# OPTIMIZATION OF WELL PLACEMENT IN COMPLEX CARBONATE RESERVOIRS USING ARTIFICIAL INTELLIGENCE

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Approval of the Graduate School of Natural and Applied Sciences

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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

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This is to certify that we have read this thesis and that in our opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

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# ABSTRACT

OPTIMIZATION OF WELL PLACEMENT IN COMPLEX CARBONATE RESERVOIRS USING ARTIFICIAL INTELLIGENCE


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This thesis proposes a framework for determining the optimum location of an injection well by using an inference method, Artificial Neural Networks and a search algorithm to create a search space and locate the global maxima. Theoretical foundation of the proposed framework is followed by description of the field for case study. A complex carbonate reservoir, having a recorded geothermal production history is used to evaluate the proposed framework ( Kızıldere Geothermal field, Turkey). In the proposed framework, neural networks are used as a tool to replicate the behavior of commercial simulators, by capturing the response of the field given a limited number of parameters (Temperature, pressure, injection location and injection flow rate) as variables. A study on different network designs is followed by introduction of a search algorithm to generate decision surfaces.

Results indicate that a combination of neural networks and an optimization algorithm (explicit search with variable stepping) to capture local maxima can be used to locate a region or a location for optimum well placement. Results also indicate shortcomings and possible pitfalls associated with the approach. With the provided flexibility of the proposed workflow, it is possible to incorporate various parameters including injection flow rate, temperature and location.

For the field of study (Kızıldere), optimum injection well location is found to be in the south-eastern part of the field. Specific locations resulting from the workflow indicated a consistent search space, having higher values in that particular region.

When studied with fixed flow rates (2500 and 4911 $m^3$/day), search run through the whole field located two locations which are in the very same region; thus resulting with consistent predictions. Further study carried on by incorporating effect of different flow rates indicates that the algorithm can be run in a particular region of interest (south-east in the case of study) and different flow rates may yield different locations.  This analysis resulted with a new location in the same region and an optimum injection rate of 4000 $m^3$/day).

It is observed that use of neural network as a proxy to numerical simulator is viable for narrowing down or locating the area of interest for optimum well placement.

Keywords: Neural Networks, Optimization, Well Placement

# ÖZ

## KOMPLEKS KARBONATLI RESERVLERDE YAPAY ZEKA İLE KUYU KONUMLANDIRMASI OPTIMIZASYONU

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Aralık 2004

Bu tez bir enjeksiyon kuyusunun optimum konumunun bir çıkarım yöntemi olan Yapay Sinir Ağları aracılığı ile tayin edilebilmesi için bir yöntem önermektedir. Önerilen yöntemin teorik temelleri sunulduktan sonra çalısma örnek bir saha üzerinde uygulanmıştır. Bu calışmanın sonuçlarını değerlendirmek için, kayıt edilmiş jeotermal üretim geçmişi bulunan bir kompleks karbonatlı rezerv seçilmiştir (Kızıldere jeotermal sahası,Türkiye). Önerilen yöntem dahilinde, yapay sinir ağları, ticari simulasyon yazılımlarının davranışlarını belirli sayıdaki değişkenlerin (Sıcaklık, basınç, enjeksiyon konumu ve enjeksiyon debisi) yarattığı sonuçları algılayarak taklit etmek üzere kullanılmıştır. Çalışma dahilinde, değişik ağ tasarımları üzerinde yapılan incelemeleri takiben, optimum kuyu konumunun bulunmasında kullanılacak karar yüzeylerini yaratmak ve kuyu konumunu belirlemek üzere bir arama algoritmasi (explicit search with variable stepping) kullanılmıştır.

Çalışmanın sonuçları yapay sinir ağları ve optimizasyon algoritması birleşiminin optimum kuyu konumunun bölge ya da nokta olarak belirlenmesinde kullanılabileceğini göstermektedir. Sonuçlar aynı zamanda önerilen yöntemle ilişkili kısıtlamara dikkat çekmektedir. Çalışma sonuç olarak önerilen yöntemin yetenekleri üzerine incelemeler ve kullanım yöntemlerine dair öneriler sunmaktadir.

Üzerinde çalışılan Kızıldere jeotermal sahası için optimum kuyu konumu olarak sahanin güneydoğu bölgesi uygun bulunmuştur. Önerilen yöntemin uygulanması sonucunda ortaya çıkan kuyu konumları bu bölgede çıkmış ve tutarlılığı gözlenmiştir.

Sabit debiler (2500 ve 4911 $m^3$/gün) ile yapılan arama yüzeyi oluşturma sonucunda bulunan iki nokta farklı enjeksiyon debilerinin farklı kuyu konumlarına sonuç vereceğini ve kuyu debisinin etkili bir değişken olduğunu göstermiştir. Bu doğrultuda değişken debi ile yapılan çalışma sonucunda kuyu konumu debiye bağlı olarak değişmiş ve 4000 $m^3$/gün debi ile enjeksiyon yapılmasi önerilen yöntem aracılığı ile en iyi secim olmuştur.

Çalışma sonucunda yapay sinir ağlarının sayısal simulatorlere vekil (proxy) olarak kuyu konum seçimini daha dar bir alana indirgemek için kullanılabileceği gözlenmiştir.

Anahtar Kelimeler: Yapay sinir Ağları, Optimizasyon, Kuyu konumlandırılması

**To my father**

# TABLE OF CONTENTS

# LIST OF FIGURES

# LIST OF TABLES

# LIST OF SYMBOLS

$E$ = Evaluation function

$e$ = exponential

$i$ = Index counter

$o$ = Actual output of a neural network

$P$ = Pressure (kPa)

$T$ = Temperature (°C)

$t$ = Target output of a neural network

$x_i$ = Input node to a neural network unit

$x_{candid}$ = new candidate location

$x_{worst}$ = worst location, minimal evaluation result

$c_{centroid}$ = centroid of the formed triangle

$x_d$ = West – east offset of search location (meters)

$w_i$ = Weight of a particular connection (unit less, between 0 – 1)

$y_d$ = North – south offset of search location (meters)

**Greek Letters**

$\sigma$ = sigmoid function

$\eta$ = Learning rate (unitless, between 0 – 1)

# CHAPTER 1

# INTRODUCTION

In any business; decisions have to be made in every stage. In the world of tight competition and scarcity; well described optimum solutions to real life problems are crucial for a successful business model. Obviously being one of the world's largest industries; there is no exception to this rule in oil business.

In any stage of reservoir development; ultimate goal of the managing /engineering teams is to develop the most accurate or "optimal" decisions. Starting from very initial discovery to late development of the field; every stage involves important decisions that shall define the success of the project. It is not always easy to reach intuitive optimal decisions as problems in hand are generally to complex. Also, the fact that decision surface may be steep yields to situation where slightly better decision results in remarkably better results.

As an example, consider a problem where a new production well is to be drilled in a mature, fluvial depositional oil reservoir. Reservoir is made of high porosity sand channels laid in non-permeable mud formations. This is a common reservoir type, especially in North America fields. In this case, it is of vital importance to place the well in correct position, as off shooting the channel will yield a non-producing well and even it is drilled within a channel a poorly chosen location may result in poor long term results. As oil will flow through channels, the chance of bypassing of some of them is high and may result in gross losses. In such a case, there is no question that engineers will want to base their decision on numerical models. Ultimately, they would like to study on all possible scenarios. Unfortunately, numerical models that are used in oil industry are CPU intensive, even with today's supercomputers.

To reach an optimum decision in such situations, numerous approaches could be applied:

1) Tackle the bottleneck of costly numerical calculations, i.e. try to run less simulation

2) Develop less costly algorithms (Numerically or Analytically)

3) Increase the processing power

Decreasing the number of simulations will produce less informed solution space, which may increase the probability of missing the global optimum. Special care should be taken to avoid local extrema and this may not be trivial. Developing less costly algorithms is not feasible, as it will decrease the accuracy of the solution and provide more assumptions which may not be true for different cases. After all, we would like to capture the most realistic physical behavior of the field. Increasing the processing power is a viable option, but even with today's supercomputers, it is not possible to run hundreds of simulations with high number of grid blocks.

This research mainly focuses on the production/field development stage of reservoir development and development of a framework for optimizing well placement from a numerical point of view. The main focus is on developing a framework to reach more informed decisions and tackling the bottleneck of doing exhaustive simulations.

# CHAPTER 2

# THEORETICAL FOUNDATIONS

## 2.1 Earth Science Problems and Modern Approaches

The nature of earth sciences forms an interesting domain for applications of computer aided inference systems. As the task is generally creating a “virtual” representation of subsurface with limited (and noisy) data gathered from multiple sources, very high computational power is required by geoscientists.

Actually, the demand for power and the amount of data processed seems to be in parallel interaction. Increase in computing power enables higher data volumes to be processed. Seismic responses from earths crust, data obtained from outcrops of subsurface layers and information gathered from already drilled wells, and previous investigation may all be integrated for interpretation. The nature of “fuzziness” in this high volume data forms a very important utility area of fuzzy sets and inference mechanisms that shall aid and improve successful representation of subsurface.

Petroleum practice, being one of the most important branches of earth science, has been a very loyal computer technology user. Oil industry has been one of the “pushers” and financial supporters for supercomputers and innovation during last decades. In recent years, most of the recent advancement has found sound application in petroleum industry.

Interest in petroleum engineering relies on discovery of probable reserves, estimation of the subsurface volume of hydrocarbon, realistic prediction of fluid flow in subsurface and accurate estimation of production from the area of study. Some very advanced simulation and interpretation software exists today and research is becoming more and more focused on combination of advanced computer science and petroleum science applications.

## 2.2 Carbonate Reservoirs

Most of the world's giant fields produce hydrocarbons from carbonate reservoirs. Distinctive and unique aspects of carbonate rocks are their predominantly intrabasinal origin, their primary dependence on organic activities for their constituents and their susceptibility to modification by post-depositional mechanisms. These three features are significant as they distinguish the productivity of carbonate rocks from other sedimentary rocks (*Al-Hanai et al, 2000*). Containing more than 50% of the world's hydrocarbon reserves, carbonate reserves generally share the property of having biochemical origin. Therefore, organisms have direct role in determining the reservoir quality.

### 2.2.1 Geology

Carbonate sediments are particularly sensitive to environmental influences and although sedimentation process is rapid, it is also easily inhibited. Effect of temperature influence biogenic activity and affect sediment production, meaning most carbonate production is dept dependent. Basin configuration and water energy are the dominant controls on carbonate deposition. Organic productivity varies with depth and light.

Carbonates are particularly sensitive to post-depositional diagenesis, including dissolution, cementation, dolomoitization and replacement.

Compaction fracturing and lithification are common diagenetic effects in carbonates, which also create high permeability zones.

### 2.2.2 Reservoir Characterization

Many challenges exist in characterizing, quantifying and predicting carbonate reservoir quality. The most important aspect in overcoming these challenges is understanding the link between heterogeneity and reservoir quality by finding the appropriate data and adequate sampling. Due to its nature, carbonate reservoirs have wide range of pore distributions, making it crucial to identify appropriate scale of sampling. Due to the rather complex porosity distribution, carbonates have wide permeability variations for the same total porosity, which makes it difficult to predict productivity and value as a source rock.

### 2.2.3 Reservoir Modeling

A 3D, geological model accounting for the heterogeneity is vital for the development of the field (due to the high variations in properties as mentioned earlier). Geological modeling in carbonates are quite complex due to the presence of discontinuous bodies, large lateral and vertical variations.

Key issues in predicting complex flow processes complex carbonate reservoirs are mass transfer/extraction processes created by viscosity variation and distribution, impact of heterogeneity and anisotropy on flow behavior and integration of discrete and continuum approaches for fracture modeling and 3D multiphase flow. It is also required to model stress changes around wellbore due to fluid injection and its pressure/thermal effects and the resulting sensitivity of the properties like permeability (*Al-Hanai et al, 2000*). Complex rock texture in carbonates produces complex interrelationships between porosity, permeability, water and hydrocarbon saturation and capillary. Established understanding of reservoir connectivity issues like orientation of flow-barriers, high permeability streaks, vertical interconnection of layers to determine migration paths, cross flow of fluids and gravity effects are very important. A detailed, consistent geological model is therefore the fundamental issue in successful reservoir management.

The prediction of permeability in heterogeneous carbonates from well-log data represents a difficult and complex problem. Generally, a simple correlation between permeability and porosity cannot be developed, and other well-log parameters need to be embedded into the correlation.

*Rahman et al (1991)* studied the performance of a complex carbonate reservoir under peripheral water injection. Study illustrated the importance of good surveillance data for characterizing reservoirs. The available data in that study, including well performance, geochemical analysis, cased and openhole logs were utilized to determine water encroachment patterns, areal and vertical sweep of the injection. Study concluded that peripheral injection is a viable and significant option which has achieved its objective of maintaining the reservoir pressure and sweeping the oil in the permeable zones of the case study. With good vertical communication and favorable mobility ratio, it is possible to achieve better flooding process.

*Suryanarayana and Lahiri (1996)* studied a case field in India for exploring the issues in characterization of a complex carbonate reservoir. The field had major hydrocarbon accumulation in the middle and lower Miocene layered carbonates with shale intercalations and many wells of the field have become underproductive due to high water cut. Characterization was carried out by integrating petrophysical, geological, reservoir and seismic data. Study concluded that subtle faults are the probable source for movement of fluids in the reservoir. Further observations indicated that the presence of cross trends of very minor faults can not be ruled out as oil water contact within each fault block is controlled by local heterogeneities.

## 2.3 Geothermal Reservoirs

During the oil crisis of 1973, world suddenly became aware that fossil fiel resources are limited and will be exhausted soon if new alternatives are not put into use immediately. Conservation measures and extensive research on new sources of energy has eased the demand on fossil fuelds, especially crude oil (*Okandan, 1988*). Geothermal reservoir engineering emerged as an important field in the assessment of geothermal resources.

Geothermal energy is the heat extracted from earth's crust. When extracted (usually in the form of hot water or steam), this energy can be utilized by transforming heat energy to electric energy, or in local use. Different types of resources classified according to their temperatures, will require different energy extraction methods and uses. Reservoir engineering assessment starts with exploration stage and continue with more importance after power plant operation (where heat is transferred to electricity).

### 2.3.1 Occurrence of Geothermal Sources

There are four main requirements for a geothermal resource to be considered as viable:

1) A heat source, magma body or hot dry rock at depth

2) A fluid migration which carries hot water

3) Permeable bed which will permit transmition and production of the fluid

4) A cap rock to seal the fluid migration paths and form a trap

Location of geothermal areas on the crust is dicated by global plate tectonics and there exists six geothermal belts where most of the geothermal fields exist (*Okandan, 1988*).

The biggest differentiating factor between geothermal energy and fossil fuels is the way they are utilized. Fossil fuels are processed in plants and are transferred through pipe lines or other means, where as geothermal energy is utilized where it is produced.

### 2.3.2 Re-injection

There are two types of geothermal reservoirs. One is the hot-water (liquid dominated) which produces saturated steam accompanied by large quantities of hot water or brine; and the other is the steam, (vapor-dominated) system which produces steam as opposed to water.

The energy recovered from the fluids produced from geothermal systems can be used for different purposes, mainly for electric generation. Electric generating plants which use condensing turbines generate an excess of spent hot liquid and condensed steam which must be discarded. Water producing fields yield large volumes of waste water which goes through turbines and release energy. Disposal of this waste water is generally a problem due to its chemical contents and temperature. One significant solution is to reinject waste water back into the reservoir. The term "reinjection" is often used to describe a process where waste water is injected to the reservoir for the first time. Reinjection is also important for optimization of a geothermal field. (*Ramey, 1981*). Reinjection process serves following purposes:

Thermal energy extraction – Recovering additional heat from the system is possible by injecting cold water to the system so that heat is extracted from source rock.

Pressure support – As natural recharge rarely replaces the large mass of fluid produced for power generation, injecting water in to the reservoir compensates for the pressure decrease caused by removal of hot water for energy generation. Especially in liquid-dominated reservoirs this is an important issue *(Einarsson et al, 1975).*

Reinjection also may affect ground subsidence in a production area. The effect of reinjection on subsidence has been discussed by *Milora and Tester (1976).*

### 2.3.3 Reinjection Process

The biggest consideration on reinjection is where to locate the well. The answer to this question lies in the evaluation of the reservoir rock and fluid properties. For a given field, both the location and flow rates of the injection wells are important parameters effecting future performance of the field. Here are some considerations in location selection:

Channeling and early breakthrough of cold liquid should be avoided. When a high permeable channel is injected with cold water, fluid bypasses the rest of the lower permeability zones thus reaching to producing wells faster with minimal sweep of the area. In a study on Ahuachapan geothermal field in *El Salvador, Bodvarsson (1970)* suggested that the lateral distance between two wells shall be at least 1.1 km and the water be injected a few hundred meters below the principal production horizons. In alignment with *Chasteen (1975)* also suggested the use of an injection interval shall be deeper than the producing interval in the adjacent producing wells.

As breakthrough of cold injected water at a discharging well causes the produced water temperature to decrease, it is very important to forecast the temperature at the discharging wells as a function of time to figure out the anticipated arrival time of the cold water front.

Various theoretical studies have been carried out to investigate the effects of reinjection on pressure maintenance in geothermal reservoirs (*Lippmann et al, 1977, Bodvarsson et al., 1985, Calore at al., 1986*). These studies have shown that injection has different effects on the reservoir response depending on the initial thermodynamic state of the reservoir. In the case of a liquid water reservoir the pressure effects of reinjection can readily be evaluated using conventional analytical and numerical techniques. In cases involving two phase liquid or vapor-dominated reservoirs the effects of reinjection on pressures and energy recovery are more difficult to quantify because of the more complex physics involved (*Bodvarsson and Stefansson et al,* 1988). Further complications are introduced when vapor-only systems , where gravity effects become dominant are investigated (*Calore et al, 1986*).

*Bodvarsson et al (1985)* examined the effects of reinjection in two-phase liquid dominated systems. They found that fluid reinjecition can cause very pronounced increases in production rates and decreases in enthalpy. Although injection and the associated mobility effects do not increase the steam rate significantly in the short term, it will greatly help in maintaining the steam rate over long periods of time. It was also pointed out that maintaining high pressure support with acceptable low level of cooling of the source, enthalpy recovered from the field (thus the total energy recover) could be maximized.

Aforementioned benefits of reinjection put great emphasis on field development stage of geothermal fields. Careful investigation of injection location and rate plays important role in the future field performance and therefore should be studied carefully. Reinjection of used water into the reservoir has become increasingly common in recent years (*Goyal, 1999; Axelsson and Dong, 1998*). Cost and environmental considerations are also important factors that need to be considered for successful reinjection process (*Stefansson, 1997*).

Reinjection location is arguably the most important parameter in a successful geothermal field reinjection project. It is possible to inject water from an outside location of the field (*Einarsson et al, 1975*) . A different strategy is to inject from a location which is near the center of the field (*Bodvarsson et al, 1988*) , enabling the injected water migrate towards producing wells at a slower speed (due to a radial behavior) thus pushing hot water to the reservoir and extracting heat from the rock. James, in 1979 suggested usage of production wells as interchangeably between production and injection, thus reducing the cost of field development and enabling a wider aerial sweep by spreading the injection process across the field.

There are also numerous studies carried on Kizildere Geothermal field (The field used as a case study) in recent years. *Arkan et al (2002)* and *Serpen and Onur (2001)* studied the effect of calcite scaling on pressure transient , using Kizildere field as case study. *Yeltekin et al (2002)* discussed the modeling of Kizildere geothermal reservoir. *Serpen in 2002* investigated the reinjection strategies for Kizildere geothermal field, using both in-site and off-site injection strategies. They suggested producing form deeper zones and injection to shallower parts, basing on the fact that deeper regions have higher $CO_2$ content. Study concluded that the most important point in reinjection to Kizildere field is downward cooling effect of injected water due to gravitational forces.

## 2.4 Optimization

As discussed briefly, petroleum engineering problems are not straight forward, as of many real world problems. Modern reservoir models try to combine many different types of information which are gathered from numerous sources. Like in any problem, as the number of constraints and parameters increase, reaching to the most feasible solution becomes more difficult. The existence of non-optimum solutions within the solution space drives us to use stochastic optimization techniques.

By nature, stochastic techniques are very suitable for algorithmic approaches. They are also effective in avoiding local solutions. The "randomness" element of these methods provides an exit route to move away from the local zones.

Prior to advancements in stochastic methods, more straight forward algorithms were used to tackle optimization problems. So called "greedy" algorithms like "hill climbing" were preferred for non-linear spaces. The chances of these algorithms to reach the global optimum are very slim. Although they are fully "structured" searches, they do not incorporate a way to the problem of getting stuck with local solutions.

Another batch of algorithms could be grouped as "randomized searches". As the name implies, in some problem specific cases (generally not too complex), it may be possible to move towards the optimum solution by applying a random search. This approach is not feasible for complex problems as they do not provide a "direction" or "structure" for the search.

Stochastic methods incorporate strengths of both approaches. Although they provide a structured search route, by combining an element of randomness, they provide a better solution that is more likely to move towards the global optimum. A balance between "randomness" and "structure" is deliberate.

Neural Networks (*Anderson, 1995*) are used as the main algorithm to generate a *proxy* of the field. Usage of Neural Networks has gained considerable popularity in the last decade. They first gained popularity as a powerful interpolation technique and recently research is shifted towards cognitive science. Tolerance to not exactly certain (i.e. noisy) data, ability to respond to complex result sets are very useful for many "fuzzy" or "not exactly defined" systems. In petroleum industry, recent research focuses on using Neural Networks as approximate replacements for Simulations.

### 2.4.1 Neural Networks , Optimization and Well Placement

There are various applicatons of neural networks in the petroleum and natural gas engineering industry. *Ali* in 1994 gave a synopsis of applications of neural network in petroleum industry. In his study, he outlined five main areas where neural networks are used:

1) Pattern / cluster analysis

2) Signal processing

3) Control applications

4) Predicition correlation

5) Optimization

He also points out that despite some advances on the design of optimal network structures, it is still largely an art to determine the best paradigm. In our study, neural networks are used for prediction correlation as a subsystem for a supervising optimization algorithm thus combining items four and five with the help of other techniques. His study argues the necessity of adopting neural networks in to field of petroleum, being influenced by the advancements and latest research that has proved the use of neural networks as a viable tool on different aspects of industry needs.

This study incorporates neural networks as an helper algorithm to optimization of well placement. As also pointed out by the study of Ali, 1994; this is a viable application scenario considering its main virtues:

1) Learning

2) Association ability

3) Real-time capability

4) Self-organization

5) Robustness against noise

6) Ability to generalize

(Capabilities of neural networks are described in detail in following sections of this chapter).

There has been various studies that incorporate neural networks as a replacement to numerical simulators or as a tool for predicting field performance.

In 1994, Neural Networks are used as proxy of the numerical simulator in a study to optimize groundwater remediation *(Rogers and Dowla, 1994)*. They used previously simulated results to train the Neural Network and there after used it to generate decision spaces.

Also in 1994, *Kumoluyi and Daltaban* discussed the genereal application of higher order neural networks inspecting various issues and application areas. Discussing the difference between conventional neural networks which have activation functions that are linear correlations of their inputs and higher order networks which have a non-linear correlation of their inputs. Discussion was presented to be a background source for application of networks, investigating general overview of pattern recognition, properties of neural networks, definition of higher order neural networks and applications of them in petroleum engineering.

In 1995 *Aanonsen et al* used different well configurations to train Neural Network and used the trained system to generate decision surfaces. Those surfaces are then used to estimate the well location. It was demonstrated that Neural Networks proved successful in simple cases and the estimated response surface was accurate enough to be used for proper location. Following the study of *Aanonsen et al*, *Pan and Horne* (1998) used Neural Networks along with kriging to reduce the number of simulations. Study proposed to use some refinement areas that are of higher interest for evaluation.

Also in 1998, *Doraisamy et al* studied key parameters controlling the performance of neuro-simulation applications in field development. They described the use of artificial neural networks in exploring field development strategies in conjunction with various recovery schemes. Study focused on important neural network parameters with relevance to recovery scenarios which have an overall objective to increase the rate of oil recovery under specified GOR and WOR constraints. As efficiency and accuracy of an artificial neural network are controlled by various parameters that are specific to a given network topology, it was argued that having a robust knowledge on those parameters are crucial for succesfull network design and implementation.

Study was carried on three cases: In-fill drilling where over-training of the neural network was investigated, Gas injection where effect of the number of middle layer neurons on the training process was discussed and water injection where again effect of number of middle layer neurons and the learning constant on the training process was examined.

Study concluded that two of the more important parameters in a neural network that control its overall performance are the learning constant and the number of middle layer neurons. It was suggested that for studies involving little or no noise, using the least possible number of middle layer neurons resulted in a well trained network. However, in the case of wide disparity between different scenarios, using higher number of middle layer neurons was found to be necessary.

*Farshad et al* (1999) studied the “prediction” cababilities of neural networks for tempereature profiles in producing oil wells. In the study , neural networks were used for replacing theoretical principals such as energy,mass and momentum balances (through regression). Study presented a novel approach of using neural networks for predicting temperature profiles of flowing fluid at any depth in oil wells. Farshad et al tested networks using temperature profiles from seventeen wells in the Gulf Coast area.

In their study Farshad et al concluded that the neural network models successfully mapped the general temperature-profile trends of naturally flowing oil wells. Among the tested networks, the better of the two model predicted the fluid temperature with a mean absolute relative percentage error of 6% where all of the networks used backpropagation algorithm for training.

*Stoisits et al* (1999) used combination of Neural Networks and Genetic Algorithms in a study for production optimization. Neural Networks were used to represent the components of the production system.

Again in 1999, a study carried out by *Centilmen et al* on nonlinear effects of well configurations used Neural Networks as a replacement for simulators. Study demonstrated the implementation of a neuro-simulation technique that forms a bridge between a mathematically rigorous reservoir simulator and neural network that uses the simulator outputs as training data sets.

The numerical model was replaced by the neural network which is used to output production profiles of the wells. Centilmen et al selected various production scenarios to generate training sets. Trained with these data sets, neural networks are then used to predict other scenarios that were not present in the training numerical models. All used neural networks had 1 hidden layer (details on neural networks are presented in next chapter) and numbers of neurons for each layer were determined by the complexity of the case. Centilmen et al grouped the input of networks into two categories; stationary and case dependent variables. Stationary parameters were the ones used for similar problems, such as training well locations and time. Non-stationary parameters were case-specific such as distance between two training wells, distance between existing wells and training wells, functional links for production time and well locations. Figure 1 shows the structure of the neural network. Once the neural network is trained, numerious scenarios are created to evaluate the prediction and optimization cababilities of neural network. Following the optimality decision, cumulative recoveries are then computed.

Centilmen et al used four different cases to test their proposed methodology. A simple square shaped homogeneous reservoir, an irregularly shaped homogeneous reservoir, an irregularly shaped heterogeneous reservoir and an irregularly shaped multiphase heterogeneous reservoir are used for evaluation of the method. It was concluded that, neuro-simulation approach gives accurate results for various problems with different difficulty levels and provides the possibility to check every configuration in a field development study, thus providing a tool for a complete screening of various scenarios.

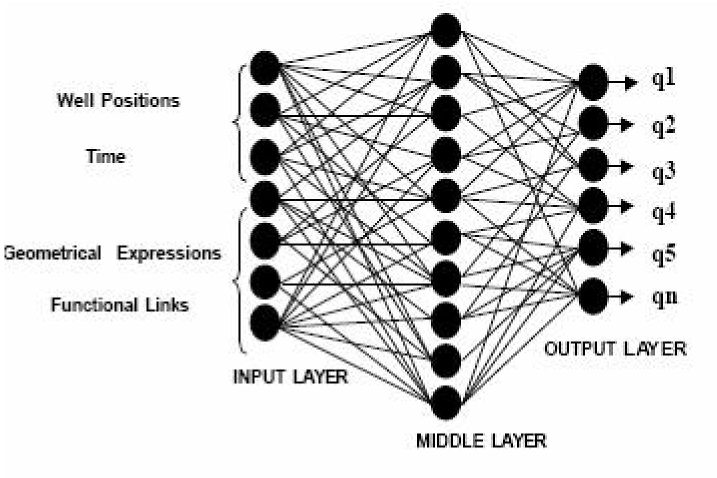



*Figure 1 – Structure of the neural networks used in field development study (Centilmen et al, 1999)*

In 2000, *Aminian et al* discussing the methods on improving the simulation of waterflood performance with the use of neural networks. They used several artificial neural networks to predict the Flow Units (which is defined according to geological and petrophysical properties that influence the flow of fluids). The study was performed in an oil field located in West Virginia and well log data and core analysis results from seven wells in that field were utilized to train and test the neural networks.

Aminian et al used correlation coefficient ($R^2$) to evaluate neural network correlation performance in other words as a measure of accuracy of prediction as compared to actual values. It was concluded that $R^2$ values for six out of seven wells were significant (above or near 0.9). It was also pointed out that the network could not predict the permeability accurately if only the various log values were provided as input and this observation was related to the noise content of well logs. The inclusion of the derivatives (of density and gamma ray log readings) allowed the network to recognize the changes in the shape of the various log responses, which led to a successful neural network development. Study concluded that the neural network predictions significantly improved the simulation of the secondary recovery performance.

*Guyaguler et al (2000)* used Neural Networks as a proxy in a research to optimize well placement. They used Neural Networks as an aid to decrease the number of simulations and an input to genetic algorithm. Figure 2 shows the flowchart of the proposed algorithm.

Acting as replacement to estimate the success of an injection location (which is governed by genetic algorithm), neural networks helped considerably to decrease the computational requirements thus enabling application of genetic algorithms in complex cases. It was proposed that, especially in cases where the evaluation is expensive to compute it may be feasible to create a proxy that approximates the behavior of the actual evaluation function, the numerical simulator. Such a proxy method (neural networks in this case) requires an initial investment of numerical simulators that will be used to calibrate the proxy in order to make it as accurate as possible. Proposed optimization method is then carried out with the proxy instead of the full numerical model.

As a case study, Guyaguler et al used the Pompano field in Gulf of Mexico. The optimum placement and the pumping rate of up to four injector wells were investigated. Well locations and water pumping rates were the decision variables. The evaluations function was a full finite difference numerical model of the field and the objective function was the net present value. Guyaguler et al investigated optimization of single well location with constant rate, optimization of multiple well locations and pumping rates.

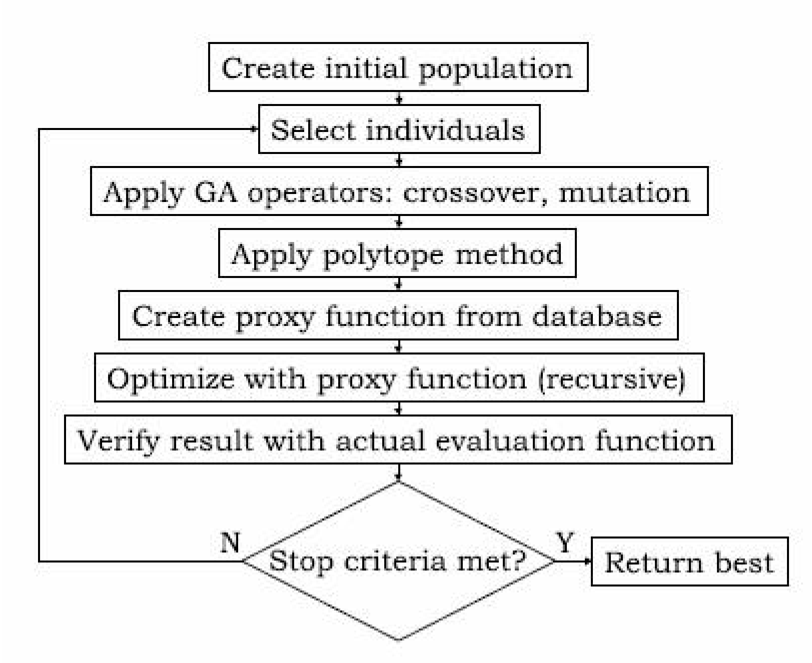



*Figure 2 - Flowchart of the algorithm proposed by Guyaguler et al (2002).*

As conclusion, study pointed out that neural networks acting as proxy has issues to be addressed. Most significant issue with neural networks was the unpredictable behavior of the trained network in some cases. It was also discussed that the benefit of using optimization algorithms, different from a human beings, the optimization procedure is able to evaluate all the effects of hundreds of factors in a straightforward and precise manner.

Proposing a similar combination of numerical simulators and optimization algorithms, *Yeten et al (2003)*; used Neural Networks to obtain approximate field responses in order to replace costly simulations for optimizing non conventional well location and trajectory. Neural Networks were chosen to act as a proxy to simulators to decrease costly runs where outputs of the network were used as rank indicators for Genetic algorithms. Yeten et al used neural networks to produce production estimates of the well, which then was used as an input to genetic algorithms. Genetic algorithm was preferred as the supervising algorithm for optimization decision; iteratively optimizing the well configuration and trajectory by ranking best candidates.

Yeten et al considered three basic cases along with several sub cases including dual-driver reservoir, a layered reservoir and a single phase flow (primary depletion) in a sealed, fluvial channel reservoir.

Study discussed that application of optimization algorithms and neural networks provide a reasonably efficient means for exploring the very broad parameter space associated with the optimization of non-conventional wells. It is pointed out that the optimal type of well may be strongly impacted by the cost function and the cost function itself can vary significantly depending on the location and reservoir type.

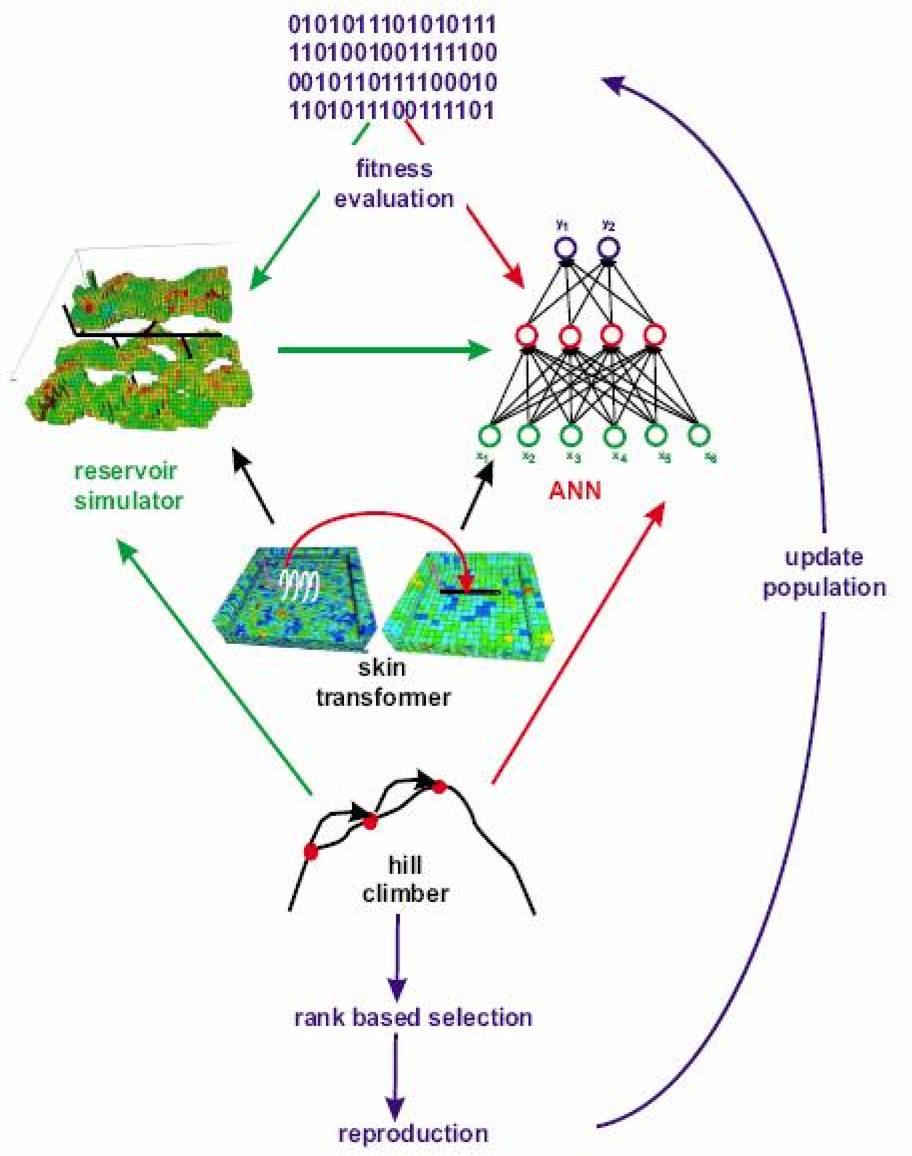



*Figure 3 – Workflow of the method used by Yeten et al (2003)*

### 2.4.2 Optimization Applications

In 1994, *Rian and Hage* carried out a study to optimize well location by using real simulators. Study indicated that, for a field scale reasonably complex problem; using direct simulations could result in high processor costs. They proposed a faster but limited front-tracking simulator that is used as the objective evaluation tool.

Simulated annealing, an optimization technique inspired from the physical annealing process was used by *Beckner and Song* (1995) study. The famous traveling salesman problem has been the basis of their approach. Beckner and Song focused on the problem set up rather than the optimization itself. Study concluded that optimization algorithms and numerical models could evaluate the effects of the parameters. Their study also indicated that optimization algorithms coupled with the numerical model has the potential to evaluate the nonlinear effects of the optimized parameters.

In 1997, *Bittencourt and Horne* used a combination of Genetic algorithms and polytope method to investigate optimization of a well placement. This hybridized approach was used to estimate the optimum locations for 33 wells. Bittencourt and Horne proposed to use “active cells” only, pointing out that of not used, optimization algorithm can place wells in inactive regions. In present study, extended flow rate study somehow utilizes the approach of active cells, focusing optimizaiton to a particular area.

*Guyaguler and Gumrah* (1999) studied optimization of a gas storage field by using Genetic Algorithms to reach the optimum parameter set. Study compared linear programming and approximate solutions and pointed some limitations of approximate models.

## 2.5 Artificial Intelligence

### 2.5.1 Intelligence

Most often Artificial Intelligence (AI) is defined as the study of intelligent behavior. This study, being mostly based on mimicking the working principles of human brain, has been widely motivated by the the investigation of the learning process of humans. All throughout the history, human behavior and learning process has been a mysterious field to delve into and many scientists have investigated the “mechanics” of human brain.

### 2.5.2 Artificial Intelligence

The term “Artificial Intelligence” which was mostly used in science fiction novels during the early 20th century, has always been a dream of mankind in one or another way. The curiosity genes of mankind coupled with the ever improving intellectual capacity; had always asked the very same question: “How do we learn? How do we infer?”. These two questions, in the quest of searching the fundamentals of human intelligence, has been the main motivation for centuries.

With the improvement of science and technology, blended with fiction, raised another question, or challenge: “How do we imitate human intelligence?”. This question, being the motivation in search for artificial intelligence, even leaded to establishment of a science discipline on its own: “Cognitive Science”. The term “Artificial” perfectly suits to its place, as the outcome is merely the imitation of something natural (which is the basic and vocabulary definition of the term Artificial).

The concept of “learning machines” has always been an interesting topic that was well received by community as a direction of advancement. Therefore, research towards these concepts emerged eventually.

With the significant improvement of science during past centuries, studies on human brain have been improved and the technological advancement enabled scientists to come with new discoveries regarding the working principles of human brain.

### 2.5.3 Nero Computing

Nero computing represents general computation with the use of artificial neural networks. An artificial neural network is a computational model that attempts to mimic simple biological learning processes and simulate specific functions of human nervous system. It is an adaptive, parallel information processing system which is able to develop associations, transformations, or mappings between objects or data. It is also the most popular machine learning technique for pattern recognition to date. The basic elements of a neural network are the neurons and their connection strengths (weights).

Given a topology of the network structure expressing how the neurons (the processing elements) are connected, a learning algorithm takes an initial model with some “prior” connection weights (usually random numbers) and produces a final model by numerical iterations. Hence “learning” implies the derivation of the “posterior” connection weights when a performance criterion is matched (e.g. the mean square error is below a certain tolerance value). Learning can be performed by “supervised” or “unsupervised” algorithm. The former requires a set of known input-output data patterns (or training patterns), while the latter requires only the input patterns (*Russel and Norvig, 1995*).

### 2.5.4 Human Brain

As stated before, the motivation and inspiration behind "Artificial Intelligence" and its derivatives is human brain itself. Human brain consists of "neurons", which are, simply stated, electric circuit switches. Tens, thousands of those switches come together to form "functions" of brain. All processes from controlling our body movements to learning a new word, is merely a process of adjustment of the setting of a particular neuron network. Here are some facts about human brain (*Mitchell, 1999*)

- Neuron switching time ~.001 second

- Number of neurons $\sim 10^{10}$

- Connections per neuron $\sim 10^{4-5}$

- Highly complex networks

- Parallel computation is necessary

Human brain is a massive system which has a very complex nature and is very advanced by all means. Therefore, it is not very easy to simply create an "artificial brain", but it is possible to imitate at least some of the subsets of the behaviors. This is where the use of artificial neural networks are valid. (Mitchell,1999)

## 2. 6 Artificial Neural Networks

### 2.6.1 Introduction

Unlike the "organic" neural networks, which are part of a very complex living structure; artificial neural networks are far simpler structures. Being relatively simple mathematical structures, artificial neurons are relatively simple concepts in the domain of mathematics. As it will be discussed further on, although they are simple in their nature and theory, when connected to each other (just like the real neurons in human brain) they form a really powerful tool for wide range of applications in many different fields. Although being different in its nature, both neural networks share the same philosophy and analogy.

Being already explained, the "organic" neural network structure is like part a. Part b is a model of an artificial neuron (which is connected to some other neurons). The mathematical model (which will be discussed further on) is a fairly simple yet powerful representation of the same functionality of human neurons. An artificial neural network, ANN, is a structure of interconnected neurons, forming an intelligent body on its own.

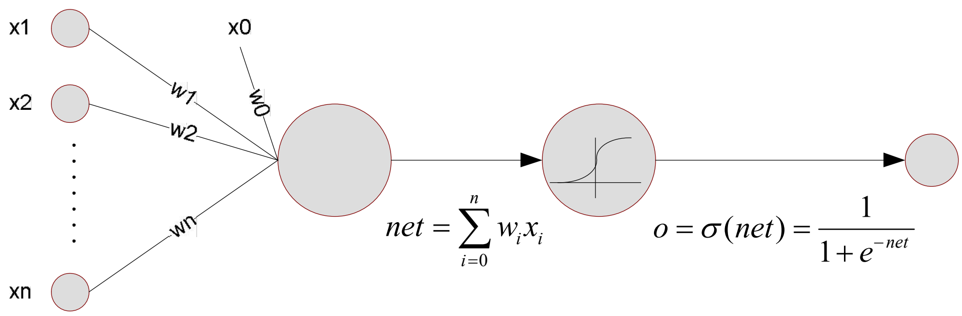



*Figure 4 An Artificial Neuron (formulation shall be introduced further on) (Mitchell, 1999)*

Here are some basic properties of neural nets (ANN's):

1) Many neuron-like threshold switching units

2) Many weighted interconnections among units

3) Highly parallel, distributed process

4) Emphasis on tuning weights automatically

### 2.6.2 When to Consider Neural Networks

In recent years, neural networks have been a very important tool in various research in very wide range of disciplines. The nature of the neural networks enables applications if:

1) Input is high-dimensional discrete or real-valued

2) Output is discrete and real valued

3) Output is vector of values

4) Data is noisy

5) Form of target function is unknown

6) Human readability of results are unimportant

One of the most important features of neural networks is its ability to "figure out" a solution even from noisy data sets. This is a very important property, especially in the domain of earth sciences, where there is always noise and imprecision.

### 2.6.3 An Alternative Approach to Neural Networks – Statistics

Till now, neural networks are described as replicates of human brain functionality. This point of view, which is mainly the approach taken by cognitive and computer scientists, tends to approach problems as "learning processes", similar to human learning. This definition and approach of neural networks mostly yield to application of ANN's in cases where human brain functionality is imitated (like character / voice recognition, man less car driving etc.) (Mitchell, 1999).

Although this approach is generally the "idea" behind ANN's , in some cases, a different explanation of neural networks seems to expand the possible applications of ANN's. Statistical approach to neural networks tends to describe the behavior as parameter estimation, classification or simple estimation problem. Neural networks are seen as perfect function estimators, which is very useful in various difficult problems where it is very difficult to tackle with other estimation methods.

In the statistical approach to Neural Networks, instead of approaching the tool as a human brain replacement, the NN's are considered to be a perfect function estimator or classifier. In most of the statistics book that covers neural network to some extend, it is possible to see the clear difference in approach. Statistical approach sees neural networks as perfect function estimators. Thus, it is true that, a two layer network is theoretically capable of estimating any function.

### 2.6.4 Artificial Neurons

Neurons are the most important and fundamental building blocks of ANN. Being fundamentally based on the idea of mimicking organic neurons, these fundamental building blocks are responsible of transferring /transforming the information they receive from their receptors and outputting a unified signal/information.

#### *2.6.4.1 Single Unit Perceptrons*

Perceptrons are the simplest type of neurons. They provide a discrete, binary output signal. They accept signals from many channels $x_1$ to $x_n$(this is a common fundamental property of neurons). The contribution of the signal to the output is controlled by the weight factors of connections, $w_1 \dots w_n$. For a single neuron system, the signal sources are the inputs to the system. In more complex systems with multiple layers, signal sources can be either system input or other neuron output signals. Actually this interconnection is the main idea behind neural networks. By interconnecting many neurons, it is possible to create highly interconnected systems, which have a higher degree of flexibility in learning (or describing) more complex tasks.

In addition to ordinary input signals, it is possible to connect a "pseudo signal" $x_0$, which has a signal strength of 1 (in normal space, this corresponds to maximum strength) and is connected with a specific weight $w_0$. This threshold unit is used to put a lower limit for of the neuron. In other words, it enables to put a bound for minimum value that is required to activate the neuron to return a specific signal.

As stated earlier, perceptrons provide discrete results. In general usage, a perceptron returns 1 if the summation of weighted input signals exceed a threshold limit (or zero if no threshold is specified), and -1 in other case.

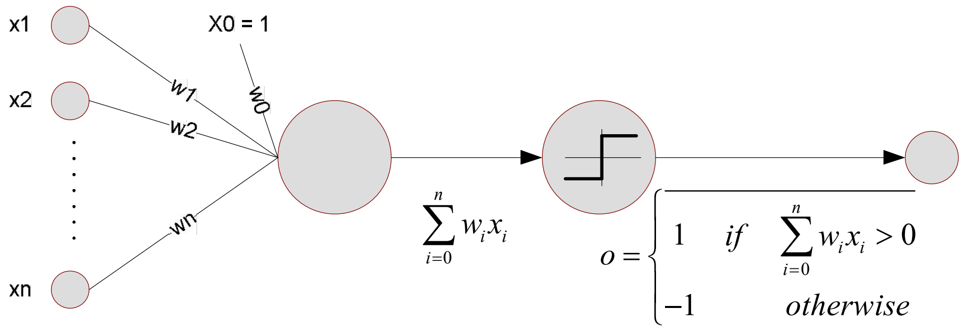



*Figure 5 - Illustration of a perceptron (Mitchell, 1997)*

Due to its binary responding nature, perceptrons are mostly used for simple decisions or XOR problems. As they provide a very predicable set of output signals, they prove useful in some cases where true of false, as an answer is sufficient.

Although they are useful, perceptrons have limited representation capability. As they have discrete output signals and a very limited set, decision surface formed by a perceptron function is linear.

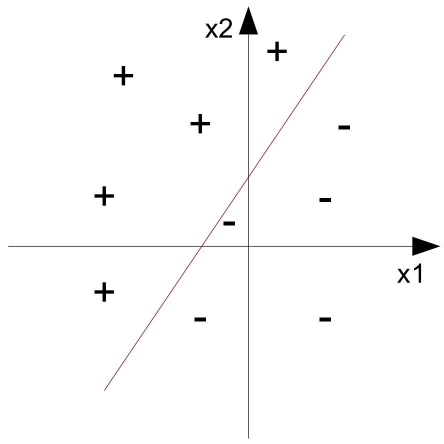



*Figure 6 - Perceptrons form a linear decision surface*

As mentioned before, a perceptron is useful in OR, AND type of problems. Thus, they are not suitable for problems where problem outputs are not linearly separable or a linear separation/classification is not a viable option.

***2.6.4.2 Sigmoid Neurons***

Instead of generating a discrete output unit, unlike perceptrons, sigmoid units generate a continuous output signal.

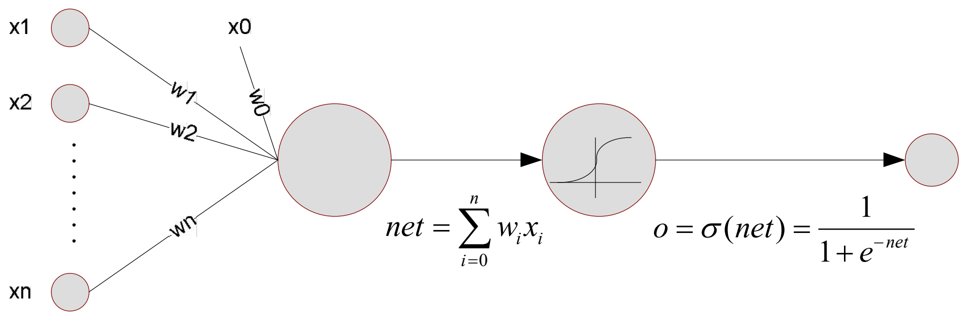



*Figure 7 - A Sigmoid Unit (Mitchell, 1999)*

Basic principle being the same, sigmoid units differs with their activation function. The activation function is a transformation function that has the net summation of all weighted signals connected to the neuron as parameter, and a single signal as output. The important property of the activation function is that, it has a wide mapping space, i.e. given a different net value, it generates a unique mapping.

Although there are various activation functions, the most widely used one is (*Mitchell, 1997*):

$$\sigma(net) = \frac{1}{1+e^{-net}} \qquad [1]$$

This activation function, which is used for our study as well, is both computationally efficient and has an important feature such that:

$$\frac{d\sigma(x)}{dx} = \sigma(x)(1-\sigma(x)) \qquad [2]$$

The first order derivative is particularly important as it is used in optimization algorithm. As having a simple, computationally efficient first order derivative, this activation function $\sigma(x)$ is advantageous in huge networks with big training sets (which is our case). Details regarding the usage of the first derivative will be discussed later.

#### *2.6.4.3 Interconnected neurons – Neural Networks*

The main strength of using neurons is unleashed when they are used to create bigger systems. This is done by connecting multiple networks in layers.

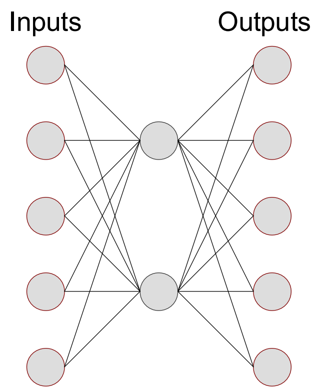



*Figure 8 - A simple neural network with 5 inputs, one hidden layer with 2 neurons and 5 output neurons.*

As illustrated in Figure 8, constructing a neural net is merely about interconnecting the neurons. Input values then propagate in the network, and desired number of outputs is generated by network.

Although forming a network sounds simple, design and layout of it is the key factor for the success of the ANN. Actually the network layout is the most important parameter that should be worked on for any ANN application. Number of neurons in a network, the way they are connected, number of layers they form and other similar design issues should be successfully addressed for any successful ANN application. These issues will be discussed in detail.

### 2.6.5 Learning in Neural Networks

As mentioned earlier, the fundamental concept of neural networks and neuro computing is the learning process. Networks are used for making the computers learn and after successfully learning the given task, applying the gained knowledge in other samples, just like humans do.

Learning in neural networks is done via adjusting the contribution of signals for each neural unit. This means that, the learning takes place with adjusting the weights for each connection. A well trained neural network is the one which has proper weights, which enable the network produce expected results.

The term "learning" for a neural network actually implies the adjustment of weights and takes place in small scale. There is no supervisor algorithm in adjusting the weights. Each neuron is responsible for adjusting its own weights, according to a given "training rule.

#### *2.6.5.1 Training rule in Perceptrons*

Perceptron training rule is as follows:

For each weight,

$$w_i \leftarrow w_i + \Delta w_i \qquad [3]$$

Where

$$\Delta w_i = \eta(t - o)x_i \qquad [4]$$

Here, $t$ is the target value; $o$ is the perceptron output and $\eta$ is the learning rate (a small constant like 0.2). The learning rate one of the few parameters that one can modify for a given network. It is used to adjust the "pace" of the learning (Mitchell, 1999).

This learning rule will converge if training data is linearly separable and $\eta$ is small enough to let the training converge without over passing the best weight update.

### 2.6.6 ANN Training: Search for the Best Fit

Aforementioned goal in training a Neural Net is finding the best weights that will produce the desired outputs of the network. So the question is: "How do we find the best weights?". This question itself implies that we actually have an optimization problem. We need to find the best fit (the instance of weights that produce the most successful results over the training set) by estimating parameters (weights). This task can be done with different optimization methods. In our study, we choose to use Gradient descent algorithm in training the neural network. Throughout the study, the networks that are studied are built with sigmoid units. By doing so, we are turning learning into an optimization problem on a continuous function (as sigmoid units form continuous signals).

There are two steps in solving this optimization problem. The first one is creating a continuous function (sigmoid units) and the second step is to introduce a measure of the performance of the network which is a continuous function of the weights and thresholds (biases). This function, called "objective function" sets the goal for the optimization algorithm. Although will be discussed later, it is important to mention that, in any type of optimization, the objective function is the key element in reaching the solution. During this study, various optimization algorithms are used in different layers. For now, our discussion is bound with the scope of Neural Network training.

The objective function used for the training for the neural network is the sum of squared error between the target output and the produced output of the network (Gill, Murray, Wright, 1981).

$$E = \sum_{pattern p} \sum_{output i} (t_i^p - o_i^p)^2 \quad [5]$$

So, the goal is minimizing the sum of errors between the target and produced results. This is actually the exact approach that humans do during a learning process. We try to get the necessary information and evaluate ourselves according to the match of our inference with the given one.

#### *2.6.6.1 Gradient Descent*

Since the transfer function is continuous, the sum-squared error, E, is a continuously varying function of the weights. One way to find the "best" weights is to find the weights which minimize the error *E(W)*, where W denotes the weights and biases of all of the neurons in the network. The weights which minimize *E(W)* will get the network outputs as close as possible to the desired outputs on as many patterns as possible.

Gradient descent is a general method for looking for optima of a continuous function iteratively. The gradient of a function is a vector which points in a direction in which that function is most increasing (most uphill). The magnitude of the vector is related to the steepness of the slope. At optima, the gradient is zero. If the error is a function of *n* weights $E(w_1, w_2, \ldots, w_n)$, then the gradient of E is a vector with n components.

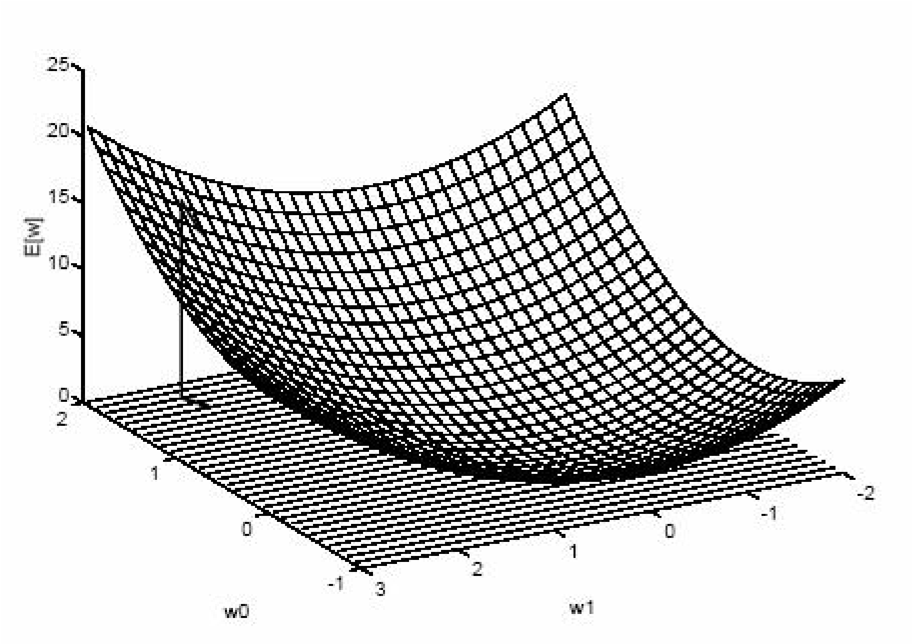



*Figure 9 - Error surface and the direction of the search (Mitchell, 1997)*

Since the gradient points most uphill, to minimize a function we can repeatedly move in the opposite direction from the gradient. In other words, given the current values of w, calculate the gradient, change the weights by a small amount in the opposite direction of the gradient, then calculate the gradient at this new position, move a small amount, and so forth. The amount which one moves is controlled by a learning rate. So the training rule to minimize a function *E:*

$$\Delta \vec{w} = -\eta \nabla E\left[\vec{w}\right] \qquad [6]$$

i.e.

$$\Delta w_i = -\eta \frac{\partial E}{\partial w_i} \qquad [7]$$

This changes $w_i$ in a direction which most decreases $E$. You can repeat this until the gradient gets very small, until E(W) gets very small, or it has run for a given number of updates.

Figure 9 shows a schematic picture of the error as a function of weights. The vertical axis is the error as a function of position in the horizontal plane. The error in the plane shows the direction which most reduces the error; this is the gradient.

Gradient descent tries to find the optimum, in our case the minimum, of a function. It can fail to find the optimum. Firstly, it uses only local information. Thus, it may move to the nearest minimum, which may be a local minimum, but may have a much larger value than the true minimum. Second, since it uses gradient information, if it is in a region which is flat or very nearly flat, the gradient will be zero or nearly zero and there will be no information with which to choose a direction.

The choice of the learning rate parameter is very important and very hard to set in an appropriate way. If it is set too small, progress will be very slow. If it is set too large, the algorithm can actually diverge from the optimum rather than move towards it. The appropriate value of the learning rate is determined by how rapidly the error changes.

The following algorithm (Figure 10) is used to incorporate gradient descent into neural network. As illustrated in the flowchart (Figure 10), gradient descent search is applied to update the weights at the output level. Thus, another supervising algorithm is needed to update rest of the weights in previous layers, in other words back propagate the updated weights. The backpropagation algorithm which is widely used for neural networks, (as cited in Mitchell, 1999) enables automated update of weights, starting from the output layer to the beginning.

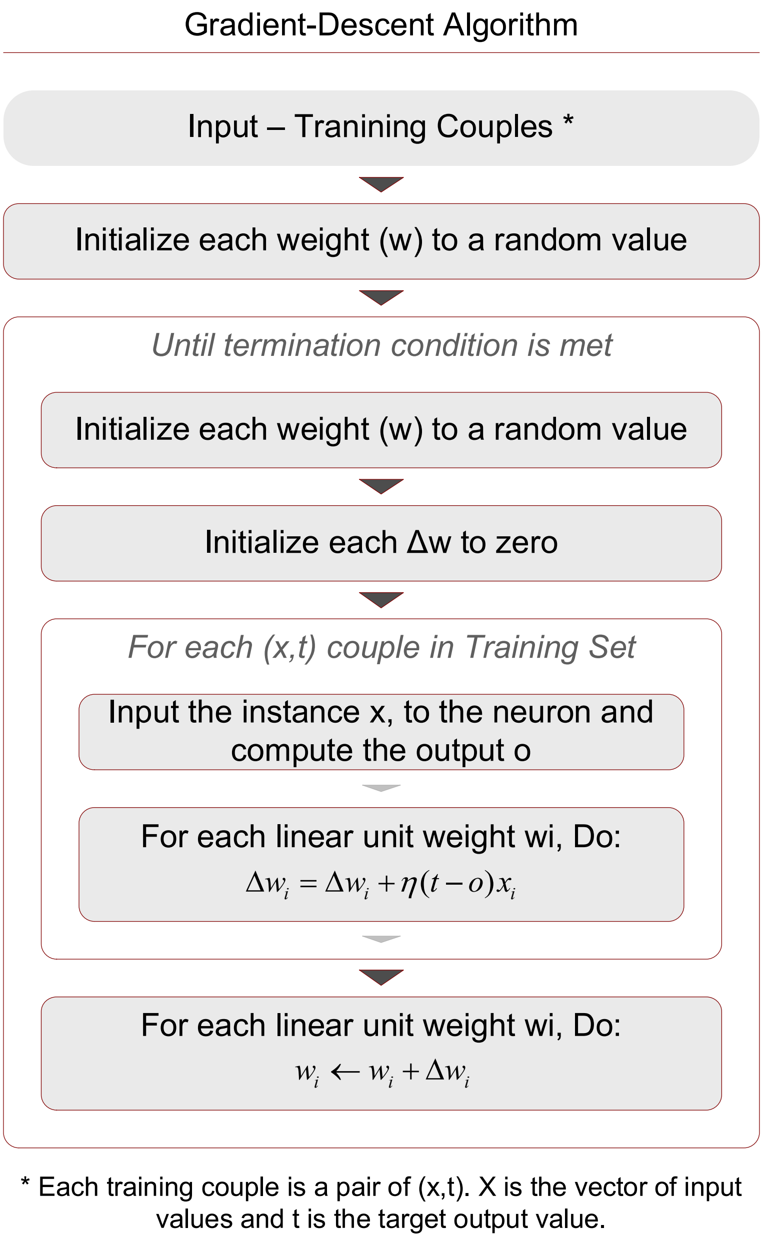
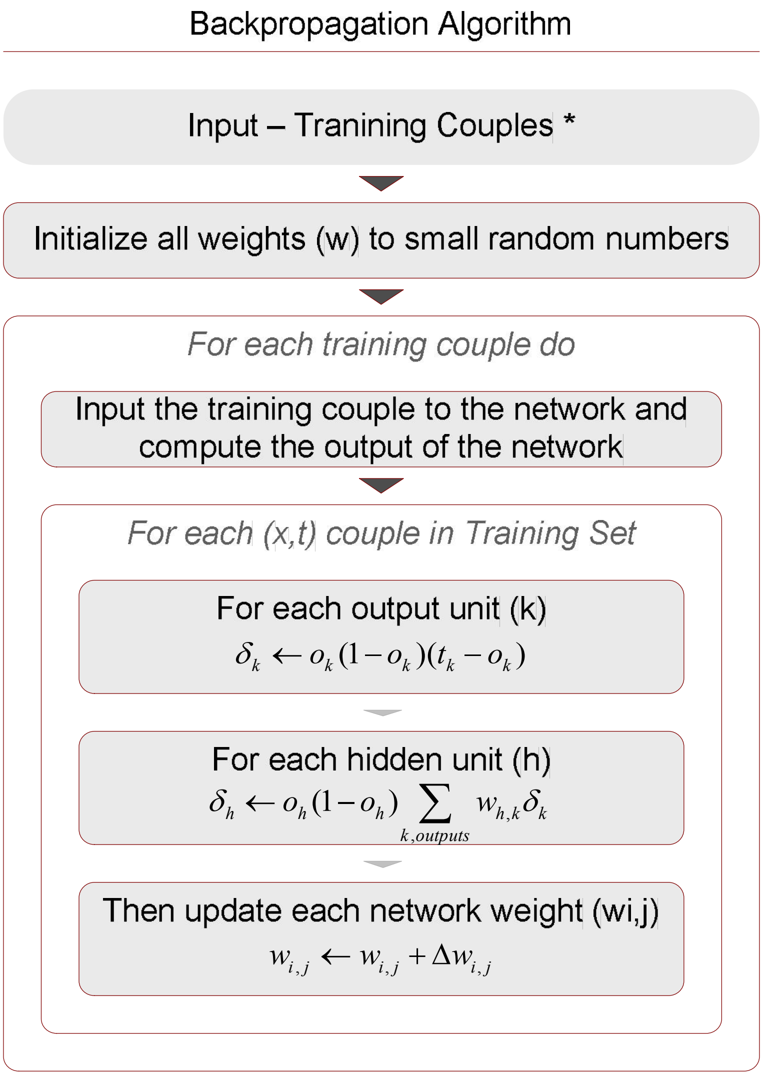



*Figure 10 - Algorithm of gradient descent*

## 2.6.7 Backpropagation Algorithm

Being one of the most widely used algorithms for neural network training, backpropagation algorithm (*Rumelhart et al, 1986*)enables a low cost weight update scheme over complex network. The following algorithm (Figure 11) propagates the new weight information that has been updated by gradient descent back to the first input connections.




* Each training couple is a pair of (x,t). X is the vector of input values and t is the target output value.

*Figure 11 - Backpropagation algorithm*

### 2.6.8 Overall Training Algorithm

Following is the final algorithm for training a neural network.

1) Initialize a network with user specified number of inputs, neurons in specified layers and outputs.

2) Initialize weights connecting the neurons (initialization is mostly done with random weights between 0 and 1).

3) Given a set of training input, calculate the outputs.

4) Use gradient descent to retrieve new weights for output layer.

5) Use backpropagation algorithm to update rest of the weights.

6) Use the same set of inputs with the updated weights and do the steps 3-5 recursively.

7) Stop training when the stopping criteria is met.

### 2.6.9 Training Sets

Neural networks need a training data set to learn. Actually, ANN's are mostly used to interpolate information, that is, given a set of samples, ANN is used to act as a proxy and approximate results given another set of input for the same problem.

Neural networks are powerful tools for replacing forward models, especially of those which are known to be governed according to consistent equations (Caers, 2004). A wide usage of ANN's in scientific problems is as follows:

Given a problem, and a known solution (mostly with CPU demanding and sometimes difficult to calculate analytical solution) a set of results are calculated or if applicable, experimental results are collected.

Then, a Neural Network is trained to learn the behavior that is governed with the equations. As using a trained ANN is far less costly than doing equation calculations, or say running simulators, afterwards, Neural Network is used in replacement.

The above mentioned methodology indicates a critical point: The training set is the only bridge between the real case and the neural network and therefore it should be as healthy as possible.

As mentioned earlier, ANN's are not very sensitive to noises and are very good at inferring results from noisy data (Mitchell, 1997; Caers 2004). This property is probably that makes a neural network a good option in deducing results from "observation" type of problems (like experiment results). The term "healthy" used in the previous paragraph does not refer to the "precision" of the training set, but rather the way it is subdivided.

For training a neural network, it is required to have 3 groups of data sets which are gathered from exactly the same source in same conditions. In other words, when we are given a data set, we will need to divide it into three sub groups. The reason we use three groups and their usage is as follows:

The first group, training set, is the one that will be used to train the neural network. It is be used in the aforementioned iterative training process.

Second set, the evaluation set, is be used to evaluate the network during the training. In other words, after each training iteration, the exact network snapshot is used to calculate the error of that particular shot and recorded. It should be noted that, the calculation of weights and backpropagation of updated values are done for the training set, evaluation set is only used for the forward pass. Same evaluation set may be used to evaluate the trained network (or this set may be sub divided into two to keep some part of it for post evaluation).

The third set is the one that is never shown to the network before it gets past the training stage. This set is used to make sure that the trained Neural Network acts as expected even for data sets it has never seen.

## 2.6.10 Stopping Criteria in Neural Network Training

### *2.6.10.1 Stopping Criteria in Optimization*

In any optimization problem, one needs to define a stopping criterion to end the iterative process for searching the "best fit". One might argue about the reason why it would be viable to stop before reaching the ultimate target, the exact match. The simple reason is that, in most of the cases, the exact match is impossible to reach. More importantly, it may be very costly to reach the fit, whereas we can obtain a "good enough" fit with far less iterations. In most of the iterative optimization algorithms and specially in derivative using methods like Gradient Descent or Newton's method and its extensions, search moves quite fast in first iterations and then the change in the value slows down (Caers, 2004).

A quick inspection on Figure 12 can be a good demonstration of why a stopping criterion other than finding the exact match can be useful. As you can see after the first couple of iterations the reduction in error starts to become too small. And after 30 iterations, it may be more feasible to stop rather then continue, if of course the solution is tolerable. This is a simple case, and we may not need to stop the optimization, or worry about the bounds of the stopping criteria. Imagine a situation where we are optimizing a very CPU demanding problem where each iteration takes an hour and the nature of the problem is very complex and a viable solution will not be reached before couple of hundred of iterations. In that case, spending few more days to get 0.5% change in some of the parameters may not be feasible.

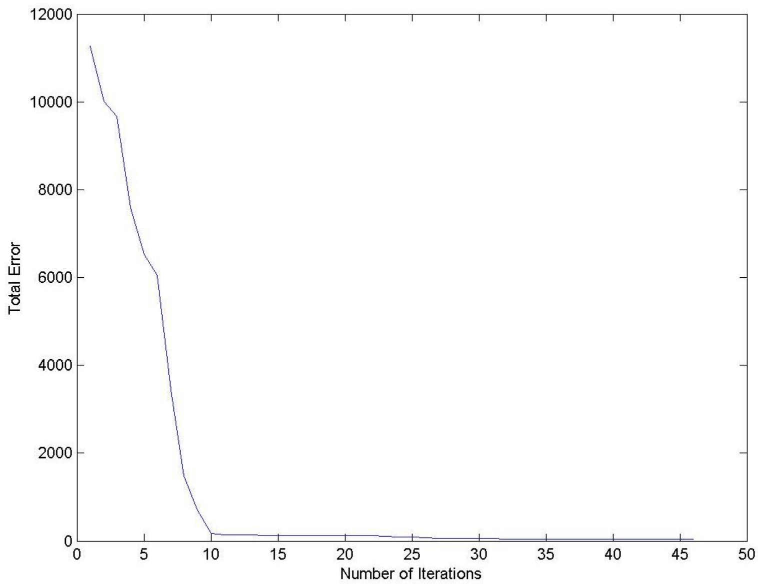



*Figure 12 - An example trace of total error reduction of the solution with a typical gradient method (Conjugate Gradient variant).*

#### *2.6.10.2 Overfitting (Memorization) Problem in Neural Networks*

As mentioned earlier, training a neural network can be seen as an optimization problem. We have to deal with the same issue of finding the best cut off criteria. In neural network training, this cut off point has even more importance than an ordinary optimization problem (Mitchell, 1997).

### 2.6.11 Design Issues in Neural Networks

As mentioned before, it is possible to create infinite number of different network designs that may address the very same problem. Although there are no "mathematically exact" tools to calculate the success of a particular network design for a specific problem, some general guidelines exists to assist in finding a reasonable network design for a problem.

#### *2.6.11.1 Effect of Number of Neurons and Layers*

The number of layers of a network does have a calculateable impact on the representation power of the neural networks.

Recalling from the statistical approach to ANN's, if networks are treated as classifiers or discriminating boundaries, it is visually possible to explain the impact of having different number of layers and nodes.

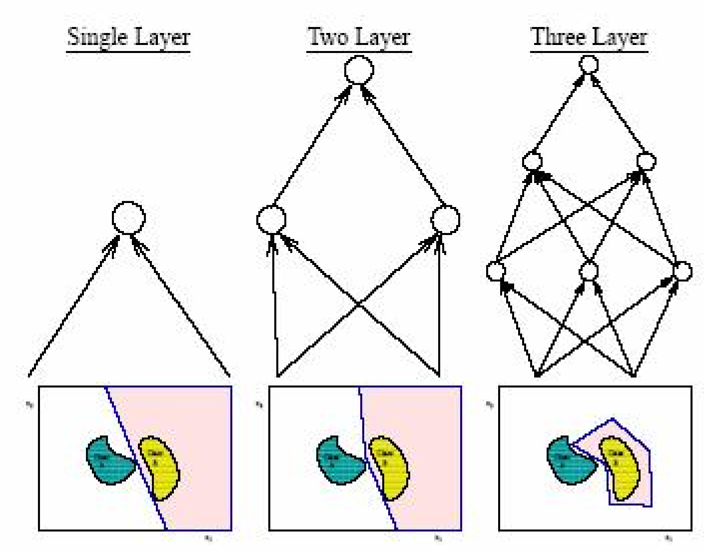



*Figure 13 - Discriminants made by Multi-layer neurons with different number of layers (Caers, J., 2004)*

As you can see, a one layer neuron makes linear discriminants, a two-layer network can form discriminants with a convex region and a three-layer network can form arbitrary discriminants.

One should note that, although increasing the number of layers do increase the representation power of the network, same does not always hold for the number of neurons in a layers. To give an example, in a 1 hidden layer network, increasing the number of hidden nodes from 5 to 15 does not mean that the later network will be more successful. This optimality should be carried with trial and error approach.

## 2.8 Optimization

### 2.8.1 Introduction

Optimization theory has applications in may fields. Every decision is based on a somehow optimized decision in any case. In petroleum engineering practice, optimum solutions are even more important. Generally, decisions are bound to multi million or billion results and can influence the success of the project dramatically (Gill, Murray, Wright, 1981).

Each optimization problem has a set of goals, i.e. "the optimum target" that is desired solution. In numerical problems generally the result is a "surface" of solutions that represents the results obtained with different values of the set of parameters that are being optimized. This surface can have multiple dimensions and vary in complexity in correlation with the number of parameters.

There are numerous algorithms to locate the optimum location over that surface. In this study, Simplex (polytope) algorithm is used. It is a well known algorithm, especially for its fast convergence to the maxima.

### 2.8.2 Simplex Algorithm

#### *2.8.2.1 Introduction*

Generally, in most of the optimization problems, the domain of interest and the task of optimization is usually very sparse or not very well defined. Also, in most cases, the optimization problem itself is quite complex and speed is a constraint. Polytope (Simplex) algorithm, having its root taken from graph theory, is based on a simple but very powerful algorithm. Being a downhill algorithm just like descent ones, it is far more intelligent and with the help of geometric approach, more efficient. (Caers, 2004, Nelder & Mead, 1965)

#### *2.8.2.2 The Algorithm*

The polytope algorithm is as follows.

Initially, 3 points are guessed and evaluated with the objective function. Then, they are ranked according to the value of the objective function.

Centroid of the formed triangle is calculated. ($x_c$)

A reflection of the best point so far is taken , $x_c$ being the reflection point. The new location, $x_{candid}$ is then evaluated. According to evaluation, one of the four possible actions are taken:

If $x_{candid}$ has a better evaluation value than the worst point but less than the best, then replace the worst point with the new one and essentially form a new triangle which has better areal coverage of "more probable candidates".

If $x_{candid}$ has a better evaluation value than the best ranked point, then this is very good, it means that we are in the right direction. As we prefer to move in this direction, we actually try to expand our candidate point:

We expand the new point according to the formula:

$x_e$: c + B($x_{candid}$ – c) where B is the expansion coefficient , c is the centroid

If the new expanded point is better than our candidate point, then $x_r$ replaces the worst point.

If the new expanded point is worse than the candidate point, than the expansion process fails and candidate point replaces the worst point in our triangle.

If $x_{candid}$ has worse evaluation value than the some of the point in our triangle, then it means that actually our polytope is large and we want to make it smaller so that we can approach to the solution. For that reason, we do a contraction operation.

If $x_{candid}$ is better than the worst point, then contraction point is found with: $x_c=c + A(x_{worst} – c)$, where A is the contraction coefficient and c is the centroid

If xcandid is worse than the worst point, then the contraction is done as: $x_c=c + A(x_{candid} – c)$.

# CHAPTER 3

# PROBLEM STATEMENT

This study focuses on development of a modern framework to optimize injection well location in complex carbonate reservoirs. Introduced framework utilizes neural networks and exhaustive search with stepping to locate injection wells in a given complex carbonate reservoir.

Location of injection well is a dominant parameter in application of recovery technique for a given field. By nature, most carbonate reservoirs have complex structures that influence production and recovery from the field significantly. When considering injection of waste water to a geothermal field or injection of water in to an oil field residing in a complex carbonate sutructure, choice of injection location plays an important role in determining future recovery from the field.

When considering well placement for a reservoir, choices are virtually limitless. With limited engineering and processing power, it is generally not possible to try every option and alternative to choose the best possible location. Engineering intuition plays an important role in eliminating fraction of the possible choices, yet most of the alternatives are eliminated due to lack of time and processing power. Development of a modern approach that automates the process and reduces the processing demand is therefore very important. This study focuses on introduction and deployment of a framework that automates the optimization process meanwhile keeping processing needs minimal.

# CHAPTER 4

# MOTIVATION

To provide a robust optimization solution, a general framework should be delivered. The framework should successfully address:

**Capability to avoid local optimums** In any optimization problem, the most challenging task is to overcome the problem of local solutions (*Caers, 2004*). A relatively complex decision surface has more than one local solutions which may be difficult to avoid. If algorithm is not capable of avoiding these "local" solutions, it may be impossible to obtain the global optimum, the ultimate solution that is desired. A capable framework should provide necessary algorithms to overcome this.

**Not being an overburden itself** One of the biggest problems in development of new numerical / algorithmic solutions to modern engineering problems is the cost of the approach itself. In other words, if the developed framework does not provide a far superior benefit in decreasing the processing cost when compared to the base approaches; then it will not be practical to use it.

**Not being problem specific** By definition, a "framework" should be a set of operation, a methodology to reach a solution. Framework should be general, so that it is problem specific and can be applied to reasonably different problems as well.

Main motivation for this study has been to develop and study a "framework" that is capable of addressing a well defined engineering problem and provide a set of tools that can be used in different problems of same type. Tools that are chosen as the building blocks for this framework will be discussed in following chapters.

## 4.2 Basis of the Approach

Prior to the years of rapid advancement in computer technologies; reservoir management was mostly based on intuitive decisions and expertise of decision makers. The fact of not having enough data and the inability of representing it accurately or lack in tools to handle it; the models developed and used in early days lacked the resolution of detail for successfully dealing with complex problems. With the introduction of Reservoir Simulators and the parallel advancement in computers; resulted more advanced predictive tools and well defined reservoir models emerged. Increasing the accuracy and value of fields, increase in detail also resulted in more "structured" solution models as input data exceed the limits of "intuitive inference".

As reservoir models incorporate more data, simulation complexity and CPU demand increases exponentially. As of today; with the help of supercomputers that has hundreds of processing units, companies are able to simulate, rarely, topping approximately million grid blocks. The real cost of running simulations are therefore important. Ideally; it would be the ultimate goal to run hundreds of simulations to get a better understanding of different development strategies; but this is merely impossible to tackle, as the number of variables and the produced space of uncertainty is not possible to define even with many simulations. The main bottle necks in looking for the "most valuable" decision are:

Time constraints. Running simulations is costly and time demanding. It is not possible to afford exhaustive run for each different possibility as deadlines are always “too soon”.

Excessive amount of information generation. Even it is possible to run exhaustive simulations to study the effect in change in variables, generated set of results may be difficult to interpret and time consuming as well.

During the rather short history of modern computers, being inspired by science fiction novels, constant research efforts has been put on building “intelligent” systems that can deduce like a normal human. Efforts of computer scientists resulted in various established methodologies like neural networks, genetic algorithms, fuzzy systems, expert systems etc. and the research is forging. Current research is based on improvement on these fundamental theories, their applications and “fresh ideas” in the world of artificial intelligence.

This study focuses on the application of those fresh ideas in the domain of reservoir engineering. The developed concept and the software package, which will be introduced briefly, aims to couple some latest advancements in computer science over the solutions in the field of earth science/petroleum engineering discipline.

# CHAPTER 5

# SOFTWARE IMPLEMENTATION

## 5.1 Software Implementation

Software implementation is an important aspect of this study as there is no tool that is capable of handling such different algorithms to run as integrated.

This study uses numerous advanced algorithms to tackle a specific problem in earth sciences domain. As it will be introduced later on, development of specific software that should integrate with other tools and use numerous algorithms automatically, it was necessary to approach the problem as a software development task.

## 5.2 Artificial Intelligence Workbench

Following chapter introduces the reader to the developed software package, named “Artificial Intelligence Workbench” and supportive tools such as text processors and converter modules used for retrieving high volumes of data from simulators. Executable of the software is provided on a Compact disk media enclosed to this thesis. Appendix A covers the necessary steps to install the software package.

### 5.2.1 Overview

The tool named Artificial Intelligence Workbench is full of some attractive features:

It is developed for Java 2 platform, enabling deployment to any platform.

1) Uses advanced graphical user interface

2) Uses platform independent property file format

3) Incorporates some of the recent elements of user interface tools

4) Installable via web / digital media

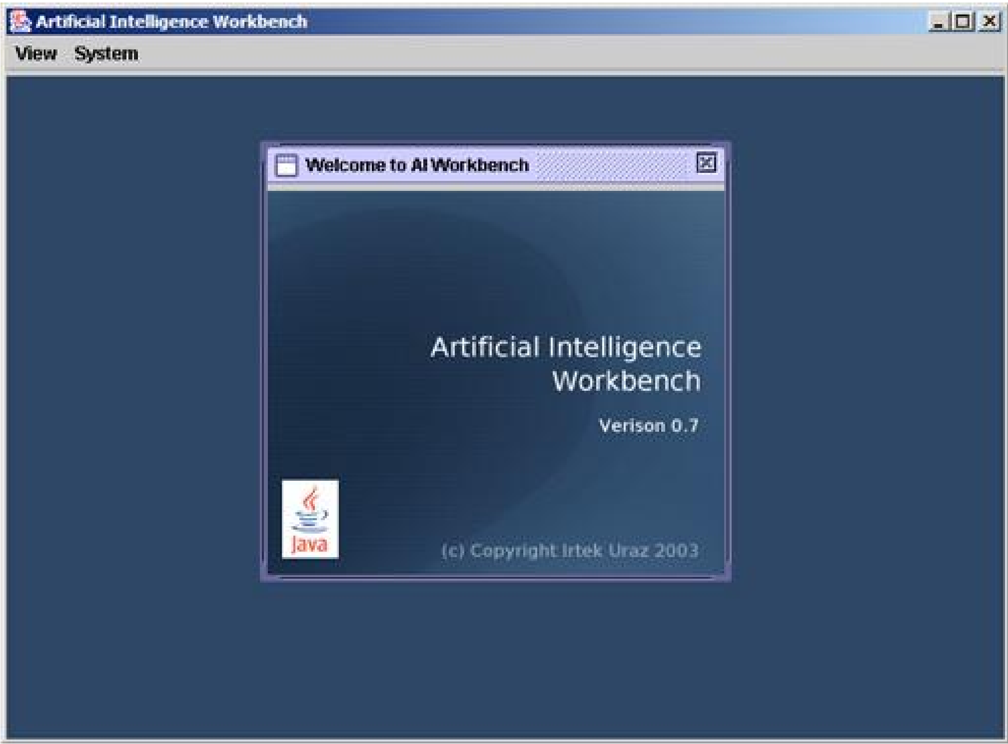



*Figure 14 - The welcome screen of Artificial Intelligence Workbench*

When launched an empty workbench the welcome screen (Figure 14) is displayed . Workbench consists of two views:

- Training Perspective

- Execution Perspective

### 5.2.2 Training Perspective

Training perspective is used for launching windows for creating new neural network design (backpropagation for time being) and Automated Nero Fuzzy Inference System. A separate input file creation dialog is presented as well.

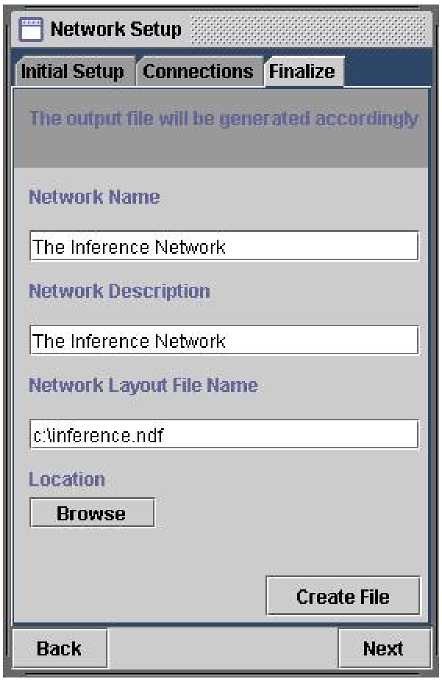



*Figure 15 - Network Design Window*

After the design of the network, a training window is launched (Figure 15).

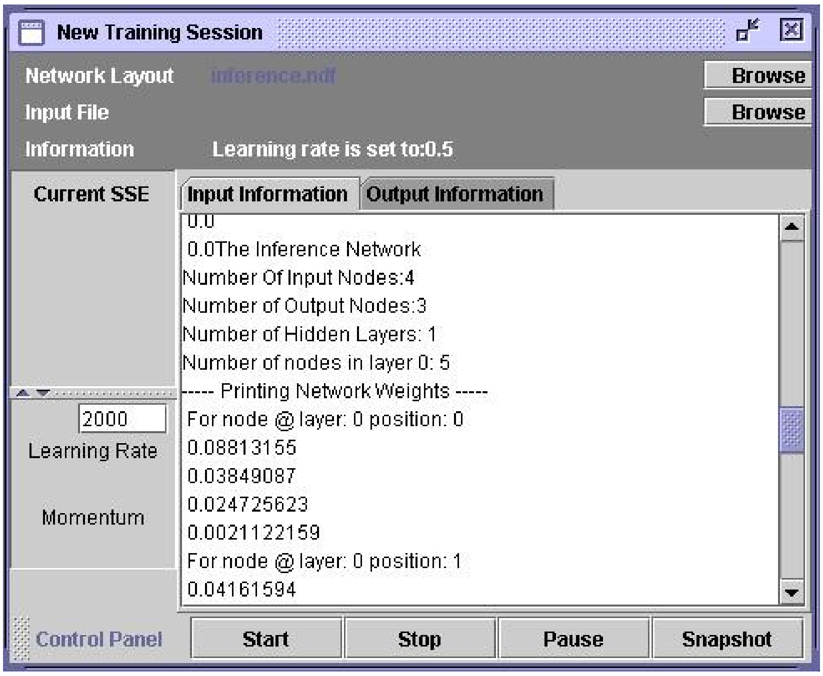



*Figure 16 - Training session is run with different learning rates and momentum*

Training window (Figure 16) enables setting the learning rate, number of epochs, momentum, input file and already designed network layout. The training is initiated with the "Start" button. When a snapshot of the current network situation is desired, "Snapshot" button can be used. Program saves the current state of the network to a permanent file. This may be particularly useful in altering the learning rate and momentum during the training process.

After the training is finished (reached the desired number of iterations or error percentage), the network state is saved.

### 5.2.3 Execution Perspective

Execution perspective is used for loading the trained network and feeding with input data.

## 5.3 Software Validation

Prior to actually using the software, each module is validated so to make sure the actual results are reliable and free of software malfunction.

### 5.3.1 Neural Network

For testing purposes, a sample network is designed with design window, for simple number recognition. A matrix of size 5x5 is used for placing 0 and 1 that form a number. Figure 17 shows an example training input of number "0". The network had 25 input values, 5 hidden nodes in 1 hidden layer and 9 outputs and it was trained for 1000 iterations.

| | | | | |
|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 1 |
| 1 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 1 |
| 1 | 0 | 0 | 0 | 1 |
| 1 | 1 | 1 | 1 | 1 |

*Figure 17 - Binary bitmap example*

The trained network responded just like expected. Numbers like "1" were identified with a %95 success. When an input of number "8" is fed to the trained network, outputs for "0", "6" and "9" also gave some signal. This is due to the similarity of those numbers when written to a 5x5 matrix.

# CHAPTER 6

# METHODOLOGY

## 6.1 Overview

Proposed work flow consists of a through development of a reservoir study. Although simulation is the core of any reservoir development project, study focuses on reducing the number of simulations to obtain a better optimization. Overview of the work flow is represented in Figure 18.

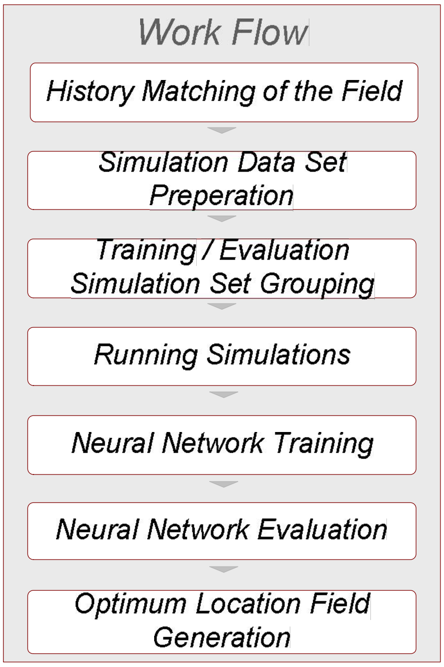



*Figure 18 – General Work Flow*

History Matching is essential to any reservoir study. To obtain a reasonable future prediction, one should have a history that is as long as the future prediction period. Prior to reservoir simulation, reservoir characterization should be carried out and a valid history match should be reached.

## 6.2 Data Generation

A considerable time of the study is devoted to the preparation of data sets that shall be used in the software. The process consisted of several steps:

1) Valid data collection from a real field

2) History matching of available data with simulation software

3) Creation of initial data files

4) Running the simulations

5) Collecting and modifying the result sets

6) Creating the training files

### 6.2.1 Valid Data Collection from the Field

As a case study, a geothermal field in Turkey, Kızıldere field, is chosen. Figure 16 shows the top view of the field. There are 11 operational wells drilled in various positions. (Yeltekin *et al,* 2002)

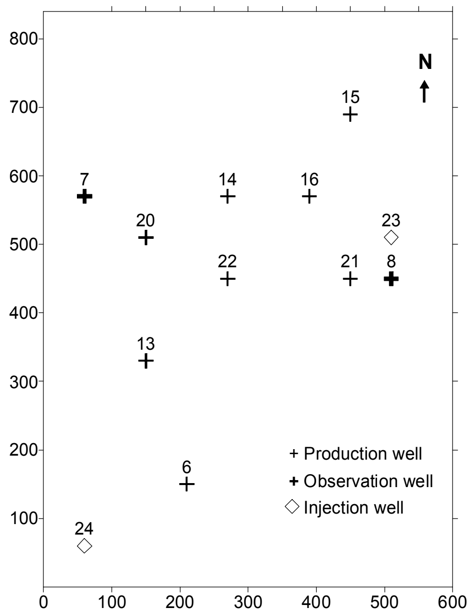



*Figure 19 - Overview of the area*

The data that is used for history matching is collected from the operational wells. Continuous records of pressure and temperature between the years 1988 to 2002 is used for that purpose.

### 6.2.2 History Matching

In this study, STARS thermal simulator (CMG, 2002) was used. Dual porosity simulation model was calibrated using historical production, temperature and pressure data from Kızıldere geothermal field, Turkey (Yeltekin *et al*, 2002).

### 6.2.3 Creation of Data Files

The developed simulation model consisted of 8x12x6 rectangular grids (Figure 8) with equal aerial dimensions (60x60 m) (Akin *et al*, 2003). The depth of the blocks matched the depth of the hot water bearing reservoir divided into five equal parts.

In order to predict the response of the field, pseudo-well locations were used for each of the grid. To reduce the already excessive size of data set, a chessboard fashion of layout is used for pseudo well locations (Figure 20).

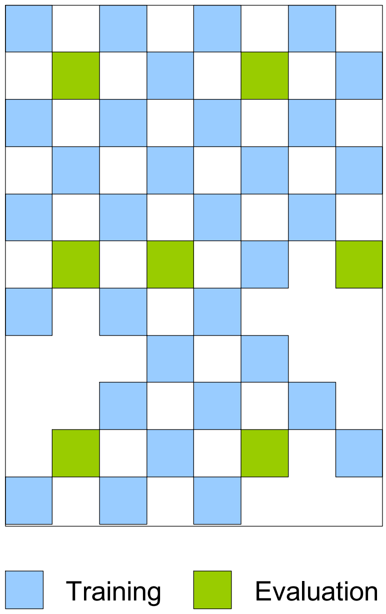



*Figure 20 - Pseudo – locations are indicated with colored tabs*

Input data files are generated for 42 different locations which are laid out as indicated. Evaluation locations are then extracted from them. It should be noted that, the missing tabs are the locations of wells. Locations of wells in given grid configuration are illustrated in Figure 18.

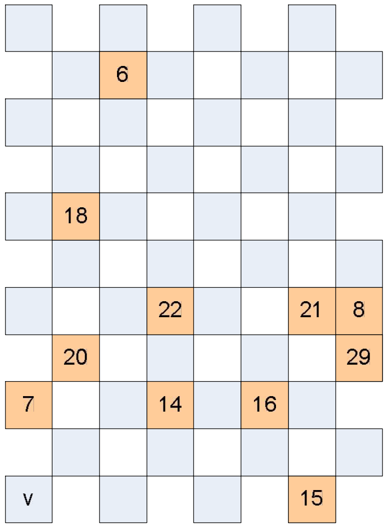



*Figure 21- Locations of Current Wells in the Field of Study*

***6.2.3.1 Running the Simulations***

As a CPU intensive process, each simulation run took considerable time to finish. It took approximately 10-20 minute to get the results for a single simulation. As total of 42 runs were done, some important time is spent on this phase. Resulting data set was approximately 4 Gigabytes in size, with more than 100000 lines of data regarding the pressure and temperature values of 11 wells. Considering the relatively small size of the field, these figures indicate the necessity of finding reliable methods to reduce the amount of data to be processed.

***6.2.3.2 Exporting the Pressure & Temperature Values***

CMG Simulation suite uses 2 different components to export Temperature & Pressure values. Interestingly, exporting from these two different tools results in completely incompatible files. To tackle this problem an intermediate program, *CMGConverter*, is developed. This tool searches the

Temperature file (in which the Temperature of each grid is grouped in time basis) and Pressure file (Pressure for each well is recorded against location) and finds the matching time labels. When appropriate match is found, it collects the temperature and pressure values from the files and writes to a new file which is Excel compatible.

### 6.2.4 Creating Training Input Files

To decrease the size of the data sets and prepare for time unfolding approach which requires constant time intervals, the exported and combined files needed to be further refined. For that purpose, 3 Excel macros have been written. These macros initially select the equal time step values (data record line for $5^{th}$ of each month) and create separate files containing only these lines. This processing decreased the data record lines from 3500+ to 119.  As the change in time and pressure values are continuous and non-fluctuating, this refinement in not expected to produce any loss of information.

# CHAPTER 7

# RESULTS AND DISCUSSION

Afore mentioned algorithms and developed software package is studied in a real life case study. This chapter introduces the nature of the discussion and the observations regarding the application of theory.

## 7.1 Field of Study

### 7.1.1 Introduction

A Geothermal field located in Kızıldere, Turkey is chosen as the field of study. Although there are some different constraints by nature of the problem; algorithmically theory is applicable to any simulation tailed problem regarding underground fluid flow. The only difference between different types of fluid flow is the "objective function" used to evaluate what is "good" and "bad" regarding field performance.

### 7.1.2 Simulation Model

In this study, STARS thermal simulator (CMG, 2002) was used. Dual porosity simulation model was calibrated using historical production, temperature and pressure data from Kızıldere geothermal field, Turkey (Yeltekin *et al*, 2002). The simulation model (Akin *et al*, 2003) (Table 1) consisted of 8x12x6 rectangular grids with equal areal dimensions (60x60 m). The depth of the blocks matched the depth of the producing reservoir (Igdecik formation) divided into five equal parts. Figure 22 shows the grid tops of the producing layer. The last *z* block was thick (5000 m) and was supported by a thermal aquifer. The developed simulation model is in accord with hydrogeological models (Satman and Serpen, 2000) that consider infiltration of meteoric water into deeper sections of the Earth and up-flow of it after heating. Sample pressure and temperature history matches for wells KD-6, KD-13 and KD-20 are provided from Figure 23 through Figure 28. The permeability data initially derived from well test analysis (Kappa, 2001) was modified to achieve a reasonable match(Figure 29). The initial and final temperature and pressure distributions at the end of 14 years of history match are given from Figure 30 to Figure 33.

*Table 1 – Simulation Model Properties of Kızıldere Field*

| ***Property*** | ***Value*** |
|---|---|
| Fracture spacing | 20 m. |
| Shape factor | Gilman - Kazemi |
| Fracture relative perm. | Power law n = 2.8 |
| Matrix permeability | 1 md. |
| Fracture porosity | 0.08 |

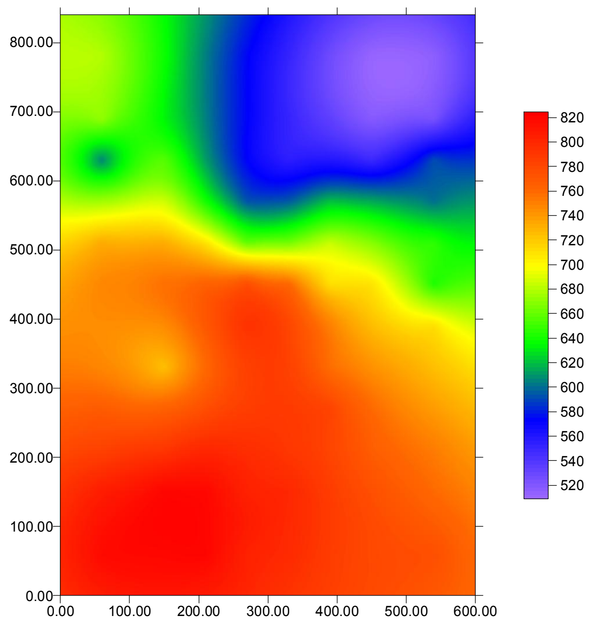



*Figure 22 – Grid tops (depth in m) of the producing layer (Uraz and Akin, 2003)*

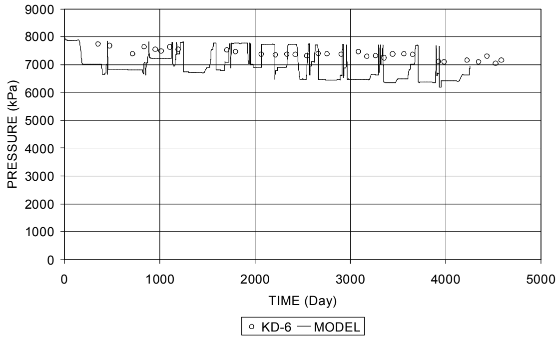



*Figure 23 – Actual production history and matched model of KD-6 well (Yeltekin et al, 2003)*

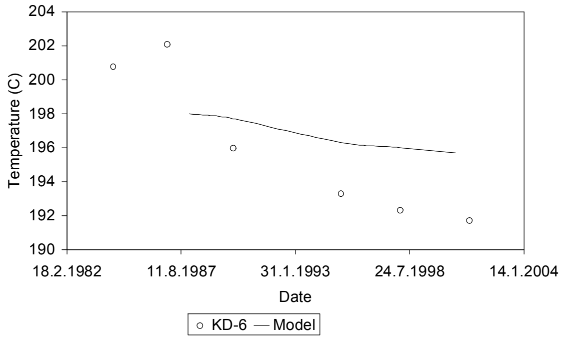



*Figure 24 – Actual temperature recordings and model values of KD-6(Yeltekin et al, 2003)*

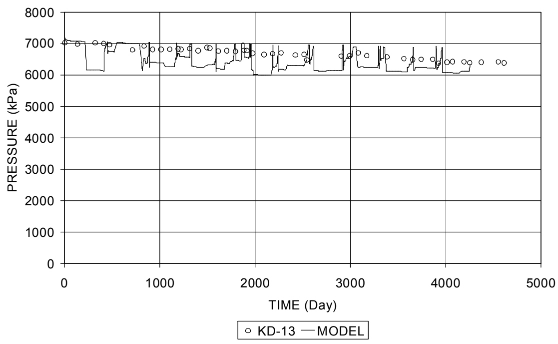



*Figure 25 - Actual production history and matched model of KD-13 well (Yeltekin et al, 2003)*


*Figure 26 - Actual temperature recordings and model values of KD-13 (Yeltekin et al, 2003)*

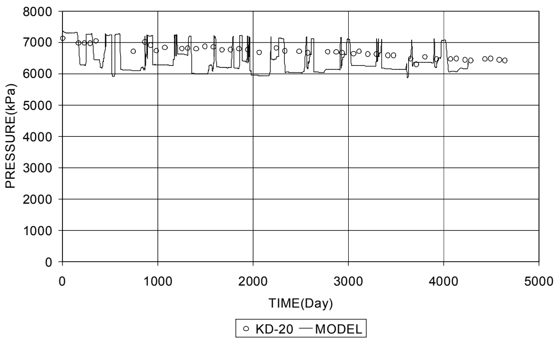



*Figure 27 - Actual production history and matched model of KD-20 well (Yeltekin et al, 2003)*

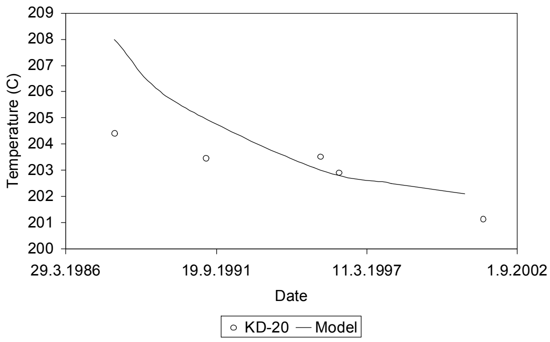



*Figure 28 - Actual temperature recordings and model values of KD-20 (Yeltekin et al, 2003)*

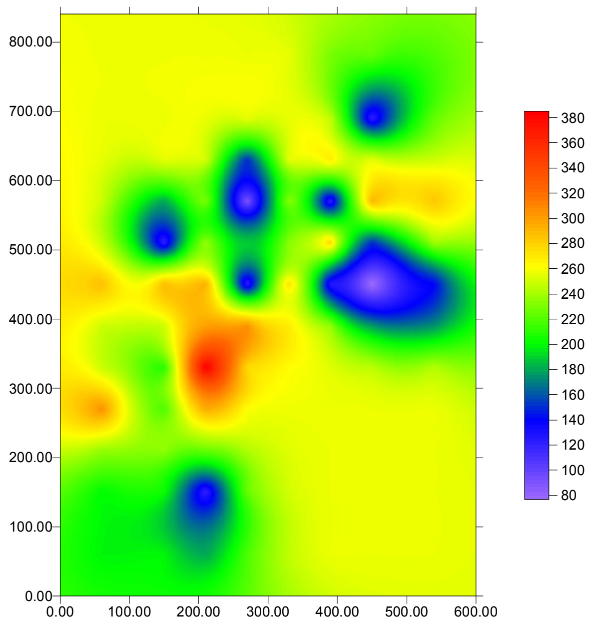



*Figure 29 – Top view of permeability distribution (md) (Uraz and Akin 2003)*

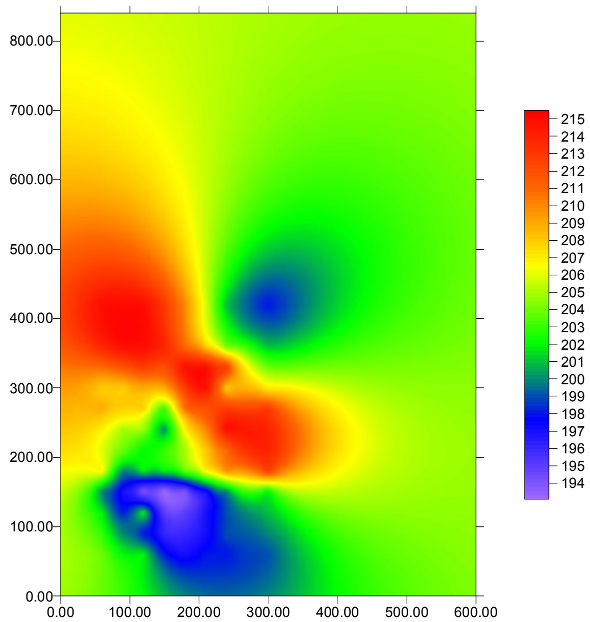



*Figure 30 - Temperature (°C) distribution at - 01/01/1988 (Uraz and Akin, 2003)*

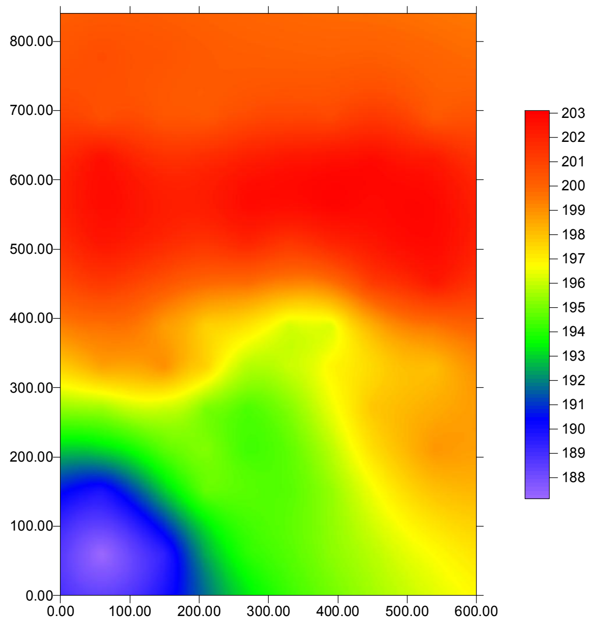



*Figure 31 - Temperature (℃) distribution at - 01/09/2002 (Uraz and Akin, 2003)*

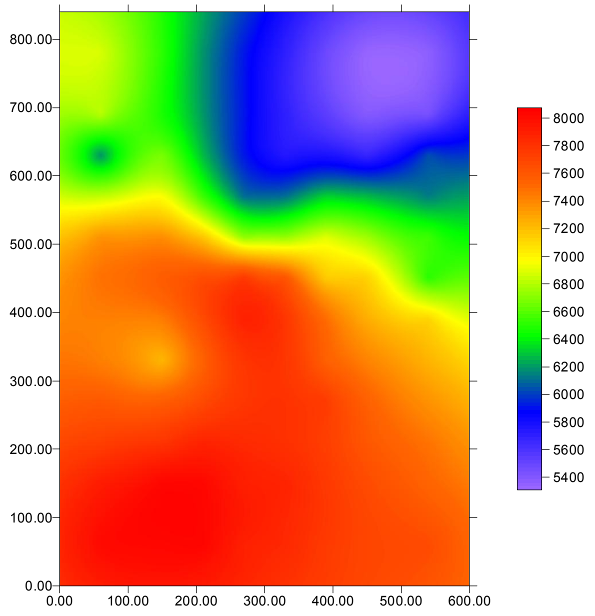



*Figure 32 - Pressure (kPa) distribution at - - 01/01/1988(Uraz and Akin, 2003)*

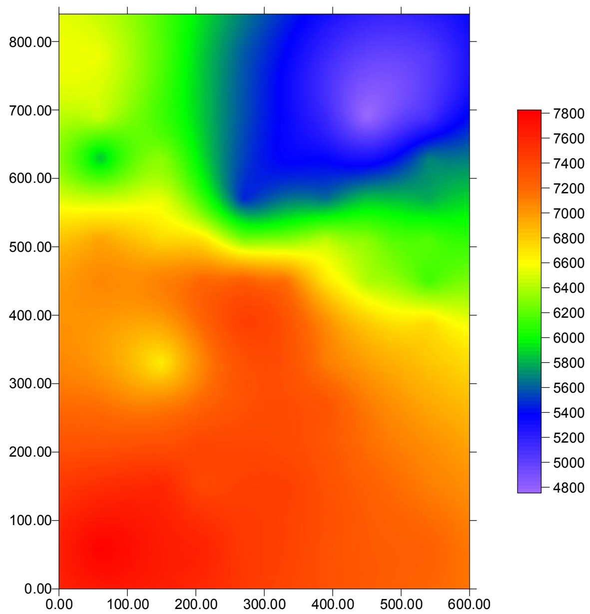



*Figure 33 – Pressure (kPa) distribution at - - 01/09/2002 (Uraz and Akin, 2003)*

## 7.2 Training of Neural Networks

Training of neural networks was done by using the aforementioned data sets and developed software. By definition, there is no exact mathematical procedure that enables determination of the most successful neural network design. For that reason, following general guidelines laid out by theory, it is desirable to train more than one network and try to grasp the nature of the problem and how training parameters are reflected to results.

Figure 34 shows the input and output parameters of the neural network subsystems. x,y,z (in meters) are the location of the pseudo-well, $q_{inj}$ and $T_{inj}$ are injection flow rate and temperature respectively.

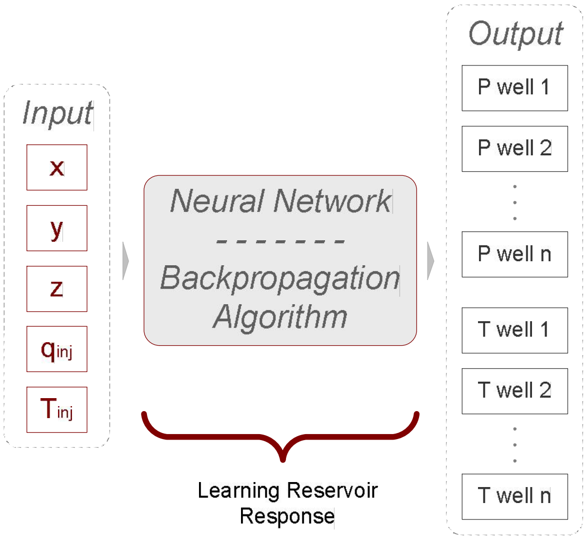



*Figure 34 – Input and output parameter configuration of the neural networks*

In this study, three different network layouts were used (Table 2).

*Table 2 – Summary of Network Layouts*

| | *Network 1* | *Network 2* | *Network 3* |
|---|---|---|---|
| Number of Hidden Layers | 1 | 1 | 2 |
| Number of Nodes Per Layer | 5 | 20 | Layer 1: 10<br>Layer 2: 5 |

All of the networks are full connected and have fixed momentum of 0.8. This fixed value is found appropriate after inspecting various networks with different parameters. Table 3 shows average training times of all three networks. The significant difference between single and dual layer networks is expected. In fully connected networks number of connection increases non-linearly when number of layers increase, which is reflected to calculation time per iteration. Therefore, although Network 3 has less hidden nodes than Network 1&2 amount of time required to process 1 iteration is considerably more. This is an important observation that indicates the "cost factor" of network design.

*Table 3 – Average training times of different networks (4000 iterations)*

| | *Network 1* | *Network 2* | *Network 3* |
|---|---|---|---|
| Average Time (hours) | 7.2 | 9.4 | 21.5 |

Instead of using a stopping criterion (such as percentile error, percentile change in consecutive iterations), a slightly different approach is used to reach optimum. In every iteration, result of the evaluation function is compared with the "current global minimum" value. If the new value is found to be smaller than the current one, it is signed as the new "current minimum" and that particular network layout (including weights of each connection) is taken as a snapshot. An example close up trace of training is shown in Figure 35. As it can be seen from the trace, error decreases significantly during first couple of iterations but than tends to stabilize (for the truncated part). This was the common behavior of unsuccessful trainings. Trainings are classified as "unsuccessful" if the error function has not decrease in any of the instances less than %25 percent after 5000 iterations. When using non-normalized errors, error value reflect the absolute difference on error; thus if study on error trace is desired (In more sensitive situations), normalized values shall be more appropriate. It should be remembered that in the scope of the algorithm developed in this workbench, stopping criterion is not bound to percent error decrease, but to iterative decrease of the error. For complex cases, this may point to a pitfall;

as it could be desirable to account for percent error decrease in addition to cross-correlation coefficient (which will be discussed in next section).

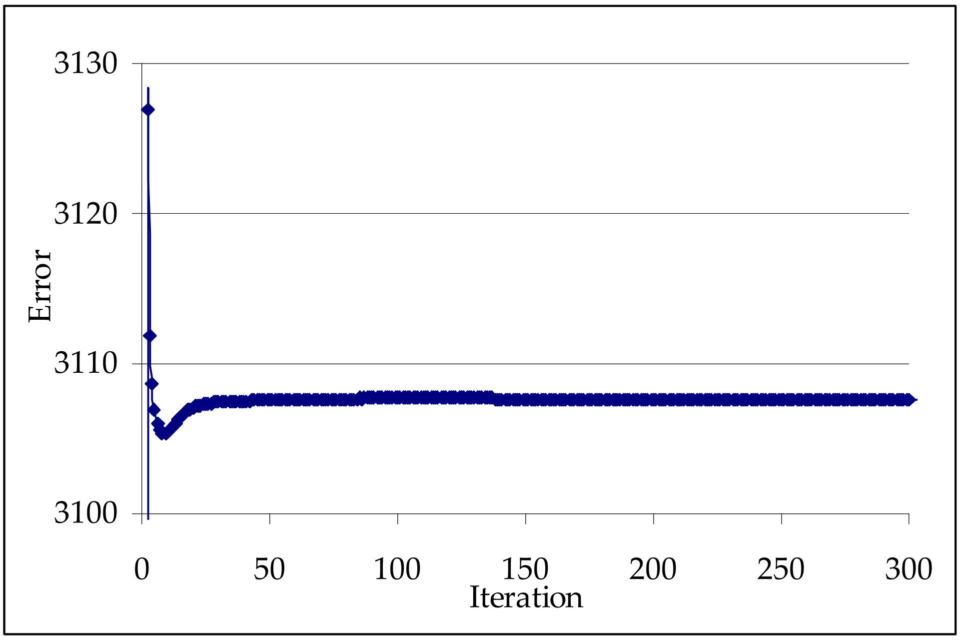



*Figure 35 – Evaluation Function trace of training (Network design 1, Partial)*

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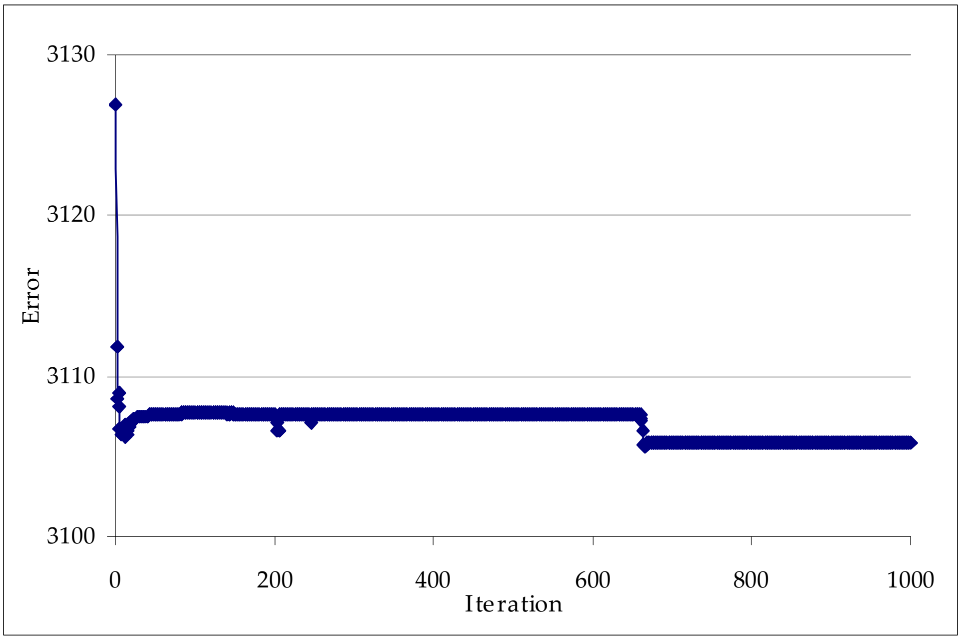


*Figure 36 – Evaluation Function trace of training (Network 2)*

Figure 36 shows a common behavior of successful training. Although error plot is mostly flat, it shows sharp changes over long term of iterations. This behavior is expected. Change in parameters over time enables moving from one particular weights distribution of neural network to another one when a certain threshold is exceeded. In most cases, trainings and error functions were observed to stabilize after several thousand iterations.

## 7.3 Evaluation Function and Decision Surfaces

As described in previous chapters; the most crucial factor affecting the success of an optimization study is the quality of the evaluation function. The important parameters should be defined and appropriate weight should be given to have a desired successful optimization of the solution.

In our case; the nature of the geothermal fields should be evaluated carefully. Two main constraints are found to be of crucial importance. Main two factors which are important in this study are Pressure support and Temperature of the field. Evaluation function, E, is described as follows:

$$E = (1-w)*(P_{init} - P_t) + w*(T_{init} - T_t) \quad [8]$$

where

$$P = \frac{1}{n}\sum_{i=1}^{n} P(i) \quad [9]$$

$$T = \frac{1}{n}\sum_{i=1}^{n} T(i) \quad [10]$$

Where n is the number of wells. Basically, for a given location on decision surface, value is the average of Pressure or Temperature values of all wells.

### 7.3.1 Evaluation Function Properties

Best way to obtain the evaluation function is to ask the question of; "what is the ultimate goal that is to be improved/optimized". In our case the answer is "To locate injection well such that; in the long run, reservoir keeps the pressure support (so that we can produce more) while injected fluid does not cool down the field (as maximum enthalpy means more energy).

Designed algorithm handles pressure and temperature separately. Output of the neural network values are separated in two sets, so that the distribution of Temperature and Pressure are trained/executed separately. Evaluation function uses weighted averaging to combine temperature and pressure values at a given location. This gives a flexibility to put more weight to different parameters.

Choosing an evaluation function is a process of decision. In our study, it would be possible to define numerous different evaluation functions; depending on the optimization target. For instance, it is possible to focus on Net Present Value (NPV) of the field production (for example as in the case of Yeten et al, 2003). Our choice for Temperature and Pressure support over NPV is due to the desire to study change in the basic parameters such as Temperature and Pressure. As net present value is also a function of Temperature and Pressure, study carried on the basic parameters and testing the reliability on those is believed to be more informative in comparing proposed workflow over numerical methods.

## 7.4 Search Method – Finding Optimum Location

Designed framework enables deployment of various search algorithms such as exhaustive search, polytope algorithm or simulated annealing. Design goal is to provide a modular approach to enable problem specific algorithms to be deployed.

For the case study and to test results of neural network in more detail, exhaustive search is used. In bigger data sets, exhaustive search would yield higher CPU cost, there fore more streamlined search algorithms should be preferred.

Search algorithm uses six parameters:

Discritization interval in X direction (West – East): $x_d$

Discritization interval in Y direction (North – South): $y_d$

Injection temperature of the pseudo-well: $T_{inj}$

Injection flow rate of the pseudo-well: $q_{inj}$

Weight of Temperature (in range of 0-1)

Weight of Pressure (in range of 0-1 and if no other constraints are introduced 1 – weight of temperature)

Search algorithm is as follows:

1) Start from North – West corner of the search area. ($x_0$ , $y_0$)

2) Place the pseudo well to $x_i = x_o + x_d$ , $y_i = y_0$

3) Input neural network the parameter set: $q_{inj}$ , $T_{inj}$ , $x_i$ , $y_i$

4) Record the Pressure and Temperature output of Neural Network nodes

5) Calculate and record the field temperature & pressure response using equation 9,10 and values of P & T from step 4

6) Calculate the evaluation function result (Equation 8) and record.

7) Proceed to next iteration where: $x_{i+1} = x_i + x_d$ , $y_i = y_0$

8) Repeat steps 2 - 7 until $x_{i+n} >= x$ (West – East size of the field)

9) Iterate $y_i = y_0 + y_d$ and reset $x_i = x_0$

10) Repeat steps 2 – 9 until $x_{i+n+k} >= x$ and $y_{I+k} >= y$ (North – South size of the field)

Output the minimum E value location (Where E is the evaluation function result calculated at given location (calculated at Step 6).

Combination of neural network and search algorithms gives a finer resolution of results than simulation grid size. If $x_d < Simulation\ Grid\ Size$ , discritization in X direction is narrowed allowing a smoother decision surface than the numerical model (Simulator). It is possible to decrease the discritization interval as low as desired, although very small intervals will result with higher CPU cost.

In general application, it may not be desirable to record evaluation result of the whole field. Instead, more cost effective search algorithms that can march to the result faster should be preferred.

## 7.6 Comparison of Neural Network results to Simulation Results

Aforementioned three neural network designs are used to evaluate the sensitivity of the outputs to layouts. Values obtained from trained networks are compared to reference simulation results.

For comparison of the results, validation set (described in Chapter 4) is used. As validation locations are excluded from the training set, they form as a valid test for neural network performance.

Table 4 and Table 5 shows the Temperature and Pressure values obtained from Neural Network runs tabulated alongside with reference Simulation results.

Figure 37 shows the evaluation locations (previously introduced in Introduced in page 61) that are used for this study.

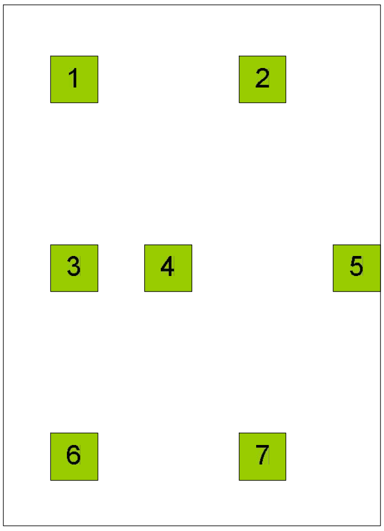


*Figure 37 – Evaluation locations*

*Table 4 – Temperature values from simulation (numerical model) and neural networks (at 01/09/2012)*

| *Evaluation Location* | Temperature Values (°C) | | | |
|---|---|---|---|---|
| | *Simulator* | *Network 1* | *Network 2* | *Network 3* |
| 1 | 201.5 | 203.4 | 202.5 | 204.1 |
| 2 | 202.0 | 202.7 | 201.2 | 203.1 |
| 3 | 200.3 | 201.4 | 201.4 | 200.5 |
| 4 | 198.4 | 197.4 | 198.2 | 199.7 |
| 5 | 199.7 | 196.3 | 197.9 | 196.5 |
| 6 | 190.6 | 193.5 | 191.8 | 192.4 |
| 7 | 196.2 | 199.5 | 197.5 | 199.5 |

Figure 38 through Figure 43 visualizes the cross-correlation between simulation results and neural network outputs. Correlation coefficient ($R^2$) of each cross plot (scattergram) is also calculated. Correlation coefficient gives an estimate of similarity between simulation results and network outputs. Ideally, all recorded values should form a straight line with 45 degrees and correlation coefficient of 1. In that case, it could be said that

"Neural network results represent the simulation results with a perfect match". In reality, it is desirable to have higher correlation coefficient, but it is not expected to have a perfect match.

*Table 5 – Pressure readings from simulation (numerical model) and neural network outputs (at 01/09/2012)*

| *Evaluation Location* | Pressure Values (kPa) | | | |
|---|---|---|---|---|
| | *Simulator* | *Network 1* | *Network 2* | *Network 3* |
| 1 | 6410 | 6249 | 6587 | 6148 |
| 2 | 4972 | 4894 | 4798 | 5198 |
| 3 | 6970 | 7358 | 7086 | 7129 |
| 4 | 7088 | 6187 | 7259 | 6521 |
| 5 | 6516 | 6048 | 6987 | 6752 |
| 6 | 7483 | 7685 | 7176 | 8036 |
| 7 | 7285 | 7362 | 6978 | 7632 |

It is observed that Network 1 and Network 3 have smaller correlation coefficient than Network 2, for both temperature and pressure values, although the difference is more significant for prior. This demonstrates that the correlation coefficient is not a function of number of network layers. Neural networks do not have linear relation with the data set and design of the system. With a correlation coefficient of 0.66 and 0.73 (for temperature) respectively, Network 1 and Network 3 are not found to have powerful representation of simulation outputs. When taken into consideration, Pressure cross-correlation of all three networks are above the 80%, although Network 2 has a slightly higher value than Network 1 and 3. It should be noted however that even for high correlation coefficient around 80%, pressure difference per location is quite significant.

It is observed that Network 2 has the highest correlation coefficient for both parameters, 0.9076 for temperature and 0.887 for pressure with accurate representation of reference simulation results. Following this analysis indicates that Network 2 is preferred for further calculations and location estimation, as it acts as a better proxy to simulator. It was also observed that the large errors recorded in the positions that reside in the middle of the field are somehow consistent through networks. This is accounted for the lack of capability in capturing transient effects that are dominant in middle region of the field due to large number of producing wells.

Ideally, this selection process can be automated; picking the network with highest correlation at a given time. If processing time and power is not a constraint, it is possible to expand the number of networks trained thus exploring a wider space of cross correlation. It should be noted that, time requirement of the framework increases non-linearly with introduction of more neural networks. Nevertheless, framework provides flexibility on number of trials (new network designs to be trained).

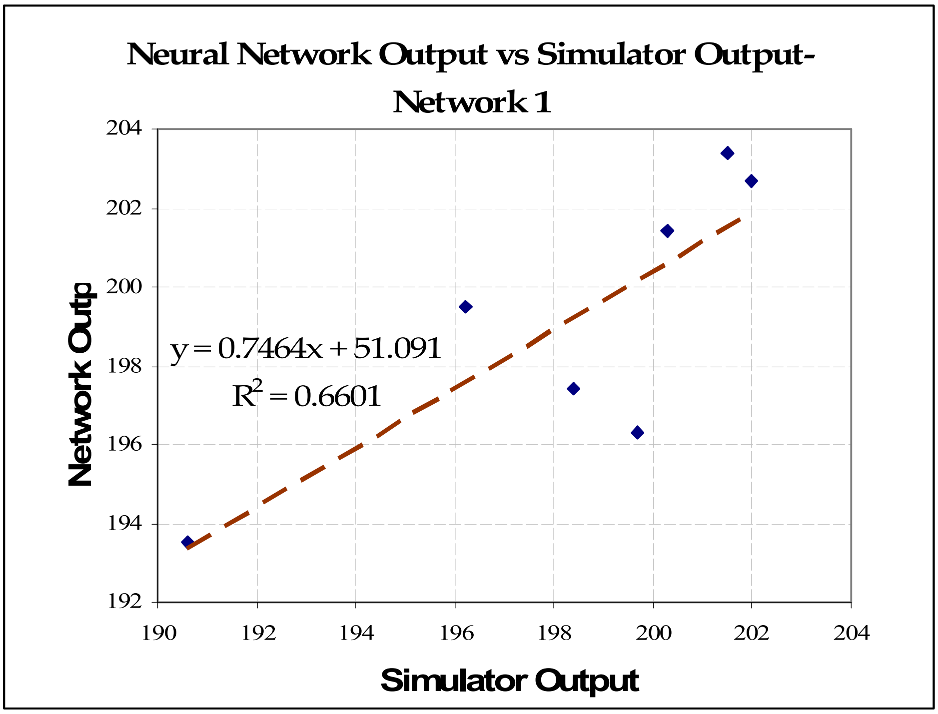


*Figure 38 – Cross plot of temperature (℃) values obtained from Simulator and Neural Network 1. Fitted linear trend line shows the correlation between two sets.*

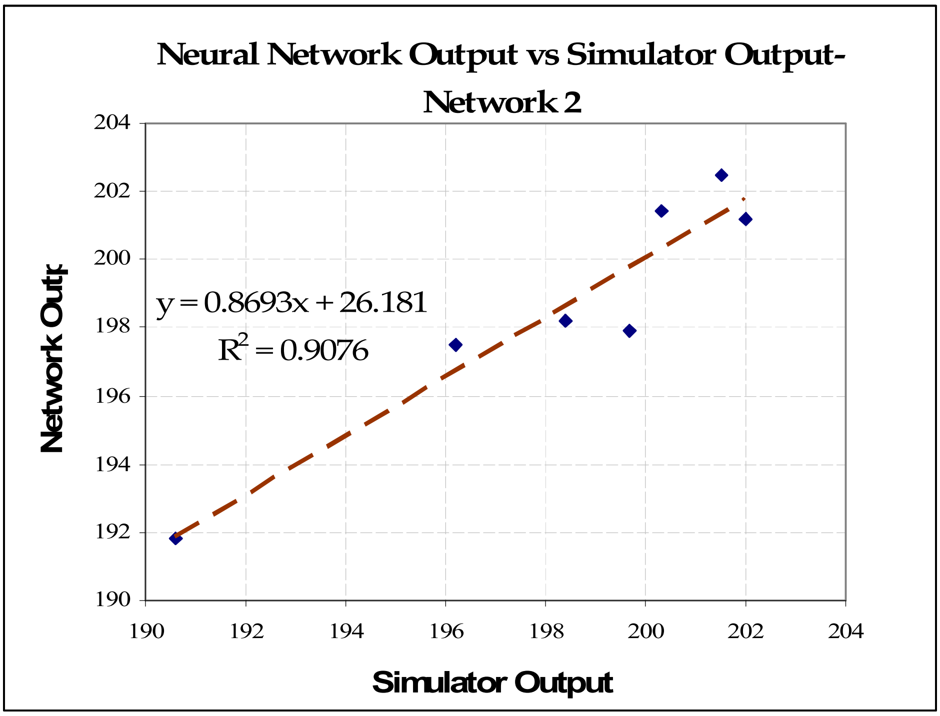


*Figure 39 – Cross plot of temperature (℃) values obtained from Simulator and Neural Network 2. Fitted linear trend line shows the correlation between two sets.*

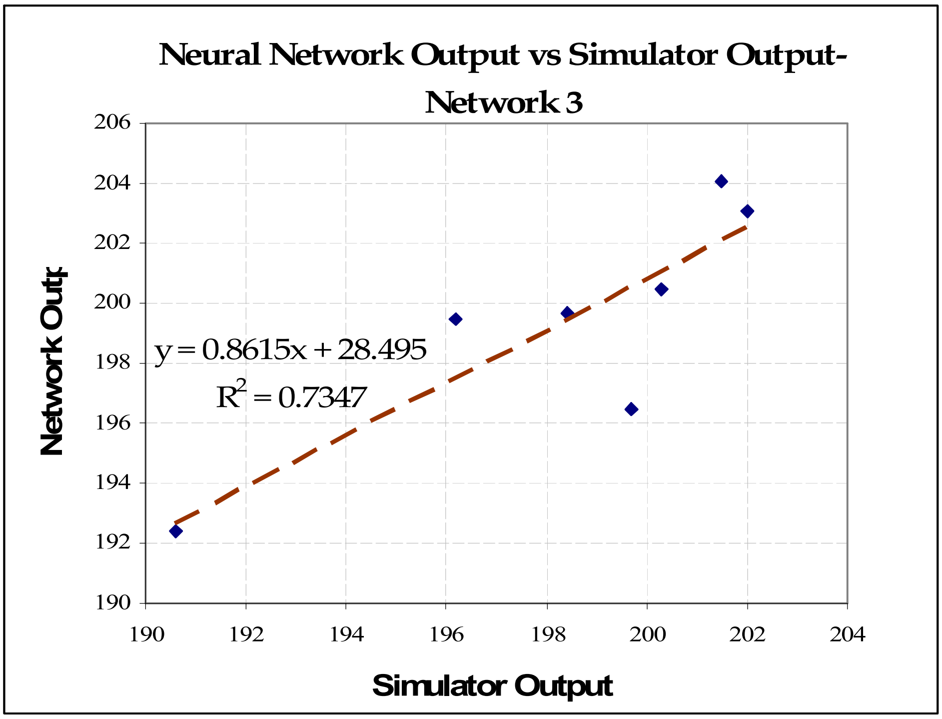


*Figure 40 – Cross plot of temperature (°C) values obtained from Simulator and Neural Network 3. Fitted linear trend line shows the correlation between two sets.*

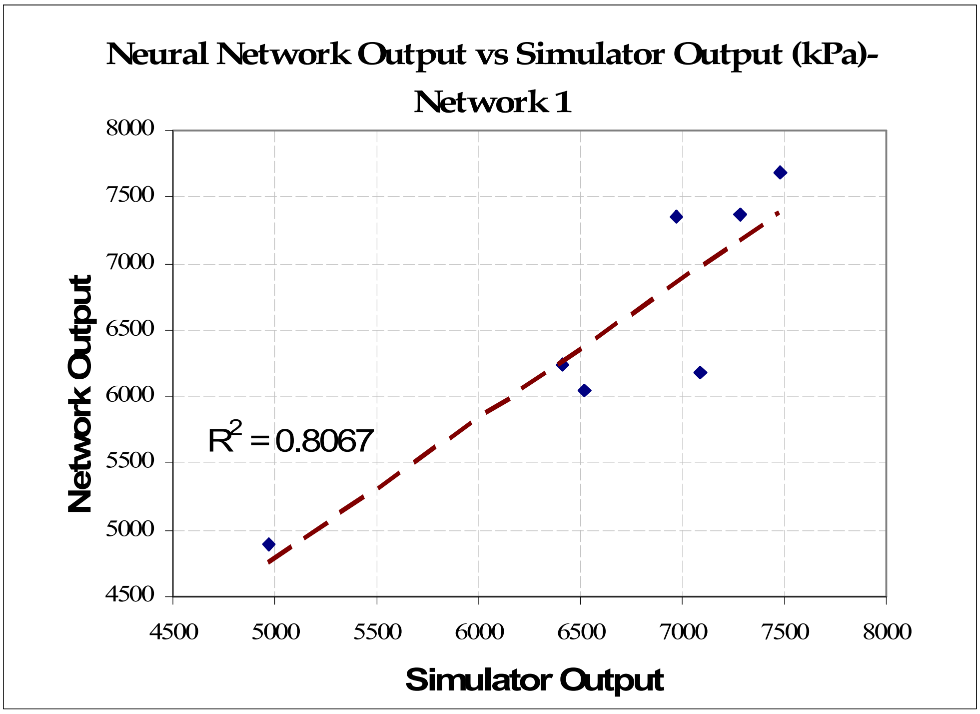


*Figure 41 - Cross plot of pressure (kPa) values obtained from Simulator and Neural Network 1. Fitted linear trend line shows the correlation between two sets.*

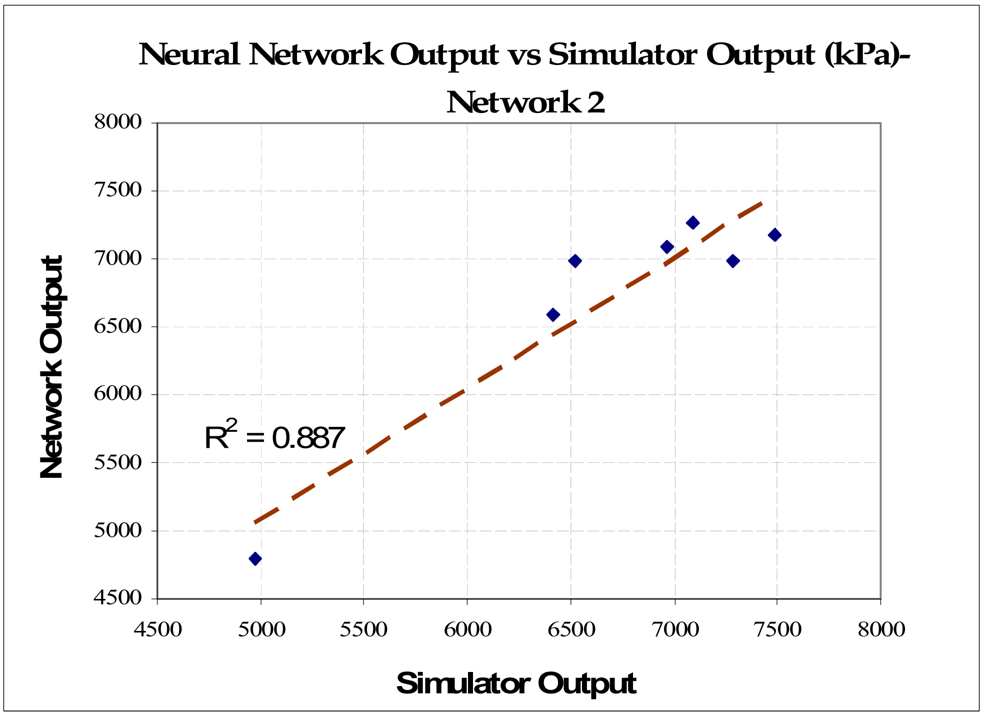


*Figure 42 - Cross plot of pressure (kPa) values obtained from Simulator and Neural Network 1. Fitted linear trend line shows the correlation between two sets.*

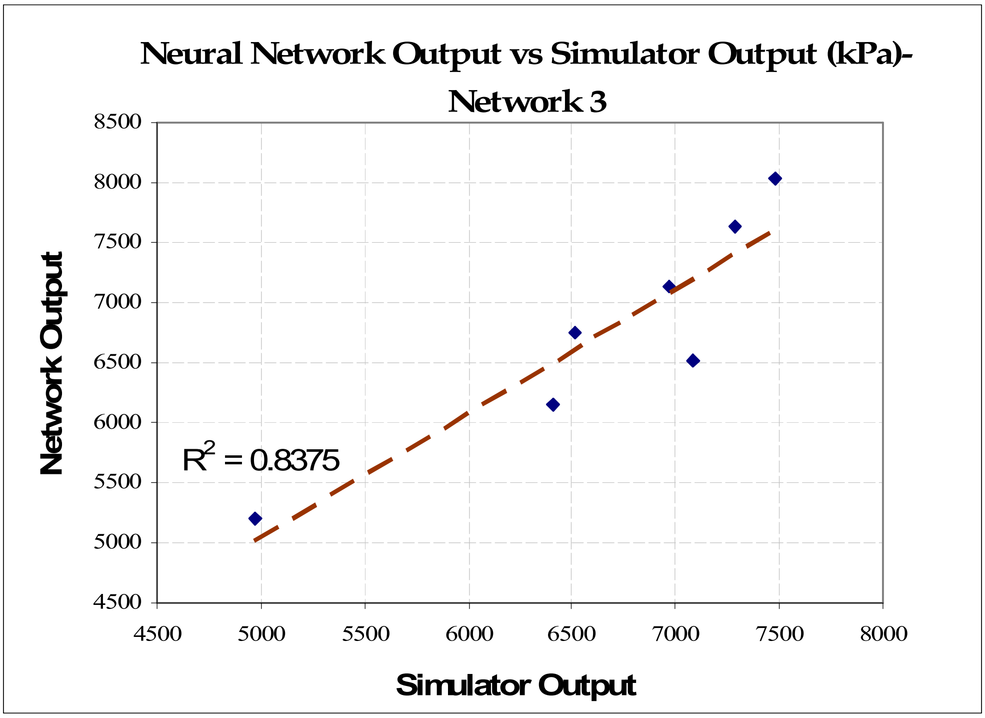


*Figure 43 - Cross plot of pressure (kPa) values obtained from Simulator and Neural Network 1. Fitted linear trend line shows the correlation between two sets.*

## 7.7 Location of Injection Well by Algorithm

In a real life case, after identification of the highest correlated neural network; it is sufficient to run search process (discussed in section 5.6) with only that particular neural network engine.

In this study, Network 2 is used to locate the optimum location and along with the spatial distribution of temperature and pressure decrease profiles. Two different search parameter sets are used, changing the flow rate of injection. Table 6 shows the search algorithm parameters used. Discretization in X and Y directions are kept same with the simulation grid size. Flow rates are set to be equal to the reference case.

*Table 6 – Search parameters*

| *Search Parameter* | *Search 1* | *Search 2* |
|---|---|---|
| Discretization in X direction | 60m | 60m |
| Discretization in Y direction | 60m | 60m |
| Injection flow rate | 4911 $m^3$ / day | 2500 $m^3$ / day |
| Injection Temperature | 150 C | 150 C |
| Weight of Temperature | 0.5 | 0.5 |
| Weight of Pressure | 0.5 | 0.5 |

Figure 44 shows the spatial distribution of average pressure decrease of Search 1. Average pressure decrease shows consistency with the reference case. Figure 45 indicates same decrease profile for temperature, having consistency between the reference case. Figure 46 shows the resulting evaluation surface (with equal weights for Temperature and Pressure). In search 1, optimum location is found to be at x=450, y=690 with an evaluation function value of 0.563.

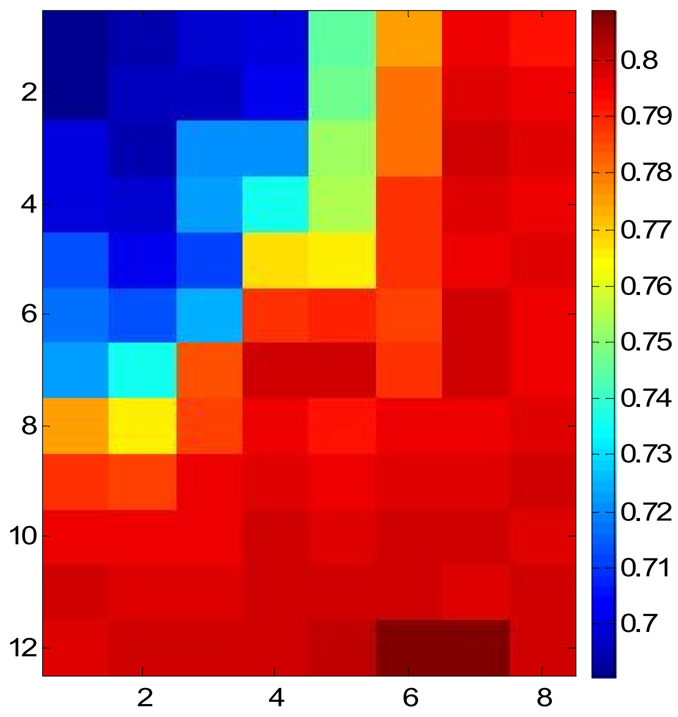


*Figure 44 – Spatial distribution of average pressure decrease (Search 1).*

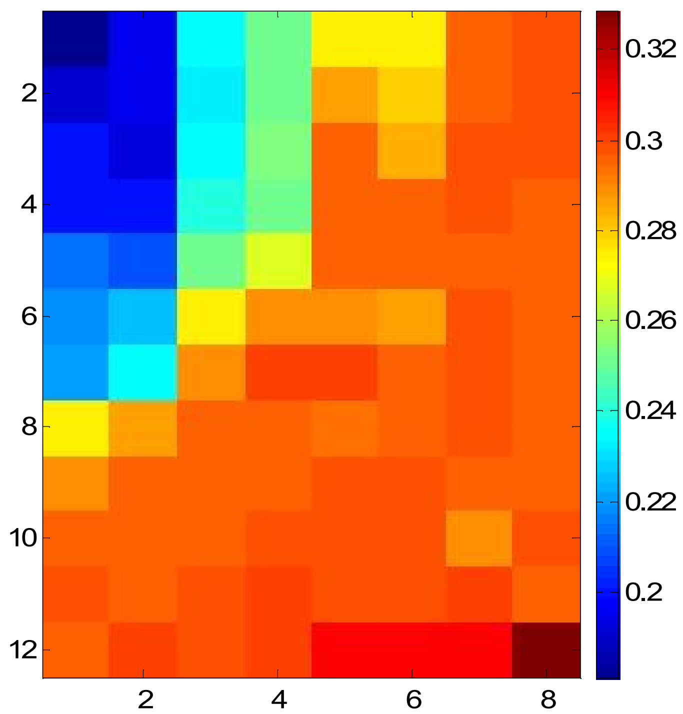


*Figure 45 - Spatial distribution of average temperature decrease (Search 1)*

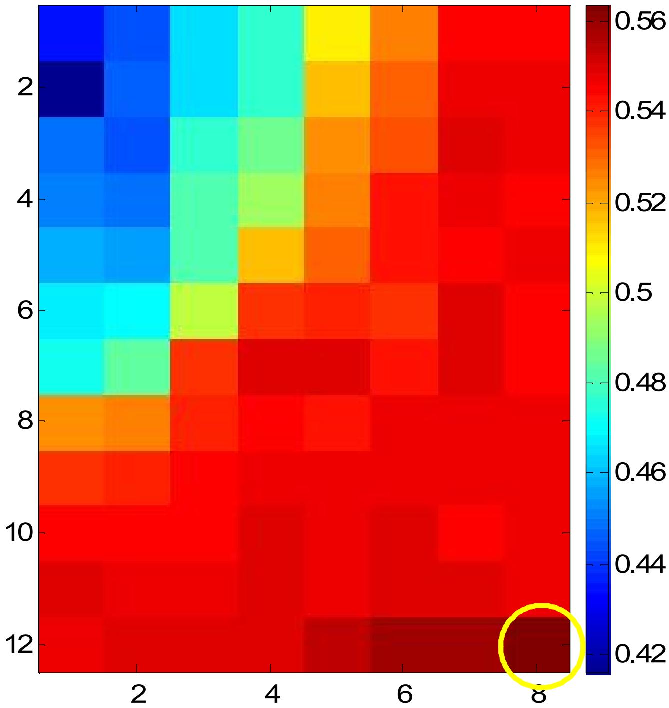


*Figure 46 – Evaluation surface for Search 1. Optimum location is found to be x=450 (Grid 8) and y=690 (Grid 12).*

Figure 47 and Figure 48 shows the spatial distribution of average pressure and average temperature decrease resulting from Search 2. Again, average pressure and average temperature decrease shows consistency with the reference case with a deviation margin of 0.1. Figure 46 shows the resulting evaluation surface (with equal weights for Temperature and Pressure). In search 2, optimum location is found to be at x=390, y=690 with an evaluation function value of 0.488.

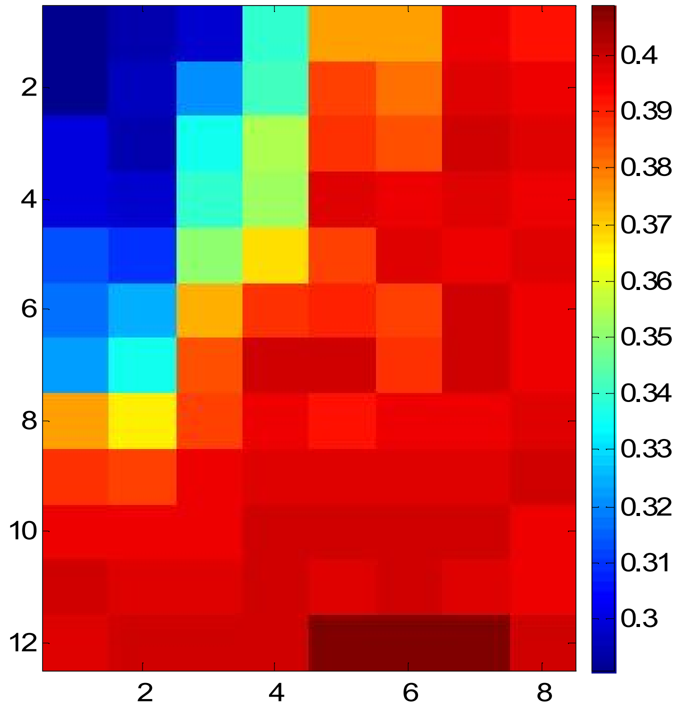


*Figure 47 - Spatial distribution of average pressure decrease (Search 2).*

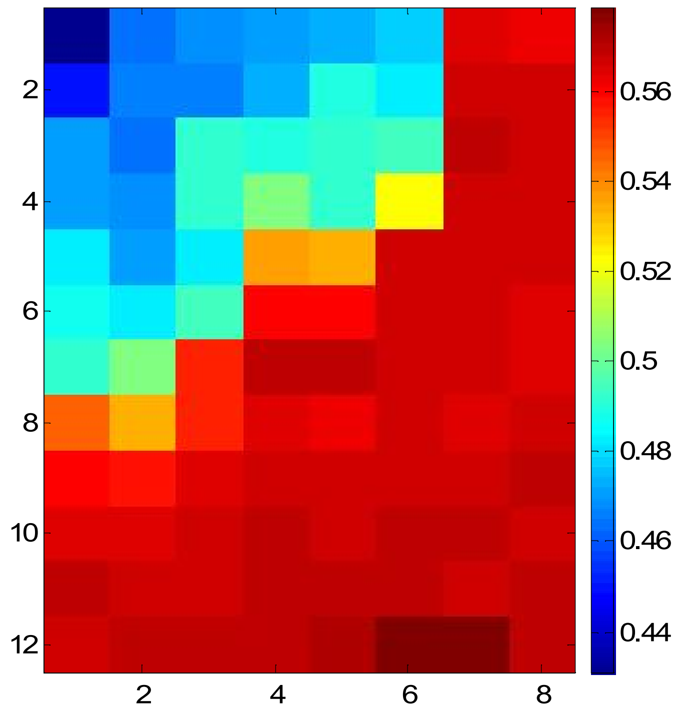


*Figure 48 - Spatial distribution of average temperature decrease (Search 2)*

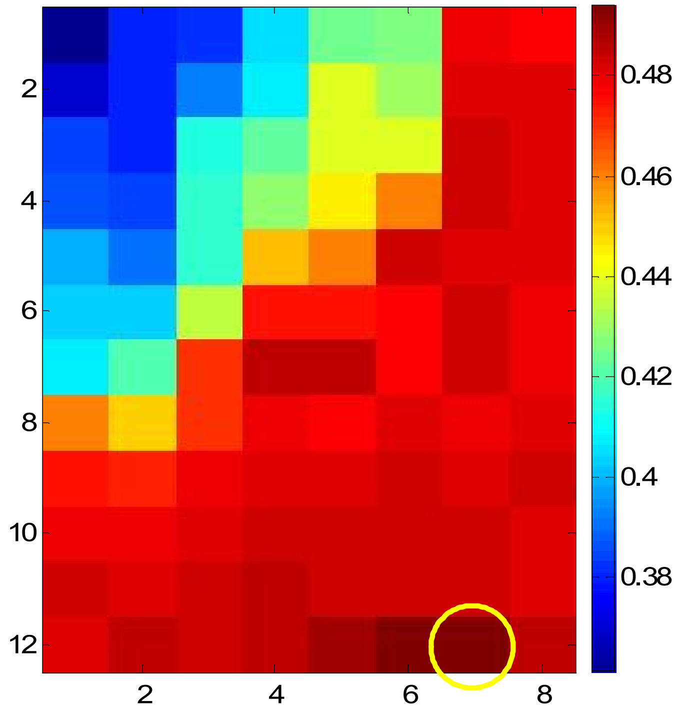


*Figure 49 - Evaluation surface for Search 2. Optimum location is found to be x=390 (Grid 7) and y=690 (Grid 12)*

It is observed that trained neural network and search algorithm gives predictable, consistent results. Nevertheless, accuracy of the results are not found to be in the error range of %5, which may suggest a cautious usage of the developed framework. Section 5.8 discusses the outcomes and general observations.

### 7.7.2 Effect of Flow Rate on Optimum Well Placement

In both oil and geothermal fields, amount of fluid injected is among the most important parameters effecting the overall recovery success. In geothermal fields, amount of fluid injected effects the overall pressure support, temperature change and total enthalpy of the field. In a given well optimization, study on flow rate is therefore inevitable.

### 7.7.3 Searching the Best Location, including Flow Rate as Parameter

Aforementioned framework developed in context of this study is flexible enough to accommodate multiple parameters as optimization constraints. Changing the search parameters, in other words extending the search process is sufficient to incorporate additional constraints into optimization problem.

In order to locate the optimum well location accounting for different levels of flow rate, 5 Different increments of flow rate are chosen to create search spaces. 2500, 3000, 3500, 4000, 4500 and the upper limit of the injection pump, 4911 $m^3$/day are chosen as the flow rates that are used as input to neural network.

As clearly observed from the previous study (in previous section), south east quartile of the field is the dominant area with highest evaluation results in all analyses. In order to reduce the search time and computational complexity, only lower right quartile of the field is considered for pseudo well placement in search algorithm. Figure 50 shows the region chosen for further study.

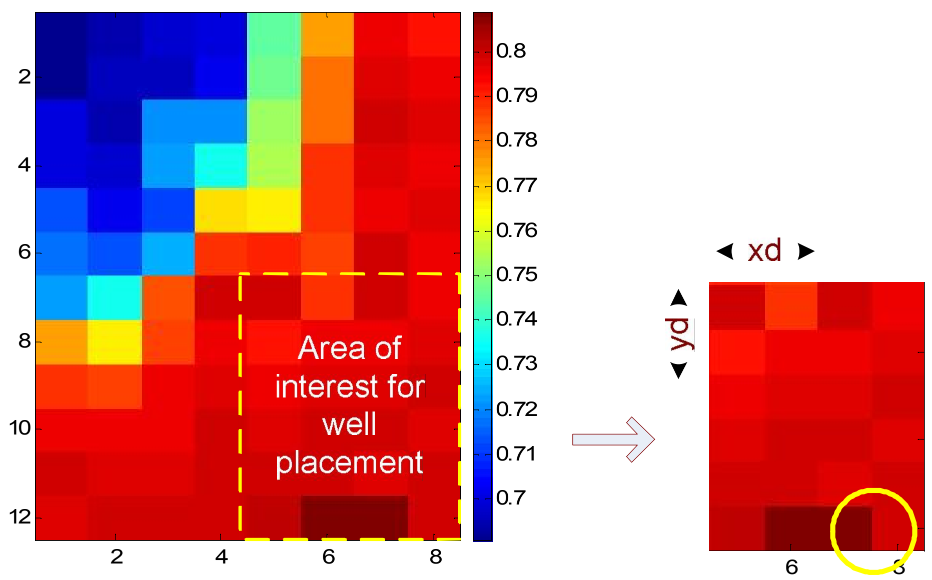


*Figure 50 – Selected region for further study on optimum well location accouting for different injection flow rates*

Figure 51 shows the flowchart of the extended study. It should be noted that, the neural network used in this study is same with previous sections, thus evaluation results reflect the whole field. Selection of a particular area of interest only bounds the "pseudo well" locations; in other words locations that are considered for well placement. Further discussion on narrowing down the area and its effects will be discussed in following chapter.

Result of the study is found to be consistent with previous sections. Aforementioned workflow resulted with an optimum well location at x=420 and y=690 meters. As search stepping size is decreased to 30m (from 60m) finer search increment was made possible.

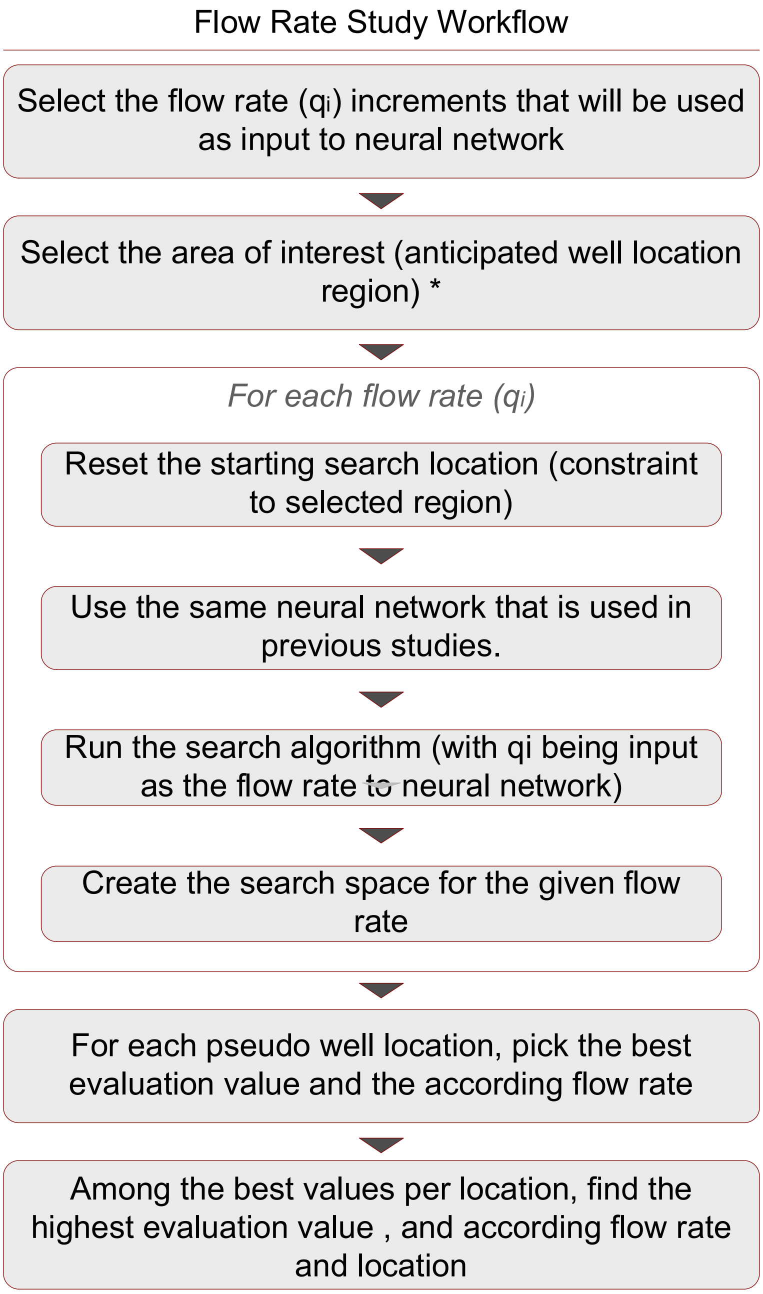


*Figure 51 – Workflow of the extended study on optimum well location accounting for flow rate*

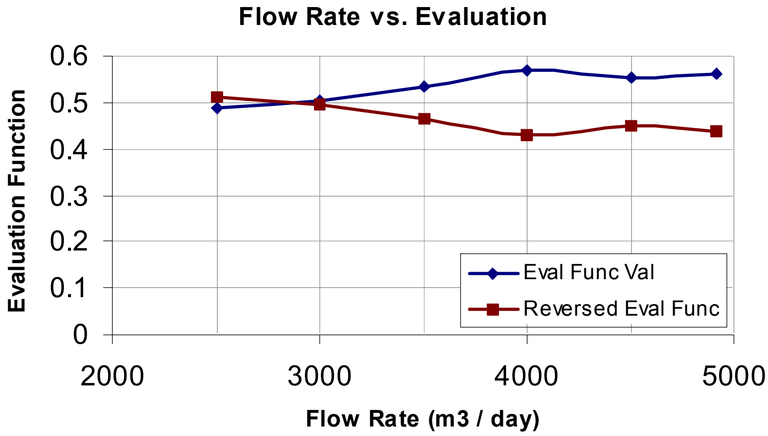


*Figure 52 – Evaluation function values at the optimum location with respect to different flow rates*

Figure 52 shows the evaluation function results in this particular location with respect to different injection flow rates. It is observed that, highest evaluation value was recorded with an injection flow rate of 4000 $m^3$ / day. The fact that equal weights are used for temperature and pressure seems to be the source of a balanced flow rate being favorable.

## 7.8 Comparison with Previous Studies

Results obtained from this study is compared to previous studies on Kizildere geothermal field.

Yeltekin et al (2003) studied 5 different injection scenarios on the same field for same time period (ending in 2012). In first two cases, KD-7 was used as reinjection well with constant injection rate of 2500 $m^3$/day or 900o kPa fixed bottom hole pressure. For the third and forth cases, KD-22 was used with constant injection rate of 4500 $m^3$/day or 9000 kPa fixed bottom hole pressure. Last two cases used KD-24 as injection location again with 4500 $m^3$/day or 9000 kPa.

Using KD-22 as reinjection location (located in middle of the field) did not increase production considerably but resulted with maximum pressure support. In comparison with our methodology, re-inection to central part of the field seemed to be in contradiction to some extend, though can be argued due to the lack of exact locations for comparison. Nevertheless, by the help of introduced framework, as more possibilities were tested, location of well was spotted in south-east region is an option that has not been investigated in the study. Serpen and Satman , in their study suggested injection from northern part of the region, where permeability is higher, thus yielding to higher sweep ratio of the region.

## 7.9 Summary of Results

Following are the final remarks on the results obtained from the study.

Design parameters of the network do not provide a measure of success of estimation. Study on different networks indicates that there is no direct relation between the design parameters and the output of the network. Having different number of nodes and layers, all three networks resulted with different correlation coefficients ranging from 0.60 to 0.90 with no particular relation to design parameters.

As different network designs can yield to considerably different correlation coefficients between simulation and neural network values for a successful prediction of simulation results, a neural network design with at least %90 cross correlation should be used. If possible, study of different layouts should be extended to improve the correlation.

Study on correlation coefficients for pressure and temperature indicate that for the case study, Temperature correlation coefficients vary more than the pressure correlation coefficients. This indicates the necessity of special attention that should be paid for choosing the governing parameters for network selection.

For the field of study (Kızıldere Geothermal field), optimum injection well location is found to be in the south-eastern part of the field. Having higher evaluation function values in that particular region, specific locations resulting from the workflow indicated a consistent search space.

When studied with fixed flow rates (2500 and 4911 $m^3$/day), search run through the whole field located two locations which are in the same region; thus resulting with consistent predictions.

Study accounting for flow rate indicated that injection flow rate is an important factor and should be considered in such optimization problem. When included in the input parameter set and search constraints, it was observed that having different flow rates altered the optimum location; though remaining consistent with previous calculations.

# CHAPTER 8

# CONCLUSION

Results indicate that usage of neural networks provide a convenient way of reducing processing demand. Especially in large fields, cost of doing an exhaustive search is beyond feasible limits and proposed framework could be deployed in such cases. Although results obtained from the case study indicate a favorable and acceptable correlation between simulation results and neural network results; it is found that neural networks shall not be used as a replacement for simulators due to high error margins and design issues. Study indicated following observations:

Introduction of neural networks provide a convenient way of reducing simulations costs. Inference capability of ANN is suitable to replicate the response of earth given a set of limited parameters.

Design of the Neural Network is an important factor determining the success of the decision. Through study of cross correlation between simulation and neural network results, it was observed that different network layouts result with considerably different correlation factors.

It is suggested that, although proposed framework can produce acceptable results (given a well trained network) for narrowing down the search area or incorporating various parameters without increasing data redundancy, it shall not be used as a replacement for numerical simulator. This conclusion is drawn from the fact that correlation of the results are more than the acceptable %5 limit and vary considerably depending on the network. The cost effective nature of the framework provides a convenient way of exploring wider space of parameters, eliminating need for exhaustive simulation runs but results are not accepted to be accurate enough to replace numerical/analytical models.

It should be noted that the “optimum well locations” picked by the framework incorporate a specific set of parameters on evaluation function; for real life deployment it is suggested to use different evaluation functions or a combination of additional constraints for future refinement of location selection. Location of the well is a function of Evaluation function.

Flexibility of the framework enabled extending the study by considering only a particular area of interest (see study on flow rate). After training a neural network that incorporates the whole field, narrowing down the search area or the area of consideration for well placement can be achieved by only narrowing the search area. This feature is also found intuitively parallel to real life cases, as it is a common practice to narrow down the area of interest after certain studies; when it is concluded that there exists a particular area of the field that the most feasible location lies.

A further study could incorporate more parameters as variable; such as dept of injection, different temperatures of injection and changing injection rates over time.

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# APPENDIX A

# SOFTWARE

## Software Installation

Provided with this document, a CD including the source code and executable of the Artificial Intelligence workbench is provided. To install the executable version of the software:

1) Install Java Runtime Enviroment – Provided in the CD, you will find Sun Microsystems Java Runtime Enviroment that is required by the AI Workbench software. It can be installed by executing the Jre.exe file in the home directory. (If Java Runtime Enviroment 1.4 or higher is already installed, this step is not necessary).

2) Install Artificial Intelligence Workbench – To install the software, run the AIWorkbench.exe file and follow the installation instructions when prompted.

Source code can be accesed by unzipping the provided archive file in the CD.

# APPENDIX – B

# KIZILDERE GEOTHERMAL FIELD

Located in the western Turkey, Kızıldere geothermal field was discovered in 1968 (Figure 53). The Menderes massif (where Kızıldere is locaed on the western extreme) was uplifted during late Pliocene and Quaternary times, and due to tensional forces, east-est grabens are formed. Magma activity increased and magma level raised under the massif and grabens where earth crust is thinner then the rest of the region. The field lies on three main fault blocks, generated by two-step normal faults.

Kızıldere geothermal field consists of two producing reservoirs in the intermediate block. İğdecik formation, the main reservoir formation, is sited in the metamorphic basement and has very high fracture permeability due to its crystalline limestone content. Sazak formation, which locally forms the caprock lies above İğdecik, Kızılburun, Kolonkaya formations. Maximum temperatures of Sazak and İğdecik formations are 198 °C and 209.1 °C, respectively (Yeltekin et al, 2002).

## Well configuration of Kızıldere Geothermal Field

With the discovery of the field in 1968, the first well; at a depth of 540m was drilled in the same year and produced a mixture of water and steaam with a reservoir temperature of 198 °C.

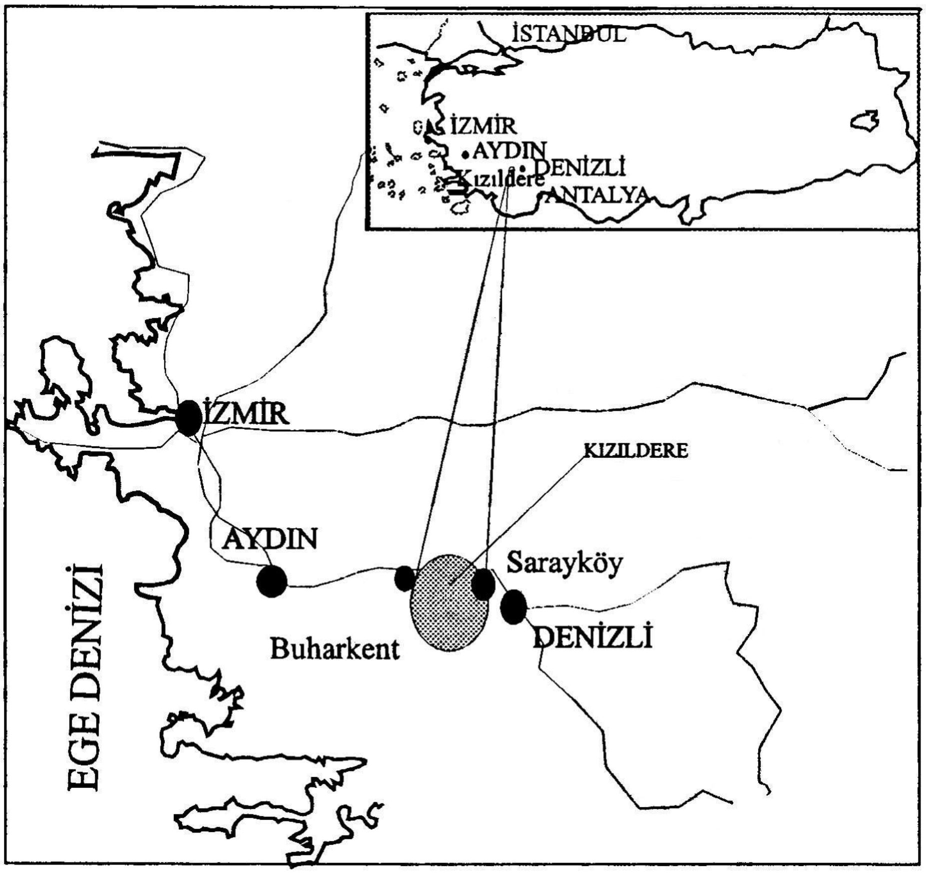


*Figure 53 – Kızıldere field is located on the western region of Turkey (cited in Yeltekin, 2002)*

During 1970's, total of 17 wells were drilled in accordance to develop the field. In 1984, Kızıldere Geothermal power plant was installed by Turkish Electricity Establishment which has a capacity of 20.4 MWe. Currently, the power plant is fed by eight producing wells. Table 7 and Table 8 gives detailed information on depth, elevation and temperature of the wells, well head pressure and temperature. (Yeltekin, et al, 2002).

In addition to the aforementioned wells, there are four monitoring wells in Kızıldere Geothermal field. Named KD-1A, KD-7, KD-8 and KD-9; locations of these wells are shown in Figure 16.

*Table 7 – Producing wells in Kızıldere geothermal field*

| *WELL* | *COMPLETION DATE* | *DEPTH (m)* | *ELEVATION (m) (Above sea level)* | *INITIAL TEMPERATURE (°C)* |
|---|---|---|---|---|
| KD-6 | 09.11.1970 | 851 | 187.73 | 197.5 (at 700 m) |
| KD-13 | 23.03.1971 | 760 | 189.29 | 196.5 (at 700 m) |
| KD-14 | 02.11.1970 | 597 | 197.02 | 207.9 (at 593 m) |
| KD-15 | 09.05.1971 | 510 | 211.05 | 205.7 (at 500 m) |
| KD-16 | 09.06.1973 | 667 | 201.03 | 209.1 (at 656 m) |
| KD-20 | 19.12.1985 | 810 | 194.60 | 204.4 (at 500 m) |
| KD-21 | 14.10.1985 | 898 | 194.60 | 208.9 (at 890 m) |
| KD-22 | 25.06.1985 | 888 | 193.35 | 201.4 (at 600 m) |

*Table 8 – Well Head Pressures and Total productions of producing wells in Kızıldere field (Yeltekin, et al, 2002)*

| | February 16, 1989 | | December 31, 2000 | | |
|---|---|---|---|---|---|
| WELL | WHP (kg/cm$^2$) | Q (t/h) | WHP (kg/cm$^2$) | Q (t/h) | TOTAL PRODUCTION ( ton ) |
| KD-6 | 15 | 37 | 13.3 | 91 | 7,849,032 |
| KD-13 | 15 | 64 | 13.6 | 91 | 8,515,330 |
| KD-14 | 15 | 94 | 13.3 | 117 | 10,389,768 |
| KD-15 | 14 | 115 | 13.6 | 131 | 11,552,856 |
| KD-16 | 15.5 | 151 | 14 | 168 | 15,693,960 |
| KD-20 | 15 | 92 | 14 | 107 | 11,392,416 |
| KD-21 | 15 | 63 | 10.8 | 109 | 10,970,448 |
| KD-22 | 15 | 68 | 13.6 | 108 | 9,687,720 |

## Geothermal Properties of Kızıldere Field

According to drilling data in Kızıldere geothermal field, production from wells KD-1, KD-1A, KD-2, KD-3, KD-4, KD-12 and KD-8 has been from the first reservoir rock of Pliocene limestones (Şimşek, 1985). KD-6, KD-7, KD-9, KD-13, KD-14, KD-15, KD-16, KD-20, KD-21, KD-22 wells are bearing second reservoir (İğdecik formation), cutting through sandstones instead of limestones. The thickness of the second reservoir varies between 100 and 300 m. When compared to the first reservoir rock, the second has relatively high secondary porosity and permeability combine with lateral continuity making it suitable for secondary recovery techniques such as water injection.

***Water Source***

Water supply of the field is mainly from precipitiation and from surface and underground water that flow into the basin through the major faults. After being heated in greater depths, water travels upwards to the reservoir through these bounding faults (Figure 54).

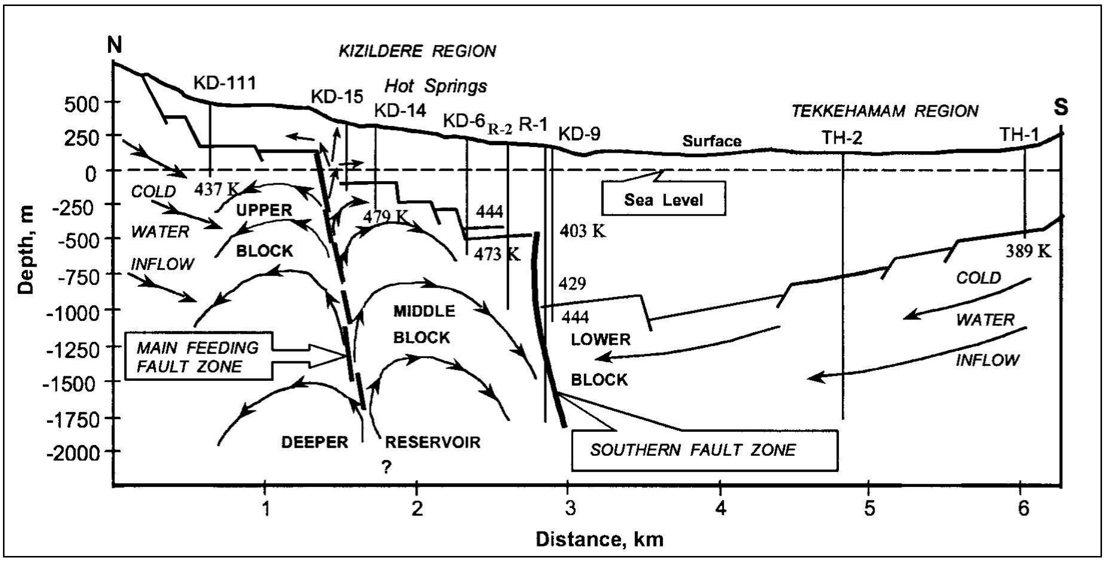


*Figure 54 – Water migration paths of Kızıldere geothermal Field (Yeltekin, et al 2002)*

***Reservoir Pressure***

In Kızıldere geothermal field aforementioned observation wells are used to constantly monitor the reservoir pressure. Reinjection of waste water back to the reservoir is the only solution to prevent the depletion of reservoir pressure. A reinjection project was prepared for this purpose in 1995 and MTA drilled 3 reinjection wells during the period 1996 and 2000. One of these wells is in the Tekkehamam area 3 km away and the others are near the Kızıldere Geothermal field. The well drilled in Tekkehamam (TH-2) is not suitable for reinjection because of low injectivity. The first reinjection well drilled in Kızıldere area (R-1) resulted with a high production capacity but low injectivity. It has a temperature of 243 °C and it is the best producer of Turkey. Its capacity is 6 Mwe. The second well drilled in Kızıldere area (R-2) showed good injectivity as well as good production capacity. It is planned to start reinjection from R-2 by the end of 2001. (Yeltekin, et al, 2002).