well parameters and the success criteria and Table 7.1 shows the first and second principal components of the well parameters when different success criteria are considered. Moreover, corresponding loading plots are presented through Figure 7.1 and Figure 7.5.

Table 7. 1 Summary of first and second principal components of the well parameters for different success criteria

Success Criteria	Principal Component	Cumulative oil production	Cumulative water production	Injectivity @ 500 psi	Thickness of Mardin perforation	Thickness of Garzan perforation	Average water cut	Oil rate before the treatment	Total rate before treatment	Total rate after treatment	Ratio of rate after the treatment and before the treatment	Average salinity	Productivity index of oil	Productivity index of water
Oil production rate one year after the treatment	**PC1**	0.040	0.381	0.176	0.040	0.216	0.048	0.222	0.418	0.417	0.043	-0.129	0.215	0.408
	PC2	0.148	-0.121	0.089	-0.249	0.011	-0.571	0.529	0.002	-0.176	-0.351	0.231	0.245	-0.087
Additional oil production during one year after the treatment	**PC1**	0.020	0.404	0.167	0.063	0.230	0.135	0.145	0.435	0.455	0.079	-0.158	0.190	0.441
	PC2	-0.035	0.007	-0.033	0.304	-0.183	0.393	-0.512	-0.200	0.019	0.431	-0.075	-0.108	-0.017
Profit during one year after the treatment	**PC1**	0.020	0.404	0.167	0.063	0.230	0.135	0.145	0.435	0.455	0.079	-0.158	0.190	0.441
	PC2	-0.035	0.007	-0.033	0.304	-0.183	0.393	-0.512	-0.200	0.019	0.431	-0.075	-0.108	-0.017
Additional oil production at the clenup region	**PC1**	0.040	0.391	0.178	0.043	0.223	0.054	0.221	0.425	0.422	0.040	-0.129	0.226	0.419
	PC2	0.166	-0.113	0.104	-0.217	-0.009	-0.573	0.520	-0.015	-0.182	-0.325	0.248	0.267	-0.086
Effectivity index	**PC1**	0.023	0.369	0.157	0.030	0.211	0.065	0.200	0.416	0.421	0.046	-0.139	0.209	0.413
	PC2	0.107	-0.109	0.063	-0.305	0.070	-0.546	0.542	0.061	-0.142	-0.406	0.193	0.230	-0.053

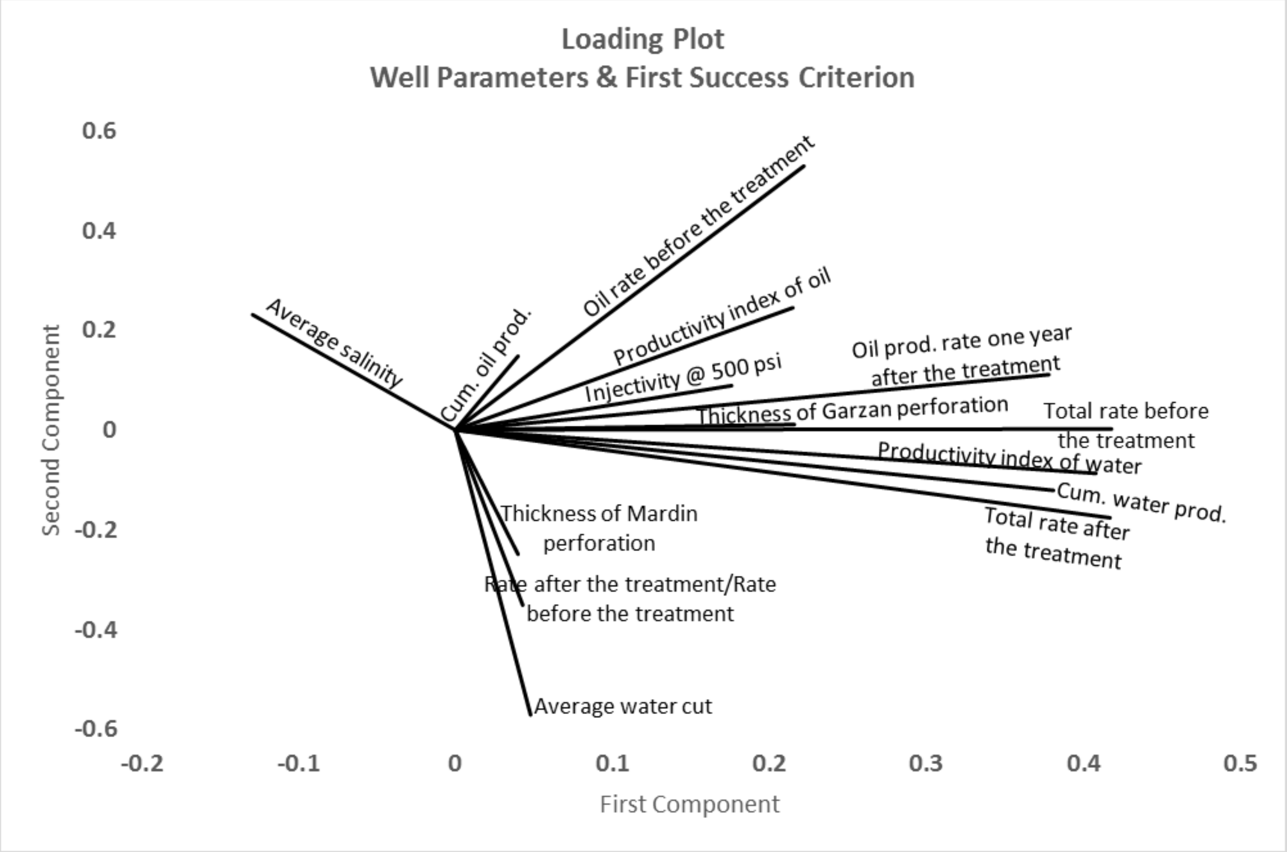

Figure 7. 1 Loading Plot of the Well Parameters & First Success Criterion
(Oil production rate during one year after the treatment)

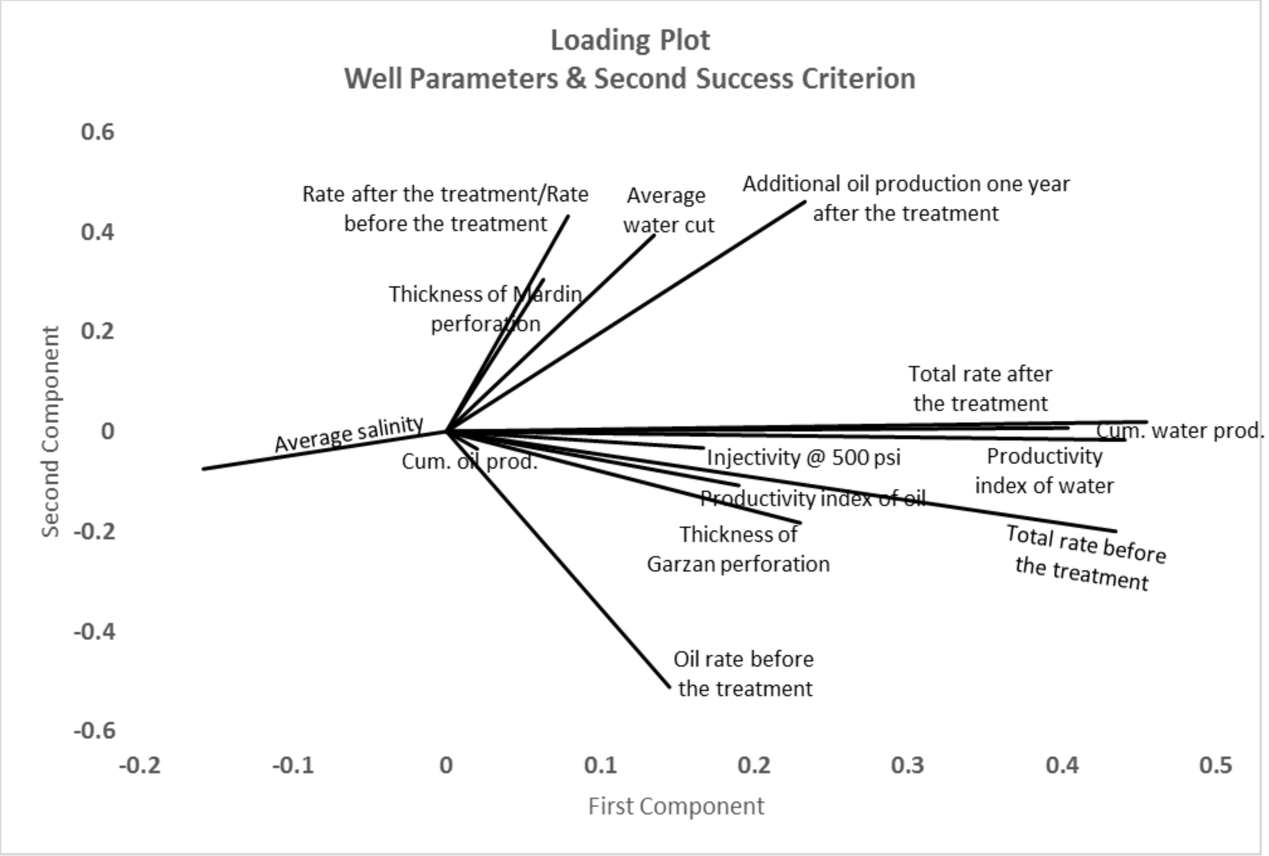

Figure 7. 2 Loading Plot of the Well Parameters & Second Success Criterion (Additional oil production during one year after the treatment)

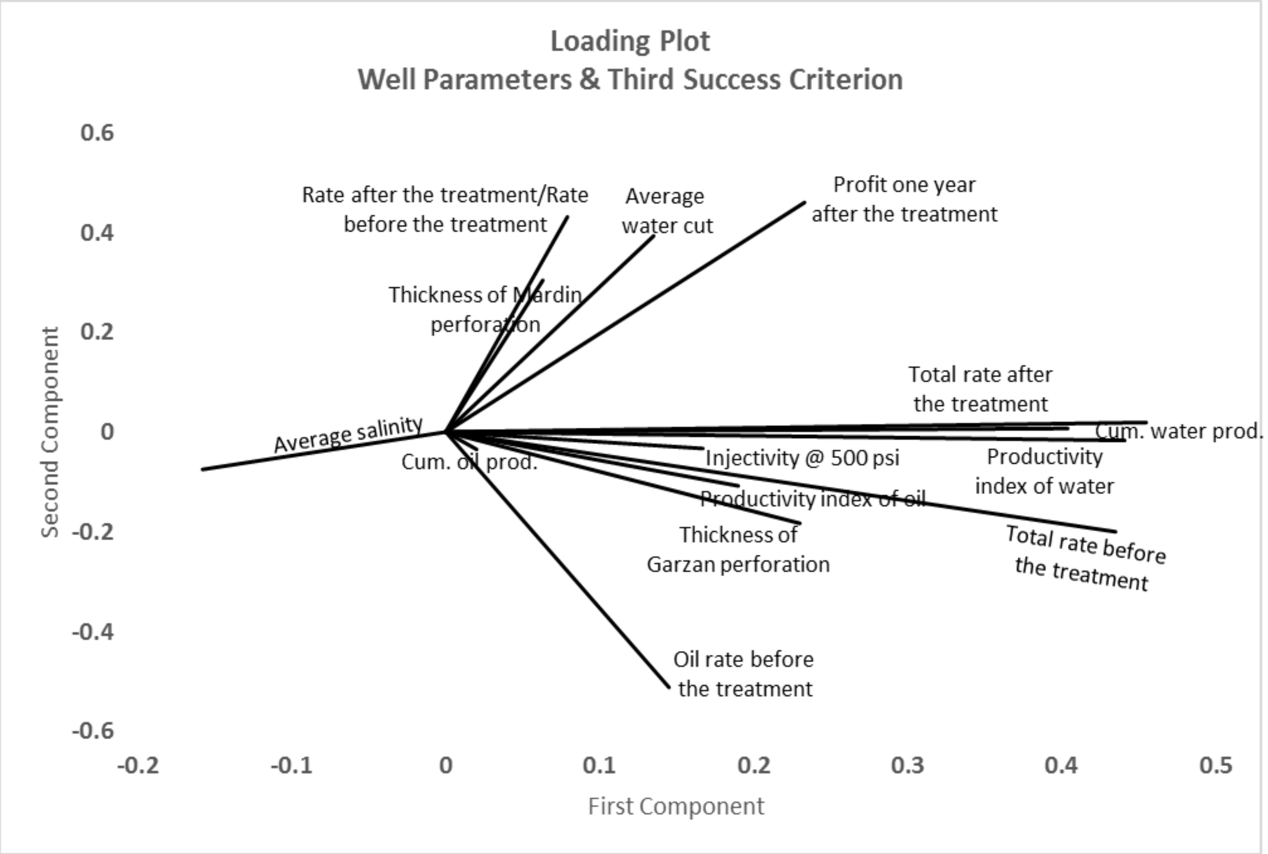

Figure 7. 3 Loading Plot of the Well Parameters & Third Success Criterion
(Profit during one year after the treatment)

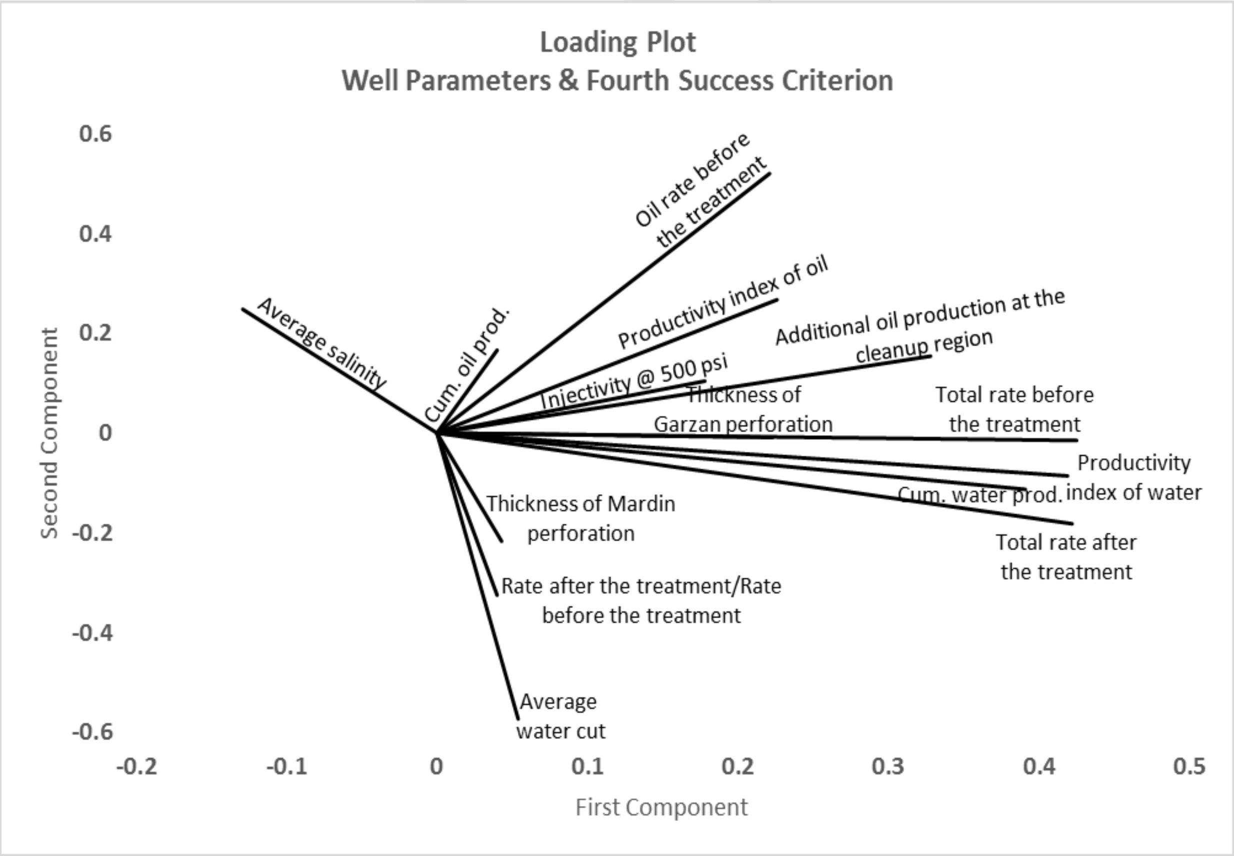

Figure 7. 4 Loading Plot of the Well Parameters & Fourth Success Criterion (Additional oil production at the cleanup region)

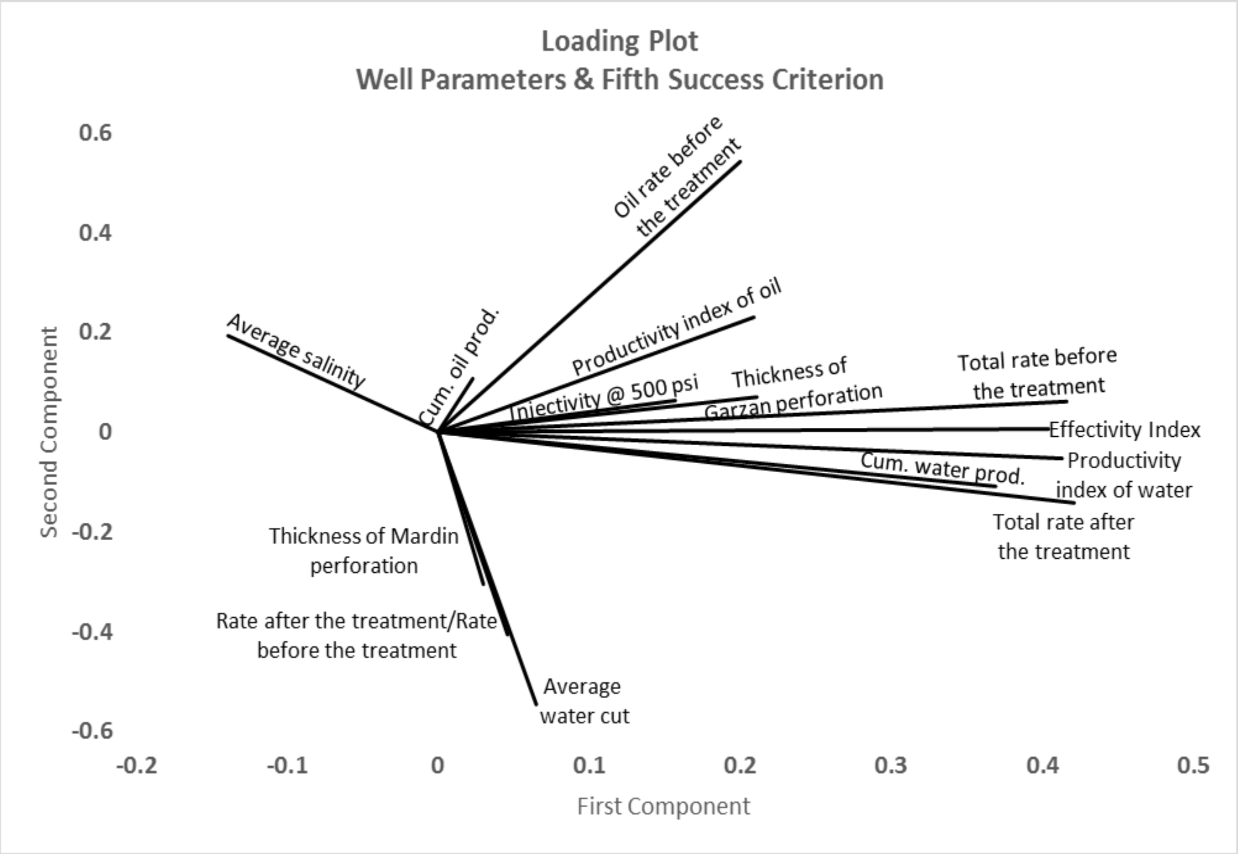

Figure 7. 5 Loading Plot of the Well Parameters & Fifth Success Criterion (Effectivity index)

In the case of first success criterion (oil production rate during one year after the treatment) (Figure 7.1) first principal component is mainly weighted by total rate before the treatment (0.418), total rate after the treatment (0.417), productivity index of water (0.408) and cumulative water production (0.381). Also, parameters like ratio of total rate after and before the treatment (0.043), cumulative oil production (0.04), thickness of Mardin perforation (0.04), average salinity (-0.129) have negligible effect on the first principal component.

In the case of second and third success criterion (additional oil production during one year after the treatment and profit during one year after the treatment) (Figure 7.2 and Figure 7.3), first principal component is mainly weighted by total rate after the treatment (0.455), productivity index of water (0.441), total rate before the treatment (0.435) and cumulative water production (0.404). Also, parameters like ratio of total rate after and before the treatment (0.079), thickness of Mardin perforation (0.063), cumulative oil production (0.02), average salinity (-0.158) have negligible effect on the first principal component. It should be stated that, for the second and the third success criteria principal component analysis gives the same results as the third success criterion, profit one year after the treatment, is directly related to the second success criterion, additional oil production one year after the treatment. Actually, third success criterion is calculated by multiplying the second success criterion with oil price and subtracting the cost of operation.

In the case of fourth success criterion (Figure 7.4), first principal component is mainly weighted by total rate before the treatment (0.425), total rate after the treatment (0.422), productivity index of water (0.419) and cumulative water production (0.391). Also, parameters like thickness of Mardin perforation (0.043), cumulative oil production (0.04), ratio of total rate after and before the treatment (0.04), average salinity (-0.129) have negligible effect on the first principal component.

In the case of fifth success criterion (Figure 7.5), first principal component is mainly weighted by total rate after the treatment (0.421), total rate before the treatment (0.416), productivity index of water (0.413) and cumulative water production (0.369). Also, parameters like ratio of total rate after and before the treatment (0.046), thickness of Mardin perforation (0.03), cumulative oil production (0.023), average salinity (-0.139) have negligible effect on the first principal component.

Consequently from the PCA, it can be concluded that, total rate after the treatment, total rate before the treatment, productivity index of water and cumulative water production are the dominating well parameters in the data set and should be used during the neural network analysis. Furthermore, parameters like ratio of total rate after and before the treatment, thickness of Mardin perforation, cumulative oil production, and average salinity are the parameters that have little impact on the first principal component; therefore, they could be excluded from the neural network analysis.

7.1.2 Correlation Analysis

The correlation coefficient is a measure of linear association between two variables. Correlation coefficient lies between -1 and +1. A correlation coefficient of +1 indicates that two variables are perfectly related in a positive linear sense, a correlation coefficient of -1 indicates that two variables are perfectly related in a negative linear sense, and a correlation coefficient of 0 indicates that there is no linear relationship between the two variables. In this part of the study, Pearson correlation coefficient (r) is calculated by using field parameters and success criteria. Also t-test is performed to observe the significance level of the correlations. Many researches assume that there is a statistically significant correlation if $p \leq 0.05$, if the value of $p \geq 0.20$, there is no correlation and if the value falls between 0.05 and 0.20, more data are needed. Furthermore, it is thought that t-score values greater than $|1.96|$ are considered significant if a 2-tailed test is performed. Results of the correlation analyses and significance levels are presented through Table 7.2 and Table 7.6. In these tables, significant correlations are illustrated with dark green color.

Table 7. 2 Correlation analysis between oil production rate one year after the treatment and the field parameters

Field Parameters	**Pearson Correlation Coefficient**	**Pearson's Tests of Significance**			
Cumulative oil production	0.17	t	1.3486	p-value	0.1827
Cumulative water production	0.62	t	6.0738	p-value	0.0000
Injectivity @ 500 psi	0.39	t	3.2308	p-value	0.0020
Thickness of Mardin perforation	0.17	t	1.3259	p-value	0.1901
Thickness of Garzan perforation	0.16	t	1.2629	p-value	0.2117
Average water cut before the treatment	-0.13	t	-0.9873	p-value	0.3276
Oil rate before the treatment	0.50	t	4.3802	p-value	0.0001
Total rate before treatment	0.53	t	4.7955	p-value	0.0000
Total rate after treatment	0.61	t	5.8136	p-value	0.0000
Ratio of total rate after and before the treatment	0.28	t	2.2075	p-value	0.0312
Average salinity before the treatment	-0.13	t	-1.0034	p-value	0.3198
Productivity index of oil before the treatment	0.61	t	5.8199	p-value	0.0000
Productivity index of water before the treatment	0.62	t	6.0548	p-value	0.0000

From the Table 7.2, it is observed that, oil production rate one year after the treatment is correlated with productivity index of water before the treatment (r=0.62), cumulative water production (r=0.62), productivity index of oil before the treatment (r=0.61), total rate after treatment (r=0.61), total rate before treatment (r=0.53), oil rate before the treatment (r=0.50), injectivity @ 500 psi (r=0.39), ratio of total rate after and before the treatment (r=0.28). However, oil production rate one year after the treatment does not have correlations with rest of the well parameters.

Table 7. 3 Correlation analysis between additional oil production one year after the treatment and the field parameters

Field Parameters	Pearson Correlation Coefficient	Pearson's Tests of Significance			
Cumulative oil production	0.03	t	0.2475	p-value	0.8054
Cumulative water production	0.35	t	2.8905	p-value	0.0054
Injectivity @ 500 psi	0.18	t	1.3646	p-value	0.1776
Thickness of Mardin perforation	0.36	t	2.9182	p-value	0.0050
Thickness of Garzan perforation	-0.05	t	-0.3483	p-value	0.7289
Average water cut before the treatment	0.46	t	3.9531	p-value	0.0002
Oil rate before the treatment	-0.43	t	-3.6526	p-value	0.0006
Total rate before treatment	0.11	t	0.8265	p-value	0.4119
Total rate after treatment	0.40	t	3.3522	p-value	0.0014
Ratio of total rate after and before the treatment	0.62	t	5.9952	p-value	0.0000
Average salinity before the treatment	-0.13	t	-0.9936	p-value	0.3246
Productivity index of oil before the treatment	0.32	t	2.6068	p-value	0.0116
Productivity index of water before the treatment	0.45	t	3.8868	p-value	0.0003

From the Table 7.3, it is observed that, additional oil production one year after the treatment is correlated with ratio of total rate after and before the treatment (r=0.62), average water cut before the treatment (r=0.46), productivity index of water before the treatment (r=0.45), total rate after treatment (r=0.40), thickness of Mardin perforation (r=0.36), cumulative water production (r=0.35), productivity index of oil before the treatment (r=0.32) and it is negatively correlated with oil rate before the treatment (r=-0.43). However, additional oil production one year after the treatment does not have correlations with rest of the well parameters.

Table 7. 4 Correlation analysis between profit one year after the treatment and the field parameters

Field Parameters	**Pearson Correlation Coefficient**	**Pearson's Tests of Significance**			
Cumulative oil production	0.03	t	0.2475	p-value	0.8054
Cumulative water production	0.35	t	2.8905	p-value	0.0054
Injectivity @ 500 psi	0.18	t	1.3646	p-value	0.1776
Thickness of Mardin perforation	0.36	t	2.9182	p-value	0.0050
Thickness of Garzan perforation	-0.05	t	-0.3483	p-value	0.7289
Average water cut before the treatment	0.46	t	3.9531	p-value	0.0002
Oil rate before the treatment	-0.43	t	-3.6526	p-value	0.0006
Total rate before treatment	0.11	t	0.8265	p-value	0.4119
Total rate after treatment	0.40	t	3.3522	p-value	0.0014
Ratio of total rate after and before the treatment	0.62	t	5.9952	p-value	0.0000
Average salinity before the treatment	-0.13	t	-0.9936	p-value	0.3246
Productivity index of oil before the treatment	0.32	t	2.6068	p-value	0.0116
Productivity index of water before the treatment	0.45	t	3.8868	p-value	0.0003

From the Table 7.4, it is observed that, profit one year after the treatment is correlated with ratio of total rate after and before the treatment (r=0.62), average water cut before the treatment (r=0.46), productivity index of water before the treatment (r=0.45), total rate after treatment (r=0.40), thickness of Mardin perforation (r=0.36), cumulative water production (r=0.35), productivity index of oil before the treatment (r=0.32) and it is negatively correlated with oil rate before the treatment (r=-0.43). However, profit one year after the treatment does not have correlations with rest of the well parameters.

Table 7. 5 Correlation analysis between additional oil production at the cleanup region and the field parameters

Field Parameters	Pearson Correlation Coefficient	Pearson's Tests of Significance			
Cumulative oil production	0.16	t	1.2627	p-value	0.2118
Cumulative water production	0.54	t	4.9493	p-value	0.0000
Injectivity @ 500 psi	0.34	t	2.7174	p-value	0.0087
Thickness of Mardin perforation	0.19	t	1.5095	p-value	0.1366
Thickness of Garzan perforation	0.10	t	0.8032	p-value	0.4251
Average water cut before the treatment	-0.13	t	-0.9780	p-value	0.3321
Oil rate before the treatment	0.39	t	3.2278	p-value	0.0021
Total rate before treatment	0.36	t	2.9776	p-value	0.0042
Total rate after treatment	0.43	t	3.6461	p-value	0.0006
Ratio of total rate after and before the treatment	0.27	t	2.1549	p-value	0.0353
Average salinity before the treatment	-0.06	t	-0.4599	p-value	0.6473
Productivity index of oil before the treatment	0.67	t	6.8054	p-value	0.0000
Productivity index of water before the treatment	0.52	t	4.6840	p-value	0.0000

From the Table 7.5, it is observed that, additional oil production at the cleanup region is correlated with productivity index of oil before the treatment (r=0.67), cumulative water production (r=0.54), productivity index of water before the treatment (r=0.52), total rate after treatment (r=0.43), oil rate before the treatment (r=0.39), total rate before treatment (r=0.36), injectivity @ 500 psi (r=0.34). However, oil production rate one year after the treatment does not have correlations with rest of the well parameters.

Table 7. 6 Correlation analysis between effectivity index and the field parameters

Field Parameters	Pearson Correlation Coefficient	Pearson's Tests of Significance			
Cumulative oil production	0.05	t	0.3710	p-value	0.7120
Cumulative water production	0.64	t	6.2983	p-value	0.0000
Injectivity @ 500 psi	0.29	t	2.2968	p-value	0.0253
Thickness of Mardin perforation	0.09	t	0.6619	p-value	0.5106
Thickness of Garzan perforation	0.19	t	1.4729	p-value	0.1462
Average water cut before the treatment	0.01	t	0.0975	p-value	0.9226
Oil rate before the treatment	0.39	t	3.1876	p-value	0.0023
Total rate before treatment	0.65	t	6.5900	p-value	0.0000
Total rate after treatment	0.78	t	9.5520	p-value	0.0000
Ratio of total rate after and before the treatment	0.29	t	2.2968	p-value	0.0253
Average salinity before the treatment	-0.24	t	-1.8447	p-value	0.0702
Productivity index of oil before the treatment	0.61	t	5.8237	p-value	0.0000
Productivity index of water before the treatment	0.79	t	9.9601	p-value	0.0000

From the Table 7.6, it is observed that, effectivity index is correlated with productivity index of water before the treatment (r=0.79), total rate after treatment (r=0.78), total rate before treatment (r=0.65), cumulative water production (r=0.64), productivity index of oil before the treatment (r=0.61), oil rate before the treatment (r=0.39), injectivity @ 500 psi (r=0.29), ratio of total rate after and before the treatment (r=0.29). However, effectivity index does not have correlations with rest of the well parameters.

Table 7. 7 Summary of first principal components and correlation status of the well parameters for different success criteria

Success Criteria	Principal Component	Cumulative oil production	Cumulative water production	Injectivity @ 500 psi	Thickness of Mardin perforation	Thickness of Garzan perforation	Average water cut	Oil rate before the treatment	Total rate before treatment	Total rate after treatment	Ratio of rate after and before the treatment	Average salinity	Productivity index of oil	Productivity index of water
Oil production rate one year after the treatment	**PC1**	0.04	0.381	0.176	0.04	0.216	0.048	0.222	0.418	0.417	0.043	-0.129	0.215	0.408
	Corr.		✓	✓				✓	✓	✓	✓		✓	✓
Additional oil production during one year after the treatment	**PC1**	0.02	0.404	0.167	0.063	0.23	0.135	0.145	0.435	0.455	0.079	-0.158	0.19	0.441
	Corr.		✓		✓		✓	✓		✓	✓		✓	✓
Profit during one year after the treatment	**PC1**	0.02	0.404	0.167	0.063	0.23	0.135	0.145	0.435	0.455	0.079	-0.158	0.19	0.441
	Corr.		✓		✓		✓	✓		✓	✓		✓	✓
Additional oil production at the clenup region	**PC1**	0.04	0.391	0.178	0.043	0.223	0.054	0.221	0.425	0.422	0.04	-0.129	0.226	0.419
	Corr.		✓	✓				✓	✓	✓	✓		✓	✓
Effectivity index	**PC1**	0.023	0.369	0.157	0.03	0.211	0.065	0.2	0.416	0.421	0.046	-0.139	0.209	0.413
	Corr.		✓	✓				✓	✓	✓	✓		✓	✓

In summary, Table 7.7 shows the first principal components and correlation status of the well parameters for different success criteria. In this table, dark green color represents the well parameters obtained from the PCA analysis and light green color represents the well parameters obtained from the correlation analysis. As it was stated before, parameters like ratio of total rate after and before the treatment, thickness of Mardin perforation, cumulative oil production, and average salinity are the parameters that have little impact on the first principal component; therefore, they are excluded from the neural network analysis. In addition, thickness of Garzan perforation is also eliminated as it does not show significant correlation with any of the success criteria. By using the Table 7.7, 9 different scenarios are constructed for each success criteria and they are presented with Table 7.8 and 7.9.

Table 7. 8 Summary of the scenarios simulated for the 1st, 4th and 5th success criteria

Scenarios	Cumulative water production	Productivity index of water	Total rate before treatment	Total rate after treatment	Productivity index of oil	Oil rate before the treatment	Injectivity @ 500 psi	Average water cut	Cumulative oil production	Thickness of Mardin perforation	Thickness of Garzan perforation	Ratio of rate after and before the treatment	Average salinity
Base	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1	✓	✓	✓	✓									
2	✓	✓	✓	✓	✓								
3	✓	✓	✓	✓		✓							
4	✓	✓	✓	✓			✓						
5	✓	✓	✓	✓	✓	✓							
6	✓	✓	✓	✓	✓		✓						
7	✓	✓	✓	✓		✓	✓						
8	✓	✓	✓	✓	✓	✓	✓						

Table 7. 9 Summary of the scenarios simulated for the 2nd and 3rd success criteria

Scenarios	Cumulative water production	Productivity index of water	Total rate before treatment	Total rate after treatment	Productivity index of oil	Oil rate before the treatment	Average water cut	Injectivity @ 500 psi	Cumulative oil production	Thickness of Mardin perforation	Thickness of Garzan perforation	Ratio of rate after and before the treatment	Average salinity
Base	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
1	✓	✓	✓	✓									
2	✓	✓	✓	✓	✓								
3	✓	✓	✓	✓		✓							
4	✓	✓	✓	✓			✓						
5	✓	✓	✓	✓	✓	✓							
6	✓	✓	✓	✓	✓		✓						
7	✓	✓	✓	✓		✓	✓						
8	✓	✓	✓	✓	✓	✓	✓						

Table 7. 10 Correlation Analysis between the well parameters

Well Parameter & Success Criteria	Cumulative oil production	Cumulative water production	Injectivity @ 500 psi	Thickness of Mardin perforation	Thickness of Garzan perforation	Average water cut	Oil rate before the treatment	Total rate before treatment	Total rate after treatment	Ratio of rate after and before treatment	Average salinity	Productivity index of oil	Productivity index of water
Cumulative oil production	1.00												
Cumulative water production	0.16	1.00											
Injectivity @ 500 psi	0.23	0.30	1.00										
Thickness of Mardin perforation	0.10	**0.42**	0.21	1.00									
Thickness of Garzan perforation	-0.01	0.37	0.04	-0.14	1.00								
Average water cut	-0.10	0.23	0.04	0.12	0.06	1.00							
Oil rate before the treatment	0.16	0.31	0.24	-0.19	0.23	**-0.63**	1.00						
Total rate before treatment	0.01	**0.74**	0.28	-0.13	**0.49**	0.21	**0.47**	1.00					
Total rate after treatment	0.05	**0.71**	0.22	0.03	0.38	0.28	0.24	**0.85**	1.00				
Ratio of rate after and before treatment	0.11	0.05	0.01	0.34	-0.14	0.17	-0.35	-0.18	0.26	1.00			
Average salinity	**0.42**	-0.12	0.19	0.07	-0.21	-0.16	-0.01	-0.25	-0.30	-0.21	1.00		
Productivity index of oil	-0.06	0.11	0.09	-0.05	0.04	-0.33	0.32	0.21	0.24	0.07	-0.12	1.00	
Productivity index of water	-0.04	**0.61**	0.21	-0.02	0.31	0.22	0.20	**0.81**	**0.85**	0.07	-0.23	**0.53**	1.00

Table 7. 11 Correlation Analysis between the well parameters and corresponding significance levels

Field Parameters	Field Parameters	Pearson Correlation Coefficient	Pearson's Tests of Significance			
Thickness of Mardin perforation	Cumulative water production	0.42	t	3.5550	p-value	0.0008
Oil rate before the treatment	Average water cut before the treatment	-0.63	t	-6.0981	p-value	0.0000
Total rate before treatment	Cumulative water production	0.74	t	8.4413	p-value	0.0000
Total rate before treatment	Thickness of Garzan perforation	0.49	t	4.2829	p-value	0.0001
Total rate before treatment	Oil rate before the treatment	0.47	t	4.0478	p-value	0.0002
Total rate before treatment	Productivity index of water before the treatment	0.81	t	10.4929	p-value	0.0000
Total rate after treatment	Productivity index of water before the treatment	0.85	t	12.4793	p-value	0.0000
Total rate after treatment	Cumulative water production	0.71	t	7.6529	p-value	0.0000
Total Rate after treatment	Total rate before treatment	0.85	t	12.3764	p-value	0.0000
Average salinity before the treatment	Cumulative oil production	0.42	t	3.5074	p-value	0.0009
Productivity index of water before the treatment	Cumulative water production	0.61	t	5.7928	p-value	0.0000
Productivity index of water before the treatment	Productivity index of oil before the treatment	0.53	t	4.7996	p-value	0.0000

Correlation analysis is also performed to observe the relationship between the well parameters. Table 7.10 and Table 7.11 show the correlation analysis between the well parameters and corresponding significance levels.

From the correlation matrix it is observed that, thickness of Mardin perforation is correlated with the cumulative water production. In Raman field, it is thought that vertical fractures connect the aquifer to the Mardin formation, for this reason thickness of Mardin perforation may trigger the excessive water production. Actually, it is wrong to expect a linear relationship between the perforation thickness and fracture intensity especially for the heterogonous reservoir structure. However, increase in perforation thickness may also increase the chance of cutting more fractures and the correlation coefficient here seems to show this chance.

From the correlation matrix it is observed that, there is a negative correlation between the oil rate and average water cut before the treatment. This kind of relationship is expected as the oil rate is calculated by multiplying the total rate with average oil cut. Exceptional situations may occur on wells that have both low water cut and low productivity index values or both high water cut and high productivity index values. In former cases, low productivity index values may limit the total rate so that low water cut values could not be enough to keep the oil rate high. In the latter cases, high total rate may offset the high water cut values and could be enough to keep the oil rate relatively high itself. For example, suppose that a well is producing with total flow rate of 100 bbl/d and water cut of 50% and another well is producing with total flow rate of 3,000 bbl/d and water cut of 98%. In this case, oil rate of the first well is 50 bbl/d and oil rate of the second well is 60 bbl/d. Therefore, it could be stated that, correlation between oil rate and average water cut may differ depending on the productivity index.

Correlation matrix shows that total rate before the treatment is correlated with cumulative water production, productivity index of water before the treatment, thickness of Garzan perforation and oil rate before the treatment. As the productivity of the wells mainly stems from the fracture intensity, highly productive wells have high water cut values and produce with higher production rates; inherently, high production rates and high water cut values result in high cumulative water production values. It is also expected that the perforation thickness increases the total rate before the treatment. Moreover, correlation between the total rate and oil rate before the treatment is not surprising as the oil rate before the treatment is found by multiplying the total rate before the treatment with average oil cut.

Correlation matrix shows that total rate after the treatment is correlated with cumulative water production, total rate before the treatment and productivity index of water before the treatment. Cumulative water production and productivity index of water before the treatment are correlated and both of them give indirect evidence about the fracture intensity of the wells. In general, total rate after the treatment is determined depending on the productivity index of the well after the treatment. Therefore, it could be argued that success of the treatments highly depends on parameters like cumulative water production, total rate before the treatment and productivity index of water before the treatment.

Correlation matrix indicates that, average salinity is correlated with the cumulative oil production. This correlation could be expected as the wells with high salinity values are producing mainly from the matrix and freshwater intrusion from the aquifer is relatively low. However, high salinity itself does not guarantee the high cumulative oil production, for example dataset may include wells that have high salinity values but short production history. From the perspective of candidate well selection, oil companies are generally looking for wells that have low salinity values as the freshwater intrusion is obvious in these wells and from the Table 7.10 it could be concluded that lower cumulative oil values could be expected on wells whose average salinity values are relatively low. At this point, it should be stated that low cumulative oil production values are also desired due to remaining oil in place considerations. It is interesting that, cumulative oil production and average salinity only correlated with each other, and lower values of both parameters may enhance the success of the polymer gel treatment.

However, it is interesting that average salinity has no correlation with rest of the parameters. In general, low salinity values are regarded as evidence of the fresh water intrusion and wells with low salinity values like 2,000 ppm are considered as good candidates for the polymer gel treatment. However, from the correlation matrix it is observed that it does not have any correlation with other well parameters. At this point it should be mentioned that, once the salinity distribution of the field is investigated regional groups are observed. For example, certain part of field is filled with wells with low salinity values, another part is filled with higher salinity values and so on. This case is also valid for the average water cut. For example, certain part of field is filled with wells with relatively high water cut values and wells with low water cut values are located at the edges of the reservoir. Lack of correlation between these two parameters may result from the distribution of these parameters throughout the filed. For example, wells located in each cluster may have correlation with different well parameter or simply introduction of additional parameters like matrix permeability and fracture distribution is required to obtain these correlations.

From the correlation matrix it is also observed that productivity index of water before the treatment is correlated with cumulative water production and productivity index of oil before the treatment. Actually, high values of the productivity index of water are the reasons of the high cumulative water production values; therefore, correlation between these parameters looks like the relation between the cause and effect. Furthermore, correlation between productivity index of water and productivity index of oil suggests that wells that have high productivity index of oil values also have high productivity index of water values; therefore, naturally they suffer from high water cut problem that makes them good candidate for the water shutoff treatment.

7.2 Candidate Well Selection by using Artificial Neural Networks

In this part, Artificial Neural Networks are constructed by using 60 different well data and 30 of them are assigned for the training, 15 of them are assigned for the testing and last 15 of them are assigned for the validation parts. Scenarios presented with Table 7.8 and Table 7.9 are simulated for each success criterion. For each scenario, 100 different data sets are prepared by varying the samples used in the training, test and validation parts for the defined success criteria. Also, for each data set, 100 different neural network structures are formed by varying the number of neurons at the hidden layer. Therefore, for each scenario 10,000 different neural network structures are formed, which makes 90,000 different neural network structures for each success criterion and 450,000 different neural network structures for the entire study. Then for each success criterion, the most successful neural networks are selected and presented here. After that, sensitivity analyses are performed by varying input parameters that are used during the neural network analysis in order to observe the factors that are thought to dominate the treatments. During sensitivity analysis, mean and standard deviation for each parameter is calculated and analysis are performed by varying the parameters between (mean - standard deviation) and (mean + standard deviation).

7.2.1 Evaluation of the Artificial Network Analysis Results

The basic idea behind this study is the utilization of the artificial neural network system to have an idea about the possible post production performance of the candidate wells. In order to obtain this information, current performance of the well (capacity of the well), success rate of the treatment and performance of the well after the treatment should be defined as representative as possible. During this study parameters like; cumulative oil and water production, injectivity at 500 psi, perforation thicknesses, average water cut before the treatment, oil rate and total rate before the treatment, total rate after the treatment, ratio of total rate after and before the treatment, average salinity before the treatment, productivity index of oil and water before the treatment are used to define the current state of the well. Furthermore parameters like; oil rate one year after the treatment, additional oil production one year after the treatment, profit one year after the treatment, additional oil production at the cleanup region and effectivity index are used as success criteria. It should be stated that, throughout this study no information is provided about the success rate of the treatments and it is assumed that all the wells are treated in a similar fashion. Success of the treatments may be inferred from; amount of injected polymer, concentration of the polymer and development of the wellhead pressure during the treatment. However, it is difficult to evaluate the success of the treatment before putting the well on production. Also, aim of this study is the use of neural network for the candidate selection and since treatment information could not be known before the treatment, networks that are using treatment information would not be helpful for the candidate selection process.

7.2.2 Artificial Network Analysis Simulation Results

In this study, various network structures are created by using different datasets and different success criteria. Developed neural network structures are evaluated by using the average absolute error, root mean squared error, regression coefficient and r-squared. Mean absolute error (MAE) is used to measure how close forecasts or predictions are to the eventual outcomes, Equation 7.1 is used to calculate the average absolute error.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|\widehat{y_i} - y_i| = \frac{1}{n}\sum_{i=1}^{n}|e_i| \tag{7.1}$$

Root Mean Squared Error (RMSE) is just the square root of the mean square error and it shows the distance of a data point from the fitted line, measured along a vertical line. Equation 7.2 is used to calculate root mean squared error.

$$\text{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}(\widehat{y_t} - y_t)^2}{n}} \tag{7.2}$$

Both RMSE and MAE have been used as a standard metric to measure the model performance in many research studies. Although both of them have been used for many years, there is no consensus on the appropriate metric for evaluating errors. On the other hand, in the field of geosciences, many researchers present the RMSE as a standard metric for model errors (McKeen et al., 2005; Savage et al., 2013; Chai et al., 2013).

Regression coefficient is the slope of a line obtained using linear least squares fitting. Linear least squares fitting is a procedure for finding the best line to a given set of points by minimizing the sum of the squares of the residuals of the points from the curve.

R-squared is a statistical measure that represents the variance in the dependent variable that is predictable from the independent variable. This term is generally used in statistical models whose aim is the prediction of future outcomes. It provides a measure of how well observed outcomes are replicated by the model, based on the proportion of total variation of outcomes explained by the model.

7.2.2.1 First Success Criterion - Oil production rate during one year after the treatment

In this part of the study, oil production rate during one year after the treatment is used as a success criterion and 9 different scenarios are simulated. For each scenario, 10,000 different neural network structures are formed and Table 7.12 shows the error values for the best neural network structure of the certain scenario.

Table 7. 12 Scenarios and corresponding error values for the first success criterion

Scenarios	Mean Absolute Error	Root Mean Squared Error	Regression Coefficient	R-Squared
Base Scenario	5.83	8.94	1.0143	0.9322
1. Scenario	7.94	11.63	0.9404	0.8889
2. Scenario	3.92	6.69	0.9901	0.9622
3. Scenario	4.54	7.25	0.9847	0.9560
4. Scenario	8.60	12.10	0.9544	0.8771
5. Scenario	4.29	6.43	0.9648	0.9674
6. Scenario	4.97	7.91	0.9816	0.9469
7. Scenario	5.79	8.76	1.0103	0.9354
8. Scenario	4.90	8.97	0.9635	0.9392

From the Table 7.12, it is observed that 2nd and 5th scenarios have lower mean absolute error and root mean squared error values and they have higher r-squared values when compared with the other scenarios. As can be seen from the Table 7.8, 2nd scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment and productivity index of oil before the treatment. On the other hand, 5th scenario includes the oil rate before the treatment additional to the well parameters on the 2nd scenario. Here, 5th scenario is selected based on the root mean squared error. Figure 7.6 and 7.7 show the comparison of the actual and predicted values by using the scatter plot and bar graph, also Figure 7.8 shows the results of the performed sensitivity analysis.

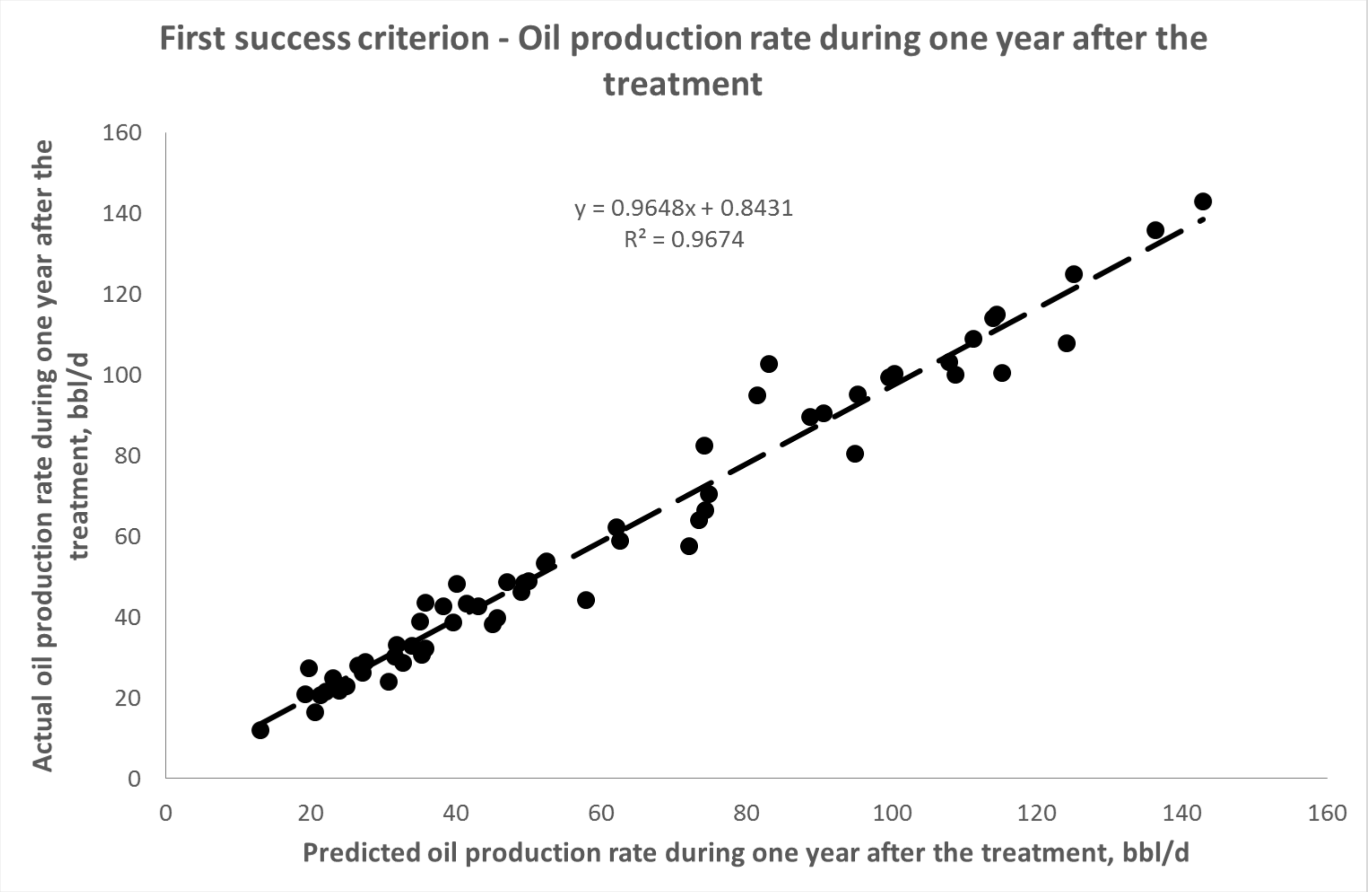

Figure 7. 6 Scatter plot of Actual oil production rate vs. Predicted oil production rate

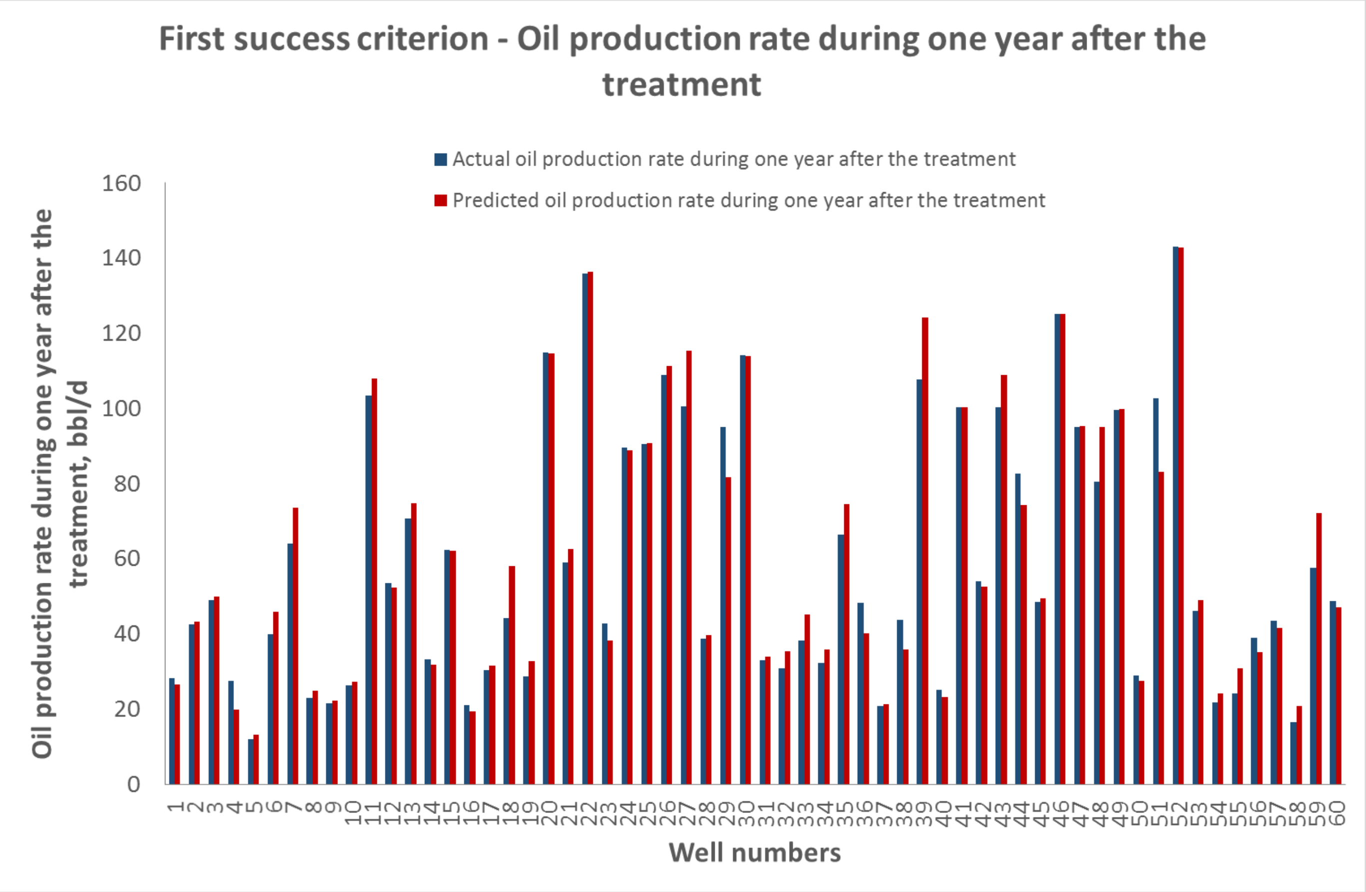

Figure 7. 7 Bar graph of Actual oil production rate vs. Predicted oil production rate

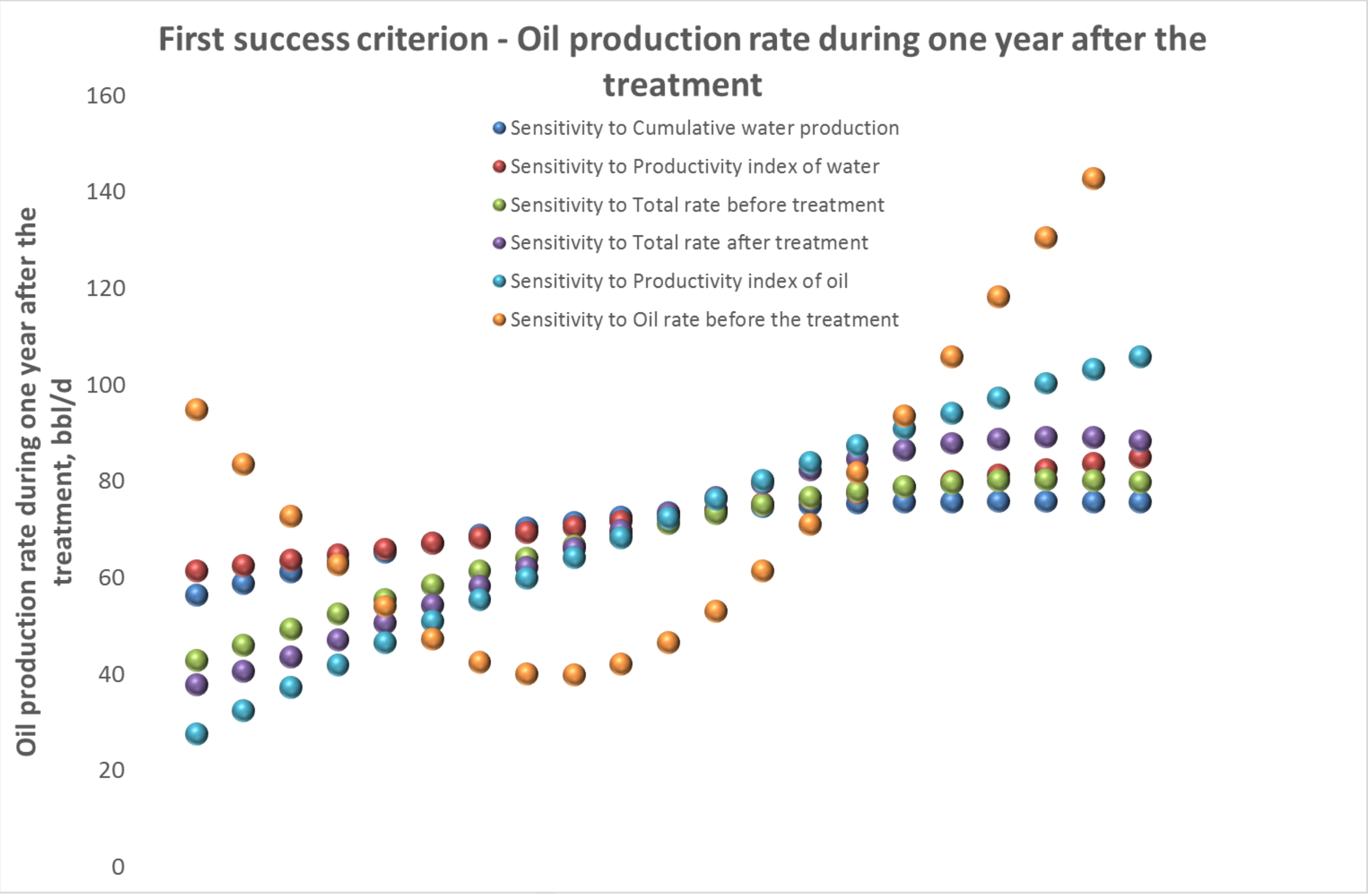

Figure 7. 8 Sensitivity analysis of the oil production rate

From the Figure 7.8, it is observed that oil production rate one year after the treatment is sensitive to cumulative water production and productivity index of water. These parameters could be used as indirect evidences of the fracture distribution and intensity; therefore, it is not surprising that the oil production rate is directly proportional to these parameters. It is also observed that, total rate before and after the treatment values have similar influences on the oil production rate. It is inferred from the sensitivity analysis that, oil production rates are relatively low for lower values of these parameters, whereas oil production rates are almost constant for higher values of these parameters. Relationship between oil production rate and total rate after the treatment is interesting as there exists a critical rate value beyond which increase in total rate after the treatment does not cause a change in the oil rate, which means that it increases the water cut. In this case, oil production rate is almost the same for total production rate of 1,000 bbl/d and 1,300 bbl/d. From there it could be concluded that, if the water cut value is approximately 92%, increasing the rate from 1,000 bbl/d to 1,300 bbl/d could increase the water cut from approximately 92% to 94%. Figure 7.8 also shows that, oil production rate after the treatment almost linearly increases with an increase in productivity index of oil, this behavior suggests that success of the treatment is directly related with the productivity index of oil and it influences the oil production rate more when compared with the other parameters except the oil rate before the treatment parameter. The relationship between oil rate and oil rate before the treatment is interesting as the oil rate is relatively higher for both lower values and higher values. Also lowest values of oil rate after the treatment generally takes place for the wells that have average oil rate before the treatment, and higher oil rates after the treatment values take place for marginal wells that have oil rates far below or far above the field average.

7.2.2.2 Second Success Criterion - Additional oil production one year after the treatment

In this part of the study, additional oil production one year after the treatment is used as a success criterion and 9 different scenarios are simulated. For each scenario, 10,000 different neural network structures are formed and Table 7.13 shows the error values for the best neural network structure of the certain scenario.

Table 7. 13 Scenarios and corresponding error values for the second success criterion

Scenarios	Mean Absolute Error	Root Mean Squared Error	Regression Coefficient	R-Squared
Base Scenario	2355	3267	0.9525	0.9298
1. Scenario	2842	4045	1.0222	0.8892
2. Scenario	1877	2620	0.9935	0.9535
3. Scenario	1729	2528	0.9897	0.9567
4. Scenario	1497	2129	1.0093	0.9740
5. Scenario	1304	2100	0.9787	0.9707
6. Scenario	1479	2030	1.0092	0.9725
7. Scenario	1582	2611	0.9379	0.9598
8. Scenario	1679	2907	1.0100	0.9449

From the Table 7.13, it is observed that 4th, 5th and 6th scenarios have lower mean absolute error and root mean squared error values and they have higher r-squared values when compared with the other scenarios. As can be seen from the Table 7.9, 4th scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment and average water cut. 5th scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment, productivity index of oil before the treatment and oil rate before the treatment. 6th scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, productivity index of oil before the treatment and average water cut. Here, 6th scenario is selected based on the root mean squared error. Figure 7.9 and 7.10 show the comparison of the actual and predicted values by using the scatter plot and bar graph, also Figure 7.11 shows the results of the performed sensitivity analysis.

From the Figure 7.11, it is observed that additional oil production one year after the treatment is sensitive to cumulative water production, average water cut and productivity index of oil. These parameters almost similarly influence the additional oil production one year after the treatment. It is also observed that additional oil production one year after the treatment is almost constant for lower values of productivity index of water. Furthermore, total rate before and after values highly influence the additional oil production one year after the treatment. In general, total rate after the treatment is lower than the total rate before the treatment; therefore, it is difficult to obtain additional oil from wells whose total rate before the treatment values are significantly lower than the field average.

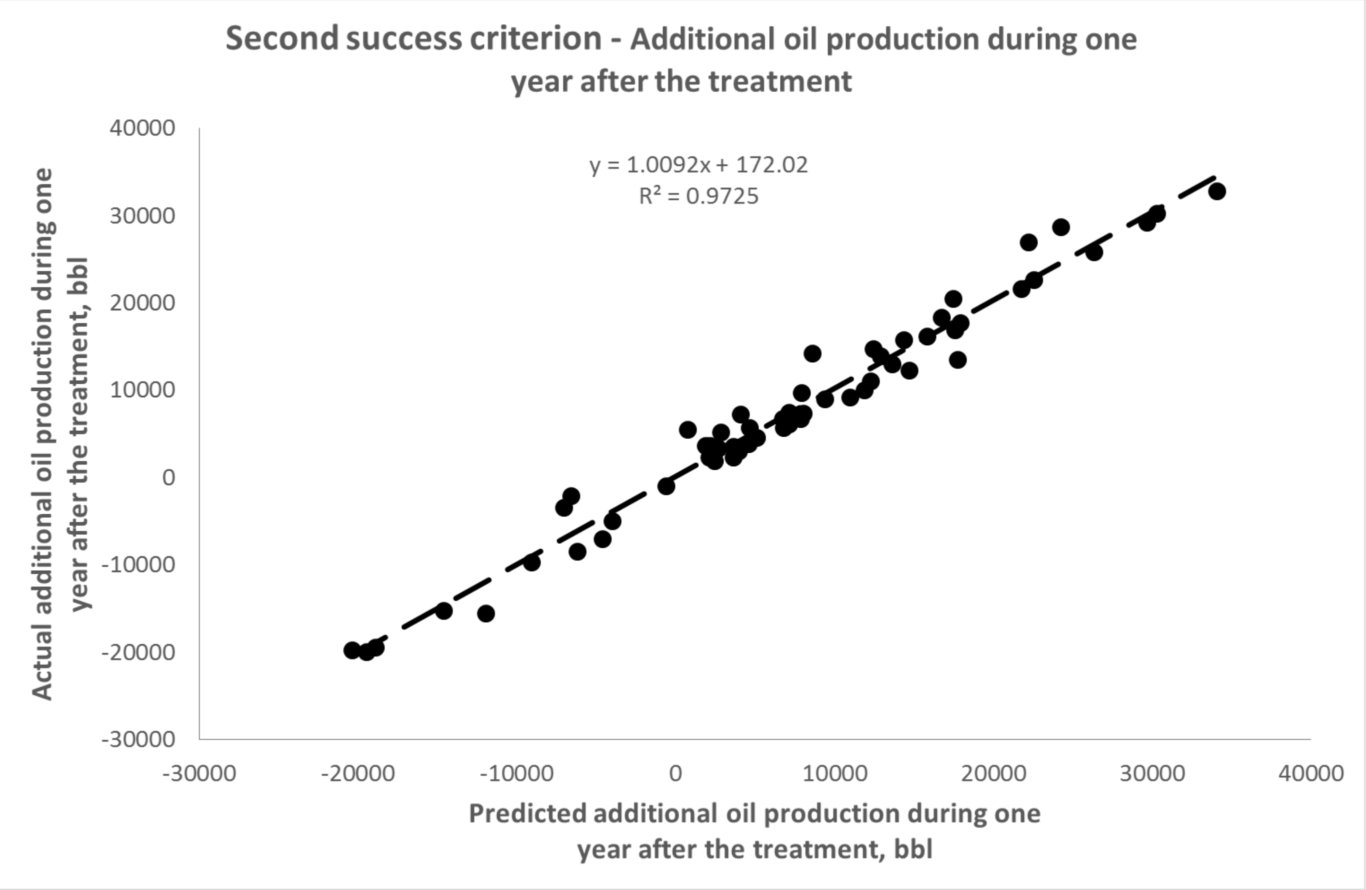

Figure 7. 9 Scatter plot of Actual additional oil production during one year after the treatment vs. Predictions

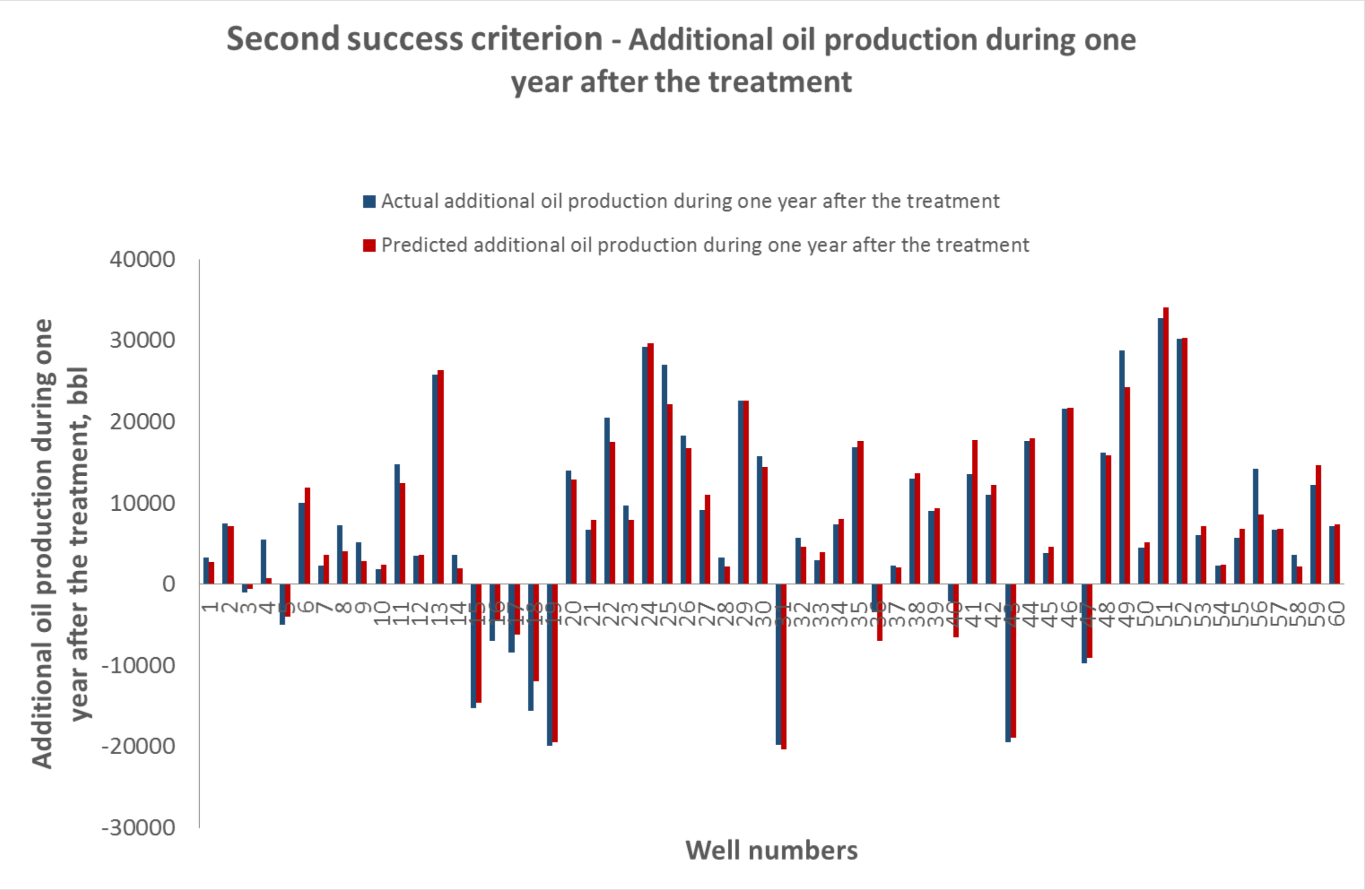

Figure 7. 10 Bar graph of Actual additional oil production during one year after the treatment vs. Predictions

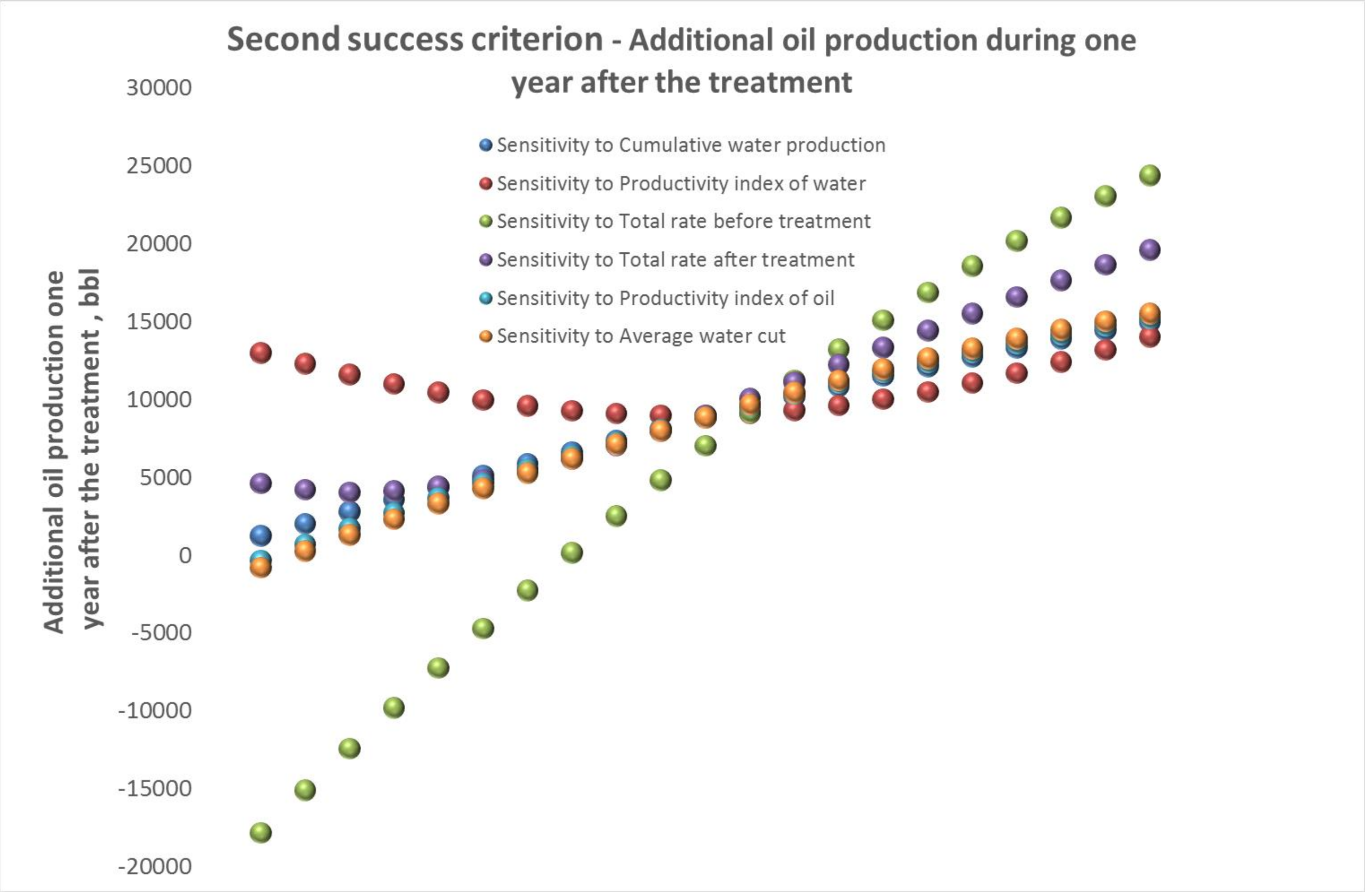

Figure 7. 11 Sensitivity analysis of the additional oil production during one year after the treatment

7.2.2.3 Third Success Criterion - Profit one year after the treatment

In this part of the study, profit one year after the treatment is used as a success criterion and 9 different scenarios are simulated. For each scenario, 10,000 different neural network structures are formed and Table 7.14 shows the error values for the best neural network structure of the certain scenario.

Table 7. 14 Scenarios and corresponding error values for the third success criterion

Scenarios	Mean Absolute Error	Root Mean Squared Error	Regression Coefficient	R-Squared
Base Scenario	118734	204983	1.0026	0.8865
1. Scenario	128341	193798	1.0048	0.8987
2. Scenario	89390	142859	0.9399	0.9486
3. Scenario	94085	138550	0.9979	0.9490
4. Scenario	75603	109359	1.0146	0.9731
5. Scenario	63786	101164	1.0254	0.9730
6. Scenario	61281	99708	1.0057	0.9735
7. Scenario	73965	129346	0.9753	0.9554
8. Scenario	72959	131848	0.9463	0.9563

From the Table 7.14, it is observed that 5th and 6th scenarios have lower mean absolute error and root mean squared error values and they have higher r-squared values when compared with the other scenarios. As can be seen from the Table 7.9, 5th scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment, productivity index of oil before the treatment and oil rate before the treatment. 6th scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, productivity index of oil before the treatment and average water cut. Here, 6th scenario is selected based on the root mean squared error. Figure 7.12 and 7.13 show the comparison of the actual and predicted values by using the scatter plot and bar graph, also Figure 7.14 shows the results of the performed sensitivity analysis.

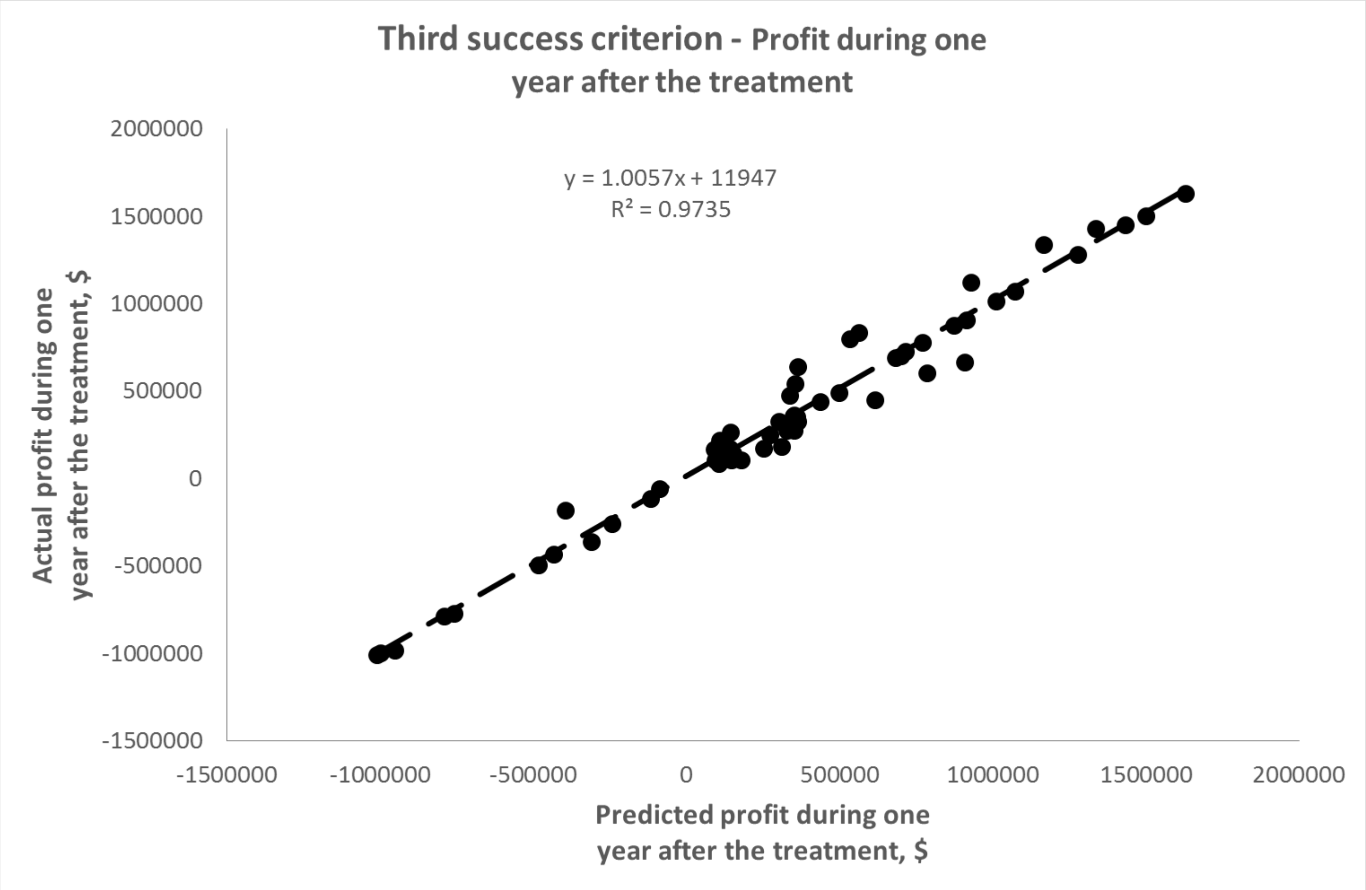

Figure 7. 12 Scatter plot of Actual profit during one year after the treatment vs. Predictions

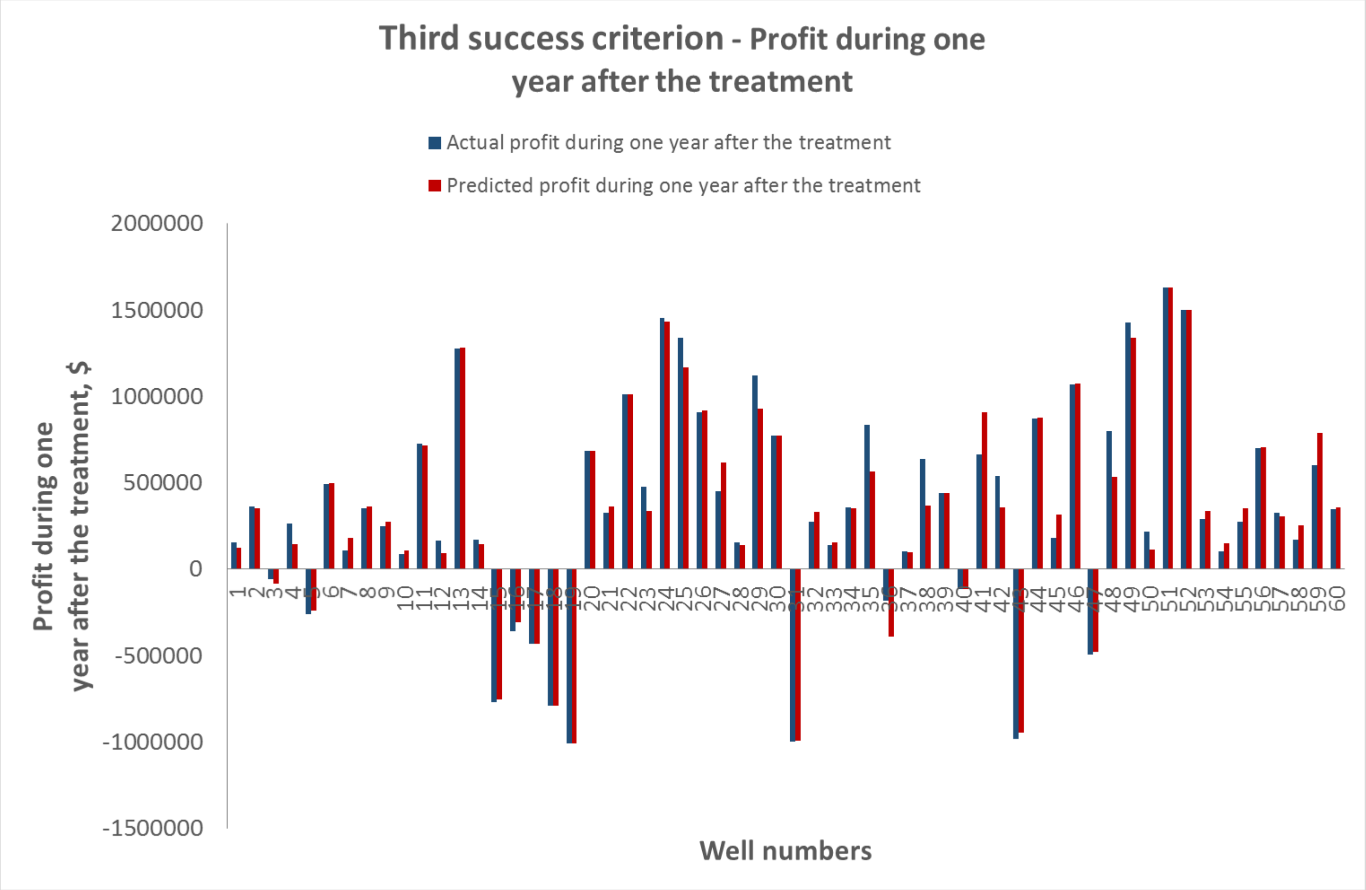

Figure 7. 13 Bar graph of Actual profit during one year after the treatment vs. Predictions

Figure 7. 14 Sensitivity analysis of the profit during one year after the treatment

From the Figure 7.14, it is observed that profit one year after the treatment is sensitive to cumulative water production, average water cut and productivity index of water. These parameters almost similarly influence the profit one year after the treatment and their effect is less when compared with the other parameters. It is also observed that profit one year after the treatment increases with an increase in productivity index of oil as long as the productivity index of oil values are lower than the field average. However, for the higher productivity index of oil values, profit one year after the treatment stays almost constant. Furthermore, total rate before and after values highly influence the profit one year after the treatment as in the case of second success criterion.

7.2.2.4 Fourth Success Criterion - Additional oil production at the cleanup region

In this part of the study, additional oil production at the cleanup region is used as a success criterion and 9 different scenarios are simulated. For each scenario, 10,000 different neural network structures are formed and Table 7.15 shows the error values for the best neural network structure of the certain scenario.

Table 7. 15 Scenarios and corresponding error values for the fourth success criterion

Scenarios	Mean Absolute Error	Root Mean Squared Error	Regression Coefficient	R-Squared
Base Scenario	2944	4054	0.9524	0.9132
1. Scenario	4148	6212	0.9632	0.7928
2. Scenario	2393	3564	0.9344	0.9380
3. Scenario	3277	4846	0.9691	0.8757
4. Scenario	4060	7004	0.8525	0.7670
5. Scenario	2897	4286	1.0085	0.9066
6. Scenario	2796	4110	1.0295	0.9091
7. Scenario	3263	4297	1.0045	0.9004
8. Scenario	3033	4516	0.9403	0.8931

From the Table 7.15, it is observed that 2nd scenario has lower mean absolute error and root mean squared error values and it has higher r-squared value when compared with the other scenarios. As can be seen from the Table 7.8, 2nd scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment and productivity index of oil before the treatment. Therefore, 2nd scenario is selected and Figure 7.15 and 7.16 show the comparison of the actual and predicted values by using the scatter plot and bar graph, also Figure 7.17 shows the results of the performed sensitivity analysis.

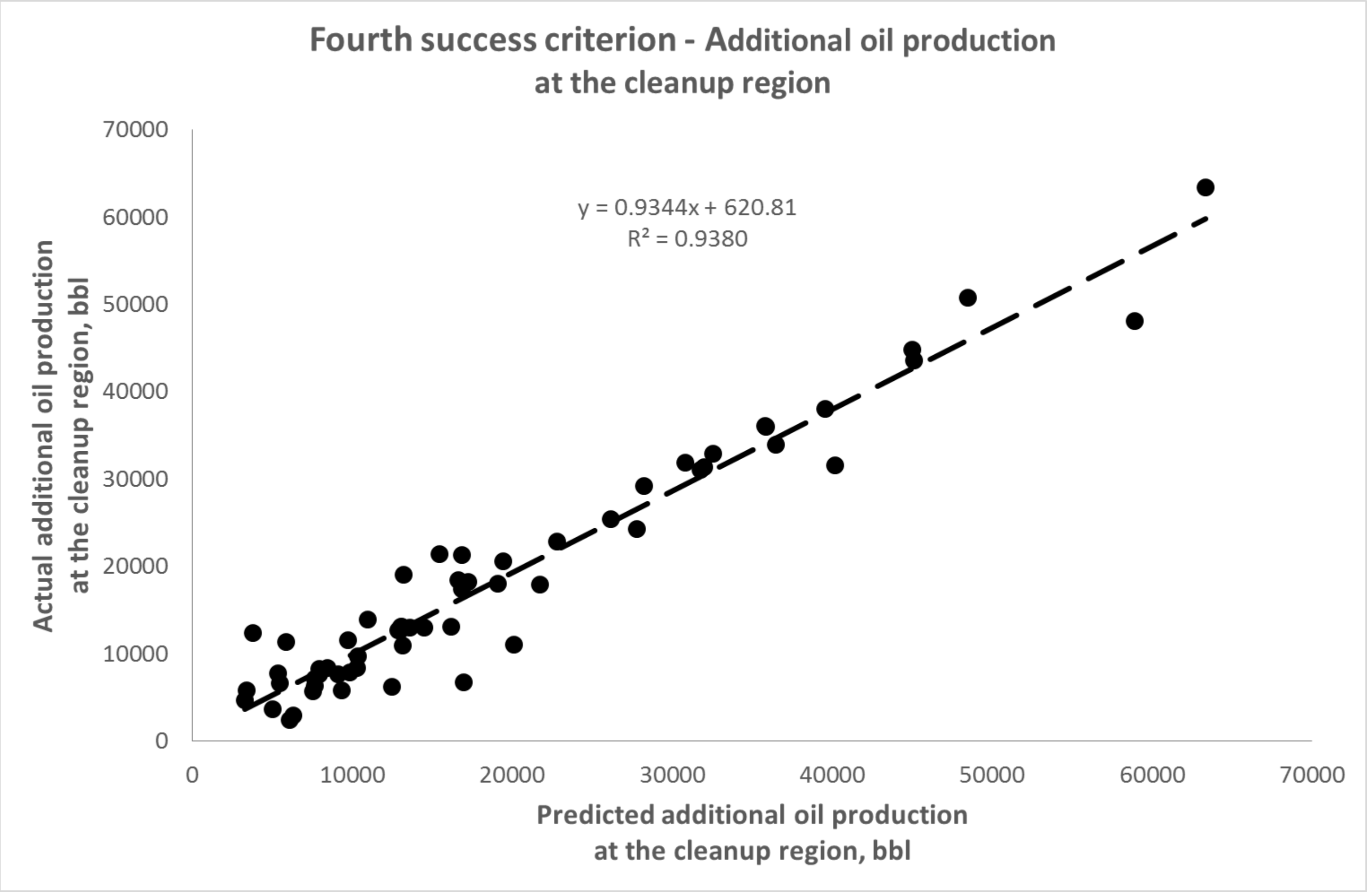

Figure 7. 15 Scatter plot of Actual additional oil production at the cleanup region vs. Predictions

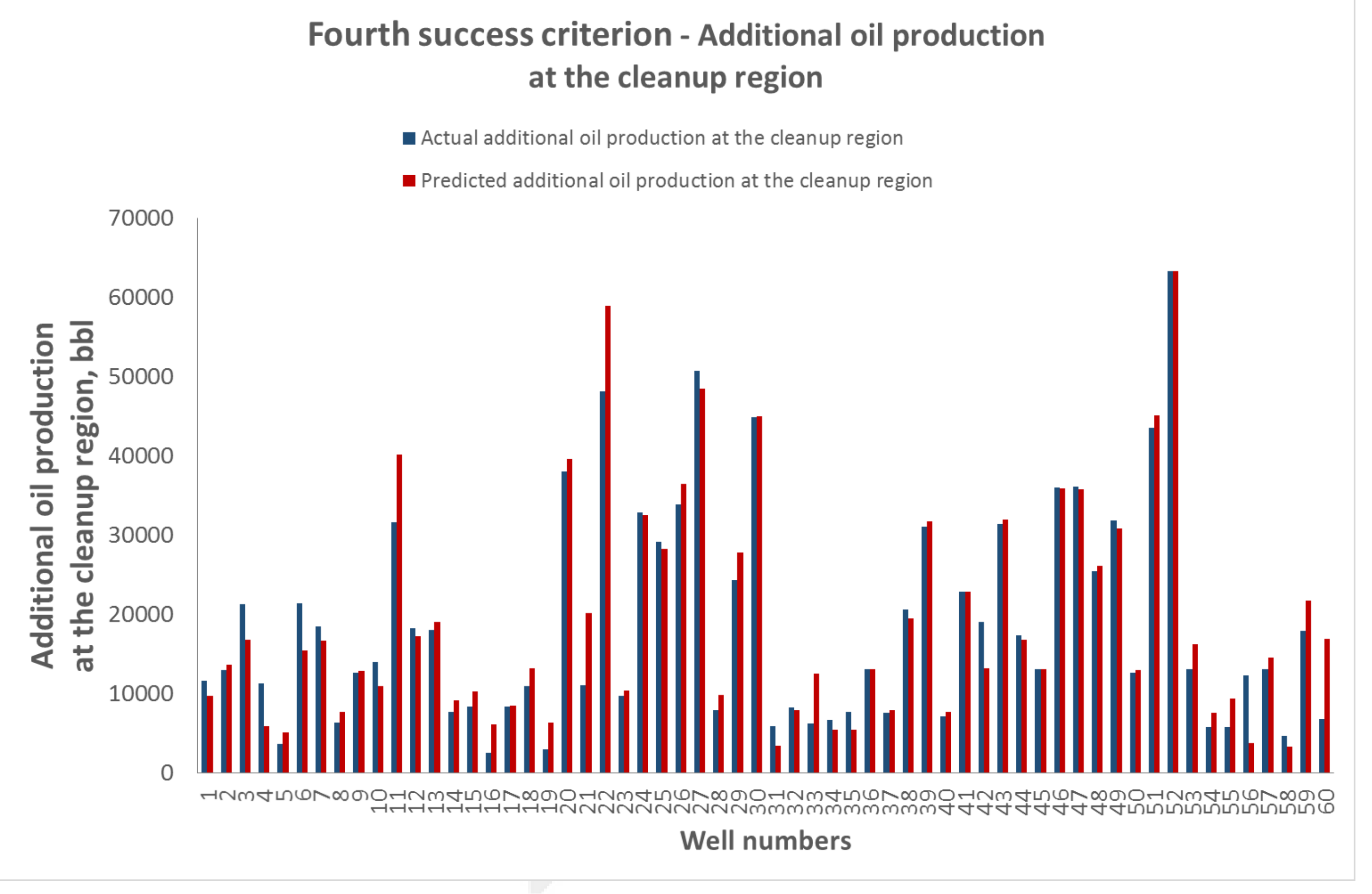

Figure 7. 16 Bar graph of Actual additional oil production at the cleanup region vs. Predictions

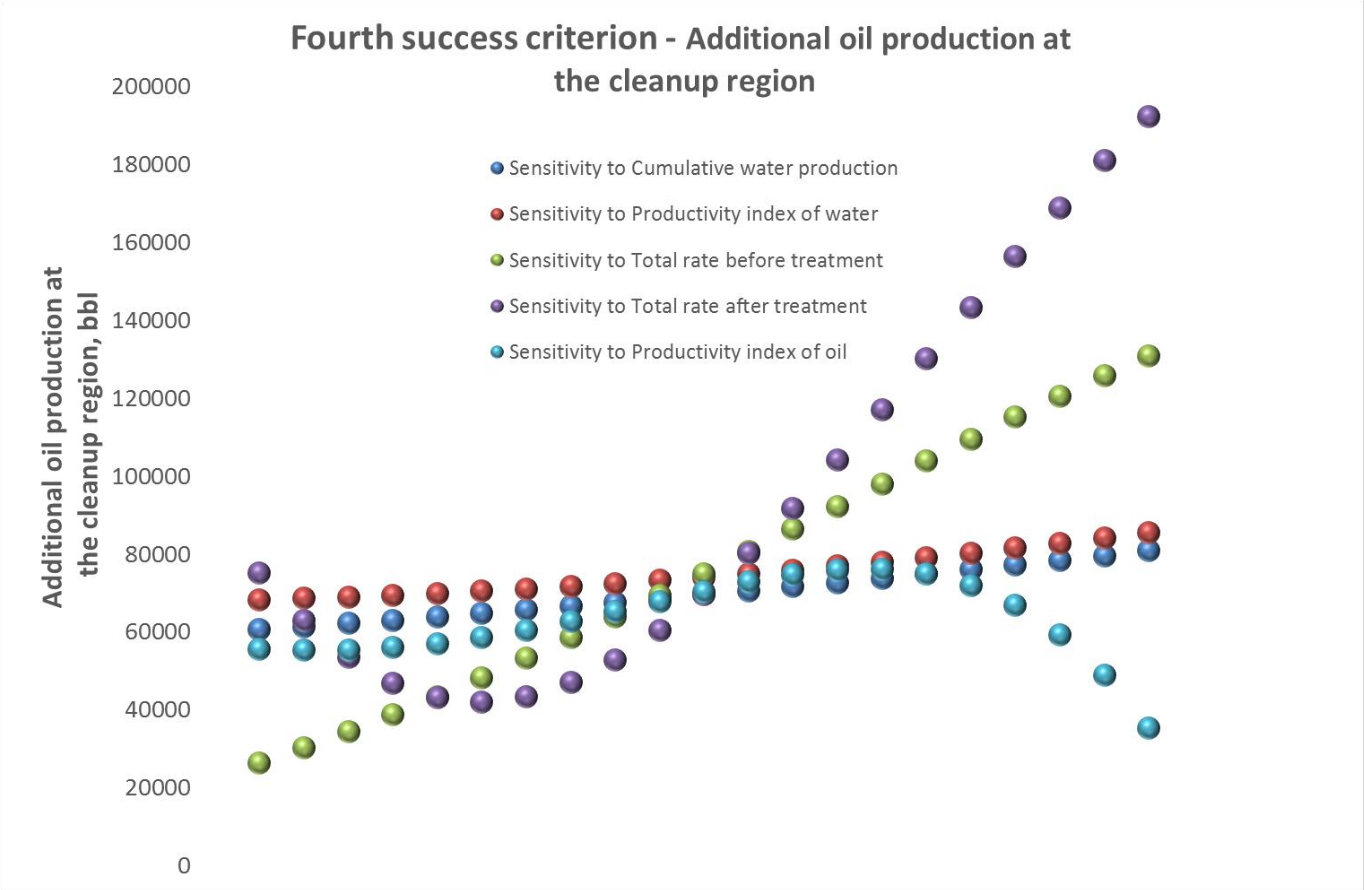

Figure 7. 17 Sensitivity analysis of the additional oil production at the cleanup region

From the Figure 7.17, it is observed that additional oil production at the cleanup region is sensitive to cumulative water production and productivity index of water. Also, productivity index of oil has the similar influence on the additional oil production at the cleanup region; however, for the productivity index of oil values greater than 0.540, fourth success criterion shows a decreasing trend. This can be explained by the fact that, wells that have high productivity index of oil values naturally have high oil production rates and this situation increases the chance of partially damaging the oil productive zones. In these situations, productivity index of oil values could be diminished after the treatment and additional oil production especially at the cleanup region may decrease. Furthermore, total rate before and after values highly influence the additional oil production at the cleanup region as in the case of second and third success criteria.

7.2.2.5 Fifth Success Criterion - Effectivity Index

In this part of the study, effectivity index is used as a success criterion and 9 different scenarios are simulated. For each scenario, 10,000 different neural network structures are formed and Table 7.16 shows the error values for the best neural network structure of the certain scenario.

Table 7. 16 Scenarios and corresponding error values for the fifth success criterion

Scenarios	Mean Absolute Error	Root Mean Squared Error	Regression Coefficient	R-Squared
Base Scenario	1299	2245	0.9941	0.9179
1. Scenario	2097	2924	0.9556	0.8530
2. Scenario	1301	1920	0.9431	0.9397
3. Scenario	1163	1984	0.9483	0.9342
4. Scenario	1758	2764	0.9764	0.8668
5. Scenario	1013	1706	0.9611	0.9511
6. Scenario	1285	1929	0.9692	0.9369
7. Scenario	1134	1861	0.9471	0.9462
8. Scenario	1447	2060	0.9959	0.9277

From the Table 7.16, it is observed that 5th scenario has lower mean absolute error and root mean squared error values and it has higher r-squared value when compared with the other scenarios. As can be seen from the Table 7.8, 5th scenario includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment, productivity index of oil before the treatment and oil rate before the treatment. Therefore, 5th scenario is selected and Figure 7.18 and 7.19 show the comparison of the actual and predicted values by using the scatter plot and bar graph, also Figure 7.20 shows the results of the performed sensitivity analysis.

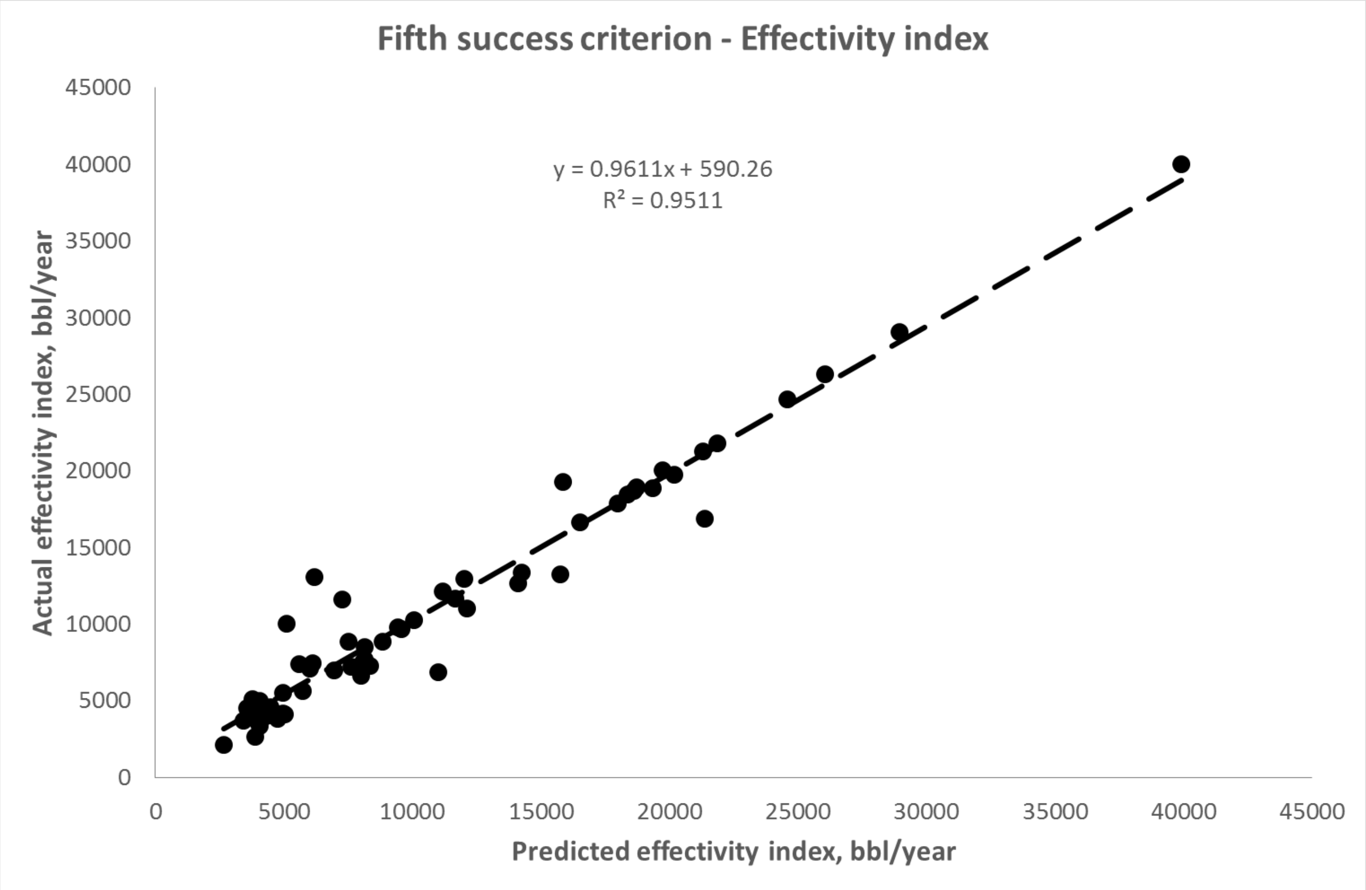

Figure 7. 18 Scatter plot of Actual effectivity index vs. Predicted effectivity index

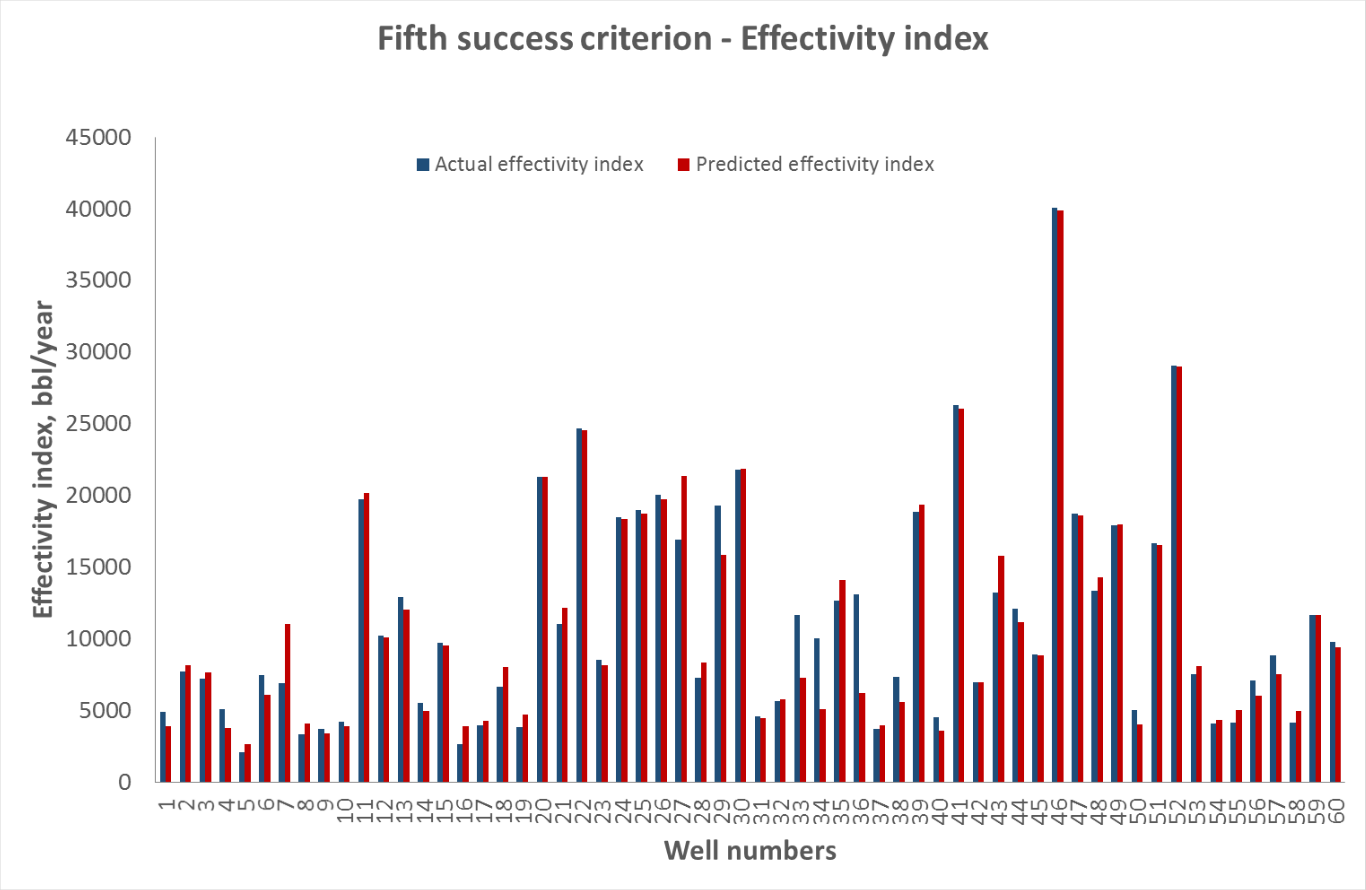

Figure 7. 19 Bar graph of Actual effectivity index vs. Predicted effectivity index

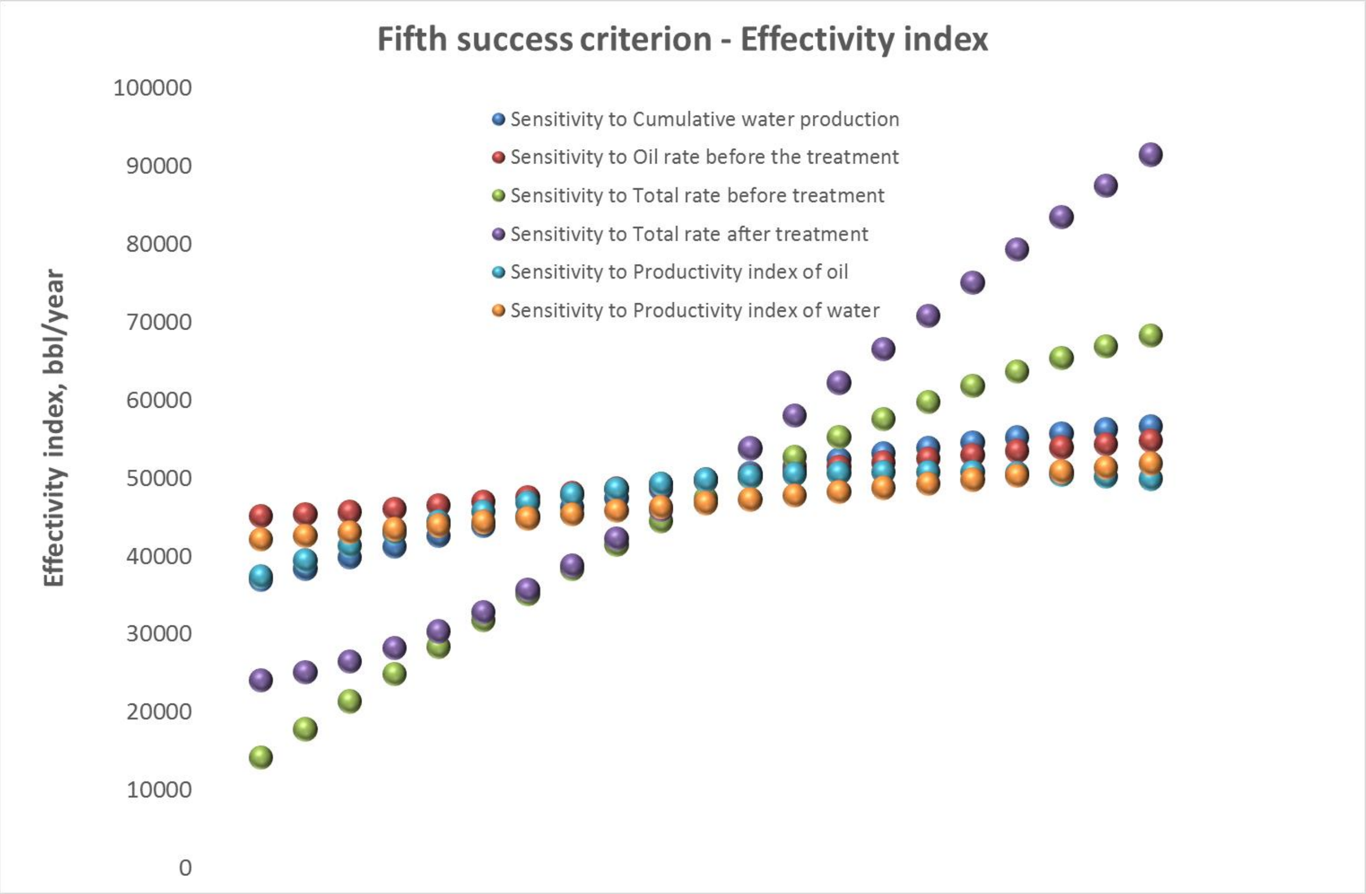

Figure 7. 20 Sensitivity analysis of the effectivity index

From the Figure 7.20, it is observed that effectivity index is sensitive to cumulative water production, oil rate before the treatment and productivity index of oil and water. All these four parameters have nearly same influence on the effectivity index and increase in these parameters slightly increases the effectivity index. On the other hand, effectivity index is highly sensitive to total rate before and after values as in the case of second, third and fourth success criteria.

7.2.3 Validation of Candidate Well Selection Methodology and Suggestions for the Future Applications

In this part of the study, prepared neural network structure for the prediction of profit one year after the treatment is validated by using the results of the polymer gel application in 2016. Actually this structure is prepared by training, testing and validating the data of the wells which are treated between 2008 and 2015. Here, wells treated in 2016 are simulated and predictions of the neural network structure are compared with the actual field data. From the Figure 7.21, it is observed that regression value (RRV) is 0.8939 and r-squared value is 0.7877.

After that whole field is simulated by using the same neural network structure. Success criterion of this neural network structure is the predicted profit one year after the treatment and perhaps the most important success criterion from the perspective of the oil companies. For this reason, 145 wells are simulated and most successful 20 wells are selected based on the predicted profits, Figure 7.22 shows the results of the simulations and predicted profits from these 20 wells.

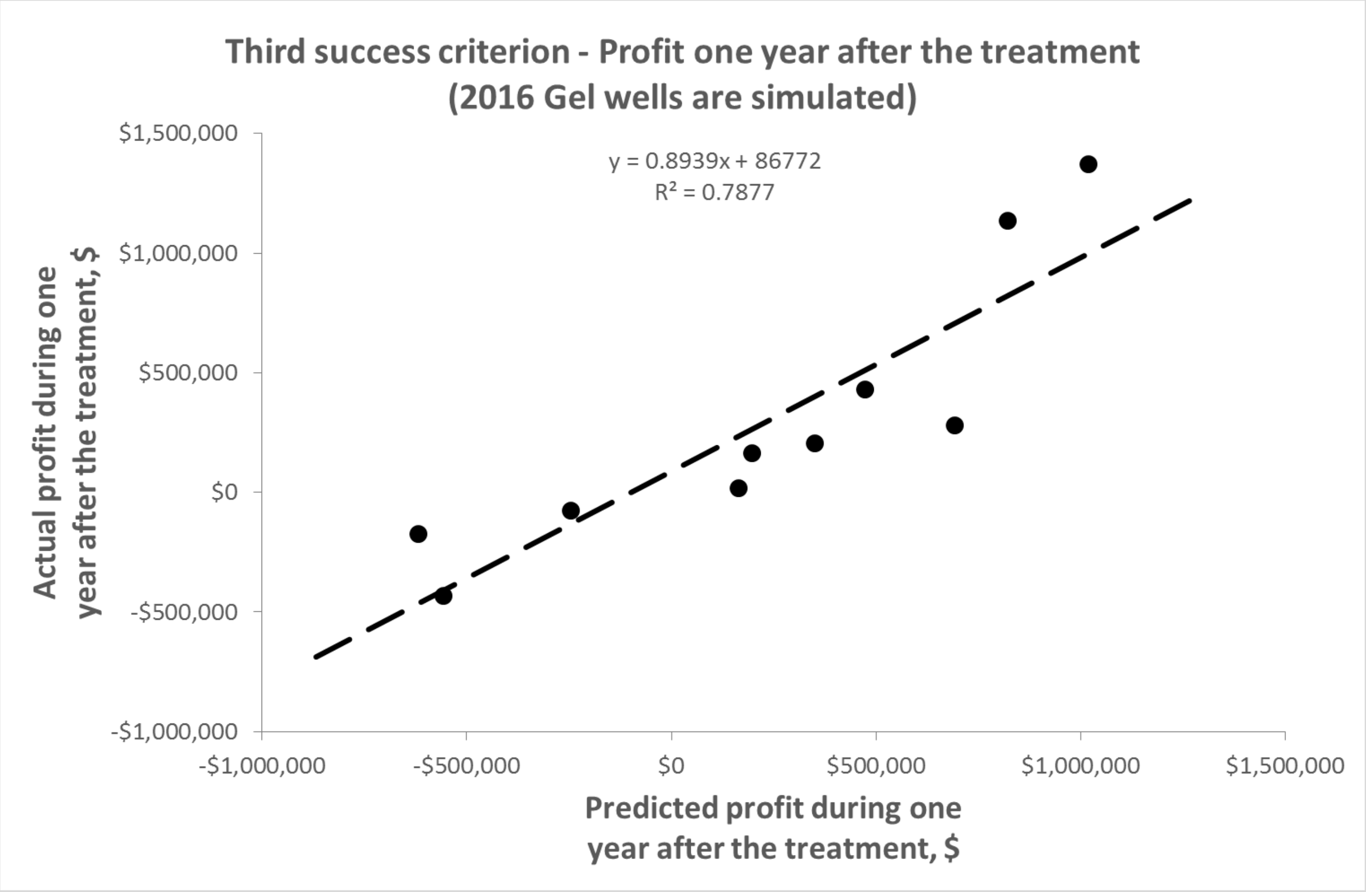

Figure 7. 21 Scatter plot of actual field data and simulation results of the treated wells in 2016

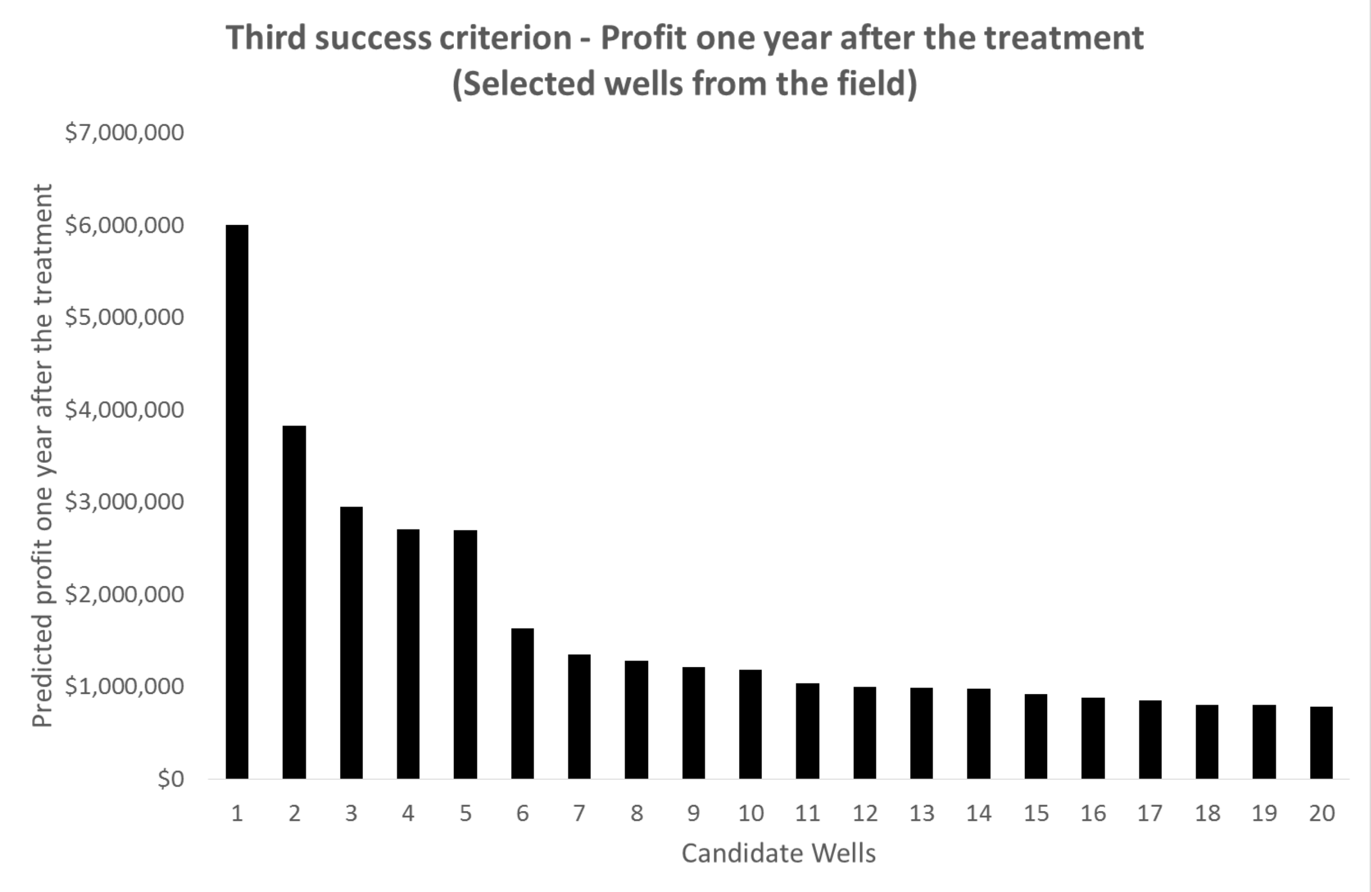

Figure 7. 22 Selected candidate wells from the field considering the third success criterion

7.2.4 Performance Evaluation of Polymer Gel Treatments

After polymer gel treatment, performance evaluation should be carried out in order to determine the profitability of the treatment. At this point, different approaches are followed by different oil companies. It is inferred from the literature that, some oil companies use water cut values before and after polymer gel treatment, some oil companies consider the oil production values before and after polymer gel treatment, and some of them evaluate the success of the project depending on the payout time (Zaitoun et al., 1998; Wibowo et al., 1999; Sydansk and Southwell, 2000; Giangiacomo, 2001; Wouterlood et al., 2002).

In this study, simple cumulative oil production (N_p) versus cumulative water production (W_p) plots are prepared for gel treated wells of the Raman field and three of them are presented in Figure 7.23, 7.25, 7.27 and their corresponding production performance plots are also presented in Figure 7.24, 7.26, 7.28. In N_p vs. W_p plots, blue line shows the cumulative production data of the well, orange dashed trend line indicates the production trend line with gel application after cleanup period, red dashed trend line indicates the possible production trend line without gel application and purple dashed line shows the cleanup region. Also in production performance plots, blue line indicates the water cut, pink line shows the possible oil production rate without polymer gel application and the red line shows the oil production rate after polymer gel treatment. In these figures, cleanup times that are found from the N_p vs. W_p plots are also indicated with gray dashed lines.

Plots are prepared immediately after the polymer gel treatments. As can be seen from the plots, production data of the wells are following more favorable trend initially but as the time passes, barrels of produced water to produced oil ratio increases. In addition, during the early stage of the plots, production data of the wells show a curvature trend that is caused by the decrease in water production as a result of gel treatment. The formation of the straight line suggests that most of the injected gel has been subjected to the syneresis process. Once the production data starts following a straight line, after a certain period of time, trend line can be plotted to fit the straight line part of the production data and can be extrapolated towards Y-axis. It is suggested that cumulative oil production value, where the trend line crosses Y-axis represents the additional oil recovery by means of polymer gel treatment. It is also proposed that the point, where the production data deviates from the trend line shows the cleanup time, at this point corresponding cumulative production data can be obtained from the plot and cleanup time can be determined from the production data. As it was mentioned before, red dashed trend line indicates the possible production trend line without gel application. This trend line is prepared by using the pre-treatment production data of the well and the trend line is plotted on the same plot to compare with the production trend after gel injection. For example, in the case of Well#X, average water cut before the treatment is 96.6% which means 3.4 barrels of oil is produced for 96.6 barrels of water. From there, it can be said that 0.0352 (3.4/96.6) barrels of oil is produced for each barrels of water and this value is the slope of the N_p vs. W_p plot. Then, dashed trend line could be plotted by using this slope and constant value 1,890, which is the additional oil recovery at the cleanup region.

As can be seen from the figures Figure 7.23, 7.25, 7.27, cleanup time of the polymer gel treatment is 0.4, 4 and 0.8 years for the X, Y, Z wells respectively. Furthermore, additional oil recovery during the cleanup region can be obtained as about 1,890, 18,410 and 35,200 barrels for the X, Y, Z wells respectively. By dividing the additional oil recovery value to the cleanup time, effectivity index can be obtained as 4,725, 4,600, 44,000 bbl/day for the X, Y, Z wells respectively. Another important consideration while evaluating the success of the treatments is the payout time. Payout time could be defined as the time required to recover the investment, during the polymer gel treatment, cost of the operation should be estimated in order to estimate the payout time. In this case, cost of the operation includes, cost of the chemicals, workover operation, supervision, workers, transportation etc. and cost of the operation could be taken as \$50,000 per well. Another cost related to the treatment is that, wells do not produce during the operation and this duration is approximately ten days (2 days – preparing the well to the treatment, 2 days – treatment process, 4 days – rest period, 2 days – preparing the well to the production). Therefore, for a certain well, average cost of the operation could be estimated by the Equation 7.1.

$$\text{Cost} = \$50{,}000 + (10\ \text{days}) * (\text{Oil rate, bbl/d}) * (\text{Oil price, \$}) \qquad (7.1)$$

Therefore, by using the above equation costs of operations could be estimated as \$55,830, \$53,900, \$86,700 for the X, Y, Z wells respectively. Also payout times could be estimated as 31 days, 19 days, 8 days for the X, Y, Z wells respectively.

It should be mentioned that, although the payout time is a quick measure, profit obtained from the whole treatment should also be considered for the satisfactory evaluation. In order to estimate the profit obtained from the whole treatment, one should know how long the effect of treatment lasts on a treated well and this duration could only be obtained from the cleanup time approximations. In this study, third success criterion, namely profit one year after the treatment is utilized; however, this success criterion includes the bias that the effect of the treatment lasts longer than one year. As can be seen from the Figure 7.27, cleanup time is found as 0.8 years for the Well#Z by using the suggested methodology in this work, similarly there are some other wells whose cleanup times are shorter than one year. In the light of this discussion, it could be argued that for the successful economic evaluation of polymer gel treatments, oil companies should have certain approach for the cleanup time estimation.

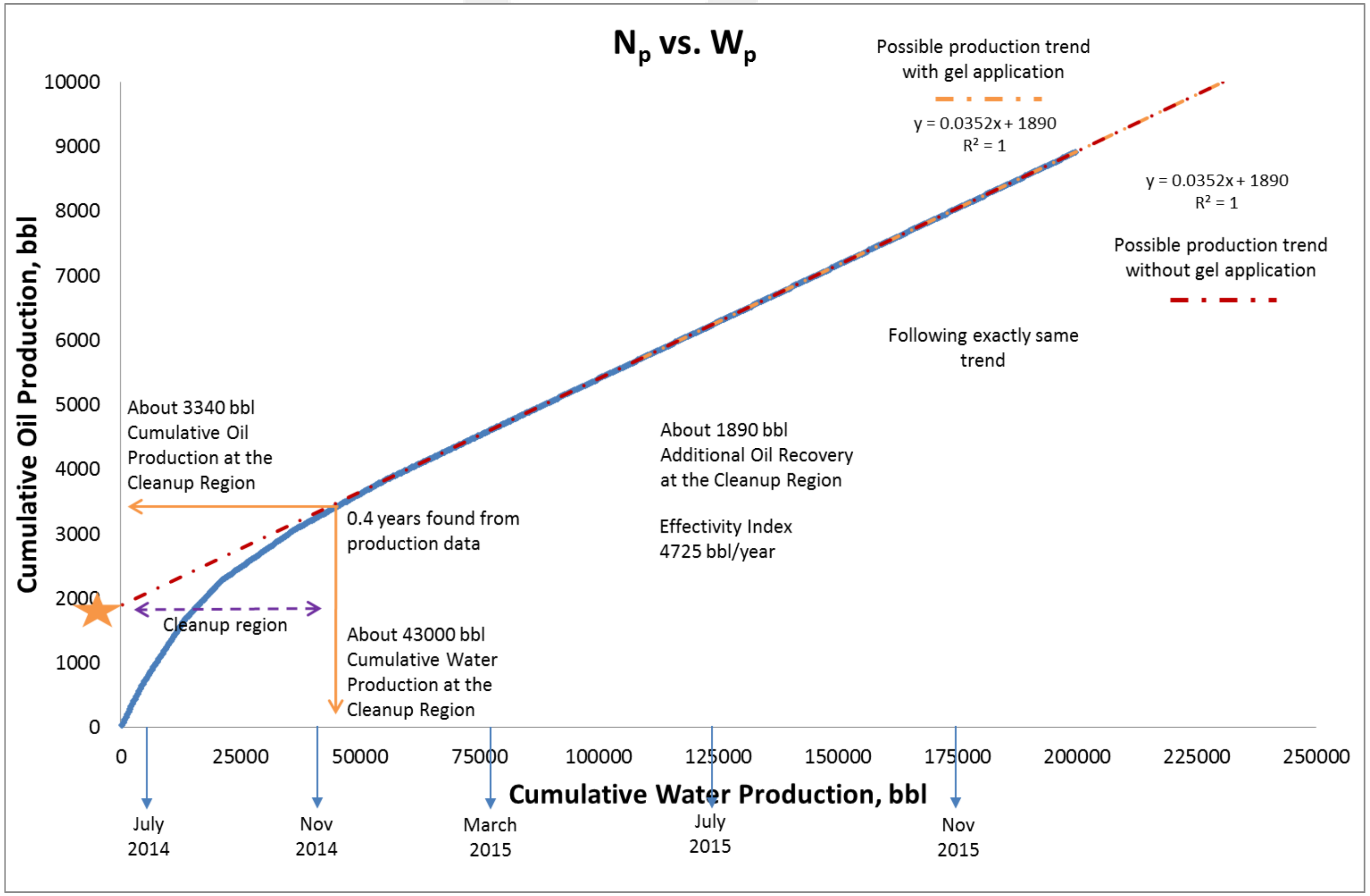

Figure 7. 23 Cumulative Oil Production vs. Cumulative Water Production Plot of Well #X

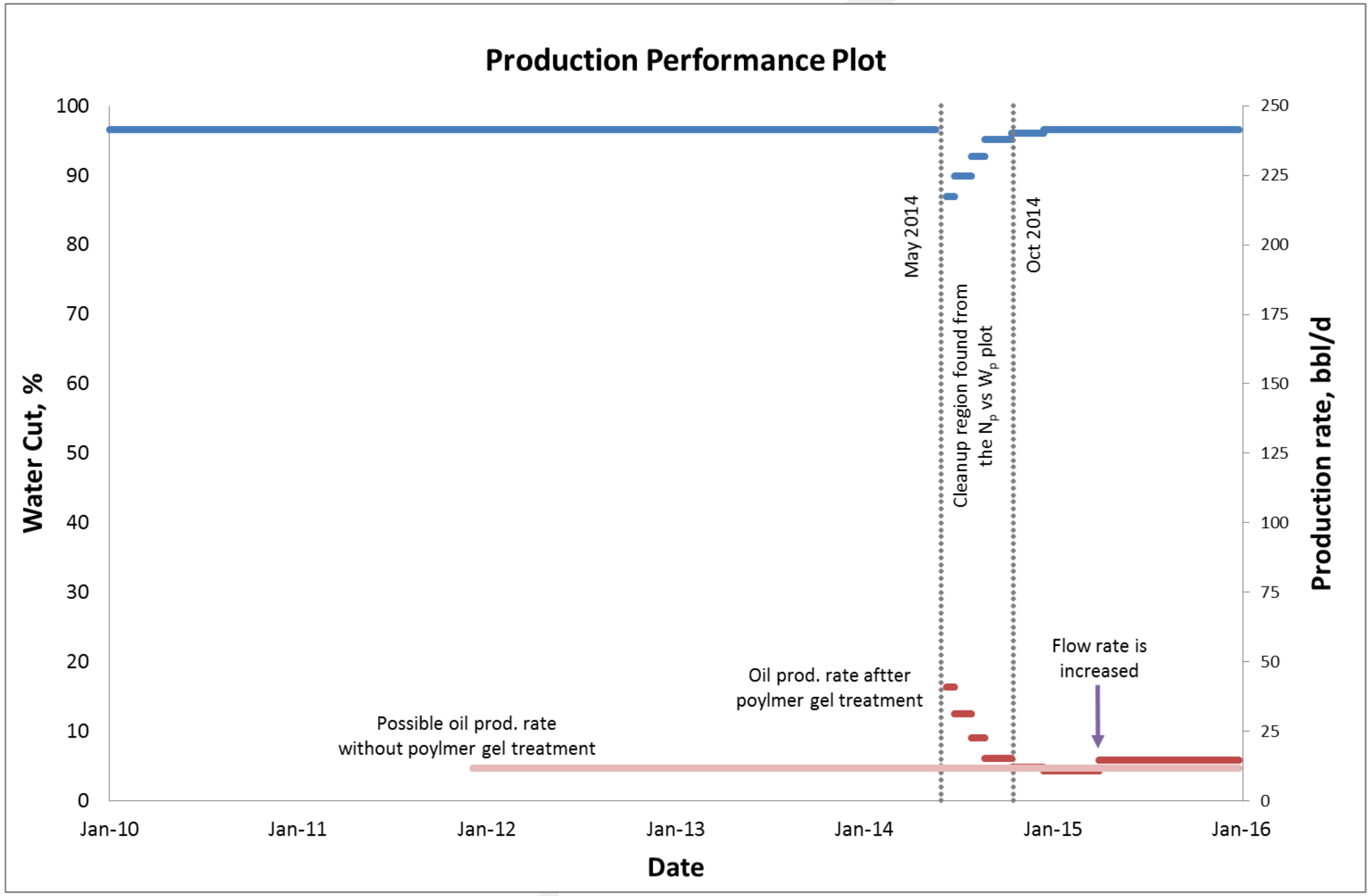

Figure 7. 24 Production Performance Plot of Well #X

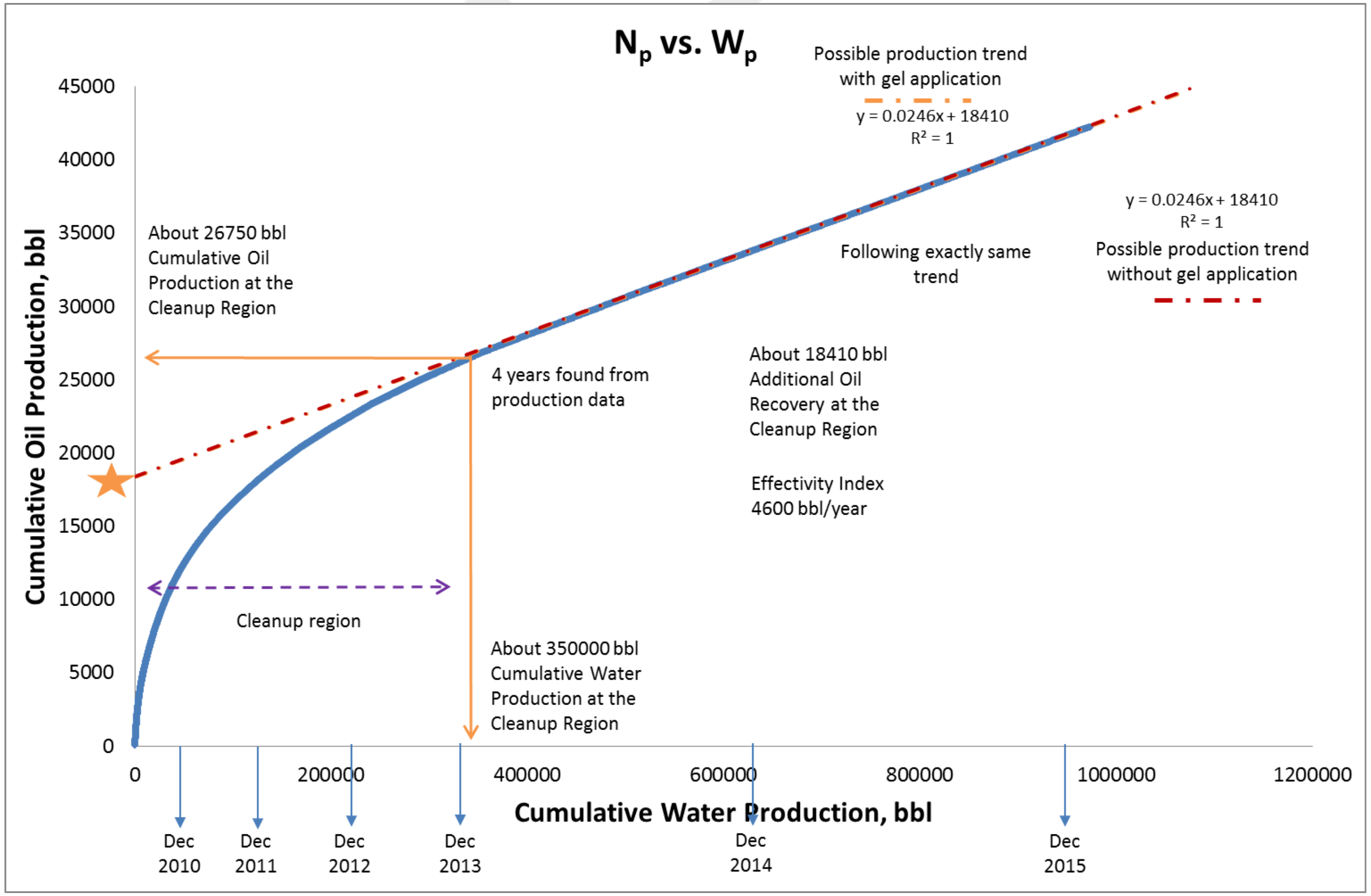

Figure 7. 25 Cumulative Oil Production vs. Cumulative Water Production Plot of Well #Y

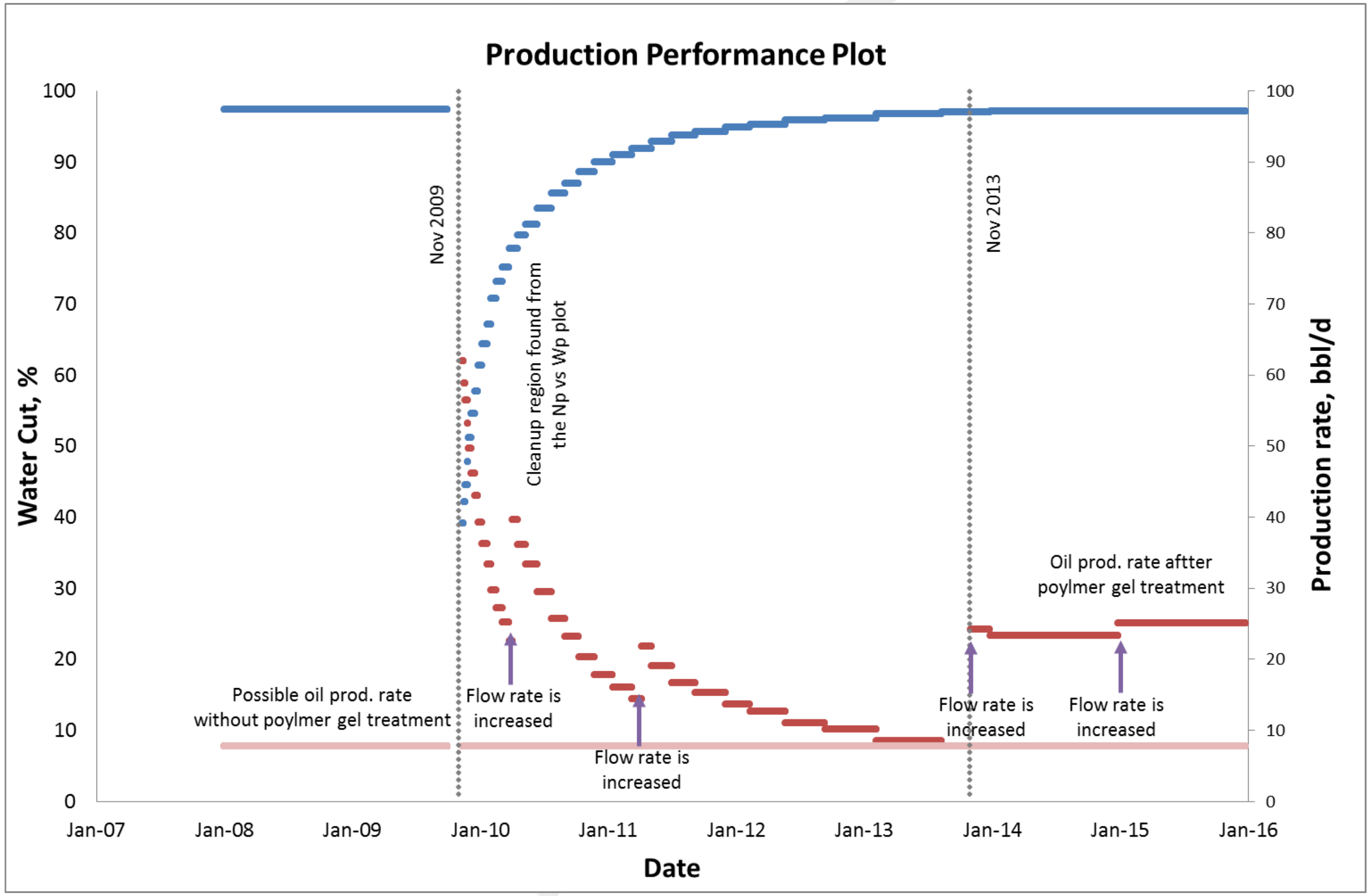

Figure 7. 26 Production Performance Plot of Well #Y

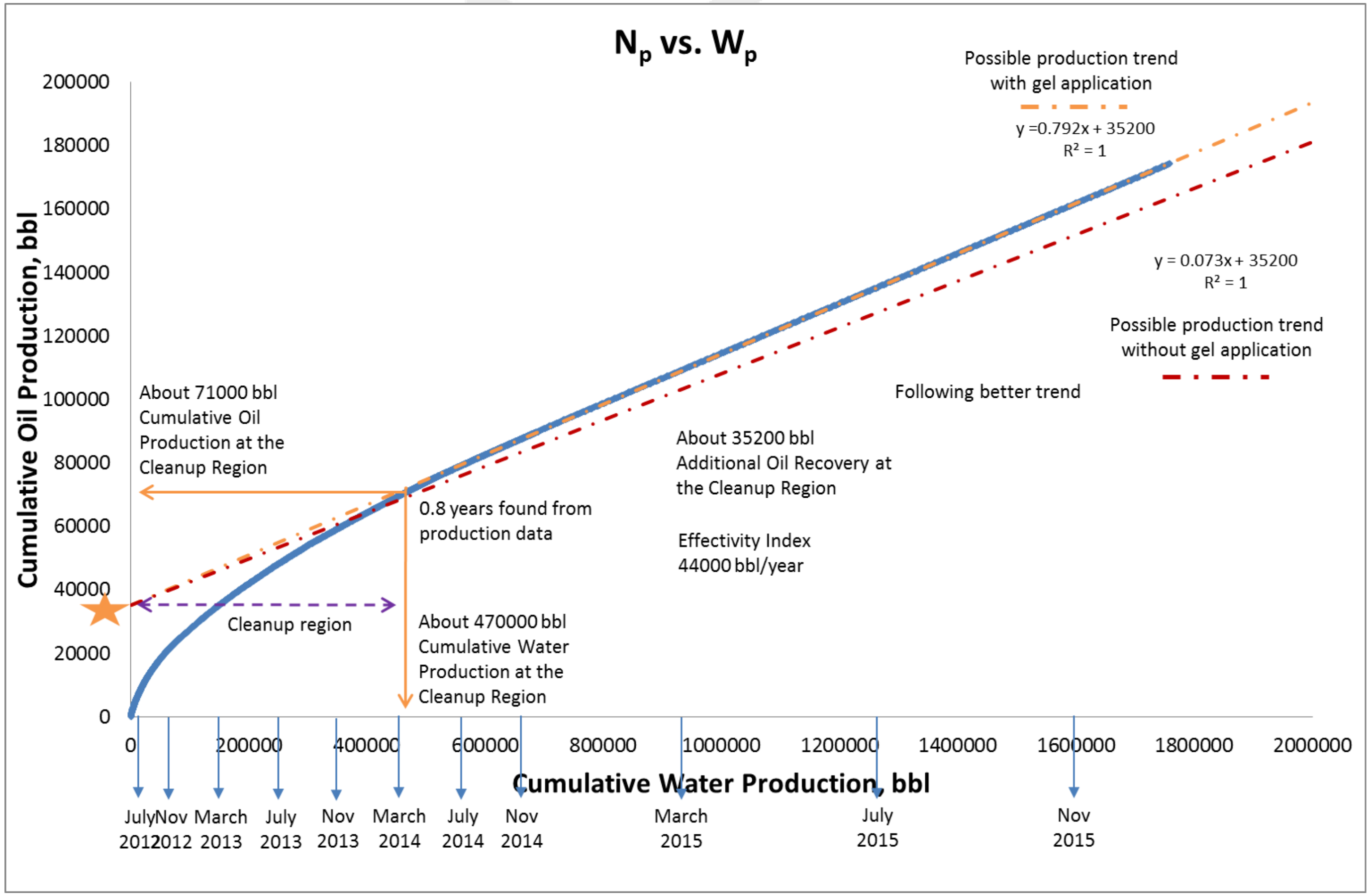

Figure 7. 27 Cumulative Oil Production vs. Cumulative Water Production Plot of Well #Z

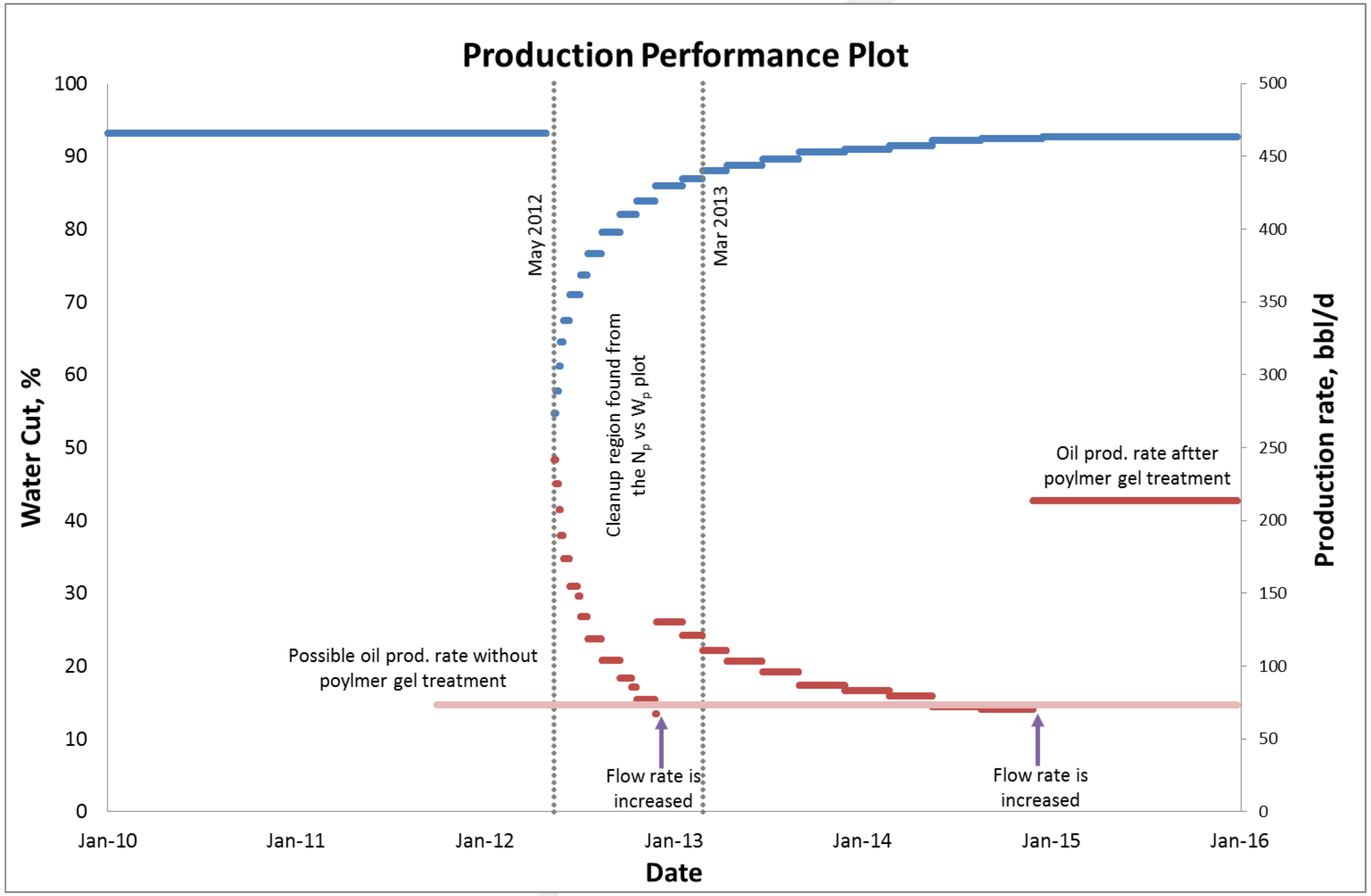

Figure 7. 28 Production Performance Plot of Well #Z

Additional oil recovery values during the cleanup region could be validated as follows, for the Well #X, average water cut before the treatment is 96.6% which means 3.4 barrels of oil is produced for 96.6 barrels of water. From there, it can be said that 0.0352 (3.4/96.6) barrels of oil is produced for each barrels of water. After polymer gel treatment, cumulative water production is found as approximately 43,000 during the cleanup region. Before the treatment, cumulative water production of 43,000 barrels corresponds to cumulative oil production of 1,510 barrels (43,000*0.0352). On the other hand, after polymer gel treatment from the production data it can be observed that cumulative water production of 43,000 barrels corresponds to cumulative oil production of 3,340 barrels. Difference between 3,340 and 1,510 gives the additional oil production at the cleanup region as 1,830. This value could also be estimated as 1,890 from the plot.

Similarly, for the Well #Y, average water cut before the treatment is 97.6% which means 2.4 barrels of oil is produced for 97.6 barrels of water. From there, it can be said that 0.0246 (2.4/97.6) barrels of oil is produced for each barrels of water. After polymer gel treatment, cumulative water production is found as approximately 350,000 during the cleanup region. Before the treatment, cumulative water production of 350,000 barrels corresponds to cumulative oil production of 8,610 barrels (350,000*0.0246). On the other hand, after polymer gel treatment from the production data it can be observed that cumulative water production of 350,000 barrels corresponds to cumulative oil production of 26,750 barrels. Difference between 26,750 and 8,610 gives the additional oil production at the cleanup region as 18,140. This value could also be estimated as 18,410 from the plot.

Finally, for the Well #Z, average water cut before the treatment is 93.2% which means 6.8 barrels of oil is produced for 93.2 barrels of water. From there, it can be said that 0.073 (6.8/93.2) barrels of oil is produced for each barrels of water. After polymer gel treatment, cumulative water production is found as approximately

470,000 during the cleanup region. Before the treatment, cumulative water production of 470,000 barrels corresponds to cumulative oil production of 34,310 barrels (470,000*0.073). On the other hand, after polymer gel treatment from the production data it can be observed that cumulative water production of 470,000 barrels corresponds to cumulative oil production of 71,000 barrels. Difference between 71,000 and 34,310 gives the additional oil production at the cleanup region as 36,690. This value could also be estimated as 35,200 from the plot.

For the production performance plots, possible oil production rate without polymer gel treatment is simply the extrapolation of the oil production rate before the treatment. For the N_p vs. W_p plots, possible production trend with gel application can be found by extrapolating the straight line part of the N_p vs. W_p curve. Furthermore, possible production trend without gel application can be found as follows; for example average water cut of the Well #X before the treatment is 96.6% which means 3.4 barrels of oil is produced for 96.6 barrels of water. From there, it can be said that 0.0352 (3.4/96.6) barrels of oil is produced for each barrels of water and this value is the slope of the trend line. In order to compare the production trend lines before and after the treatment, it is better to initiate the trend line without gel application from the cumulative oil production value, where the trend line with polymer gel injection crosses Y-axis.

It should be stated that, although some treatments are still effective beyond the cleanup region, additional oil gained for a barrel of produced water is maximum immediately after the treatment and it diminishes as the time passes. In this regard, cleanup time is evaluated as a threshold point and effectivity index values are calculated accordingly. To maximize the profitability of the treatments it may be suggested to retreat the well at the end of the cleanup region.

In general, flow rate of the gel treated wells are increased outside the cleanup region. However, if sudden drop on the oil production rate is observed or the additional oil recovery via treatment decreases to a critical state, production rate could be increased regardless of the region. From Figure 7.24, it can be observed that, oil production rate after the treatment is lower than the possible oil production rate without the treatment for a while. During this interval, although the water cut values before and after the treatment are almost the same, difference between the oil production rates results from the flow rate. From Figure 7.26, it is observed that flow rate of the Well #Y is increased twice during the cleanup region. In this well, flow rate is increased gradually since sharp increase in water production and corresponding decrease in oil production is observed. However, at the end of the cleanup region, instead of gradual increase, flow rate of the well and oil production rate of the well is tripled. From Figure 7.28, it is observed that flow rate of the Well #Z is increased twice (inside the cleanup region and outside the cleanup region) as the oil production rate falls below the possible oil production rate before the treatment. Again for the Well #Z, at the end of the cleanup region, instead of gradual increase, flow rate of the well and oil production rate of the well is tripled.

As can be seen from the Figure 7.23 and Figure 7.25, production trend lines of the Well #X and Well #Y out of the cleanup region are exactly same with the production trend lines of the same wells before the treatment. On the other hand, Well #Z (Figure 7.27) follows more favorable production trend line when compared with the pre-treatment trend line. This behavior suggests that, polymer gel treatment may affect the production trend line beyond the cleanup region. This phenomenon can be explained as follows; after polymer gel treatment, in following days or months, some of the polymer gel is produced back to the surface, some of them are dehydrated; however, survived gel structure at the reservoir section still hinders the flow of fluid to a certain extent.

Possible benefits that can be inferred from the N_p vs. W_p plot are listed below;

- Production trend line after gel treatment can be extrapolated to obtain an insight about the future production trend. If the recoverable oil ratio of the well is known, one should be able to estimate the amount of water that will be produced during the remaining production life of the well.
- Possible deviations from the trend line can be identified and the reasons can be examined (Workover operation, production/injection rate optimization on nearby wells, regional increase in water cut etc.).
- Trend line of different wells may follow similar or exactly same trend, if this is the case, common properties of these wells can be examined. Also, if production rate optimization on one of these wells turns out to be a satisfactory, then there will be a good reason to make production rate optimization on the other well.
- Cleanup time, effectivity index and additional oil recovery values can be compared and common properties of successful and unsuccessful wells can be examined (Productivity index, injectivity index, treatment volume, well location etc.).
- Cleanup time, effectivity index and additional oil recovery values may give an idea about possible future gel treatments on the same well. These parameters may also give an idea about the frequency of the treatments not only for the specific well, but also for the field.
- Trend line of newly treated wells can be compared with the trend line of wells treated before, if match is obtained, it is then possible to estimate cleanup time, effectivity index and additional oil recovery values for the freshly treated wells.

CHAPTER 8

CONCLUSIONS

Excessive water production is one of the most important obstacles against the profitability of the oil companies. This problem may become more serious especially for the mature and heavily fractured oil fields. Raman field, which is a naturally fractured limestone reservoir located in the southeastern part of Turkey, has been struggling with the high water-oil ratio problem especially for the last decade. For this reason, cross-linked polymer gel (polyacrylamide-chromium gel) treatments have been applied and successful results were obtained. However, topics like candidate selection, treatment design and performance evaluation still remain controversial for the operator of the field. In literature, some rule of thumbs, screening guidelines and some approaches based on field experience or laboratory work exist but more acute approaches are necessary especially during the candidate selection process. Therefore, this study aims to develop a strategy for the evaluation of post treatment production performance, to analyze the contribution of different well parameters on the success rate of the treatments and to propose a strategy for the candidate selection process to increase the success rate of the applications. Consequently, this study focuses on utilization of the artificial neural network system for candidate selection, analysis of the field parameters that influence the success of the treatments and analysis of the post treatment performances of the wells.

In this study, instead of subjective and results-oriented methodology, objective and process-oriented methodology which considers the past experience and well parameters is developed for the candidate well selection procedure. Furthermore, two new success criteria namely, additional oil production at the cleanup region and effectivity index are introduced as the evaluations considering the certain period of time after the treatment may give unrealistic results. Also, principal component analysis and correlation analysis are performed to observe the relationship between the input parameters and success criteria.

In this study first aim is the use of artificial neural networks for the candidate well selection. In order to accomplish this aim, Artificial Neural Networks (ANN's) are constructed by using 60 different well data and different scenarios are generated based on different success criteria and based on different input parameters which are determined by using statistical analysis. As a result, 450,000 different neural network structures are developed for the entire study and for each success criterion, the most successful neural networks are selected and their error levels are also presented. Then whole field is simulated by using the third success criterion, namely profit one year after the treatment and best 20 wells are selected and presented with Figure 7.22. Simulation results indicate that predicted average profit one year after the treatment is about \$3,600,000 for the first 5 wells and it is about \$1,000,000 for the last 15 wells. Demir et al. (2008) stated that during the successful operation in 2007, 38,500 bbls of incremental oil is produced within 8 months from the 7 wells, from this information it could be concluded that average profit during one year after the treatment is about \$400,000 for each well. However, results of this study claims that about \$1,000,000 could be obtained from each well even the 5 wells that have outstanding expectations are not considered.

In this study, neural network structures are constructed for different success criteria and whole field could be simulated any time for the certain success criterion. Selected structure for the first success criterion, oil production rate during one year after the treatment, includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment, productivity index of oil before the treatment and oil rate before the treatment. Selected structure for the second success criterion, additional oil production one year after the treatment, includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, productivity index of oil before the treatment and average water cut. Selected structure for the third success criterion, profit one year after the treatment, includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, productivity index of oil before the treatment and average water cut. Selected structure for the fourth success criterion, additional oil production at the cleanup region, includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment and productivity index of oil before the treatment. Selected structure for the fifth success criterion, effectivity index, includes the well parameters like cumulative water production before the treatment, productivity index of water before the treatment, total rate before the treatment, total rate after the treatment, productivity index of oil before the treatment and oil rate before the treatment.

The second aim is the analysis of the influences of different parameters on the success of the treatments. In order to accomplish this aim, PCA is performed and it is concluded that total rate after the treatment, total rate before the treatment, productivity index of water and cumulative water production are the dominating well parameters in the data set and should be used during the neural network analysis. It is also concluded that the parameters like ratio of total rate after and before the treatment, thickness of Mardin perforation, cumulative oil production, and average salinity are the parameters that have little impact on the first principal component; therefore, they could be excluded from the neural network analysis. Furthermore, by combining the results of the PCA with the results of the correlation analysis, different scenarios are generated for the ANN’s.

The third aim is the analysis of the post treatment performances. In order to accomplish this aim, cumulative oil production (N_p) versus cumulative water production (W_p) plots are prepared for gel treated wells of the Raman field and three of them are presented in Figure 7.23, 7.25, 7.27 and their corresponding production performance plots are also presented in Figure 7.24, 7.26, 7.28. These plots are firstly introduced in this study in order to better evaluate the performance of the treatments and to take more profitable decisions. Possible benefits that can be obtained from this plot are discussed on previous chapter but perhaps the most important ones are cleanup time and effectivity index that are obtained from the plot. These parameters and plots could be used in performance evaluation, candidate well selection, production rate optimization and obtaining an insight about the future production trend.

The fourth aim is the statistical analysis of parameters that may influence the success of the treatments. In order to accomplish this aim, sensitivity analysis is performed to see the effects of each factor on each success criterion and it is observed that total rate before and after the treatment are the well parameters that dominate the success rate of the polymer gel application. Furthermore, statistical analyses like correlation and principal component analysis are performed to analyze the relationship between the well parameters and success criteria. From these analyses, it is concluded that parameters like ratio of total rate after and before the treatment, thickness of Mardin perforation, cumulative oil production, and average salinity have little impact on the first principal component and they do not have significant correlation with the success criteria; therefore, they are excluded from the neural network analysis. In addition, thickness of Garzan perforation is also eliminated as it does not show significant correlation with any of the success criteria. Moreover, correlation matrix is constructed to observe the degree of correlation between well parameters and significant correlations are also discussed.

All in all, this study aims to combine information gained from the neural network analysis, statistical analysis, diagnostic plots and field experience. This study could be used as a guideline for the future polymer gel treatments on the Raman field. Also, operators of the other oil fields may use the same strategy to develop a guideline for the polymer gel treatments or they may investigate their field parameters to find out the dominating parameters.

CHAPTER 9

RECOMMENDATIONS

In this study, well parameters like cumulative oil and water production, injectivity at 500 psi, perforation thicknesses, average water cut before the treatment, oil rate and total rate before the treatment, total rate after the treatment, ratio of total rate after and before the treatment, average salinity before the treatment, productivity index of oil and water before the treatment and success criteria like oil rate one year after the treatment, additional oil production one year after the treatment, profit one year after the treatment, additional oil production at the cleanup region and effectivity index are utilized during the neural network analysis and statistical analysis. Further studies could be performed with the introduction of new field parameters, for example, if it is available FMI (Formation Micro Imager) log readings could be utilized. Also, success criteria used in this study could be modified or completely new ones could be generated. Furthermore, more than one success criteria could be utilized during the neural network analyses. Moreover, data from different fields could be compared or they can be used on the same analysis, in this way larger datasets can be obtained. In addition, parameters like polymer concentration and polymer volume could also be included in the well parameters.

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APPENDIX A

TEST

```
clc
clear
% Open the text file that includes the data
% Take the data in a vector form
load GELWELLS1.txt;
ra=GELWELLS1(:,1);
a=ra';
rb=GELWELLS1(:,2);
b=rb';
rc=GELWELLS1(:,3);
c=rc';
rd=GELWELLS1(:,4);
d=rd';
re=GELWELLS1(:,5);
e=re';
rf=GELWELLS1(:,6);
f=rf';
rg=GELWELLS1(:,7);
g=rg';
% Normalize the data between norm and (1-norm)
mma=minmax(a);
mmb=minmax(b);
mmc=minmax(c);
mmd=minmax(d);
mme=minmax(e);
mmf=minmax(f);
mmg=minmax(g);
norm=0.01;
pa=(1-2*norm)*((a-mma(1))/(mma(2)-mma(1)))+norm;
pb=(1-2*norm)*((b-mmb(1))/(mmb(2)-mmb(1)))+norm;
pc=(1-2*norm)*((c-mmc(1))/(mmc(2)-mmc(1)))+norm;
pd=(1-2*norm)*((d-mmd(1))/(mmd(2)-mmd(1)))+norm;
pe=(1-2*norm)*((e-mme(1))/(mme(2)-mme(1)))+norm;
pf=(1-2*norm)*((f-mmf(1))/(mmf(2)-mmf(1)))+norm;
pg=(1-2*norm)*((g-mmg(1))/(mmg(2)-mmg(1)))+norm;
```

```
% Put the pre-processed input vectors in an array form
in(1,:)=pa;
in(2,:)=pb;
in(3,:)=pc;
in(4,:)=pd;
in(5,:)=pe;
in(6,:)=pf;
% Put the pre-processed output vectors in array form
out(1,:)=pg;
% This step separate the total data into three separate data sets for training, validation and testing
% Sample size is 60, 30 for training, 15 for test, and 15 for validation
indxtr=1:1:30;
indxtst=31:1:45;
indxval=46:1:60;
% Take the first 30 data for the training
% Take the next 15 data for the testing
% Take the last 15 data for the validation
intr=in(:,indxtr);outtr=out(:,indxtr);
test.P=in(:,indxtst); test.T=out(:,indxtst);
val.P=in(:,indxval); val.T=out(:,indxval);
% Construct set of neural networks with number of hidden neurons varying between "inhl" and "fnhl" at "ss" step
inhl=1;
fnhl=100;
ss=1;
for hl=inhl:ss:fnhl;
% Construct the neural network with the following properties
net=network;
net.numInputs=1;
net.inputs{1}.size=6;
net.numLayers=2;
net.layers{1}.size=hl;
net.layers{2}.size=1;
net.inputConnect(1)=1;
net.layerConnect(2,1)=1;
net.outputConnect(2)=1;
net.layers{1}.transferFcn='logsig';
net.layers{2}.transferFcn='purelin';
net.biasConnect(1)=1;
net.biasConnect(2)=1;
```

```
% The network performance measuring function and the training algorithm
net.performFcn='mse';
net.trainFcn='trainlm';
% Training parameters for the training algorithm
net.trainParam.epochs=500;
net.trainParam.goal=0;
net.trainParam.max_fail=100;
net.efficiency.memoryReduction=1;
net.trainParam.min_grad=1e-10;
net.trainParam.mu=0.001;
net.trainParam.mu_dec=0.1;
net.trainParam.mu_inc=10;
net.trainParam.mu_max=1e10;
net.trainParam.show=1;
net.trainParam.time=1200;
% Training procedure
[net,tr]=train(net,intr,outtr,[],[],val,test);
% Predict output values via trained neural network
pr=sim(net,in);
% Back-normalization
poutg=((pr(1,:)-norm)*(mmg(2)-mmg(1))/(1-2*norm))+mmg(1);
% Root mean squared error for each network model
eep(hl,:)=sqrt(mean((g-poutg).^2));
% Mean absolute error for each network model
delg(hl,:)=sum(abs(g-poutg))/length(a);
% Regression analysis between the network prediction and target values
[gg1(hl),gg2(hl),gg3(hl)]=postreg(poutg,g);
end
% Write outputs to file
outputs1=eep;
dlmwrite                              ('C:\Users\oytun\network\GELWELLS1RMSE.dat',
outputs1,'delimiter','\t','newline','pc');
outputs2=delg;
dlmwrite                                ('C:\Users\oytun\network\GELWELLS1MAE.dat',
outputs2,'delimiter','\t','newline','pc');
outputs3=gg3';
dlmwrite                                 ('C:\Users\oytun\network\GELWELLS1REG.dat',
outputs3,'delimiter','\t','newline','pc');
%End program
```

APPENDIX B

FORM

```
clear
% Open the text file that includes the data
% Take the data in a vector form
load GELWELLS12.txt;
ra=GELWELLS12(:,1);
a=ra';
rb=GELWELLS12(:,2);
b=rb';
rc=GELWELLS12(:,3);
c=rc';
rd=GELWELLS12(:,4);
d=rd';
re=GELWELLS12(:,5);
e=re';
rf=GELWELLS12(:,6);
f=rf';
rg=GELWELLS12(:,7);
g=rg';
% Normalize the data between norm and (1-norm)
mma=minmax(a);
mmb=minmax(b);
mmc=minmax(c);
mmd=minmax(d);
mme=minmax(e);
mmf=minmax(f);
mmg=minmax(g);
norm=0.01;
pa=(1-2*norm)*((a-mma(1))/(mma(2)-mma(1)))+norm;
pb=(1-2*norm)*((b-mmb(1))/(mmb(2)-mmb(1)))+norm;
pc=(1-2*norm)*((c-mmc(1))/(mmc(2)-mmc(1)))+norm;
pd=(1-2*norm)*((d-mmd(1))/(mmd(2)-mmd(1)))+norm;
pe=(1-2*norm)*((e-mme(1))/(mme(2)-mme(1)))+norm;
pf=(1-2*norm)*((f-mmf(1))/(mmf(2)-mmf(1)))+norm;
pg=(1-2*norm)*((g-mmg(1))/(mmg(2)-mmg(1)))+norm;
```

```
% Put the pre-processed input vectors in array form
in(1,:)=pa;
in(2,:)=pb;
in(3,:)=pc;
in(4,:)=pd;
in(5,:)=pe;
in(6,:)=pf;
% Put the pre-processed output vectors in array form
out(1,:)=pg;
% This step separate the total data into three separate data sets for training,
validation and testing
% Sample size is 60, 30 for training, 15 for test, and 15 for validation
indxtr=1:1:30;
indxtst=31:1:45;
indxval=46:1:60;
% Take the first 30 data for the training
% Take the next 15 data for the testing
% Take the last 15 data for the validation
intr=in(:,indxtr);outtr=out(:,indxtr);
test.P=in(:,indxtst); test.T=out(:,indxtst);
val.P=in(:,indxval); val.T=out(:,indxval);
% Construct the neural network with the following properties
net=network;
net.numInputs=1;
net.inputs{1}.size=6;
net.numLayers=2;
net.layers{1}.size=33;
net.layers{2}.size=1;
net.inputConnect(1)=1;
net.layerConnect(2,1)=1;
net.outputConnect(2)=1;
net.layers{1}.transferFcn='logsig';
net.layers{2}.transferFcn='purelin';
net.biasConnect(1)=1;
net.biasConnect(2)=1;
% The network performance measuring function and the training algorithms are
set here
net.performFcn='mse';
net.trainFcn='trainlm';
```

```
% Training parameters for the training algorithm used above are manipulated here
net.trainParam.epochs=500;
net.trainParam.goal=0;
net.trainParam.max_fail=100;
net.efficiency.memoryReduction=1;
net.trainParam.min_grad=1e-10;
net.trainParam.mu=0.001;
net.trainParam.mu_dec=0.1;
net.trainParam.mu_inc=10;
net.trainParam.mu_max=1e10;
net.trainParam.show=1;
net.trainParam.time=1200;
% Training procedure
[net,tr]=train(net,intr,outtr,[],[],val,test);
% Predict output values via trained neural network
pr=sim(net,in);
% Back-normalization
poutg=((pr(1,:)-norm)*(mmg(2)-mmg(1))/(1-2*norm))+mmg(1);
%Save Network
network='C:\Users\oytun\network\net';
save(network,'net');
% End of Program
```

APPENDIX C

SIMULATE

```
clear
% Load Network
load 'C:\Users\oytun\network\net';
% Verilerin olduğu txt dosyasını açar
% Verileri sıra ile alır ve matrix haline getirir
load CANGELWELLS.txt;
ra=CANGELWELLS(:,1);
a=ra';
rb=CANGELWELLS(:,2);
b=rb';
rc=CANGELWELLS(:,3);
c=rc';
rd=CANGELWELLS(:,4);
d=rd';
re=CANGELWELLS(:,5);
e=re';
rf=CANGELWELLS(:,6);
f=rf';
% Normalizasyon aşaması
% Verileri norm değeri ile (1-norm) değerleri arasında normalize eder
mma=minmax(a);
mmb=minmax(b);
mmc=minmax(c);
mmd=minmax(d);
mme=minmax(e);
mmf=minmax(f);
mmh=[11.9 143];
norm=0.01;
pa=(1-2*norm)*((a-mma(1))/(mma(2)-mma(1)))+norm;
pb=(1-2*norm)*((b-mmb(1))/(mmb(2)-mmb(1)))+norm;
pc=(1-2*norm)*((c-mmc(1))/(mmc(2)-mmc(1)))+norm;
pd=(1-2*norm)*((d-mmd(1))/(mmd(2)-mmd(1)))+norm;
pe=(1-2*norm)*((e-mme(1))/(mme(2)-mme(1)))+norm;
pf=(1-2*norm)*((f-mmf(1))/(mmf(2)-mmf(1)))+norm;
```

```
% Put the pre-processed input vectors in array form
in(1,:)=pa;
in(2,:)=pb;
in(3,:)=pc;
in(4,:)=pd;
in(5,:)=pe;
in(6,:)=pf;
% Simulate ANN
an=sim(net,in);
% This is the data post-processing step
pouth=((an(1,:)-norm)*(mmh(2)-mmh(1))/(1-2*norm))+mmh(1);
out(1,:)=pouth;
% Write output to file
outputs=out';
dlmwrite ('C:\Users\oytun\network\Outputs.dat',
outputs,'delimiter','\t','newline','pc');
% End of Program
```

CURRICULUM VITAE

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Professional Experience

- Student Assistant at Department of Petroleum and Natural Gas Engineering, Middle East Technical University (2009-2010)
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Publications

- Kok, M. V. & Ors, O. (2012): The Evaluation of an Immiscible-CO_2 Enhanced Oil Recovery Technique for Heavy Crude Oil Reservoirs, Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 34:8, 673-681
- Ors, O. (2012): Investigation of the interaction of CO_2 and CH_4 hydrate for the determination of feasibility of CO_2 storage in the Black Sea sediments. (Master of Science thesis, Middle East Technical University).
- Oytun Ors, Caglar Sinayuc, (2014): An experimental study on the CO_2–CH_4 swap process between gaseous CO_2 and CH_4 Hydrate in porous media, Journal of Petroleum Science and Engineering, http://dx.doi.org/10.1016/j.petrol.2014.05.003