Application of Neural Network Meta-modeling to Steam Assisted Gravity Drainage Oil Recovery Processes

Najeh Alali, Mahmoud Reza Pishvaie[1], Vahid Taghikhani

Department of Chemical & Petroleum Engineering, Sharif University of Technology

Abstract – The production of highly viscose tar sand bitumens using Steam Assisted Gravity Drainage (SAGD) with a pair of horizontal wells has advantages over conventional steam flooding. This paper explores the use of artificial neural networks (ANNs) as a valid alternative to the traditional SAGD simulation approach. Feed forward, multi-layered neural network meta-models were trained through the back-error-propagation (BEP) learning algorithm to provide a versatile SAGD forecasting and analysis framework. The constructed neural network architectures were capable of satisfactorily estimating the recovery factors of the SAGD production as an enhanced oil recovery method. Rigorous studies around the hybrid static-dynamic structure of the proposed network were conducted to avoid the over-fitting phenomena. The FANN-based simulations were able to fairly capture the underlying relationship between several parameters/operational conditions and rate of bitumen production, which proves that ANNs are a viable tool for SAGD simulation.

Keywords: Artificial Neural Network, Meta-modeling, Enhanced Oil Recovery, Steam Assisted Gravity Drainage

Introduction:

Besides the oil and gas sources are going to be finished all over the world, but still oil has rested as the main energy source in the globe. This procedure would definitely continue till a near future. In the past, oil production engineers have been concentrating on the simplest methods of production. However, as the sources got old and their production went down, they started thinking about solutions in order to produce from reservoirs which had not been much considered before, such as heavy oil resources.

According to the estimation of reservoirs, only in US there are 125 milliards barrel of heavy oil in place [1, 2]. Besides, huge sources of heavy oil exist in different parts of the world like

[1] Corresponding Author, pishvaie@sharif.edu

Canada, Venezuela, China, Indonesia and also precedent Soviet. In order to deplete these amounts of heavy oil, modern methods are needed. One of these methods is a specific steam-drive (thermal) recovery method, named as Steam Assisted Gravity Drainage (SAGD)[3]. SAGD could be effective even in reservoirs containing highly viscous oil or bitumen [4] and have proven to be economically viable at a variety of pilot and commercial recovery projects [5, 6].

In the mechanism of SAGD, heavy oil or bitumen may be produced by the help of gravity power and injection of water vapor. Normally, in this mechanism a couple of horizontal wells are used, one for injection of steam and the other for production (Figure 1). Just as the steam enters the reservoir, it causes the oil and the rock aside to get warm. When oil gets warmer, its viscosity reduces more and more, and hence liquid flows toward producing well at the bottom of the reservoir because of gravity. In an ordinary SAGD process, the live steam is injected into the reservoir through the whole length of injecting well which is located exactly and drilled upon the producing well, and in essence a triangular space, the so-called steam chamber is formed around injecting well. Figure 2 provides a visual description of the process.

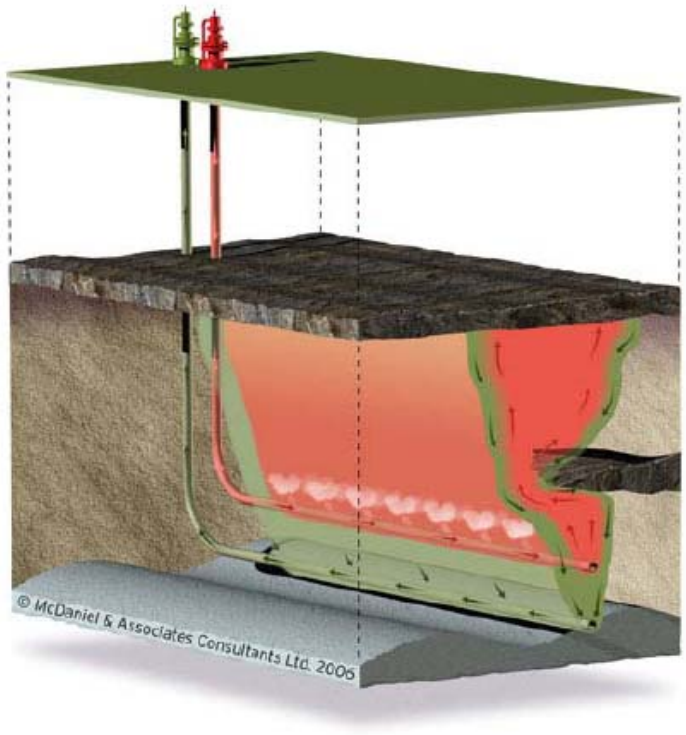

Figure 1. SAGD Principle, (courtesy of McDaniel)

In a reservoir where cold oil is very viscous and will not flow easily, initial production rates via SAGD are very low. Conceptually this makes sense when the SAGD process is visualized. In a strict definition of SAGD, steam only enters the reservoir to fill void space caused by produced oil. However, if the oil is cold and will not gravity drain into the wellbore at appreciable rates, we must heat the oil to reduce the viscosity so that it will flow. Therefore, initial heating (pre-heating) of the area around the wellbore is required so that SAGD can take place. Since project economics are sensitive to early production response, we are normally interested in optimizing the start-up procedure.

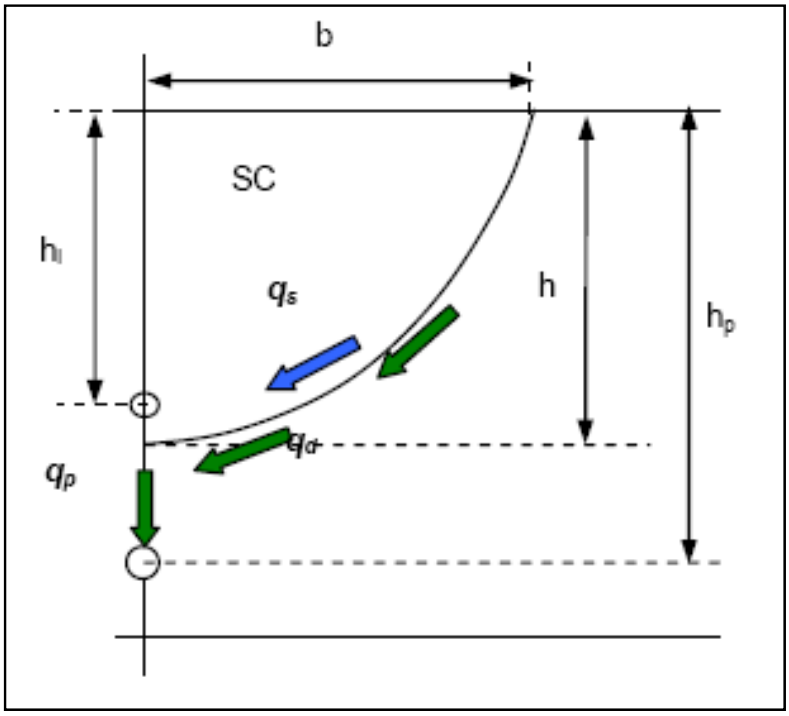

Figure 2. Schema of SAGD process. (SC: Steam chamber)

After starting the process a steam chamber is formed around injecting well which at first it expands upward (vertically) and finally horizontally. On the boundary of steam chamber, steam condenses. The liquefied vapor starts to move in steam chamber along with mobile oil to exit from producing well [7]. Joshi found out that the steam chamber right after it is formed, covers a great volume of the reservoir, and generally the production efficiency is to an accepted level high [8]. He gained the results by laboratory methods and under different patterns of injecting-producing wells.

One contribution to the simplification of the optimization and forecasting studies might consist of the development of a system that can perform a rapid evaluation of different alternatives, without the necessity of computer simulation expertise.

An artificial neural network (ANN) is one of the Artificial Intelligence (AI) techniques that have gained an important role in solving problems with extreme difficult or unknown analytical solutions. An ANN consists of an interconnected web of special units, called neurons, with associated connection weights that, after receiving a proper training, are capable of achieving a desired response to new inputs. Its ability of learning from examples makes ANN an extremely powerful programming tool when domain rules are not completely certain or when some amount of inaccuracy or conflicting data exist.

Simulation metamodeling is very important through artificial neural networks (ANNs), and provides general guidelines for the development of ANN-based simulation metamodels. Such guidelines were successfully applied in the development of two ANNs trained to estimate the manufacturing lead times (MLT) for orders simultaneously processed in a four-machine job shop [9].

The design of intelligent systems such as ANNs may help to avoid some of the drawbacks of traditional computer simulation. Metamodels offer significant advantages regarding time consumption and simplicity to evaluate multi-criteria situations. Their operation is notoriously fast compared to the time required to operate conventional simulation packages [10]. Further, the neural network could be used as a metamodels in many complex systems like: dispatching system (planning system of transport routes), multicommodity network and bank system with several cash registers [11]. However, the main purpose of simulation meta-modeling is to reduce the cost, time, and amount of effort required during a simulation analysis. A meta-model, or response surface, is an approximation of the input/output function implied by the underlying simulation model. It is usually a supplementary model that can be alternatively used to interpret a more detailed model.

Systems simulation has become a powerful decision-making instrument for SAGD processes. It requires a few simplifying assumptions, captures many of the true characteristics of the real model, and provides good insights about the interactions and relationships between qualitative and quantitative variables. However, a major shortcoming of simulation is the need for expert assistance any time a change is required in a model. Another drawback is encountering with probable high computational load, when conducting simulation runs through rigorous numerical simulators.

The performance of the SAGD process can be significantly affected by the selection of the geometrical and operational parameters. Examples of the former are the vertical spacing, lengths of the producer and injector wells, and the horizontal separation between well pairs. The latter include parameters such as steam-injected enthalpy, injection pressure, and

subcooling. Even though there have been significant contributions regarding screening of reservoir candidates [12, 13] (Singhal et al., 1996; Edmunds and Suggett, 1995), theoretical aspects [14, 15] (Butler, 1987, 1994), analytical and numerical modeling [15-17] (Butler, 1985; Reis, 1992; Scott Ferguson and Butler, 1988), laboratory experiments [18,19] (Yang and Butler, 1992; Nasr et al., 2000), the optimal or near optimal selection of the aforementioned parameters have been addressed only by a few sensitivity studies [20,21] (Kamath and Hatzignatiou, 1993; Kisman and Yeung, 1995).

Queipo [22], 2002 presented a solution methodology called neural network-based efficient global optimization (NEGO) for the optimization of the geometrical and operational parameters in a SAGD process. The solution methodology includes the construction of a ‘‘fast surrogate’’ of an objective function whose evaluation involves the execution of a time-consuming mathematical model (i.e. reservoir numerical simulator) based on neural networks. The parameters involved were only vertical spacing, injection pressure, steam-injected enthalpy, and subcooling.

In this project, all effective factors have been studied and their results for the first 10 years of production are entered in the neural network. The working of neural network is in this way that, according to the rate of recovery factor in three months, the rate of recovery factor of the 4^{th} month can be predicted and consequently we have reached a suitable network which could have provided a real scenario for the production of the first 10 years.

The objectives which are followed in this project are as followed. 1) Survey of parameters which are effective on primitive production in SAGD process. 2) Execution of sensitivity analysis of parameters relating to reservoir, well, liquid and rock and 3) Use of neural network.

The SAGD process, Parametric Sensitivity Analysis

In order to have a correct conception of operational variables to increase the rate of oil production in primary time, we should survey and investigate different methods of pre-heating around the wells and we should use the best of them. What that is clear to us is that, we should warm the area around the wells quickly as possible and with the best quality, so that the primary production becomes satisfactory. By using sensitivity analysis, we can measure the effect of reservoir parameters, fluid variables and different strategies of well accomplishment and their relation to these variables according to the rate of production.

In order to survey the production rate, we have compared several methods like cycle injection of steam and circulation of steam in the well. After the simulation of these processes in primitive time, the SAGD process was followed to the end which was continuous injection of water vapor from the upper injecting well and oil production from the lower producing well.

To do sensitivity analysis we have changed parameters by concerning a reference model (base case) and by simulating the process by using the simulator STARS we have surveyed and investigated the effect of those parameters. We have divided the parameters into four groups as follow:

1- Reservoir parameters: permeability ratio (k_h/k_v), thickness (h), drainage area (A) and initial pressure (p_i).

2- Liquid parameters: Oil gravity ($API°$), viscosity in the initial temperature (μ_{oi}), the temperature of water vapor (T_s, the rate of injecting vapor (q_{inj}) and steam quality (x).

3- Rock parameters: critical gas saturation (S_{gc}) and residual oil saturation (S_{or}).

4- Well parameters: distance between injecting and producing well (d_{ip}), well length (L_p), well radius (r_w), injecting well length to producing well length (L_p/L_{inj}) and skin factor (S).

Base case - Base reservoir model is indicative of specifications of one of the reservoirs of Alberta State of Canada. Operational characteristics and well completion are changing in a way that we can create many models, get their results and compare them by using the simulator. The base case is composed of a cube reservoir by the area of 10200m^2 and 50m thickness. Respecting the symmetry a half of the reservoir has been studied, in fact volume of producing oil is twice more than the produced volume. Other specifications of the reservoir, liquid and rock are brought in Table 1. The schematic plan of base case is also observed in Figure 3. Two horizontal wells by length of 850 m and radius of 8.6 cm are drilled in 235 and 247 m depths, from which the upper well the water vapor is injected and from the lower one, oil is produced.

The curves of PVT, permeability ratio and other properties such as water volume factor (B_w), density and viscosity of water phase, density, viscosity and gas solution for oil phase and also permeability ratio of water and oil phases have been prepared and were introduced to simulator.

Table 1. Base case properties

Variables	Values
Oil Gravity, $API°$	10.57
Reservoir coordinate in the X direction, m	120
Reservoir coordinate in the Y direction, m	850
Reservoir thickness, m	50
S_{gc}, %	5
S_{Wi}, %	20
S_{or}, %	15
k_x, md	3400
k_y, md	800
A, m^2	102000
P_i, psi	2100
h, m	50
r_w, m	0.0875
L_p, m	850
Reservoir type	Heavy Oil Conventional Reservoir
S	0

STARS simulator - STARS is one of the CMG software simulators which simulates the operations regarding steam injection, thermal processes and complicated processes of EOR. STARS provides a situation that we can have different kinds of liquid properties (PVT region), rock type and curves of permeability ratio related to each region in a reservoir.
Regardless of size and complexity of studying reservoir, STARS is a suitable tool that we can do the management studies of the reservoir by its use.

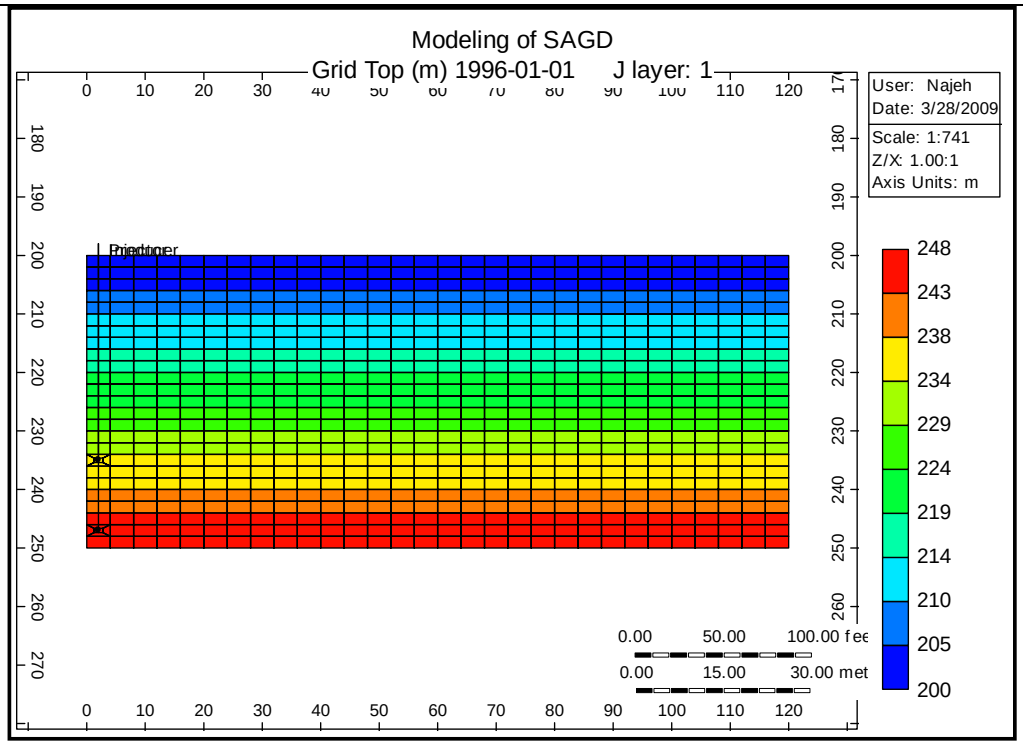

Figure 3- Base case model (cross view).

Optimal gridding- Prior to running several simulations, it is necessary to select the proper block sizes of problem domain. Seven cases with different gridding schemes were considered to select and tolerate the accuracy and low computational load. The explanations of these models including the number of grid blocks are depicted in Table 2.

Table 2. Different grindings properties

Local Grid Refinement (LGR)	Block Number	Gridding Type
No	23250	Non Uniform Fine Grid
Yes	23250	Non Uniform Fine-Hybrid Grid
Yes	7250	Non Uniform Medium-Hybrid Grid
No	750	Uniform Coarse Grid
No	21700	Uniform Fine Grid
Yes	21700	Uniform Fine-Hybrid Grid
Yes	7500	Uniform Medium-Hybrid Grid

When Peaceman [23] brought his method about the relation among well and reservoir grids, he used uniform gridding. But as we know the use of non uniform gridding can increase the accuracy of calculations without increasing the period of program execution. Further, in simulation of some events (such as conning) and in special conditions in reservoirs (such as layered ones), the use of non uniform gridding looks vital and necessary to preserve the stability and accuracy of simulation.

In Figures 4, the production oil rate during 10 years of simulation is drawn regarding the number of gridding.

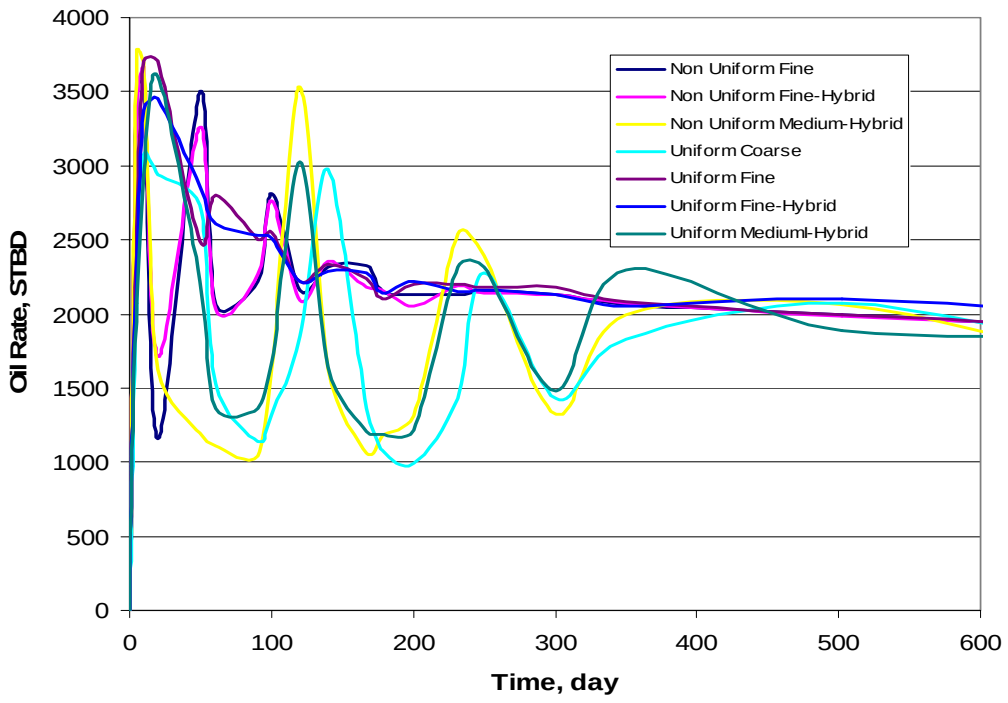

Figure 4- Effect of different grindings over oil rate.

According to the figure 4 we observe that by increasing the number of grids the rate of daily production in all cases except uniform fine grid and uniform fine hybrid in the first 300 days had fluctuation and it is indicative of incompatibility of the model with gridding system. Between these two gridding types, uniform fine hybrid grid is preferred. This is done because the Local Grid Refinement (LGR) option in STARS let the simulator solve the problem more accurate. This is the case in simulation of processes like SAGD that wells are horizontally drilled and further, by steam injection in a well, the pressure gradient and high temperature will be set up around it. The number of grids in this model is 21700 (62*14*25) and for the

grids where well is completed, are refined by local grid refinement method. Each grid is divided in radial type to two parts, in angular type to 4 parts and in axial type to one part.

The reservoir on which we study in the STARS simulator is actually a model composed from many patterns which have been previously developed in the field. Therefore, boundary condition requirement for simulation of each pattern is no flow. In simulation of the flow inside the well, the Discretized Wellbore (DW) technique which can model the pressure and temperature drop inside the well has been considered. It makes the results reliable and acceptable.

Preheating – Effective initial heating of the cold oil is important for the formation of the steam chamber in gravity drainage processes [24]. To enhance the slow process of SAGD, an early-time preheating is performed in which steam may be circulated in both wells. The freed space becomes filled with steam or hot water if high pressure is achieved. There are other methods of heating the reservoir. The methods include continuous steam injection into both wells, extreme pressure difference between injection and production well and cyclic steam injection into both wells. Each initial operating period will be followed immediately by SAGD; that is, continuous steam injection and oil production with injection and production rates roughly balanced.

For heating the surroundings of the wells prior to the SAGD phase, four methods have been simulated as the following:

1- Vapor circulation inside the wells for 200 days.
2- A vapor injection cycle from the upper well and the production from the lower one for 200 days.
3- Two vapor injection cycles for 200 days.
4- Three vapor injection cycles for 200 days.

In the vapor circulation method, the injecting and producing wells are circulated within 200 days by water vapor with the quality of 0.7 and temperature of 245C and injection rate 1000 cubic meters daily. In this method, the vapor enters into the wells from tubing and is produced from annuals. Using this circulation, an amount of heat in the form of conduction permeates into the surroundings of the wells resulting in the increased temperature and decreased viscosity accordingly.

The results of the simulations show that it is possible to improve the initial amount of production of the reservoir through pre-heating step. Generally, cyclic vapor injection has yielded better results compared to vapor circulation in the wells.

Parametric Study- In this section we intend to study the evolving parameters and their effects on the oil production using the SAGD method. As was mentioned earlier, one should change the parameters of the wells, fluid and reservoir rock to see how they affect the oil production using the SAGD method. The parameters have been categorized into 4 groups, leading to totally 15 items enumerated as below:

Group 1 (reservoir parameters):

1- k_h/k_vratio,
2- initial pressure (p_i),
3- thickness (h) and
4- drainage area (A)

Group 2 (fluid parameters):

1- API gravity
2- oil viscosity in the initial temperature of the reservoir (μ_{oi}),
3- injecting vapor temperature (T_s) ,
4- steam injection rate (q_{inj}) and
5- steam quality (x)

Group 3 (reservoir rock-fluid parameters):

1- critical gas saturation (S_{gc}) and
2- residual oil saturation (S_{or})

Group 4 (well parameters):

1- distance between injecting and producing wells (d_{ip}),
2- well length (L_p),
3- well radius (r_w),
4- ratio of injecting well length to producing well (L_p/L_{inj}) and
5- skin factor (s)

Each of above items was varied and deviated from the base case value, while the others remained constant to their original base case values. For totally 277 simulation sessions were run to study the relative effect of parameters on oil rate and its cumulative production (recovery factor). For all the scenarios, the time zero is considered when the preheating operation has been terminated. Amongst them, the most effective parameter was steam injection rate and the least one, was the API gravity parameter. However, due to space limit, only the corresponding graphs of steam injection rate are depicted in Figures 5 and 6.

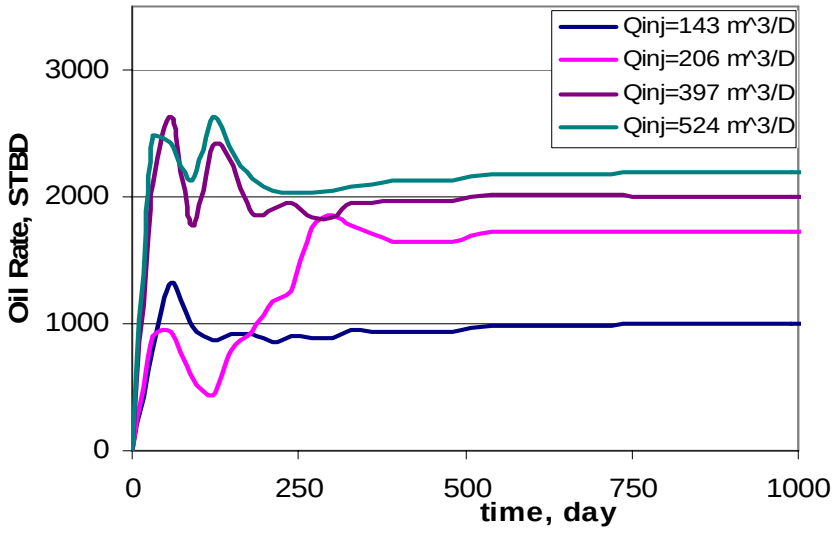

Figure 5- Influence of Steam Injection Rate on Oil Rate via SAGD.

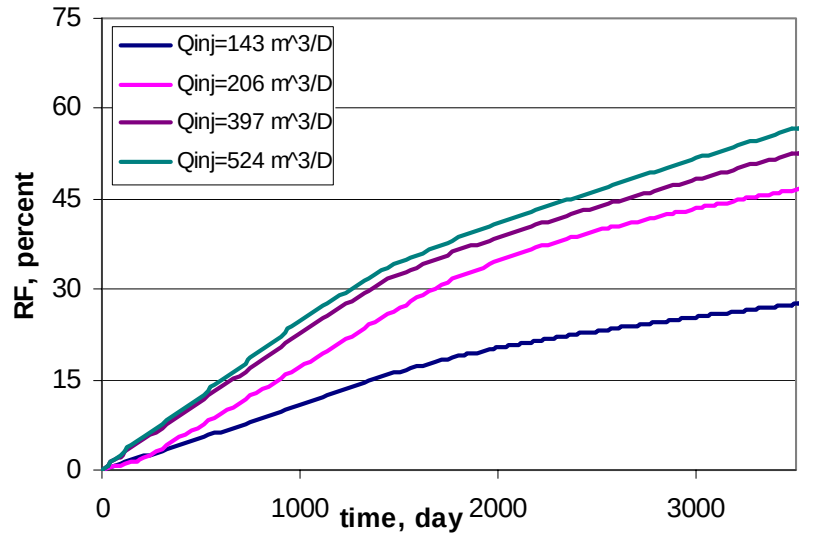

Figure 6- Influence of Steam Injection Rate on Recovery Factor via SAGD.

Neural network meta-modeler

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. Neural networks have been

trained to perform complex functions in various fields, including pattern recognition, identification, classification, speech, vision, and control systems. One can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. A trained network can perform the intended mapping of input space to output space in almost instantaneously fashion. Therefore, it can act as a meta-modeler instead of a running a time-consuming and rigorous simulator or modeler. The neuron model and the architecture of a neural network describe how a network transforms its input into an output. This transformation can be viewed as a computation.

To define our problem in the context of neuro-computing, we should arrange a set of input vectors. Then, we arrange another set of corresponding target vectors (the correct output vectors for each of the input vectors) into an appropriate database. However, the main objective is such that the trained net-modeler should be capable of predicting next month recovery factor for any probable combination of early-mentioned parameters, instead of running a professional, complex and time-consuming simulator such as STARS.

Data preparation for training- There are two basic types of input vectors: those that occur concurrently (at the same time or in no particular time sequence), and those that occur sequentially in time. For concurrent vectors, the order is not important, whereas for sequential vectors, the order in which the vectors appear is important. Concurrent inputs are appropriate for static networks while the sequential inputs are suitable for pure dynamic networks. However, the proposed network is specially designed in a mixed static-dynamic network. Therefore, the input data structure comprises of two parts; 16 parameters of well, reservoir and fluid properties, all taking part as factors or affecting parameters and three sequential producing well recovery factors of last three months, representing the dynamic feature of the SAGD process. This leads totally to a 19-dimensional input vector. The corresponding target vector (outputs) includes the current temperature and recovering factor. In summary, the proposed network maps the 19-dimensional input (16 parameters and the three past values of recovery factors) into the 1-dimensional output (current recovery factor) space, as below:

Input vector: $API°$, q_{inj},T_s , x, μ_{oi}, A, p_i, k_h/k_v, h, S_{gc}, S_{or} , d_{ip} , L_p/L_{inj}, L_p, r_w, s, RF_{k-1}, RF_{k-2} and RF_{k-3}

Output vector: RF_k

Neural network topology – Back-propagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. Standard back-propagation is a gradient descent algorithm, as is the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term back-propagation refers to the manner in which the gradient is computed for nonlinear multilayer networks.

Neural network structure includes 19 inputs, 35 neurons (for the time being) in hidden layer and one-element output. Activation function in hidden layer neurons is *tansig* and in output layer is *purelin* and finally it applies Error Back Propagation algorithm and training method of Levenberg-marquardt.

Training – Once the network weights and biases are initialized, the network is ready for training. The training process requires a set of examples of proper network behavior. During training the weights and biases of the network are iteratively adjusted to minimize the network performance function.

To train the proposed neural network, we used MATLAB software (NNET toolbox) and after determination of topology as recommended, we prepared the training vector pairs into two matrixes (input matrix and target matrix). Further, we should determine some parameters related to training algorithm. The most important parameters are Epochs number and the acceptable Error rate.

Improving Generalization – One of the problems that occur during neural network training is called over-fitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network

has memorized the training examples, but it has not learned to generalize to new situations.

One method for improving network generalization is to use a network that is just large enough to provide an adequate fit. The larger network we use, the more complex the functions the network can create. If a small enough network is used, it will not have enough power to over-fit the data. Unfortunately, it is difficult to know beforehand how large a network should be for a specific application. However, there are two other methods for improving generalization that are implemented in NNet Toolbox™ software: early stopping and regularization.

In the early stopping algorithm (the default technique in NNet Toolbox) the available data is divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on the validation set is monitored during the training process. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to over-fit the data, the error on the validation set typically begins to rise. When the validation error increases for a specified number of iterations (epochs), the training is stopped.

The test set error is not used during training, but it is used to compare different models. If the error in the test set reaches a minimum at a significantly different iteration number than the validation set error, this might indicate a poor division of the data set. However, according to the hybrid structure (static/dynamic) of the proposed network, it is very difficult to find an appropriate dividing criterion to separate the training, validation and test data set. Therefore, this technique was put aside in this work.

Another method for improving generalization is called regularization. This involves modifying the performance function, which is normally chosen to be the sum of squares of the network errors on the training set.

The typical performance function used for training feed-forward neural networks is the mean sum of squares of the network errors:

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

It is possible to improve generalization if the performance function is modified by adding a term that consists of the mean of the sum of squares of the network weights and biases:

$$msereg = \gamma mse + (1 - \gamma)msw$$

where γ is the performance ratio, and

$$msw = \frac{1}{n}\sum_{i=1}^{n}(w_i)^2$$

Using this performance function causes the network to have smaller weights and biases, and this forces the network response to be smoother and less likely to over-fit.

The problem with regularization is that it is difficult to determine the optimum value for the performance ratio parameter. If this parameter is assigned too large, we might get over-fitting. If the ratio is too small, the network does not adequately fit the training data. Therefore, it is desirable to determine the optimal regularization parameters in an automated fashion. One approach to this process is the Bayesian framework of MacKay [25]. In this framework, the weights and biases of the network are assumed to be random variables with specified distributions. The regularization parameters are related to the unknown variances associated with these distributions. We can then estimate these parameters using statistical techniques. A detailed discussion of the use of Bayesian regularization, in combination with Levenberg-Marquardt training, can be found in [26].

One feature of this algorithm is that it provides a measure of how many network parameters (weights and biases) are being effectively used by the network.

The algorithm generally works best when the network inputs and targets are scaled so that they fall approximately in the range [-1, 1]. That is the case for the proposed network here.

Analysis of NNet meta-modeler

In this research we produced and simulated the data of 277 injecting and producing pair well by CMG software and applied these results as input data on neural network. To produce mentioned neural network we used MATLAB. The neural network structure and the way we allocated input and target data mentioned in previous parts.

In this part we involve with analysis and optimization of neural network parameters. Here, we should notice that the neural network not to be affected by common errors of training like generalization and memorization.

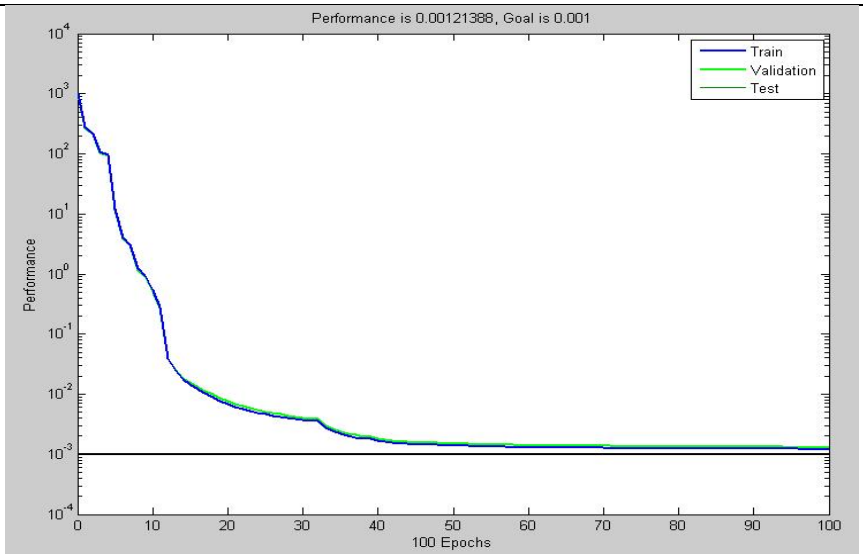

Figure 7. Neural network training diagram with 35 neurons in hidden layer

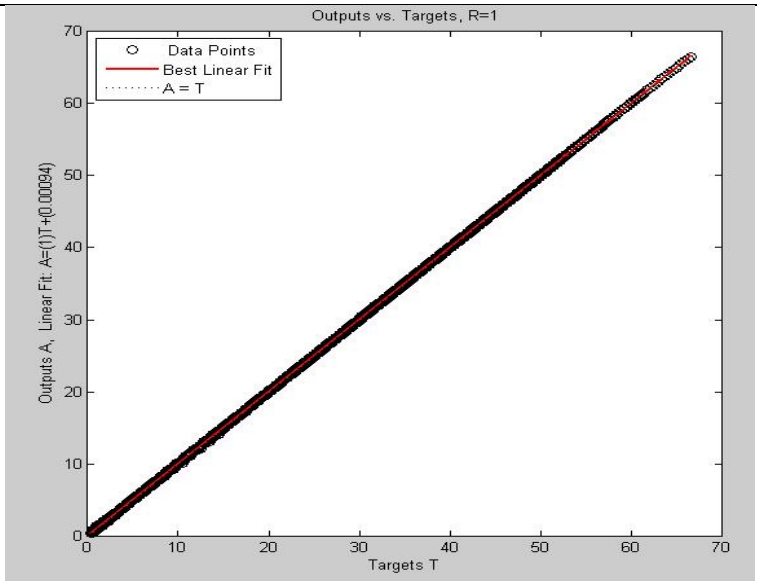

Figure 8. Comparison diagram of neural network output and real data related to test cases

In this research, first we consider a neural network with 19 inputs and 35 neurons in hidden layer and 1 neuron in output layer. Error threshold and epochs number are determined 0.001 and 100 times, respectively. Obtained results presented that neural network was well trained and in test stage provided very accurate results. Figures 7 to 9 show neural network results.

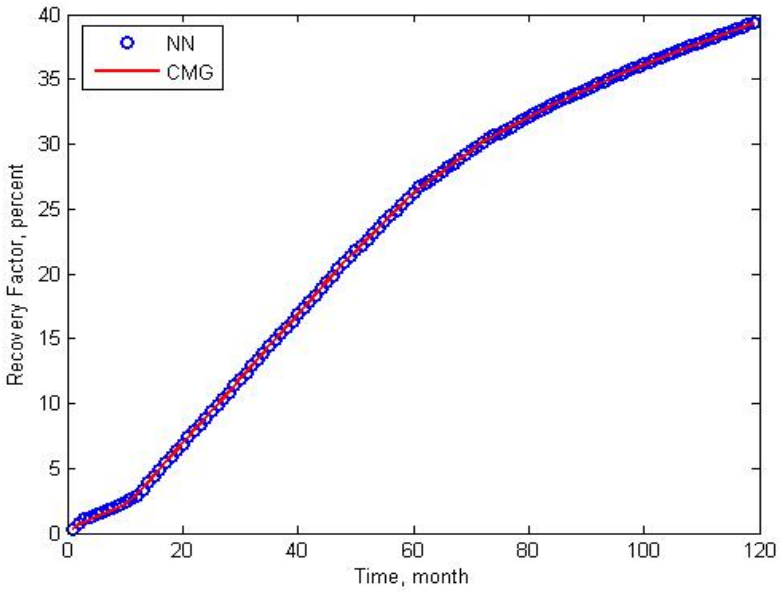

Figure 9. Comparison of recovery factor obtained from neural network and real one obtained from CMG for one of the 55 test cases.

By verifying neural network weights, it is found that the 35-neuron network had only considered some particular inputs. In other words, the networks may be involved in memorization error due to overtraining. By reduction of neuron number and also, the epoch number this problem can be solved. Therefore, the results led us toward the study of generalization power and over-fitting mirage. The results of training experiments, equipped by Bayesian regularization for several candidates of hidden layer nodes are depicted in Table 3. As it is clear, there is an optimum number of hidden layer (16 neurons in the hidden layer) at which the most generalization power occurs. It should be remarked that all the combination result to the same order of magnitude of *mse*, around 0.001.

Table 3 – The effect of node numbers in empowering the generalization.

Number of Nodes	Number of Parameters	Num. of effective Effective Parameters	% of efficiency
5	108	83	76.8
6	129	123	95.3
7	150	124	82.6
8	171	144	84.2
9	192	140	72.9
10	213	168	78.8
11	234	170	72.5
12	255	124	48.6
13	276	113	40.9
14	297	224	75.4
15	318	149	46.8
16	339	298	87.9
17	360	213	59.1
18	381	224	58.8
19	402	194	48.2
20	423	227	53.6
21	444	93	20.9
22	465	93	20.0
23	486	103	21.2
24	507	83	16.4
25	528	102	19.3
26	549	106	19.3
27	570	252	44.2
28	591	100	16.9
29	612	95	15.5
30	633	322	50.8
31	654	88	13.4
32	675	114	16.8
33	696	103	14.8
34	717	325	45.3
35	738	147	19.9

Discussion

Steam assisted gravity drainage (SAGD) maximizes the role of gravity forces during steam flooding of heavy oils. Generally, it is applied with a pair of horizontal wells. Since heat is transferred by conduction, convection, and latent heat of the steam in a complex manner, the simulation studies become a difficult and time-consuming task. Metamodel-based or black-box simulation as an alternative to rigorous modeling has been a major research field during the last decade. A primary conclusion reached here is that to improve and accelerate the performance of forecasting and/or optimization calculations, it is necessary to use a meta-modeler instead of a rigorous SAGD simulator. The sensitivity analysis performed here indicates that SAGD meta-modeler is applicable to the most of heavy oil reservoirs. The main novelties embedded in the proposed work include introducing a new hybrid (static/dynamic) structure of neural network and also the optimal selection of hidden layer neurons to avoid over-fitting.

Our analysis of the proposed network performance provided qualitative ideas on how to get the most use of neural network meta-modelers to estimate the SAGD production response. An obvious extension of this work is to capture the transient modes of SAGD performance when the steam injection rate is a time-varying variable. This is the case when preheating SAGD is a demanding issue or in a systematic and dynamic optimization sense, when an optimal policy for steam injection rate is required. There are also interesting issues regarding the SAGD process, temperature variation and steam-chamber development. The sensitivity analysis we performed provided insight into the effect of oil viscosity, reservoir thickness, and permeability anisotropy to name a few. However, short-circuiting between the injection and production sections still occurs; methods to reduce steam short-circuiting should be studied. Finally, cyclic steaming prior to SAGD is the most thermally efficient method of increasing the early-time response of SAGD. Optimizing the cyclic process and the number of cycles prior to SAGD is an important topic for future study.

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Nomenclature

B_w	Water volume factor, Rbbl/STB
S_{Wi}	Initial water saturation, %
k_x	Reservoir permeability in x direction, (md)
k_y	Reservoir permeability in y direction, (md)
k_z	Reservoir permeability in z direction, (md)
d_{ip}	Injector-Producer distance, (m)
S	Skin factor
S_{or}	residual oil saturation, %
S_{gc}	critical gas saturation, %
k_h	Horizontal permeability, (md)
k_v	Vertical permeability, (md)
L_{inj}	Injection well length, (m)
L_P	Production well length, (m)
A	Drainage area, m^2
h	Reservoir thickness, (m)
μ_{oi}	Viscosity in the initial temperature, (cp)
T_s	The temperature of vapor, ° C
p_i	Initial pressure, psi
q_{inj}	The rate of injecting vapor, (m^3/day)
x	Steam quality
r_w	Well radius, (m)
I	Inputs vector
T	Outputs vector
D	Unnormalized initial data
E	Neural network error